DISCUSSION PAPER SERIES

IZA

IZA DP No. 2455

U.S. Labor Market Dynamics Revisited

Eran Yashiv

November 2006

Forschungsinstitut
zur Zukunft der Arbeit
Institute for the Study
of Labor

U.S. Labor Market Dynamics Revisited

Eran Yashiv
Tel Aviv University, CEPR
and IZA Bonn

Discussion Paper No. 2455
November 2006

IZA

P.O. Box 7240
53072 Bonn
Germany

Phone: +49-228-3894-0
Fax: +49-228-3894-180
E-mail: iza@iza.org

IZA Discussion Paper No. 2455
November 2006

ABSTRACT

U.S. Labor Market Dynamics Revisited

The picture of U.S. labor market dynamics is opaque. Empirical studies of U.S. gross worker flows have yielded contradictory findings, and it is not easy to get a sense of the key moments of the data. Debates have emerged regarding the implications of these flows for the understanding of the business cycle. The early view was that worker separations from jobs are the more dominant cyclical phenomenon (relative to the hirings of workers), and that therefore it is important to analyze the causes for separations or job destruction. Later, this view was challenged by the claim 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 job finding rate. This paper aims at clarifying the picture, trying to determine what facts can be established, what are their implications for the business cycle, and what remains to be further investigated. The main findings are: (i) There is considerable cyclicality and volatility of both accessions and separations. Hence, both are important for the understanding the business cycle. The paper delineates the key business cycle facts of the labor market. (ii) The major remaining problems, in need of further study, are the disparities in the measurement of flows between employment and the pool of workers out of the labor force, disagreements on the relative volatility of job finding and separation rates across data sets, and the fact that the fit of the gross flows data with net employment growth data differs across studies and is not high.

JEL Classification: E24, J63, J64

Keywords: gross worker flows, labor market dynamics, job finding rate, separation rate, business cycle facts

Corresponding author:

Eran Yashiv
Naftali 052
Tel Aviv University
Tel Aviv 69978
Israel
E-mail: yashiv@post.tau.ac.il

U.S. Labor Market Dynamics Revisited[1]

1 Introduction

The picture of U.S. labor market dynamics and its implications for the study of business cycles remain disturbingly opaque. There are two, related issues of concern:

First, different empirical studies of U.S. gross worker flows and 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.

Second, debates have emerged regarding the implications of these worker flows for the understanding of the business cycle. The 'conventional wisdom,' based on the reading of Blanchard and Diamond (1989, 1990), Davis and Haltiwanger (1999), and Bleakley, Ferris, and Fuhrer (1999), was that worker separations from jobs are the more dominant cyclical phenomenon than hirings of workers, and that therefore it is important to analyze the causes for separations or job destruction. 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 (2005b), 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 job finding rate.

To add to these concerns, there is also disagreement as to how much the search and matching model – a key model in this context – can explain the data. Thus, for example, Mortensen and Pissarides (1994) extended the basic Pissarides (1985) model to cater for endogenous separations in order to capture the stylized facts on the importance of job destruction. But a number of subsequent papers claimed that the model does not fit the data well and that the key patterns of the data (to be fitted) are different from what Mortensen and Pissarides had in mind.

This paper aims at clarifying the picture. 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

[1] I am grateful to Fabiano Bastos, Wouter den Haan, and Robert Hall for useful conversations, to seminar participants at Tel Aviv University, the Bank of England, and the University of Bristol for useful comments, to Olivier Blanchard, Joe Ritter, Jeff Fuhrer, Hoyt Bleakley, Ann Ferris, Elisabeth Walat, Bruce Fallick, and Robert Shimer for the provision of their data, and to Gili Greenberg for able research assistance. Any errors are mine.

paper examines CPS data used by five key studies, as well as JOLTS data, and establishes the key facts.

The main findings are the following:

(i) Some of the disagreement in the literature stems from the fact that different worker flow concepts were used. In particular, while the earlier papers compared rates of hiring into employment and rates of separation from it, the more recent papers focused on job finding rates and on total separations from jobs, including job to job flows.

(ii) In terms of the data, while flows between employment and unemployment are measured similarly across studies, there are disparities in the measurement of flows between employment and the pool of workers out of the labor force. The fit of the gross flows data with net employment growth data differs across studies and is not high.

(iii) There is basic agreement across data sets and filtering methods on the cyclicality of flows: counter-cyclicality for flows between unemployment and employment, pro-cyclicality for flows between out of the labor force and employment, and counter-cyclicality for the aggregate flows. Job finding rates are pro-cyclical.

(iv) In terms of volatility, hiring rates are in the same order of magnitude as separation rates, but some studies find that the latter is somewhat more volatile, while others find the reverse.

(v) There are contradictory findings as to the volatility of the job finding rate vs. the separation rate across data sets and filtering methods.

(vi) There is some indication that the macro studies examined are partially consistent with micro-based studies. This point merits further study.

The paper proceeds as follows: Section 2 looks at the dynamic equations of the labor market and determines the key flows that need to be studied. It then summarizes the claims made in the literature regarding these flows. Section 3 discusses data sources and measurement issues. The latter discussion facilitates the explanation of the disparities across studies which use the same data source. Section 4 examines the data properties and undertakes cyclical analysis. It attempts to draw findings that are robust across studies, as well as to delineate the differences. Section 5 examines more closely some data features relating to the issues in contention. Section 6 lists key facts that can be agreed upon, as well as issues in need of further study. Section 7 concludes.

2 The Issues

I begin by looking at the equations describing gross flows (2.1). These serve to clarify the key concepts and variables to be examined. I then summarize (2.2) how the thinking in the literature on labor market dynamics has evolved.

2.1 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.

The evolution of employment proceeds according to the following equation

$$E_{t+1} = E_t + M_t^{UE+NE} - S_t^{EU+EN} \tag{1}$$

where E is the employment stock, M^{UE+NE} are gross hiring flows from both unemployment and out of the labor force and S^{EU+EN} are separation flows to these pools. In terms of rates this equation may be re-written as:

$$\frac{E_{t+1}}{E_t} - 1 = \frac{M_t^{UE+NE}}{E_t} - \delta_t^{EU+EN} \tag{2}$$

where $\delta = \frac{S}{E}$ is the separation rate from employment.

A similar equation holds true for unemployment dynamics:

$$U_{t+1} = U_t(1 - p_t^{UE}) + \delta_t^{EU} E_t + F_t^{NU} - F_t^{UN} \tag{3}$$

where U is the unemployment stock, p^{UE} is the job finding rate (moving from unemployment to 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).

This can be re-written:

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

In steady state there is a constant growth rate of unemployment at the rate of labor force growth to be denoted g^L:

$$\frac{U_{t+1}}{U_t} - 1 = g^L \tag{5}$$

Thus the unemployment rate is constant at $\overline{u}$:

$$\overline{u} = \frac{U}{L} \tag{6}$$

The dynamic equation (4) becomes:

$$g^L = -p^{UE} + \delta^{EU}(1 - \overline{u})\frac{1}{\overline{u}} + \frac{F^{NU} - F^{UN}}{L} \frac{1}{\overline{u}} \tag{7}$$

Hence steady state unemployment is given by

$$\overline{u} = \frac{\frac{F^{NU} - F^{UN}}{L} + \delta^{EU}}{p^{UE} + g^L + \delta^{EU}} \tag{8}$$

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

$$\overline{u} = \frac{\delta^{EU}}{\delta^{EU} + p^{UE}} \tag{9}$$

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

Note some 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 $\frac{M^{UE}}{E}$ and job finding rates $\frac{M^{UE}}{U}$; 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}, $\frac{F^{NU}-F^{UN}}{L}$ and g^{L}. In the next sections I study their behavior.

2.2 Interpretation of the Data

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. A number of studies recognized trends in the data: Ritter (1993) discussed a downward trend in gross job finding and separation rates that starts around 1984. Bleakley, Ferris, and Fuhrer (1999) too noted a trend decline in flows in and out of employment 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, Ferris, and Fuhrer (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 places the emphasis on comparing hiring rates $\frac{M^{UE}}{E}$ to the separation rate from employment δ^{EU}. But recently Shimer (2005b) and Hall (2005) claimed that separation rates are not as volatile as job finding rates p (not hiring rates) and that they can be taken roughly as constant (in detrended terms). These studies typically refer to the total separation rate $\delta^{EU+EN+EE}$, which includes job to job flows.

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, Ferris, and Fuhrer (1999) found that the flow into 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. Fallick and

Fleischmann (2004) noted that the cyclicality of the flow into employment is unclear, as it combines a countercyclical flow from unemployment to employment with a procyclical flow from not in the labor force to employment. They concluded that the total flow out of employment is probably weakly countercyclical in the United States.

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] He concluded that this necessitates a revised view of the labor market: during a recession unemployment rises entirely because jobs become harder to find. Recessions involve no increases in the flow of workers out of jobs. Another important finding from the new data is that a large fraction of workers departing jobs move to new jobs without intervening unemployment.

Shimer (2005b,c) 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. He concluded that the results contradict the conventional wisdom of the last fifteen 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 (2005b,c) focus on comparing p and δ, rather than $\frac{M}{E}$ and δ,and that – as noted above – they often refer to the total separation rate, including job to job flows.

In what follows I look at these characterizations and reconcile some of the differences.

[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 bit over 3 percent (p.12); the other is that the data on separations come from different sources showing different patterns and the evidence is not strong (p.15 and p.17).

3 The Data

Understanding U.S. data on labor market dynamics requires an appreciation of the measurement issues involved. I discuss the data sources (3.1) and then the key measurement issues (3.2). I go on to explain why these issues may lead to data series being computed differently on the basis of the same source (3.3).

3.1 Data Sources

There are two main sources for U.S. aggregate worker flow data: the CPS and JOLTS, both of the BLS. The CPS, available at http://www.bls.gov/cps/, is a household survey and offers a worker perspective. JOLTS data, available at http://www.bls.gov/jlt/home.htm, are based on a survey of employers. This data set includes monthly figures for hires, separations, quits, layoffs, and vacancies.

The CPS is the main basis for the data sets to be analyzed below. These data were computed and analyzed by Blanchard and Diamond (1989, 1990), Ritter (1993), Bleakley, Ferris and Fuhrer (1999),[3] Fallick and Fleischmann (2004), and Shimer (2005b).[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.

JOLTS data were reported and discussed by Hall (2005). I take the JOLTS data from the BLS website.

3.2 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

[3] Updated further till 2003:12.

[4] A summary of data sources and a discussion of them is to be found in Farber (1999), Davis and Haltiwanger (1998,1999), Fallick and Fleischmann (2004) and Davis, Faberman, and Haltiwanger (2006).

doing so. Thus, while such flows have been tabulated monthly from the CPS since 1949, the BLS has not published them because of their "poor quality." More specifically, missing observations and classification error were noted. These issues are discussed in detail in Abowd and Zellner (1985) and in Poterba and Summers (1986), who offer corrective measures. Additional issues involve methods of matching individuals across months, weighting individuals, aggregation across sectors and over time, survey methodology changes (in particular the 1994 CPS redesign), and seasonal adjustment. The above two studies, as well as the five studies which data are examined here, offer extensive discussion. Therefore, in what follows I just briefly note the main measurement problems.

3.2.1 Missing Observations and Misclassification

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 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.

3.2.2 Time Aggregation

Shimer (2005b) discusses the issue of time aggregation. To see the problems involved, he presents the following dynamic equation for unemployment in continuous time:

$$\dot{u}_{t+\tau} = e_{t+\tau}\delta_t - u_{t+\tau} f_t$$

where δ and f are the instantaneous separation and job finding rates, respectively. Solving this equation forward he gets:

$$u_{t+1} = \frac{(1 - e^{-f_t - \delta_t})\delta_t}{f_t + \delta_t}(u_t + e_t) + e^{-f_t - \delta_t} u_t \tag{10}$$

To relate his framework to the discrete framework used in Section 2 above, assume $F_t^{NU} - F_t^{UN} = 0$ and note the following definitions:

$$\begin{aligned} f_t &\equiv -\ln(1 - p_t^{UE}) \\ \delta_t &\equiv -\ln(1 - \delta_t^{EU}) \end{aligned} \tag{11}$$

Comparing the continuous time equation (10) to the discrete time equation (3), Shimer (2005b) notes that the former allows workers to lose a job and find another, or vice versa, within the period. This means that the distinction between the equations is quantitatively important for the transition probability and its cyclicality. Hence, when the job finding rate f_t is high, equation (10) captures the fact that a worker who loses a job is more likely to find a new one without experiencing a measured spell of unemployment. As these separations are missed in equation (3), the latter yields fewer separations and a negative bias in the measured correlation between the job finding and separation rates. Shimer notes that ignoring time aggregation biases the findings towards a countercyclical separation probability, because when the job finding probability falls in recessions, a worker who loses a job is more likely to experience a measured spell of unemployment.[5]

[5] In the empirical work Shimer (2005b) employs the following procedure:

(i) He constructs time series of gross worker flows, using Joe Ritter's tabulation of the gross flows from June 1967 to December 1975 and the monthly CPS public-use microdata from 1976 to 2005. He computes the sample-weighted transition probabilities between labor market states during the relevant month and seasonally adjusts the time series using a ratio-to-moving average technique. This gives series for the six gross flows, labelled $N_t^{XY}(\tau)$ with X, Y denoting the states of employment, unemployment and out of the labor force, X denoting the state at t, Y denoting the state at $t+\tau$. This computation sets $\tau = 1$.

3.3 Why data series may differ

In the next section I present an analysis of five data sets, all computed by the different authors on the basis of raw CPS data. They turn out not to be the same. Why 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, pages 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 misclasssification substantially reduce the transitions between labor market states. The N - E flows have the largest reduction, almost 50 percent. Likewise, Shimer's (2005b) framework (discussed above) caters for time aggregation and leads to the capturing of more transitions relative to the other data sets that do not deal with this issue.

Application of adjustment methods may vary. The different authors have not used the same corrections of the data. One revelatory example is the following passage from Bleakley et al (1999, page 75):

"In order to apply Abowd and Zellner's adjustments to the gross flows, we obtained adjusted gross flow data for January 1968 to May 1986 from Olivier Blanchard (Blanchard and Diamond 1990). The data have been Abowd-Zellner adjusted, using the reinterview surveys, and are not seasonally adjusted. By dividing these adjusted data by the raw gross flows, we obtained the multiplicative adjustment factors for each month from January 1976 to May 1986...Adjusting the data

(ii) He then defines the associated share of workers who were in state X at t by $n_t^{XY}(\tau) = \frac{N_t^{XY}(\tau)}{\sum_z N_t^{XZ}(\tau)}$. Using the six $N_t^{XY}(1)$ obtained above, he gets $n_t^{XY}(1)$.

(iii) He defines the shock that moves a worker from state X to state Y by λ_t^{XY} so that $\Lambda_t^{XY} = 1 - e^{-\lambda_t^{XY}}$ are the transitions probabilities.

(iv) He then numerically solves the following differential equation system for the λ_t^{XY} and consequently for Λ_t^{XY} :

$$\dot{n}_t^{XY}(\tau) = \sum_z n_t^{XZ}(\tau)\lambda_t^{ZY} - n_t^{XY}(\tau)\sum_z \lambda_t^{YZ}$$

In what follows I use Shimer's time series on the transition rates λ_t^{XY} and the transition probabilities Λ_t^{XY} thus obtained, focusing on the latter.

after May 1986 proves to be a difficult issue because Abowd and Zellner have not updated their series and we do not have the reinterview survey information to extend their findings. Based on the adjustment information we do have, the adjustment factors do change over time. We have estimates of misclassification for 1994 and 1995 from the BLS, which indicate that the 1994 misclassification rates differ dramatically from those for the 1976–86 period. Most error rates dropped substantially, with the exception of those between N and U. Therefore, to accurately adjust the gross flows using reinterview data, we plan on obtaining reinterview survey data from 1986 to the present. For this paper, we have chosen to use the mean adjustment for the period February 1976 to May 1986 for each seasonally adjusted transition (flow).”

This passage makes it clear that Abowd-Zellner adjustments depend on time-varying factors, with the possible result that they will be applied differently by different authors. Moreover, Bleakley et al (1999) use 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 X-11 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 (2005b) 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.

4 Data Properties

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. Some of these are well-cited studies, so the idea is to clarify the picture as to where they concur and where they differ. 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 in 3.3 above. I present the first two moments (4.1) and then undertake cyclical analysis (4.2). Subsequently I look at the dynamics of unemployment and their relation to the job finding and separation rates (4.3).

4.1 Key Moments of the Gross Flows Data

The following summarizes the data availability from the different sources:

		BD	**Ritter**	**BFF**	**FF**	**Shimer**	**JOLTS**
hiring rates	$\frac{M^{UE}}{E}$	✓	✓	✓	✓	√	NA
	$\frac{M^{NE}}{E}$	✓	✓	✓	✓	NA	NA
	$\frac{M^{UE}+M^{NE}}{E}$	✓	✓	✓	✓	NA	✓
job finding rates	$p^{UE}=\frac{M^{UE}}{U}$	✓	✓	✓	✓	✓	NA
separation rates	$\frac{S^{EU}}{E}$	✓	✓	✓	✓	✓	NA
	$\frac{S^{EN}}{E}$	✓	✓	✓	✓	✓	NA
	$\frac{S^{EU}+S^{EN}}{E}$	✓	✓	✓	✓	✓	✓

where NA indicates 'not available,' and the superscripts denote the states between which the flows occur.[6]

Table 1 presents the first two moments of the flows based on these data and Figures 1-6 show their time series plots.[7] The figures include the NBER-dated recessions that are analyzed in the next sub-section.

Table 1 and Figures 1-6

The key findings are as follows.

Flows from Unemployment. Table 1 and Figure 1 indicate that:

a. The monthly hiring rate ($\frac{M^{UE}}{E}$) is around 1.5%-1.7%, with a standard deviation of 0.1%-0.3%. Four series give a very similar picture. The series from Shimer (2005b), with a 2% mean,

[6] In the case of the Shimer (2005b) data, for the most part I use one data set based on the computation described in 3.2.2.above. 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.

[7] While all data series are originally monthly, where noted they are presented as quarterly averages in monthly terms.

is somewhat higher than the four others. This is probably due to the fact that he captures more transitions by correcting for time aggregation.

b. The monthly job finding rate ($p^{UE} = \frac{M^{UE}}{U}$) is around 25%-32% on average. The series from Shimer (2005b), with a 32% mean, is again somewhat higher than the four others. These numbers imply quarterly rates of around $60\% - 70\%$. The average monthly volatility of this rate is around 3%-6%.

Flows from Out of the Labor Force. Using flows from out of the labor force to employment, Table 1 shows hiring rates $\frac{M^{NE}}{E}$ and Figure 2 plots the series. There are no comparable, publicly available data from Shimer. There seem to be two data sets here: Blanchard and Diamond (1989) and Bleakley et al. (1999), report mean hiring rates of 1.3%-1.5% and standard deviation of 0.1%-0.3%. The other two data sets span different sample periods but indicate mean hiring rates of 2.5%-2.9% and standard deviation of 0.2% or 0.4%.

Total Hires. Summing up the above flows into employment, Table 1 and Figure 3 report the findings of the various studies. The total hires flows reflect the differences between the data sets as discussed above. There is one addition, though, and that is JOLTS. While it has a mean rate of 3.2% and standard deviation of 0.2%, similar to Bleakley, Ferris and Fuhrer (1999), it has a negative correlation of -0.22 with the latter series.[8]

Flows from employment to unemployment. Table 1 shows the separation rate δ^{EU} for the various studies while Figure 4 plots the series. The table and figure indicate that the monthly separation rate into unemployment is around 1.3%-1.5% on average for all studies, except Shimer who puts it at 2%, again because of the treatment of time aggregation. The former imply quarterly separation rates of around 4%, while the latter implies 5.9%. Its volatility is around 0.1%-0.3% in monthly terms according to all studies.

Flows from Employment to Out of the Labor Force. Using flows from employment to out of the labor force, Table 1 shows the separation rate δ^{EN} for the various studies, while Figure 5 plots the series. The different data sets again seem to suggest different moments: a monthly mean ranging from 1.5% to 3.2% and a standard deviation ranging from 0.2% to 0.5%.

[8] It should be remarked, though, that there are only 49 overlapping monthly observations for these two series.

Total Separations. Summing up the two separation flows out of employment, Table 1 and Figure 6 report the findings of the various studies, now including JOLTS. As in the case of total hires, the total separations flows reflect the differences between the data sets discussed above; and, again, there is the addition of the JOLTS data set. The picture that emerges is the following: the mean separation rate ranges from around 3% a month according to three sources to as high as 5% according to Shimer. The standard deviation ranges from a low of 0.15% according to the JOLTS data to as high as 0.47% according to Shimer.

Comparing the Data Sets. The afore-going 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.

Table 2

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 high, as can be expected from the discussion above. Panel (b) looks at total flows – both between U and E and between N and E – in terms of $\frac{M}{E}$ and δ. Here the pairwise correlations are much lower, reflecting the different computations of the flows between N and E.

JOLTS vs CPS data. JOLTS data are available only from the end of 2000. The total hiring rate and the total separation rate for this source and the three relevant studies are shown for the period starting at that time in Figure 7.

Figure 7

The figure indicates that the discrepancies across data series are not reconciled by the JOLTS series, which describes a different pattern. Notably, in the 2001 recession, the hiring rate rose according to Bleakley, Ferris and Fuhrer (1999) and Fallick and Fleischman (2004) but fell according to JOLTS; the separation rate rose and then fell according to Shimer (2005b) and Fallick and Fleischmann (2004), stayed roughly constant according to JOLTS, and rose, fell, and rose again according to Bleakley, Ferris and Fuhrer (1999). Panel (b) of Table 2 also indicates that JOLTS has low, sometimes even negative, correlations with the CPS-based series.

4.2 The Cyclical Behavior of Flows

A key issue in the literature is the cyclical properties of these flows. Table 3 reports correlations and relative standard deviations of hiring rates (U to E, N to E, and both U and N to E), job finding rates,[9] and separation rates (E to U, E to N, and E to both U and N) with real GDP. It uses four alternative detrending methods (all on the logged series): first differences, the HP filter with the standard smoothing parameter ($\lambda = 1600$), with a low frequency filter ($\lambda = 10^5$), and the Baxter-King band-pass filter. Figure 8 plots selected series, including plots of the filter i.e., of the trend series.

Table 3 and Figure 8

Note that, looking back at equation (9), there are two key variables determining the steady state unemployment rate: the job finding rate p^{UE} and the separation rate δ^{EU}. If one considers the relevant pool of unemployment to be bigger than the official pool, then the relevant p and δ pertain also to flows related to the pool of workers out of the labor force. As discussed above, these two variables have received special attention in the literature but the emerging picture is confusing. In particular, it is not clear whether separation flows are more volatile and cyclical, and therefore are the dominant element in accounting for labor market dynamics as claimed by some studies, or whether job finding rates fulfill this role, while separation rates are acyclical and not as volatile, as claimed by others. The table and the figure indicate the following patterns:

Trends. Starting from the trend, it is clear that there is a monotone downward trend in the separation rate δ^{EU} and that there are protracted periods of rise or fall in p^{UE}. In this sense none of these variables can be taken to be constant over time.

Filtering effects. As to the cyclical series, the table 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 (over and beyond seasonality). Note, too, that the key comparison –

[9] It is not obvious what would be a correct measure of aggregate p, i.e. incorporating both p^{UE} and p^{NE}. See the discussion in Section 5.1 below.

the one between p and δ – depends on the filtering method.

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

(i) Hiring rates from unemployment to employment ($\frac{M^{UE}}{E}$) are counter-cyclical, while hiring rates from out of the labor force to employment ($\frac{M^{NE}}{E}$) are pro-cyclical. Summing up the two ($\frac{M^{UE}+M^{NE}}{E}$) yields a flow that is moderately counter-cyclical. This can be seen graphically in Figures 1a, 2 and 3 for the NBER-dated recessions.

(ii) Job finding rates from unemployment to employment (p^{UE}) are pro-cyclical. This can be seen graphically in Figure 1b for the NBER-dated recessions.

(iii) Separation rates from employment to unemployment (δ^{EU}) are counter-cyclical, 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 counter-cyclical. This can be seen in graphically Figures 4,5, and 6 for the NBER-dated recessions.

(iv) The cross correlation analysis of panel f in Table 3 indicates that these cyclical patterns hold true at leads and lags of up to six months. This means that job finding is pro-cyclical, separation is counter-cyclical (for EU and EU+EN) and pro-cyclical (for EN) at lags and leads of up to six months.

Volatility. Across studies the following holds true:

(i) Hiring rates $\frac{M}{E}$, job finding rates p, and separation rates δ are highly volatile, roughly 2 to 4 times the volatility of real GDP.

(ii) Hiring rates from unemployment to employment ($\frac{M^{UE}}{E}$) are less volatile than the corresponding separation flows (δ^{EU}).

(iii) The reverse if true for flows between out of the labor force and employment (i.e., $\frac{M^{NE}}{E}$ is more volatile than δ^{EN}).

(iv) The sum of the hiring flows ($\frac{M^{UE}+M^{NE}}{E}$) 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, Ferris and Fuhrer (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 (2005b) data indicate that for most filtering methods the opposite holds true, i.e. p^{UE} is more volatile than δ^{EU}. However, even for the latter, it is important to note that the volatility of aggregate job finding p^{UE+NE} is very similar to that of aggregate separations δ^{EU+EN}.

4.3 Unemployment Dynamics, Job Finding Rates, and Separation Rates

What are the implications of the cyclical findings above for the evolution of unemployment? Rewriting equation (4) I get:

$$\frac{U_{t+1}}{U_t} - 1 = -p_t^{UE} + \frac{\delta_t^{EU}}{\frac{U_t}{E_t}} + \frac{F_t^{NU} - F_t^{UN}}{U_t} \tag{12}$$

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. Figure 9 plots these series (using the Bleakley, Ferris and Fuhrer (1999) data):

Figure 9

It is clear from the graph that main elements of this equation, in terms of mean and variance, are p_t^{UE} and $\frac{\delta_t^{EU}}{\frac{U_t}{E_t}}$. Hence the following is a reasonable approximation:

$$p_t^{UE} = k + \frac{\delta_t^{EU}}{\frac{U_t}{E_t}} + \epsilon_t \tag{13}$$

with k a constant and ϵ_t a random error. Figure 10 shows this equation; it is a scattergram of the two variables p_t^{UE} and $\frac{\delta_t^{EU}}{\frac{U_t}{E_t}}$ together with a regression line

Figure 10

In a boom (recession) $\frac{U_t}{E_t}$ and δ_t^{EU} are both low (high). Because the former has the stronger effect, the ratio $\frac{\delta_t^{EU}}{\frac{U_t}{E_t}}$ is high (low) and so is the job finding rate. This is an expression of the pro-cyclicality of p and counter-cyclicality of δ discussed above, in conjunction with the well known counter-cyclicality of the unemployment rate $\frac{U_t}{E_t}$. Unemployment growth ($\frac{U_{t+1}}{U_t} - 1$) is then fairly stable, as p_t^{UE} and $\frac{\delta_t^{EU}}{\frac{U_t}{E_t}}$ 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).

5 Some Features of the Data

I take a closer look at some of the features of the data, in light of the issues in contention, as described in the introduction.

5.1 The Job Finding Rate and Flows from Out of the Labor Force to Employment

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. Noting that this rate is $p = \frac{M}{U}$ the preceding discussion raises two issues: first, there are discrepancies in the measurement of the numerator M (between N and E); second, there is a question as to size of the relevant pool in the denominator. 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 sub-section 3.3 above. Thus, flows series are measured differently across studies, probably due to the different adjustment methods used. As Table 1 indicates, these flows, between the out of the labor force and employment pools, are sizeable: unemployment to employment flows are on average 1.9 million workers per month, while out of the labor force to employment flows are 1.5 million workers per month on average.

The second issue, namely what is the "correct" pool in the denominator, has received attention in the literature. To note some prominent examples, Clark and Summers (1979) have argued that there is substantial misclassification of unemployment status and that "many of those not in the labor force are in situation effectively equivalent to the unemployed" (p.29), providing several measures to substantiate this claim. Flinn and Heckman (1983) proposed to assess the equivalence of two labor market states by testing whether the transition probabilities out of the two states are equal, either unconditionally or conditional on a set of explanatory variables.[10] 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 first group (see their Figure 1), ranging between 20% and 35%, which is in line with the results of Table 1a. Their estimated monthly transition rates into employment for the other two groups, the marginally attached and the unattached, ranges from about 10% to 20% for the former and about 4%-5% for the latter. Shimer (2005b) has an average of 4.2% for the out of the labor force job finding rate in this period.[11] This comparison suggests that the latter job finding rate may be too low and that a more comprehensive micro-macro comparison study is called for.

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

This last discussion suggests that flows between out of the labor force and employment may be important. It is therefore natural to ask if all flows in and out of this pool (N) are important. Note that the pool out of the labor force is sizeable: 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% of the employment pool; over time this ratio declined to 51%.

Table 4 looks at the first two moments of all the flows to and from this pool, scaled by the relevant stock, at their cyclical properties, and at the net flows disaggregated into the gross flows. The flows are denoted F^{XY} which indicates flow from state X to state Y, and where the states are E, U and N.

Table 4

Panel a shows that the monthly gross flows have a mean of 2%-3% of the employment stock,

[10] For recent treatment of this issue, albeit with Canadian data, see Jones and Riddell (2006).

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

i.e., in the same order of magnitude as the separation flows from employment; their volatility is similar too. The net flows are much lower on average and are much less volatile.

Panel b shows that gross flows between N and U are counter-cyclical 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. The volatilities of the different gross flows are of the same order of magnitude..

Panel c shows that the gross flows are 13 to 22 as big on average as the net flows, with the largest being the E to N flow; the gross flows are 3 to 4 times as volatile (in terms of variance) as the net flows. It also shows that 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 two sets of facts are related: the net flows have much lower magnitude, in terms of the two first moments, because the gross flows offset each other.

5.3 How Much Are Net Flows Explained?

One way to gauge the validity of the various studies is to compute the BLS net employment growth series $\frac{E_t}{E_{t-1}}-1$ and compare it to the predicted series, using the RHS of (2) i.e., $\frac{M_t^{UE}+M_t^{NE}}{E_t}-\delta_t^{EU+EN}$. This is reported in Table 5.[12]

Table 5

The first panel shows some relevant moments, for each series in its own sub-sample 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 a R^2 value of around 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, Ferris and Fuhrer (1999) – that have reasonably close moments (mean and standard deviation) to the actual ones.

The second panel looks at these last two series. This panel relates to the relevant sub-period of the sample, considering the actual and predicted series as well as the residual, which is obtained

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

by subtracting the measured $\frac{M_t^{UE}+M_t^{NE}}{E_t} - \delta_t^{EU+EN}$ from actual $\frac{E_t}{E_{t-1}} - 1$. For the Blanchard and Diamond (1989) series the residual is zero on average and the standard deviation of the predicted series is 81% 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 Durbin Watson statistic reported in the first panel. In the third panel this impression is reinforced using Ljung-Box Q-statistics and their p-values. For the Bleakley, Ferris and Fuhrer (1999) series the residual is somewhat higher than zero on average, and the standard deviation of the predicted series is 66% of the actual one. But this last 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 show 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% of the variance of actual net growth. One possible reason for these discrepancies is that while all series are seasonally adjusted, the gross flows are seasonally adjusted individually. Thus a linear combination of these adjusted gross flows ($\frac{M_t^{UE}+M_t^{NE}}{E_t} - \delta_t^{EU+EN}$ each flow adjusted separately) does not necessarily yield the same series as the adjusted total net flows (the same expression, $\frac{M_t^{UE}+M_t^{NE}}{E_t} - \delta_t^{EU+EN}$, seasonally adjusted as one expression).

6 Determining U.S. Labor Market Facts

In order to determine U.S. labor market facts that can be agreed upon so as to guide modelling, I present a list of facts that are supported across studies (6.1) and a list of open issues left for further study (6.2).

6.1 U. S. Labor Market Facts

There is basic agreement across data sets and filtering methods that:

(i) Hiring rates and separation rates are counter-cyclical for flows between unemployment and employment, pro-cyclical for flows between out of the labor force and employment, and counter-cyclical for aggregate flows.

(ii) Job finding rates are pro-cyclical.

(iii) In terms of volatility, hiring rates are of the same order of magnitude as separation rates.

(iv) Despite disagreements noted below, the volatilities of p and δ in the aggregate (UE+NE and EU+EN) flows are also similar.

(v) All these rates – hiring, job finding, and separation – are highly volatile, in the order of 2-4 times the volatility of real GDP. Cross correlation analysis indicates robustness of the cyclicality patterns at leads and lags of up to 6 months.

Taken together these facts imply that there is considerable cyclicality and volatility of both accessions and separations. Hence, both are important for the understanding the business cycle.

6.2 Areas of Disagreement

As the discussion above has revealed, there are issues not agreed upon that merit further investigation.

(i) While flows between employment and unemployment are measured similarly across studies, flows between N and E are problematic:

a. The series are not the same across data sets.

b. The data are only partially consistent with micro-based studies.

(ii) Shimer's (2005b) treatment of the data indicate that time aggregation is an issue to be considered, otherwise some transitions are not well captured.

(iii) The fit with net employment growth data differs across studies and is not high.

(iv) There are basically two contradictory findings as to the volatility of p vs. δ 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 (2005b) data find that the reverse holds true. There are cases where the results seem to be in between these two extremes. But, as noted, the volatilities of aggregate rates for p and δ are similar.

These discrepancies and inconsistencies are probably due to the different adjustment methods discussed above. 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.

7 Conclusions

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.

Among the former, the following are the key points: some of the disagreement in the literature is the result of comparing different concepts; in particular some authors studied total separations, including job to job flows, while others looked at separations from the employment pool; the key moments of the flows between the employment and unemployment pools were found to be similar across studies; a set of clear business cycle facts has emerged, including countercyclical and volatile hiring and separation rates, pro-cyclical job finding rates, with considerable volatility of both accessions and separations.

Two points remain to be further explored. The key one relates to the computation of flows between the out of the labor force and employment pools, on which there is no agreement. The different computations – probably due to differential adjustments of the raw data – affect the implied series of job finding and separation rates, and the reconciliation of gross and net flows. The second issue is the lack of consensus between data sets on the relative volatility of the job finding rate and the separation rate. The exploration of these issues is essential, as the complete picture of labor market dynamics is important both for the understanding of the labor market in and of itself and for the study of business cycles.

References

[1] Abowd, John and Arnold Zellner, 1985. "Estimating Gross Labor-Force Flows," **Journal of Business and Economics Statistics** 3, 254-293.

[2] Blanchard, Olivier Jean and Peter Diamond, 1989. "The Beveridge Curve," **Brookings Papers on Economic Activity** 1, 1-60.

[3] Blanchard, Olivier Jean and Peter Diamond, 1990. "The Cyclical Behavior of the Gross Flows of U.S. Workers," **Brookings Papers on Economic Activity** 2, 85-155.

[4] Bleakley, Hoyt, Ann E. Ferris, and Jeffrey C. Fuhrer, 1999. "New Data on Worker Flows During Business Cycles," **New England Economic Review** July-August, 49-76.

[5] Davis, Steven J., R. Jason Faberman and John C. Haltiwanger, 2006. "The Flow Approach to Labor Markets: New Data Sources and Micro-Macro Links." NBER Working Paper No. 12167.

[6] Davis, Steven J. and Haltiwanger, John C., 1998. "Measuring Gross Worker and Job Flows." In John C. Haltiwanger, Marilyn Manser and Robert Topel (eds.) **Labor Statistics Measurement Issues**, Chicago, IL: University of Chicago Press.

[7] Davis, Steven J. and Haltiwanger, John C., 1999. "Gross Job Flows." In Orley Ashenfelter and David Card (eds.), **Handbook of Labor Economics,** Volume 3, pp. 2711-2805. Amsterdam: Elsevier Science.

[8] Fallick, Bruce and Charles A. Fleischman, 2004. "Employer to Employer Flows in the U.S. Labor Market: The Complete Picture of Gross Worker Flows," mimeo.

[9] Farber, Henry S., 1999. "Mobility and Stability: the Dynamics of Job Change in Labor Markets," In Orley Ashenfelter and David Card (eds.), **Handbook of Labor Economics,** Volume 3, pp. 2439-2480. Amsterdam: Elsevier Science.

[10] Hall, Robert E., 2005."Job Loss, Job Finding, and Unemployment in the U.S. Economy over the Past Fifty Years," in M.Gertler and K.Rogoff (eds). **NBER Macroeconomics Annual,** 101-137, MIT Press, Cambridge.

[11] Jones, Stephen R.G,.and W.Craig Riddell, 2000. "The Dynamics of U.S. Labor Force Attachment," working paper.

[12] Jones, Stephen R.G,.and W.Craig Riddell, 2006. "Unemployment and Non-Employment: Heterogeneities in Labor Market States," **Review of Economics and Statistics** 82(2), 314-323.

[13] Mortensen, Dale T. and Christopher A. Pissarides, 1994. "Job Creation and Job Destruction in the Theory of Unemployment," **Review of Economic Studies** 61, 397-415.

[14] Pissarides, Christopher A., 1985. "Short-Run Equilibrium Dynamics of Unemployment, Vacancies and Real Wages," **American Economic Review** 75, 676-90.

[15] Poterba, James M. and Lawrence H. Summers, 1986. "Reporting Errors and Labor Market Dynamics." **Econometrica,** vol. 54, no. 6, pp. 1319–38.

[16] Ritter, Joseph A., 1993. "Measuring Labor Market Dynamics: Gross Flows of Workers and Jobs," **Federal Reserve Bank of St Louis,** November/ December, 39-57.

[17] Shimer, Robert, 2005a. "The Cyclical Behavior of Equilibrium Unemployment and Vacancies: Evidence and Theory," **American Economic Review**, 95(1), 25-49.

[18] Shimer, Robert, 2005b. "Reassessing the Ins and Outs of Unemployment." http://home.uchicago.edu/~shimer/wp/

[19] Shimer, Robert, 2005c. "Mismatch." NBER Working Paper No. 11888.

Table 1

Moments of the Gross Flows

a. Hiring Flows to Employment

study	sample	$\frac{M^{UE}}{E}$		$p^{UE} = \frac{M^{UE}}{U}$		$\frac{M^{NE}}{E}$		$\frac{M^{UE+NE}}{E}$	
		mean	**std.**	**mean**	**std.**	**mean**	**std.**	**mean**	**std.**
BD	1968:1-1986:5	0.017	0.002	0.257	0.053	0.015	0.002	0.033	0.002
R	1967:6-1993:5	0.017	0.002	0.263	0.046	0.029	0.004	0.046	0.003
BFF	1976:2-2003:12	0.016	0.002	0.247	0.030	0.013	0.001	0.030	0.003
FF	1994:1-2004:12	0.015	0.001	0.288	0.029	0.025	0.002	0.040	0.002
S	1967:4-2004:12	0.020	0.003	0.321	0.050	–	–	–	–
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	1968:1-1986:5	0.014	0.003	0.017	0.002	0.031	0.002
R	1967:6-1993:5	0.015	0.003	0.032	0.004	0.047	0.003
BFF	1976:2-2003:12	0.013	0.002	0.015	0.001	0.029	0.003
FF	1994:1-2004:12	0.013	0.001	0.027	0.002	0.040	0.002
S	1967:4-2004:12	0.020	0.003	0.030	0.004	0.050	0.005
S II	1951:1-2004:12					0.035	0.005
J	2000:12-2005:06	–	–	–	–	0.031	0.001

Notes:

1. In first column BD stands for Blanchard and Diamond (1989,1990), R stands for Ritter (1993), BFF stands for Bleakley, Ferris and Fuhrer (1999), FF stands for Fallick and Fleischmann (2004), S stands for Shimer (2005b), SII stands for another computation from that same reference (see Note 4 to Table 3 below), and J stands for JOLTS data.

2. All numbers are the relevant flows as adjusted by the authors and are divided by seasonally-adjusted employment.

3. All data are monthly except for Shimer (2005b) data, which are quarterly averages of monthly data. The latter were computed by converting the computed transition rate f to the probability rate F using the relation $F_t \equiv 1 - e^{-f_t}$

Table 2

Pairwise Correlations

a. Flows Between U and E

p^{UE}

	BD	**Ritter**	**BFF**	**FF**	**S**
Blanchard and Diamond (1989)	1				
Ritter (1993)	0.88	1			
Bleakley, Ferris and Fuhrer (1999)	0.72	0.93	1		
Fallick and Fleischmann (2004)	NA	NA	0.86	1	
Shimer (2005b)	0.76	0.88	0.91	0.84	1

δ^{EU}

	BD	**Ritter**	**BFF**	**FF**	**S**
Blanchard and Diamond (1989)	1				
Ritter (1993)	0.91	1			
Bleakley, Ferris and Fuhrer (1999)	0.81	0.95	1		
Fallick and Fleischmann (2004)	NA	NA	0.62	1	
Shimer (2005b)	0.86	0.94	0.84	0.53	1

b. Total Flows

$\frac{M^{UE+NE}}{E}$

	BD	Ritter	BFF	FF	JOLTS
Blanchard and Diamond (1989)	1				
Ritter (1993)	0.68	1			
Bleakley, Ferris and Fuhrer (1999)	0.62	0.81	1		
Fallick and Fleischmann (2004)	NA	NA	0.65	1	
JOLTS	NA	NA	-0.57	-0.14	1

δ^{EU+EN}

	BD	Ritter	BFF	FF	S I	S II	JOLTS
Blanchard and Diamond (1989)	1						
Ritter (1993)	0.77	1					
Bleakley, Ferris and Fuhrer (1999)	0.69	0.88	1				
Fallick and Fleischmann (2004)	NA	NA	0.26	1			
Shimer (2005b) I	0.63	0.82	0.58	0.50	1		
Shimer (2005b) II	0.37	0.54	0.51	0.21	0.50	1	
JOLTS	NA	NA	-0.29	0.61	0.33	0.39	1

Notes:

1. In first column BD stands for Blanchard and Diamond (1989,1990), R stands for Ritter (1993), BFF stands for Bleakley, Ferris and Fuhrer (1999), FF stands for Fallick and Fleischmann (2004), S or SII stand for Shimer (2005b), and J stands for JOLTS data.

2. The underlying series are the relevant flows as adjusted by the authors and are divided by seasonally adjusted employment. The series are filtered by an HP filter with smoothing parameter 10^5.

3. All data are monthly except for Shimer (2005b) data, which are quarterly averages of monthly data. The latter were computed by converting the computed transition rate f to the probability rate F using the relation $F_t \equiv 1 - e^{-f_t}$

Table 3

Business Cycle Properties

a. Blanchard and Diamond (1989,1990) data

$1968:I-1986:II$

$n=74$

	1st diff.		**HP** (1600)		**HP** (10^5)		**BK**	
	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$
$\frac{M^{UE}}{E}, \mathbf{y}$	-0.37	6.2	-0.75	4.4	-0.73	3.8	-0.85	4.2
$\frac{M^{NE}}{E}, y$	0.18	11.2	0.56	4.9	0.55	4.0	0.90	3.5
$\frac{M^{UE}+M^{NE}}{E}, \mathbf{y}$	-0.04	6.7	-0.20	2.6	-0.25	2.0	-0.45	1.1
$\mathbf{p}^{UE}, \mathbf{y}$	0.33	5.9	0.80	3.7	0.72	3.7	0.92	3.4
$\delta^{EU}, \mathbf{y}$	-0.46	9.8	-0.81	7.2	-0.77	6.1	-0.91	6.7
$\delta^{EN}, \mathbf{y}$	0.15	10.6	0.54	4.6	0.52	3.7	0.90	2.9
$\delta^{EU+EN}, \mathbf{y}$	-0.16	7.6	-0.41	3.0	-0.42	2.4	-0.68	2.0

b. Ritter (1993) data

$1967:II - 1993:II$

$n = 105$

	1st diff.		**HP** (1600)		**HP** (10^5)		**BK**	
	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$
$\frac{M^{UE}}{E}, \mathbf{y}$	-0.34	7.2	-0.70	4.3	-0.77	3.8	-0.85	3.7
$\frac{M^{NE}}{E}, y$	0.03	5.7	0.33	2.2	0.40	1.8	0.77	1.2
$\frac{M^{UE}+M^{NE}}{E}, \mathbf{y}$	-0.18	4.6	-0.37	1.9	-0.46	1.5	-0.68	1.0
$\mathbf{p}^{UE}, \mathbf{y}$	0.25	7.2	0.75	4.4	0.82	4.3	0.92	3.9
$\delta^{EU}, \mathbf{y}$	-0.46	8.3	-0.80	5.7	-0.84	5.0	-0.90	5.3
$\delta^{EN}, \mathbf{y}$	-0.02	4.4	0.41	1.9	0.46	1.5	0.73	1.2
$\delta^{EU+EN}, \mathbf{y}$	-0.29	4.2	-0.50	1.8	-0.59	1.5	-0.68	1.4

c. **Bleakley, Ferris and Fuhrer (1999) data**

$1976 : I - 2003 : IV$

$n = 112$

	1st diff.		**HP** (1600)		**HP** (10^5)		**BK**	
	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$
$\frac{M^{UE}}{E}, \mathbf{y}$	-0.23	6.9	-0.68	3.9	-0.82	3.7	-0.84	3.4
$\frac{M^{NE}}{E}, y$	0.06	7.1	0.31	2.8	0.44	2.2	0.54	2.0
$\frac{M^{UE}+M^{NE}}{E}, \mathbf{y}$	-0.12	5.9	-0.43	2.5	-0.59	2.1	-0.66	1.7
$\mathbf{p}^{UE}, \mathbf{y}$	0.31	7.3	0.76	4.5	0.83	4.8	0.89	4.1
$\delta^{EU}, \mathbf{y}$	-0.41	8.4	-0.77	4.9	-0.84	4.7	-0.88	4.4
$\delta^{EN}, \mathbf{y}$	-0.01	6.3	0.35	2.5	0.40	1.9	0.65	1.8
$\delta^{EU+EN}, \mathbf{y}$	-0.28	6.1	-0.53	2.6	-0.66	2.3	-0.71	1.8

d. Fallick and Fleischmann (2004) data

$1994:I-2004:IV$

$n=44$

	1st diff.		**HP** (1600)		**HP** (10^5)		**BK**	
	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$
$\frac{M^{UE}}{E}, \mathbf{y}$	-0.07	9.1	-0.46	4.6	-0.72	4.1	-0.54	4.8
$\frac{M^{NE}}{E}, y$	0.16	12.5	0.26	5.2	0.35	3.6	0.04	3.9
$\frac{M^{UE+NE}}{E}, \mathbf{y}$	0.12	8.0	0.01	3.5	-0.13	2.5	-0.31	2.8
$\mathbf{p}^{UE}, \mathbf{y}$	0.49	8.9	0.83	6.0	0.92	6.2	0.85	5.1
$\delta^{EU}, \mathbf{y}$	0.10	14.7	-0.48	6.3	-0.67	5.1	-0.87	6.0
$\delta^{EN}, \mathbf{y}$	-0.01	10.4	0.33	4.6	0.44	3.3	-0.03	3.5
$\delta^{EU+EN}, \mathbf{y}$	0.05	7.3	0.02	3.6	-0.04	2.6	-0.47	3.5

e. Shimer (2005b) data

$1967 : II - 2004 : IV$

$n = 151$

	1st diff.		**HP** (1600)		**HP** (10^5)		**BK**	
	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$
$\frac{M^{UE}}{E}, \mathbf{y}$	-0.44	6.6	-0.72	3.9	-0.80	3.4	-0.87	3.2
$\frac{M^{NE}}{E}, y$	NA	NA	NA	NA	NA	NA	NA	NA
$\mathbf{p}^{UE+NE}, \mathbf{y}$	-0.10	5.6	0.20	2.2	0.33	1.8	0.58	1.5
$\mathbf{JF}, \mathbf{y}$	0.41	5.1	0.83	4.9	0.87	5.3	0.88	4.8
$\mathbf{p}^{UE}, \mathbf{y}$	0.20	6.7	0.75	5.1	0.80	5.0	0.83	4.9
$\delta^{EU}, \mathbf{y}$	-0.38	8.8	-0.70	4.7	-0.74	3.8	-0.80	3.4
$\delta^{EN}, \mathbf{y}$	0.02	5.7	0.38	2.4	0.43	2.0	0.62	2.0
$\delta^{EU+EN}, \mathbf{y}$	-0.25	5.3	-0.35	2.2	-0.37	1.7	-0.32	1.5

f. Cross Correlations Analysis [Shimer (2005b) data]

	lags					leads			
j	**12**	**6**	**3**	**1**	**0**	**1**	**3**	**6**	**12**
$\mathbf{JF}_{t\pm j}, \mathbf{y}_t$	-0.16	0.20	0.57	0.80	0.87	0.87	0.72	0.25	-0.35
$\mathbf{p}_{t\pm j}^{UE+NE}, \mathbf{y}_t$	-0.21	-0.03	0.15	0.28	0.33	0.40	0.41	0.26	-0.10
$\mathbf{p}_{t\pm j}^{UE}, \mathbf{y}_t$	-0.23	0.09	0.47	0.73	0.80	0.84	0.72	0.28	-0.38
${\delta_{t\pm j}}^{EU}, \mathbf{y}_t$	0.21	-0.19	-0.53	-0.73	-0.74	-0.63	-0.35	0.04	0.21
${\delta_{t\pm j}}^{EN}, \mathbf{y}_t$	-0.12	-0.01	0.22	0.38	0.43	0.46	0.35	0.08	-0.22
${\delta_{t\pm j}}^{EU+EN}, \mathbf{y}_t$	0.10	-0.20	-0.34	-0.40	-0.37	-0.25	-0.06	0.09	0.03

Notes:

1. y is real GDP.

2. All variables are logged; then they are either first differenced or are filtered using the Hodrick-Prescott filter (with smoothing parameter 1600 or 10^5) or with the Baxter King filter.

3. $\frac{\sigma_{\cdot}}{\sigma_y}$ is the relative standard deviation, where the standard deviation of filtered GDP is in the denominator.

4. For the Shimer (2005b) data in panels e and f the following computation was used:

a. 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/

b. To obtain $\mathbf{p}^{UE+NE}$, the following formula was used:

$\mathbf{p}^{UE+NE} = (1 - e^{\lambda_t^{UE}}) * \frac{CPS\_U}{CPS\_U+CPS\_N} + (1 - e^{\lambda_t^{NE}}) * \frac{CPS\_N}{CPS\_U+CPS\_N}$

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.'

c. 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 (2005b) F is given by:

$$F_t = 1 - \frac{u_{t+1} - u_{t+1}^s}{u_t}$$

where u_{t+1} = number of unemployed in period $t+1, u_t$ = number of unemployed in period t and u_{t+1}^s = 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 is to be found in Shimer (2005b), Appendix A.

Table 4

Out of the Labor Force Flows

a. Key Moments

$\frac{F^{UN}}{E}$		$\frac{F^{NU}}{E}$		$\frac{F^{UN}-F^{NU}}{E}$	
mean	**std.**	**mean**	**std.**	**mean**	**std.**
0.017	0.003	0.02	0.003	-0.003	0.001

$\frac{F^{EN}}{E}$		$\frac{F^{NE}}{E}$		$\frac{F^{EN}-F^{NE}}{E}$	
mean	**std.**	**mean**	**std.**	**mean**	**std.**
0.03	0.004	0.026	0.004	0.004	0.001

b. Cyclical Analysis

	1st diff.		**HP** (1600)		**HP** (10^5)		**BK**	
	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$
$\frac{F^{NU}}{N}, \mathbf{y}$	-0.09	6.8	-0.38	3.3	-0.56	3.2	-0.57	2.2
$\frac{F^{NU}}{U}, \mathbf{y}$	0.41	8.1	0.79	5.8	0.76	5.4	0.88	5.5
$\frac{F^{NU}}{E}, \mathbf{y}$	-0.14	6.8	-0.51	3.8	-0.66	3.9	-0.69	2.9
$\frac{F^{UN}}{N}, \mathbf{y}$	-0.25	5.7	-0.68	3.5	-0.78	3.6	-0.77	3.2
$\frac{F^{UN}}{U}, \mathbf{y}$	0.39	6.3	0.76	4.6	0.74	4.2	0.83	4.4
$\frac{F^{UN}}{E}, \mathbf{y}$	-0.31	5.9	-0.74	4.2	-0.81	4.4	-0.81	3.9

	1st diff.		**HP** (1600)		**HP** (10^5)		**BK**	
	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$	$\boldsymbol{\rho}$	$\frac{\sigma_\cdot}{\sigma_y}$
$\frac{F^{NE}}{E}, \mathbf{y}$	-0.02	6.75	0.26	2.69	0.33	2.22	0.59	1.55
$\frac{F^{NE}}{N}, \mathbf{y}$	0.04	6.98	0.45	3.05	0.58	2.61	0.77	2.10
$\frac{F^{EN}}{E}, \mathbf{y}$	0.02	5.73	0.38	2.44	0.43	1.95	0.65	1.65
$\frac{F^{EN}}{N}, \mathbf{y}$	0.09	5.81	0.57	2.85	0.66	2.44	0.79	2.27

c. Net Flows

$$N_{t+1} - N_t = F_t^{UN} + F_t^{EN} - F_t^{NU} - F_t^{NE}$$

Mean

	relative mean
F_t^{UN}	12.71
F_t^{EN}	21.62
F_t^{NU}	14.83
F_t^{NE}	18.50

All entries are divided by the mean of $F_t^{UN} + F_t^{EN} - F_t^{NU} - F_t^{NE}$

Variance-covariance matrix

	F_t^{UN}	F_t^{EN}	F_t^{NU}	F_t^{NE}
F_t^{UN}	4.39			
F_t^{EN}	1.37	3.66		
F_t^{NU}	4.08	1.64	4.23	
F_t^{NE}	1.20	2.86	1.41	2.72

All entries are divided by $var(F_t^{UN} + F_t^{EN} - F_t^{NU} - F_t^{NE})$

Correlation matrix

	F_t^{UN}	F_t^{EN}	F_t^{NU}	F_t^{NE}
F_t^{UN}	1			
F_t^{EN}	0.34	1		
F_t^{NU}	0.95	0.42	1	
F_t^{NE}	0.35	0.91	0.42	1

Notes:

1. The moments are based on the Shimer (2005b) data.

2. y is real GDP.

3. All variables are logged; then they are either first differenced or are filtered using the Hodrick-Prescott filter (with smoothing parameter 1600 or 10^5) or with the Baxter King filter.

4. $\frac{\sigma_{\cdot}}{\sigma_y}$ is the relative standard deviation, where the standard deviation of filtered GDP is in the denominator.

Table 5

Net Employment Growth $\frac{E_t}{E_{t-1}} - 1$

a. Moments

	average	std.	correlation	regression D.W.	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 $\frac{E_t}{E_{t-1}} - 1$

Blanchard and Diamond (1989)			
	actual	*predicted*	*residual*
mean	0.001727	0.001707	2.00×10^{-5}
std.	0.003079	0.002490	0.003241
correlations			
actual	1		
predicted	0.69	1	
residual	0.34	-0.45	1

Bleakley, Ferris and Fuhrer (1999)			
	actual	*predicted*	*residual*
mean	0.001343	0.001121	0.000222
std.	0.002668	0.001754	0.001828
correlations			
actual	1		
predicted	0.73	1	
residual	0.77	0.11	1

c. Residual Tests (Q Statistics and their p values)

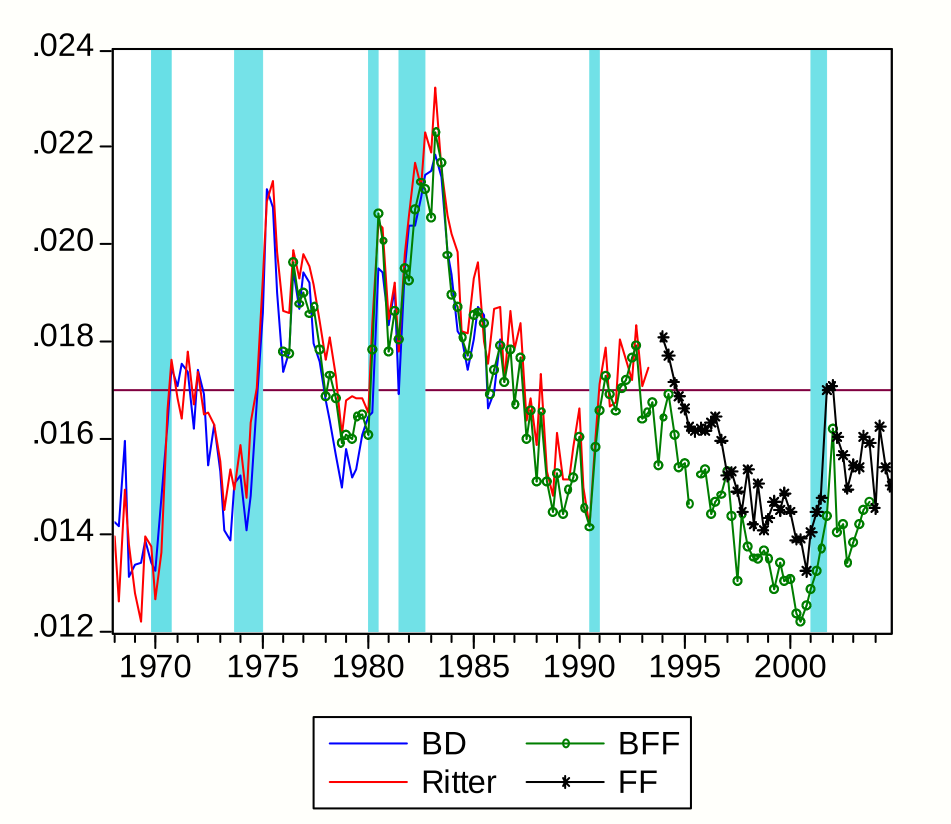
lag	**1**	**5**	**10**	**20**
Blanchard and Diamond (1989)	13.52	33.80	51.28	84.49
	(0.00)	(0.00)	(0.00)	(0.00)
Bleakley, Ferris and Fuhrer (1999)	0.23	9.53	18.79	32.43
	(0.63)	(0.09)	(0.04)	(0.04)

Notes:

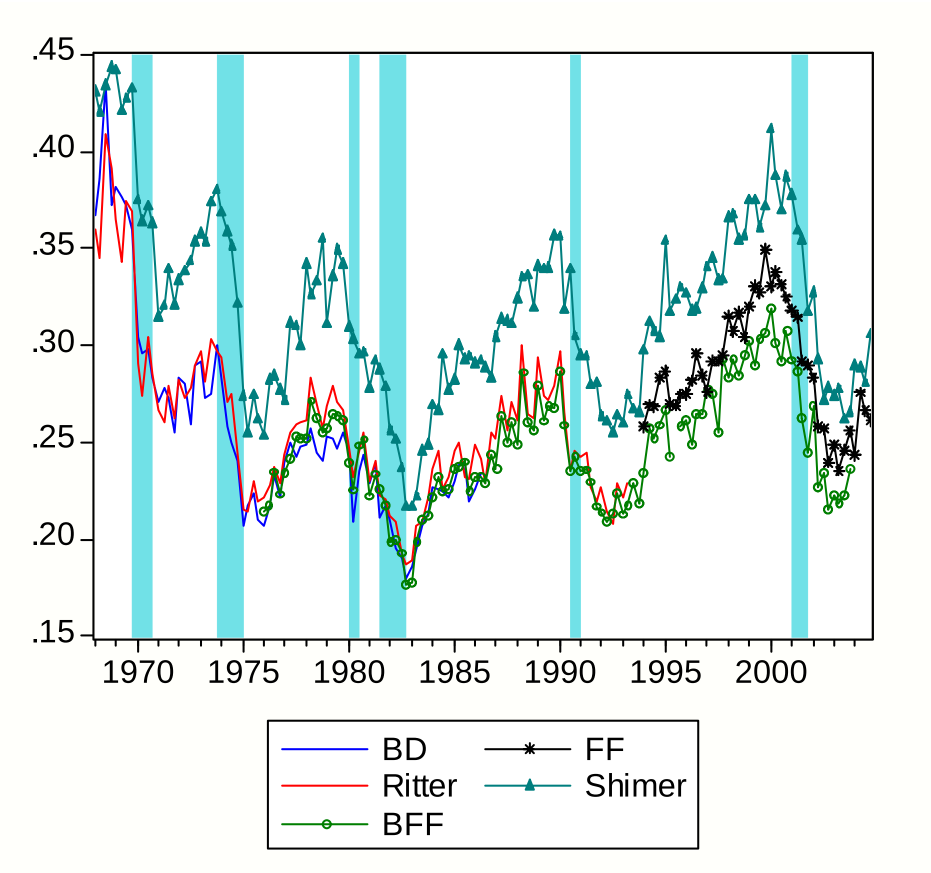
1. 'Actual' refers to actual $\frac{E_t}{E_{t-1}} - 1$ from the CPS.
2. 'Predicted' refers to $\frac{M_t^{UE}+M_t^{NE}}{E_t} - \delta_t^{EU+EN}$ as computed by the cited studies.
3. 'Residual' is the difference between actual and predicted..

Figure 1

Flows from Unemployment to Employment



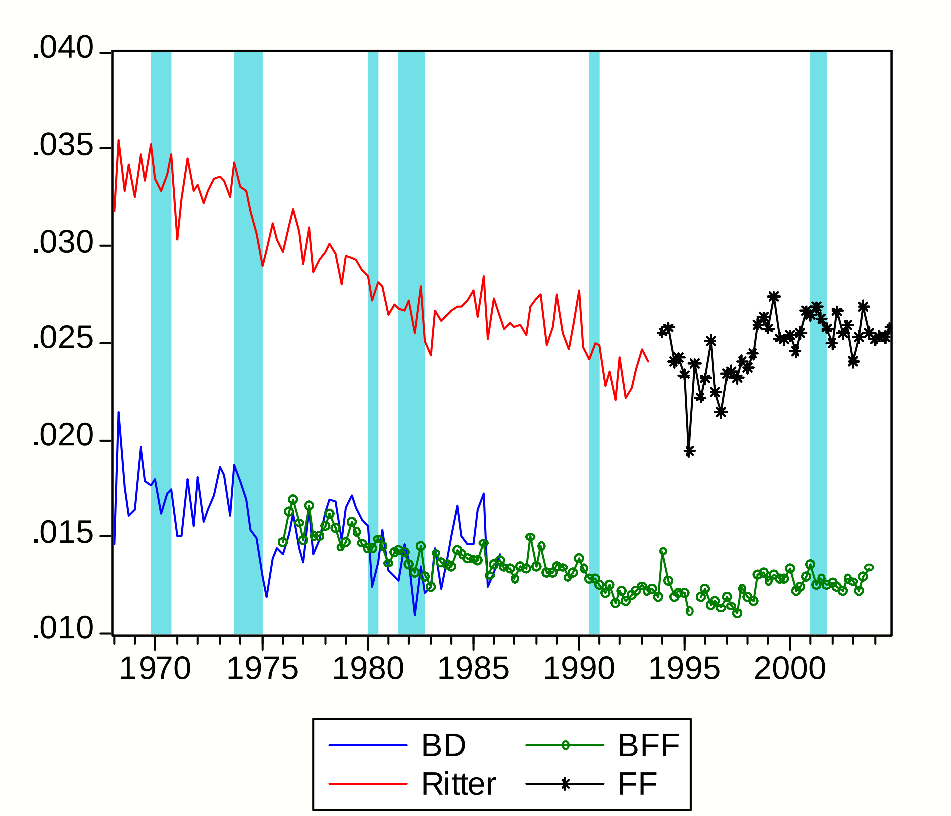
a. Hiring Rates $\frac{M^{UE}}{E}$



b. Job Finding Rates $\frac{M^{UE}}{U}$

Figure 2

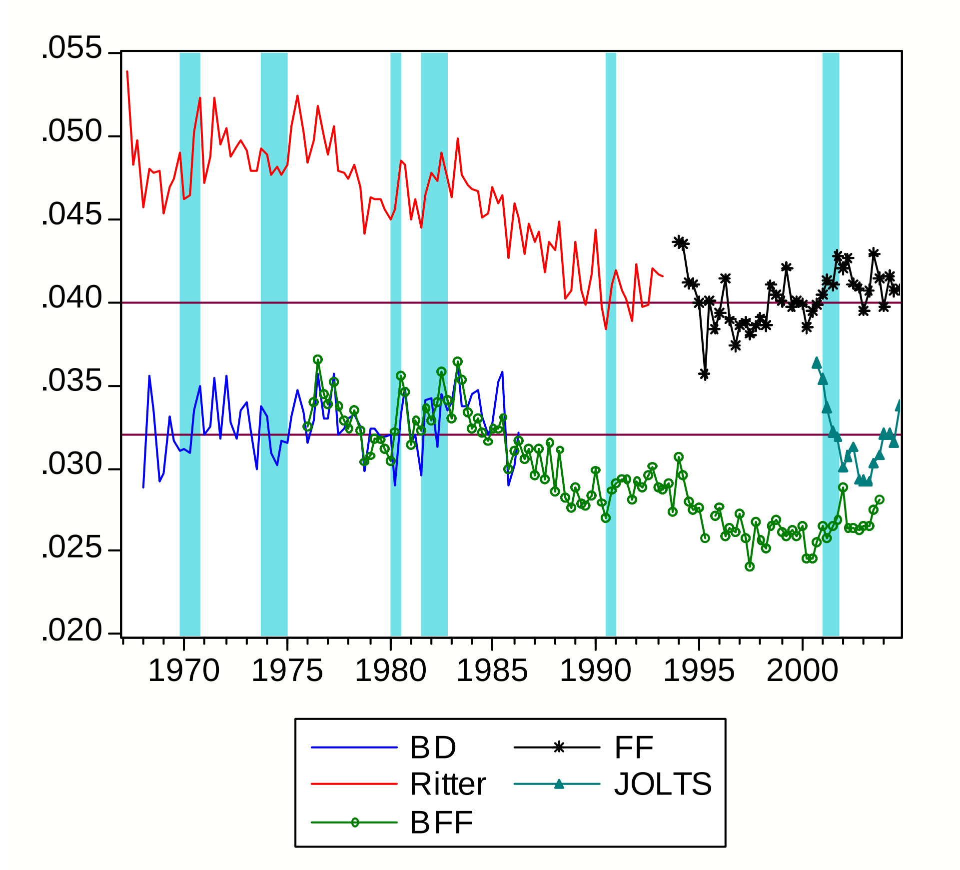
Flows from Out of the Labor Force to Employment



Matching Rates $\frac{M^{NE}}{E}$

Figure 3

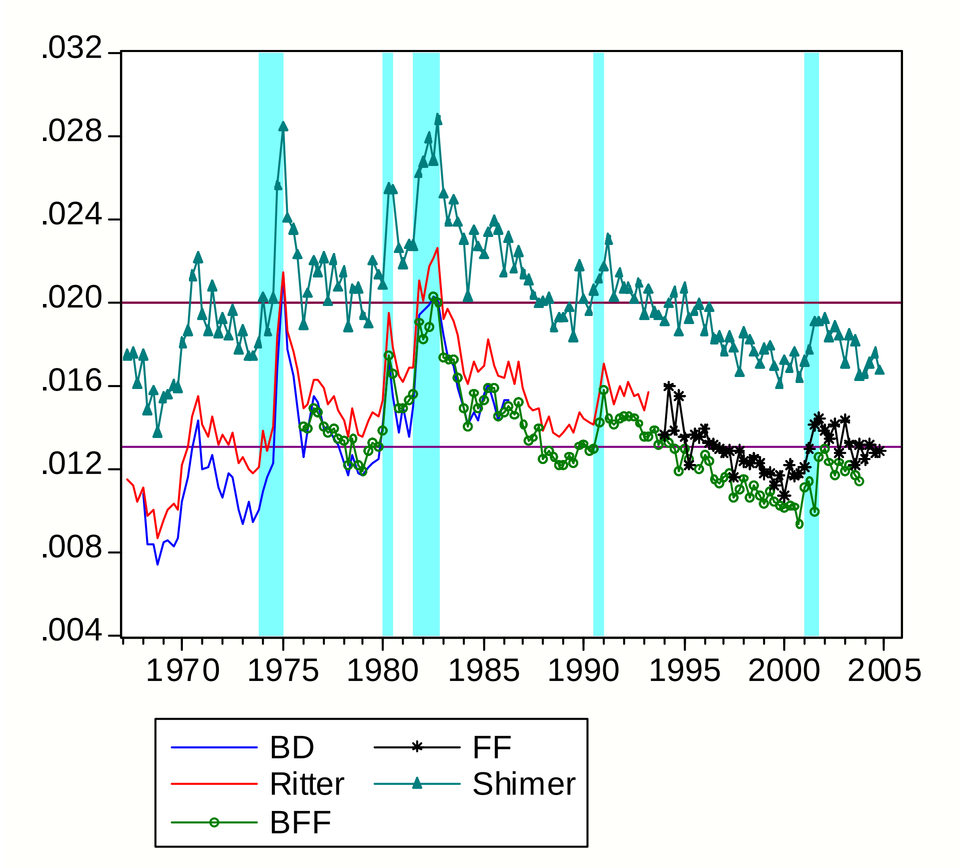
Total Hirings



Hiring Rates $\frac{M^{UE+NE}}{E}$

Figure 4

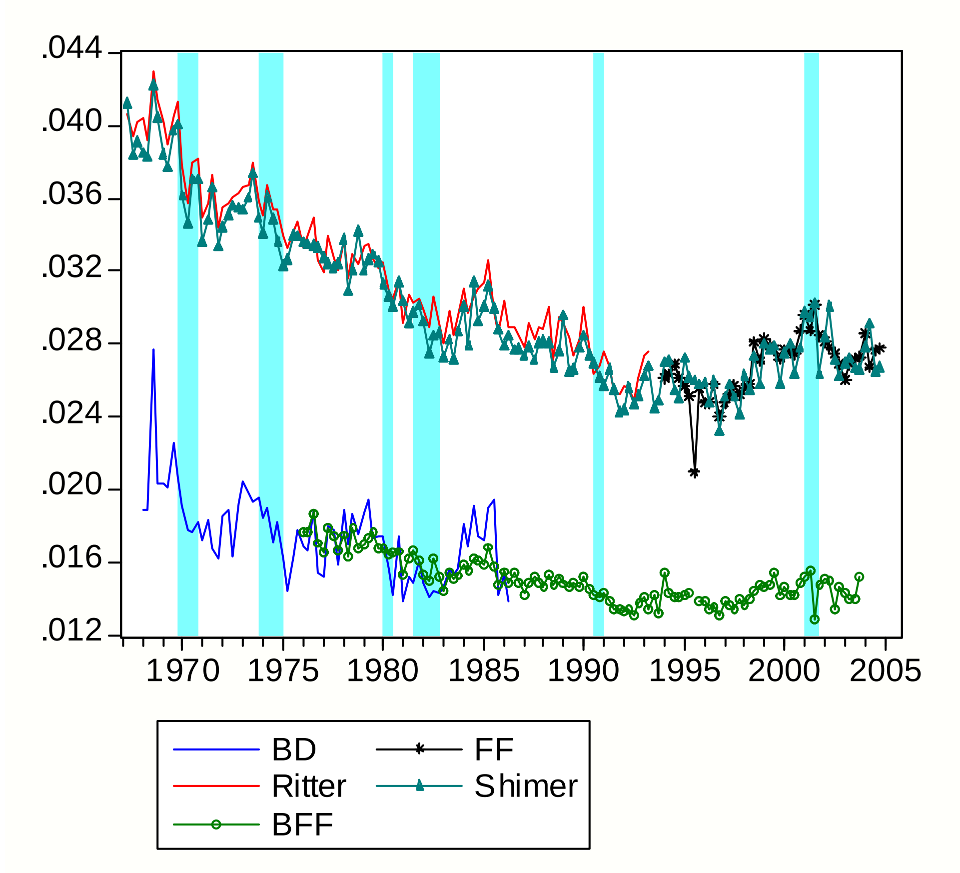
Flows from Employment to Unemployment



Separation rates δ^{EU}

Figure 5

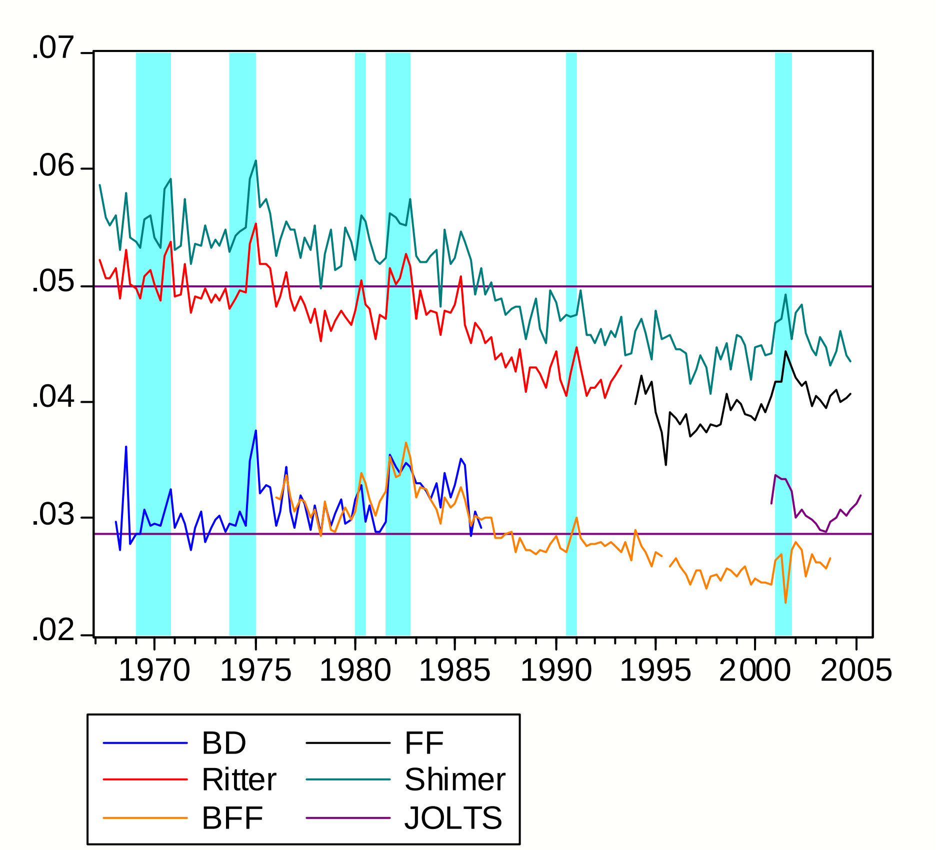
Flows from Employment to Out of the Labor Force



Separation Rates δ^{EN}

Figure 6

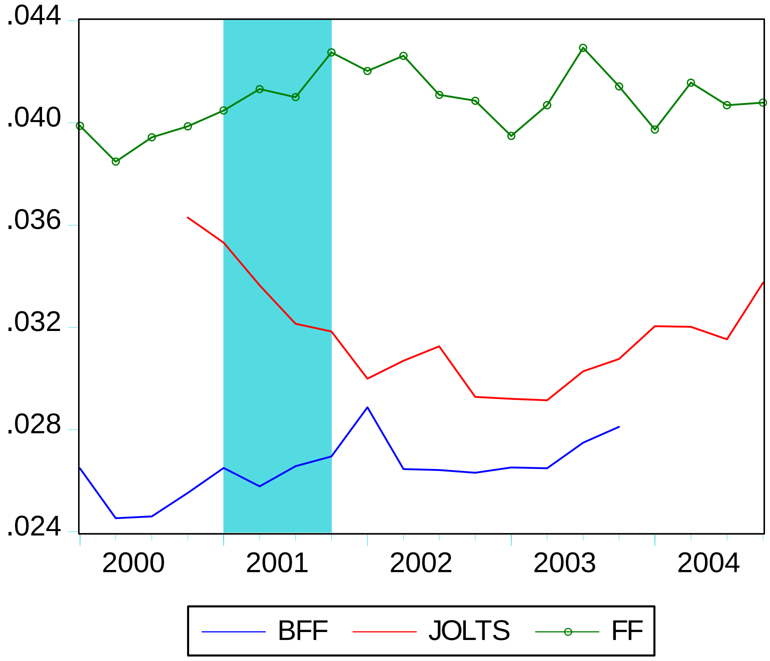
Total Separation Rates



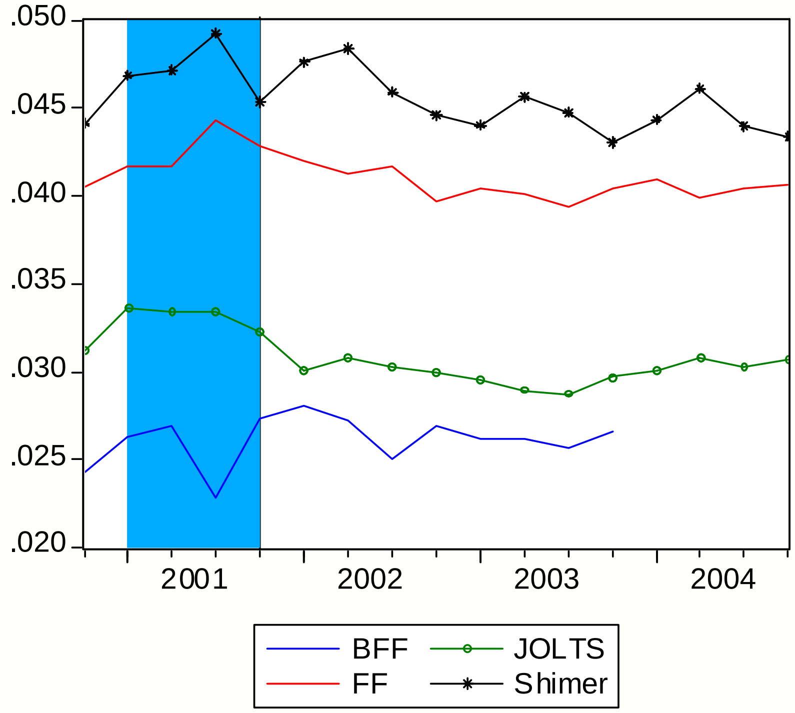
Separation Rates δ^{EU+EN}

Figure 7

Selected Hiring and Separation Rates 2000-2004



Hiring Rates $\frac{M^{UE+NE}}{E}$



Separation Rates δ^{EU+EN}

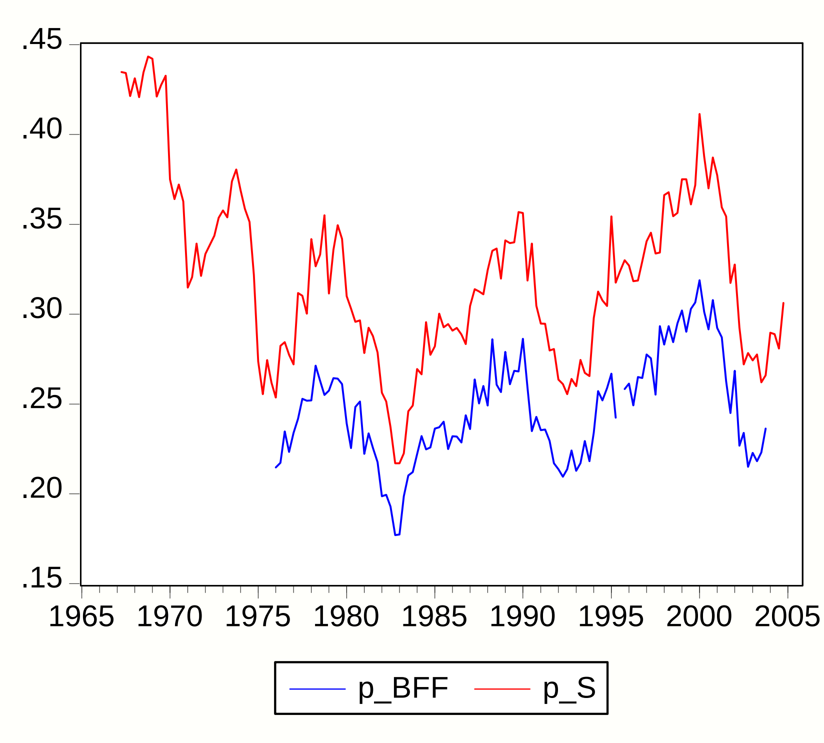
Figure 8

Job Finding and Separation Rates

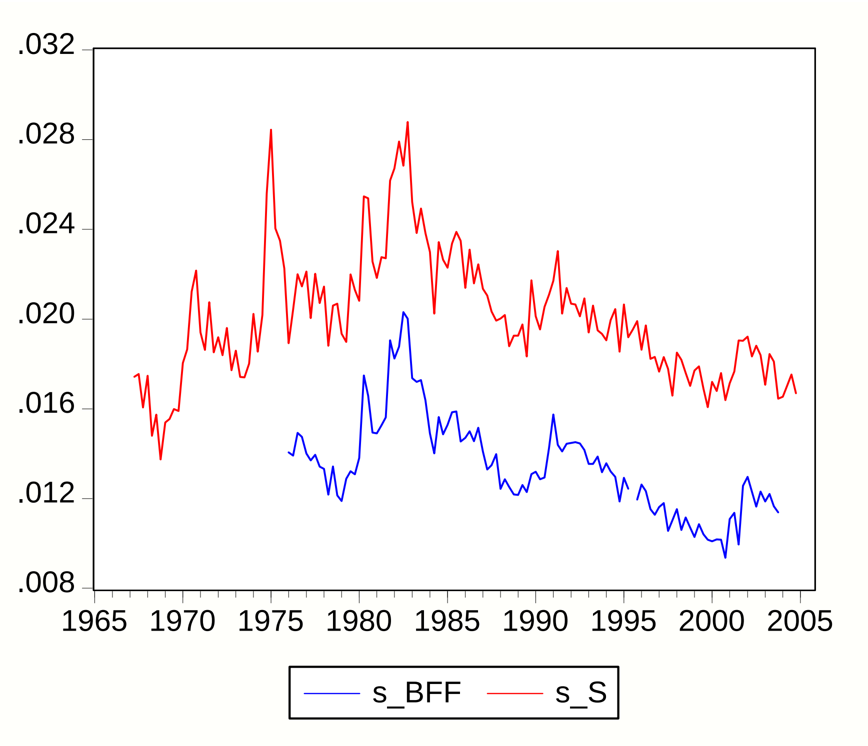
BFF=Bleakely et al (1999) data

S=Shimer (2005b) data

a. Original series

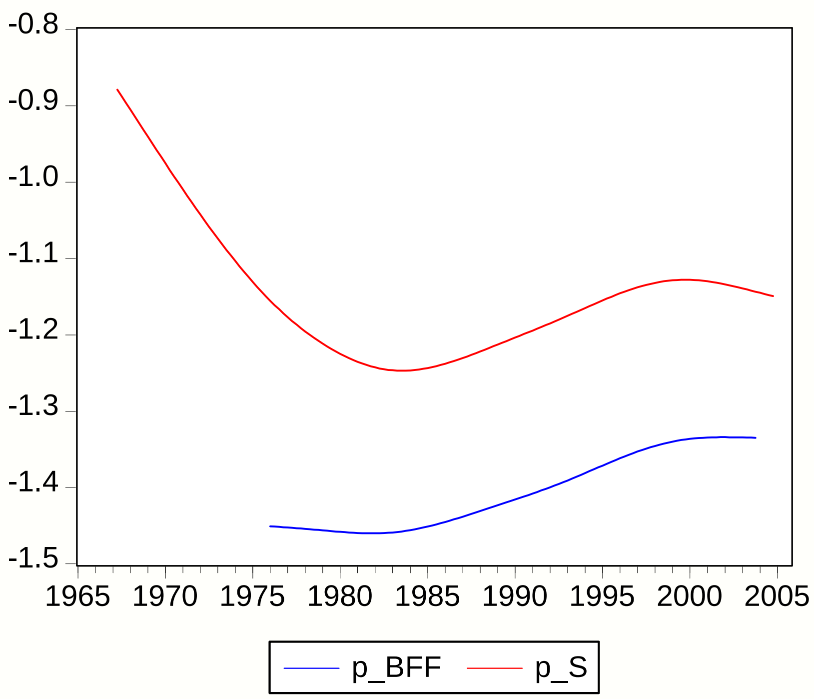


Job Finding Rates U to E

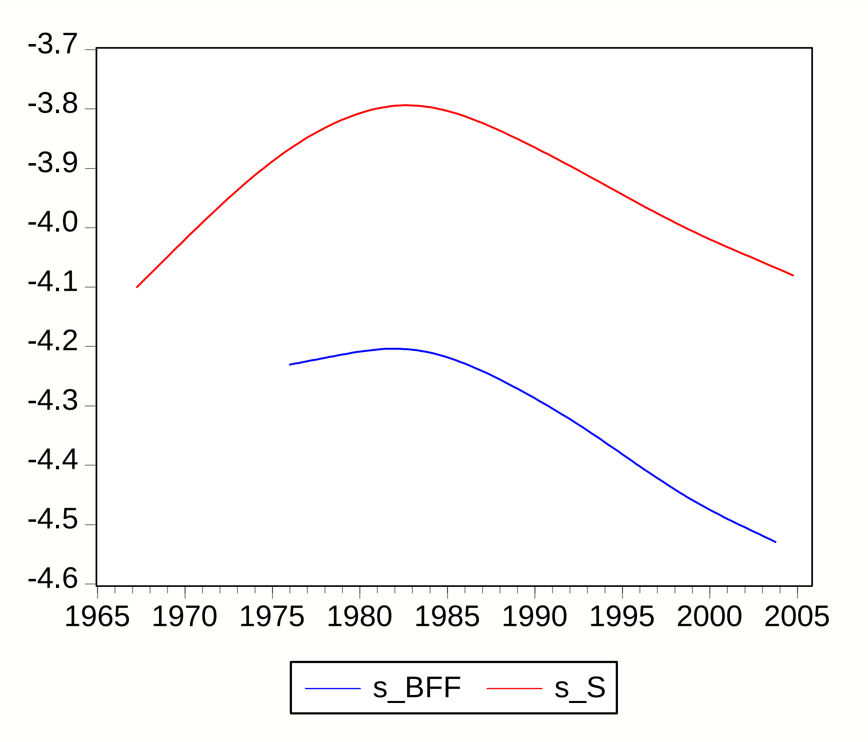


Separation Rates E to U

b. HP Trend (smoothing parameter 10^5)

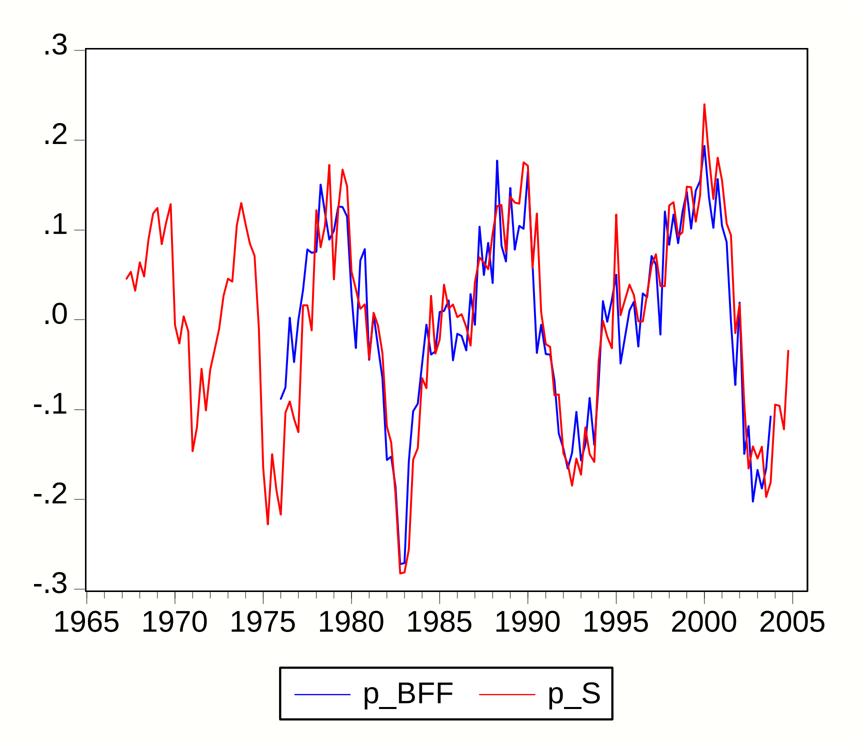


Job Finding Rates U to E

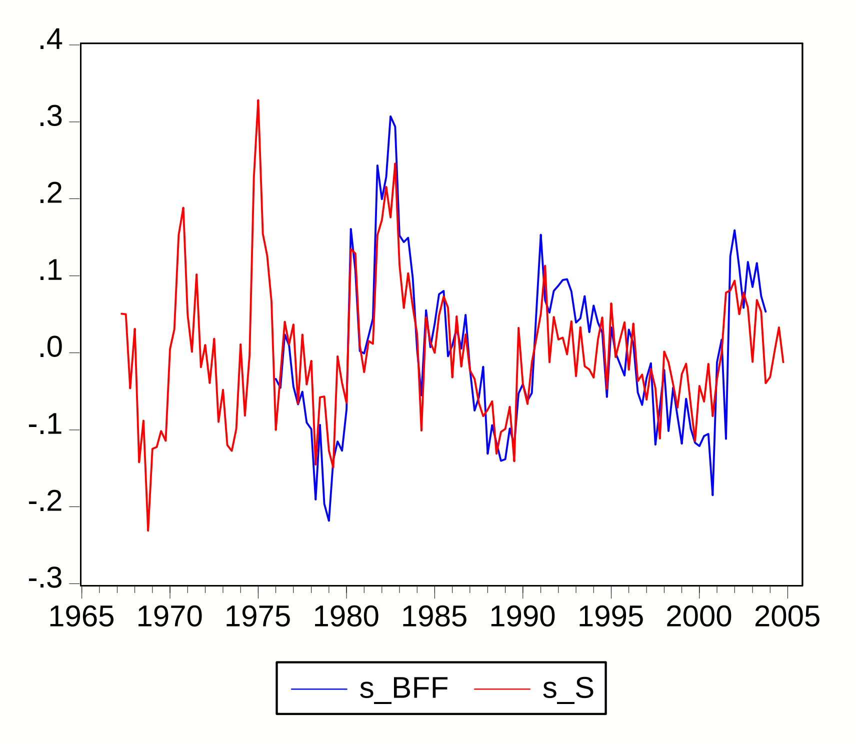


Separation Rates E to U

c. HP filtered (smoothing parameter 10^5)



Job Finding Rates U to E



Separation Rates E to U

Figure 9

Variables in the Unemployment Dynamics Equation

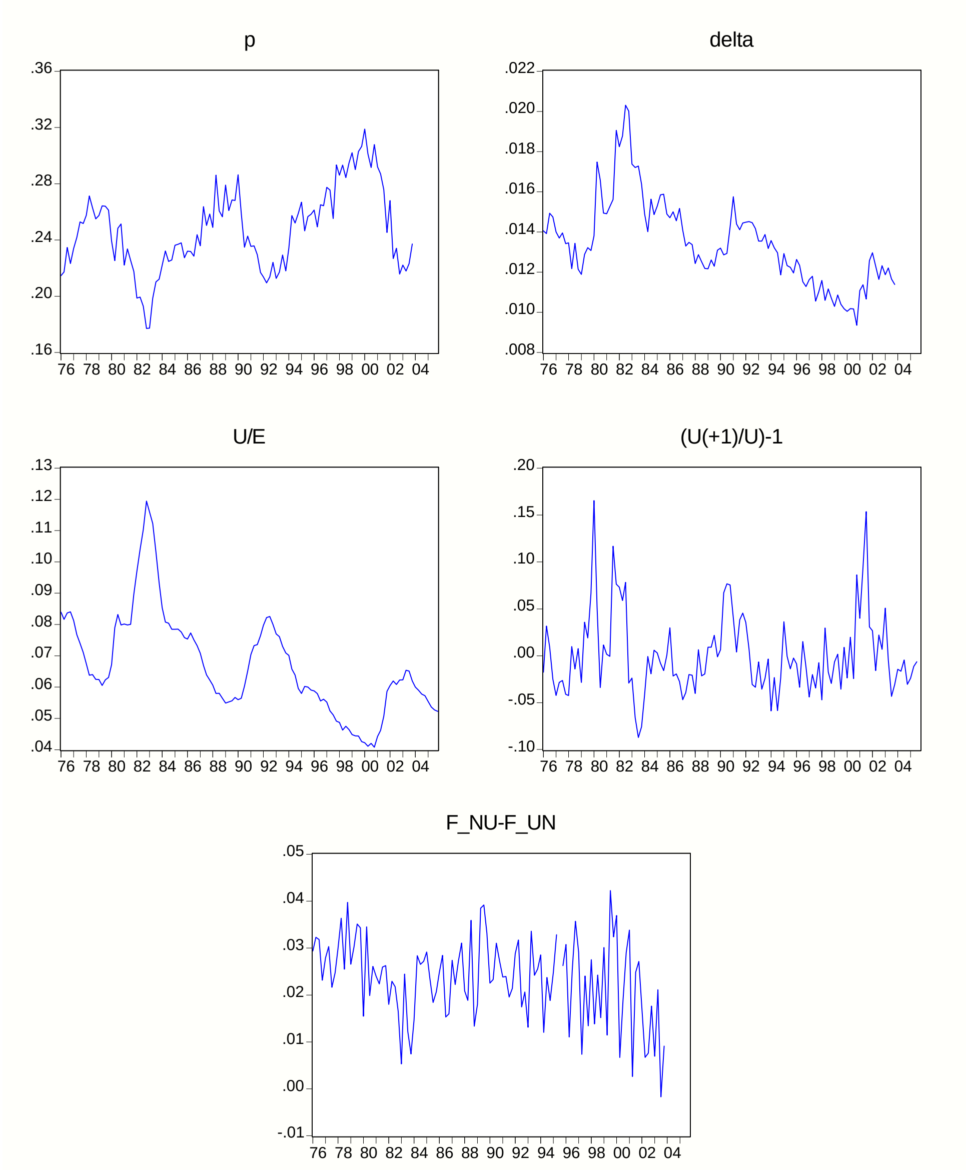
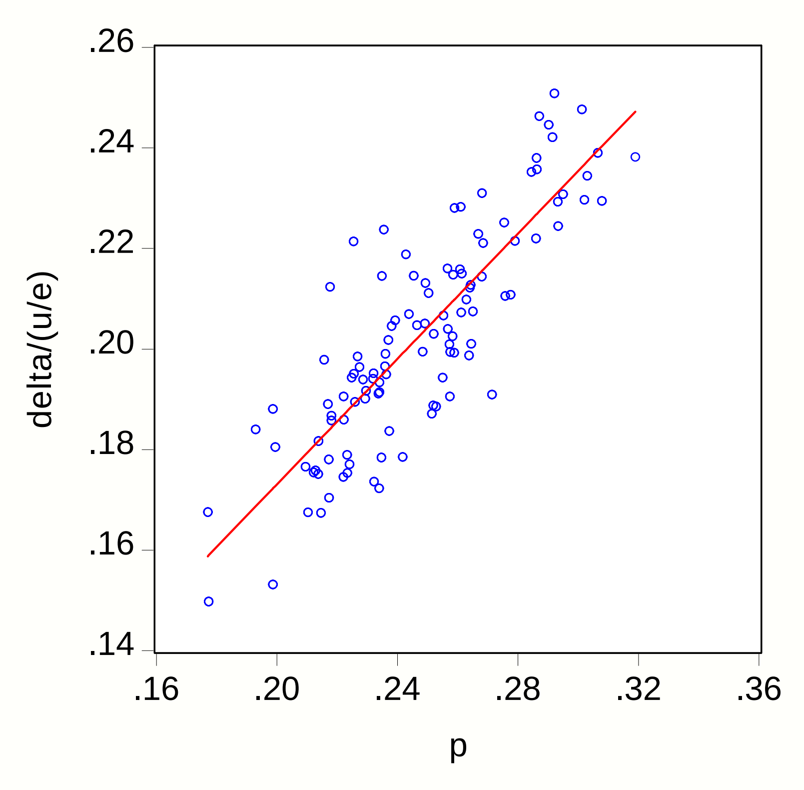


Figure 10

Approximated Unemployment Dynamics Equation



p vs $\frac{\delta}{\frac{U}{E}}$