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The Cyclicality of Separation and Job Finding Rates*

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Abstract

This paper uses CPS gross flow data to analyze the business cycle dynamics of separation and job finding rates and to quantify their contributions to overall unemployment variability. Cyclical changes in the separation rate are negatively correlated with changes in productivity and move contemporaneously with them, while the job finding rate is positively correlated with and tends to lag productivity. Contemporaneous fluctuations in the separation rate explain between 40 and 50 percent of fluctuations in unemployment, depending on how the data are detrended. This figure becomes larger when dynamic interactions between the separation and job finding rates are considered.

JEL codes: J63, J64

Keywords: Separation rate, Job finding rate, Unemployment, CPS worker flows

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1 Introduction

The empirical behavior of U.S. job loss and hiring over the business cycle remains an elusive and controversial subject, despite decades of research. While much early work considered gross flows of workers and jobs, more recent papers have stressed the importance of transition rates faced by individual workers.[1] Furthermore, researchers have highlighted the variability of unemployment as a key measure of aggregate labor market activity.[2] In this paper we assess the cyclical behavior of worker transition rates into and out of unemployment for the aggregate U.S. labor market. We focus on two specific dimensions of cyclical behavior. First, how do separation and job finding rates *comove* with the business cycle? Second, to what extent do movements in these rates *contribute* to overall unemployment variability?[3]

These questions are central to evaluating the relative roles of separation versus job finding activity in explaining unemployment movements. Higher unemployment during downturns might be triggered by higher separation rates, which generate waves of job loss. Alternatively, an initial phase of low job finding rates may drive unemployment upward. Sorting out the timing and magnitude of these channels is important for understanding the mechanisms that underlie unemployment fluctuations.

This paper addresses these issues by analyzing gross flow data from the Current Population Survey (CPS) over the 1976-2006 period. The data are adjusted for margin error in line with the approach of Abowd and Zellner (1985). We measure quarterly separation and job finding hazard rates using Shimer's (2005a) time aggregation correction. Comovement is analyzed by considering the correlations between the two hazard rates and labor productivity at various leads and lags. To quantify the contributions of separation and job finding rates, we decompose total unemployment variations into components that depend separately on each rate. We consider both HP filtering and first differencing as methods

[1] For analyses of gross worker and job flows, see Poterba and Summers (1984, 1986), Abowd and Zellner (1985), Darby et al. (1986), Davis (1987), Blanchard and Diamond (1989, 1990), Davis and Haltiwanger (1992), Davis et al. (1996), Bleakley et al. (1999), Fallick and Fleischman (2004), Nagypál (2004), Fujita and Ramey (2006, 2007), Fujita et al. (2007) and Yashiv (2006a,b). Transition hazard rates have been considered in Nagypál (2004), Hall (2005a), Shimer (2005a,b), Elsby et al. (2007), Fujita and Ramey (2006, 2007), Fujita et al. (2007) and Yashiv (2006a,b).

[2] Hall (2005b) and Shimer (2005b) stress the salience of unemployment variability as a statistic for evaluating job matching models.

[3] Throughout the paper we use the terms "separation" and "job finding" to denote movements of workers out of and into employed status. Thus, we do not consider movements directly between jobs.

for detrending the data.

Our results show that the separation rate is highly countercyclical, having a peak correlation with productivity of -0.58 in the HP filtered data, and -0.22 in the first differenced data.[4] Moreover, the peaks are achieved at a lag of zero, and the correlations at other horizons are roughly symmetric about zero. This means that changes in the separation rate occur contemporaneously with the productivity. For the job finding rate, in contrast, the correlations are positive, and their peak occurs at leads of two to three quarters, meaning that the job finding rate tends to trail the cycle.[5]

To evaluate the direct comovement between the separation and job finding rates, we evaluate their cross correlations. Peaks are attained when the separation rate is lagged by one quarter, at values of roughly -0.7 and -0.4 in the HP filtered and first differenced data, respectively. Thus, the separation rate leads the job finding rate.

To analyze the contributions of the hazard rates to unemployment variability, we follow Shimer (2005a) by approximating the unemployment rate using the theoretical steady state value associated with the contemporaneous separation and job finding rates. This allows unemployment variability to be readily decomposed by means of a conventional factor analysis. In the HP filtered data, fluctuations in the separation rate relative to trend explain 41 percent of overall fluctuations in unemployment. The figure rises to 51 percent in the first differenced data. We conclude that both job finding and separation rates are important in accounting for unemployment variability.

We also consider the contributions of the separation and job finding rates since 1985. For this subsample, we find that the separation rate explains 34 and 46 percent of unemployment fluctuations under the respective filtering methods. Thus, although the separation rate explains a smaller proportion in recent decades, its contribution remains substantial.

The aforementioned decompositions abstract from dynamic interactions. As such, they may understate the role of the separation rate, since fluctuations in the separation rate are negatively correlated with future changes in the job finding rate, and thus with future unemployment fluctuations. To investigate this effect, we recast our decompositions to

[4] Note that it is natural for the correlations to be smaller in magnitude when the first difference filter is used.

[5] We also consider cross correlations between the hazard rates and unemployment. We find that the separation rate leads unemployment, while the job finding rate moves contemporaneously with it. This is consistent with our productivity results, since unemployment tends to lag productivity.

reflect the contributions of current and past variations in the separation and job finding rates to unemployment variability. In this case, the proportion of unemployment variability explained by the separation rate rises to 60-70 percent over the full sample. Thus, the contemporaneous decompositions may understate the true importance of the separation rate.

Our findings bear on the current debate over the cyclical behavior of the separation rate. Using both gross flow- and unemployment duration-based data derived from the CPS, Shimer (2005a) argues that once time aggregation bias is taken into account, measured separation rates are nearly acyclic and play a small role in explaining unemployment fluctuations. We find, however, that the separation rate is highly countercyclical, even when we consider Shimer's own data. Shimer models unemployment variability by constructing "counterfactual" unemployment approximations that hold the separation or the job finding rates constant at their historical averages. Our method, on the other hand, decomposes unemployment fluctuations into two linear terms, corresponding to the respective contributions of the separation and job finding rates. This allows us to carry out a variance decomposition of unemployment fluctuations in a systematic manner. When our method is applied to Shimer's data sets, we find that the separation rate explains between 28 and 56 percent of unemployment variability. Thus, the explanatory power of the separation rate is substantial by any measure.

In evaluating Shimer's duration-based findings, Elsby et al. (2007) interpret the first differences of separation and job finding rates as a decomposition of unemployment variability. Their evidence suggests a more substantial role for separation rates than that suggested by Shimer, particularly when job loss is distinguished from labor force entry. We build on their approach by developing an exact decomposition of unemployment variability and extending the method to fluctuations in the unemployment level. Yashiv (2006a,b) carefully analyzes several existing data sources to discern the cyclical properties of U.S. gross worker flows and transition hazard rates. Among other findings, he shows that separation rates are strongly countercyclical and job finding rates are strongly procyclical when real GDP is used as the cyclical indicator.

The paper proceeds as follows. Section 2 describes the data construction, Section 3 evaluates comovement, Section 4 considers the decomposition of unemployment variability, and Section 5 concludes.

2 Data

We consider measures of separation and job finding rates derived using monthly data from the Current Population Survey (CPS) for the period 1976-2006. Month-over-month transitions by individual workers between employed, unemployed and not-in-labor-force (NILF) status can be measured by matching workers that are sampled in consecutive months. Owing to sample rotation and temporary absences of individuals, transition information is unavailable for a substantial subset of the sample. This failure to match individual workers across months is referred to as *margin error*, and it leads to omission of possible transitions from the survey data.

The most common correction for margin error, the missing-at-random (MAR) method, simply drops the missing observations and reweights the transitions that are measured. This procedure leads to biases, however, if types of transitions differ in their likelihood of omission. Following the important work of Abowd and Zellner (1985), we use an alternative correction that employs information on worker stocks. In particular, the MAR-based worker flow measures are reweighted in a manner that minimizes the discrepencies between officially-reported stocks of workers and the stocks that would be imputed from the flow measures. See Fujita and Ramey (2006) for details of our margin error correction.

A second problem with the data concerns the point-in-time measurement of worker status, which fails to capture transitions that are reversed within the month. To correct for this, we use the method suggested by Shimer (2005a), which links the month-over-month gross flow measures to underlying continuous-time adjustment equations.[6] Let eu_t and ue_t denote the margin-error-adjusted gross flows from employment to unemployment and from unemployment to employment, respectively, and let e_{t-1} and u_{t-1} indicate the measured stocks of employed and unemployed workers. Then the average monthly separation and job finding rates are determined by

$$\widehat{s}_t = \frac{eu_t}{e_{t-1}}, \qquad \widehat{f}_t = \frac{ue_t}{u_{t-1}}. \tag{1}$$

Assume that actual worker transitions are determined by a continuous-time process under which separation and job finding events arrive at constant rates within the month. The continuous-time separation and job finding hazard rates, denoted by s_t and f_t, will satisfy

$$\widehat{s}_t = \frac{s_t\left(1 - e^{-(s_t+f_t)}\right)}{s_t + f_t}, \qquad \widehat{f}_t = \frac{f_t\left(1 - e^{-(s_t+f_t)}\right)}{s_t + f_t}. \tag{2}$$

[6] See Shimer (2005a), footnote 9.

We use formulas (1) and (2) to compute our hazard rate series s_t and f_t from the adjusted CPS data. These monthly series are then converted to quarterly frequency by simple averaging. The resulting series cover the sample period 1976Q1-2005Q4.

For comparison purposes we consider two additional sets of measures constructed by Shimer, based on CPS gross flow and unemployment duration data, respectively. In his gross flow-based series, margin error is handled using the MAR procedure, while time aggregation error is corrected using the method discussed above. His duration-based series are adjusted for time aggregation error using a related method. See Shimer (2005a) for further details concerning his data construction.[7]

3 Business Cycle Comovement

In this section we assess the dynamic relationships at business cycle frequencies between the separation and job finding rates s_t and f_t and labor productivity.[8] The dynamic relationships are measured in terms of cross-correlations at various leads and lags. We consider both HP filtering and first differencing. For the HP filter we use the standard smoothing parameter of 1600.

Results for the two detrending methods are shown in Figure 1. For HP filtered data, the separation rate and productivity achieve a peak correlation of -0.58 at a lag of zero. Moreover, the correlations at other leads and lags are roughly symmetric about zero. This means that the separation rate is highly countercyclical and adjusts contemporaneously with the cycle. When the first difference filter is used, the magnitudes of the correlations are naturally reduced. However, one can clearly see in the upper right panel of the figure that the same dynamic pattern is preserved.

The correlation between the job finding rate and productivity peaks at 0.60 at a lead of two to three quarters in the HP filtered data. Thus, the job finding rate is highly procyclical and trails the cycle. A similar pattern may be observed in the first differenced data.

To assess the robustness of these findings to the choice of cyclical indicator, Figure 2 repeats the exercise using unemployment in place of labor productivity. The correlation

[7] Sample periods are 1967Q2-2004Q4 for the gross flow-based data and 1951Q1-2004Q4 for the duration-based data. The data are available at Shimer's web page, http://robert.shimer.googlepages.com/flows.

[8] We measure labor productivity as GDP divided by the number of employed persons reported in the CPS.

between the separation rate and unemployment lies above 0.50 at lags of zero to four quarters in the HP filtered data, whereas the correlation between unemployment and the future separation rate reaches almost zero after four quarters. Thus, the separation rate leads unemployment. This dynamic pattern is preserved in the first differenced data. The job finding rate and unemployment exhibit strong negative correlation, and the job finding rate moves roughly contemporaneously with productivity. These results conform to the preceding ones, in that unemployment is a lagging indicator of the business cycle. We conclude that the separation rate is highly countercyclical and moves contemporaneously with the cycle, while the job finding rate is highly procyclical and trails the cycle.

Figure 3 reports the cross correlations between the separation and job finding rates under the two filtering methods. These provide a direct assessment of comovement between the two rates themselves. Observe that the HP filtered rates are strongly negatively correlated at lags of 0-4 quarters, while the first differenced rates exhibit strong negative correlation at a lag of one quarter. It follows that declines in the job finding rate tend to be preceded by increases in the separation rate.

In Figures 4 through 6 we replicate this analysis using Shimer's gross flow-and duration-based data sets. The results are essentially unaltered except for the first differenced duration data, where a backward phase shift in the unemployment-job finding correlations may be observed. We favor the gross flow-based findings since they are derived from direct measurements of the flows between employment and unemployment. In the duration data, these flows are confounded with flows between NILF and unemployment, leading to less reliable measures of separation and job finding rates.

4 Contributions to Unemployment Variability

We now quantify the contributions of separation and job finding rates to overall unemployment variability. Shimer (2005a) argues that the measured magnitudes of the two hazard rates make it reasonable to use the following approximation:

$$u_t \simeq \frac{s_t}{s_t + f_t} \equiv u_t^{ss}.$$

This approximation may also be applied to the trends. Let $\overline{u}_t$, $\overline{s}_t$ and $\overline{f}_t$ denoted the trend components of the three series obtained via the HP filter. We then have:

$$\overline{u}_t \simeq \frac{\overline{s}_t}{\overline{s}_t + \overline{f}_t} \equiv \overline{u}_t^{ss}.$$

Log-linearizing u_t^{ss} around the trend values $\overline{u}_t^{ss}$ yields the following decomposition:

$$\ln\left(\frac{u_t^{ss}}{\overline{u}_t^{ss}}\right) = (1-\overline{u}_t^{ss})\ln\left(\frac{s_t}{\overline{s}_t}\right) - (1-\overline{u}_t^{ss})\ln\left(\frac{f_t}{\overline{f}_t}\right) + \epsilon_t. \tag{3}$$

Observe that (3) expresses the deviations of unemployment from trend as a sum of factors that depend separately on the deviations of separation and job finding rates from trend, together with a residual term.

In the case of first differencing, the trend components are given by u_{t-1}^{ss}, s_{t-1} and f_{t-1}, and the decomposition becomes:

$$\Delta \ln u_t^{ss} = (1-u_{t-1}^{ss})\Delta \ln s_t - (1-u_{t-1}^{ss})\Delta \ln f_t + \epsilon_t. \tag{4}$$

Equations (3) and (4) may be expressed generically as:

$$du_t^{ss} = du_t^{sr} + du_t^{jfr} + \epsilon_t. \tag{5}$$

Figure 7 plots the factors du_t^{sr} and du_t^{jfr} together with the unemployment deviations du_t^{ss} under each of the filtering methods. Under HP filtering, the factor du_t^{sr} is somewhat less variable than du_t^{jfr}, while the variabilities are comparable under first differencing. In either case, both factors display substantial variability relative to du_t^{ss} throughout the sample period.

The linear decomposition (5) makes possible a quantitative assessment of unemployment variability in terms of the separate contributions of separation and job finding rates. Note that the variance of du_t^{ss} may be written:

$$\begin{aligned} Var(du_t^{ss}) &= Var(du_t^{sr}) + Var(du_t^{jfr}) + Var(\epsilon_t) \\ &\quad +2Cov(du_t^{sr}, du_t^{jfr}) + 2Cov(du_t^{sr}, \epsilon_t) + 2Cov(du_t^{sr}, \epsilon_t) \\ &= Cov(du_t^{ss}, du_t^{sr}) + Cov(du_t^{ss}, du_t^{jfr}) + Cov(du_t^{ss}, \epsilon_t). \end{aligned} \tag{6}$$

The term $Cov(du_t^{ss}, du_t^{sr})$ gives the amount of variation in du_t^{ss} that derives from variation in du_t^{sr}, both directly and through its correlations with du_t^{jfr} and ϵ_t. This may be expressed as a proportion of total variation:

$$\beta^{sr} = \frac{Cov(du_t^{ss}, du_t^{sr})}{Var(du_t^{ss})}.$$

Observe that β^{sr} is formally equivalent to the concept of beta in finance. Correspondingly, the proportions of variation in du_t^{ss} that derive from du_t^{jfr} and ϵ_t are given by

$$\beta^{jfr} = \frac{Cov(du_t^{ss}, du_t^{jfr})}{Var(du_t^{ss})}, \qquad \beta^{\epsilon} = \frac{Cov(du_t^{ss}, \epsilon_t)}{Var(du_t^{ss})}.$$

From (6) we have $1 = \beta^{sr} + \beta^{jfr} + \beta^{\epsilon}$. Thus, the three betas serve to decompose the total variation in du_t^{ss} into the separate components that derive from fluctuations in separation and job finding rates, together with a residual component.

Panel A of Table 1 reports the values of betas calculated under the two filtering methods. In the HP filtered data, fluctuations in the separation rate relative to trend explain 41 percent of overall fluctuations in unemployment. The figure rises to 51 percent in the first differenced data. We conclude that separation and job finding rates account for comparable proportions of unemployment variability. In particular, cyclical fluctuations in the separation rate explain between 40 and 50 percent of the fluctuations in unemployment.

Betas for the post 1985 subsample are also reported. The contribution of the separation rate falls to 34 and 46 percent under the respective filtering methods. Thus, while the separation rate explains a smaller proportion of unemployment fluctuations in recent decades, its contribution remains substantial.

Results obtained using the Shimer data sets are reported in panel B. The proportions explained by the separation rate are somewhat greater in his gross flow-based data, which are not corrected for margin error. In his duration-based data, the proportion explained by the separation rate drops to 28 percent under HP filtering, and 40 percent under first differencing. The proportions for the post 1985 subsample lie in a range of 15 to 42 percent, with lower values associated with the duration data. Again, we favor the gross flow-based findings since they directly isolate the flows between employment and unemployment. In the duration data, these flows are confounded with flows between NILF and unemployment. As demonstrated by Elsby et al. (2007), rates of unemployment inflow from employment are more countercyclical than overall unemployment inflow rates. In any event, all three data sets show that the separation rate makes an important contribution to unemployment variability.

Dynamic decomposition. The foregoing analysis decomposes unemployment variability in terms of contemporaneous deviations of the separation and job finding rates from trend. As demonstrated in Section 3, however, the separation rate is strongly negatively correlated with the job finding rate in future periods. This suggests that deviations of the separation rate may play a somewhat larger role than the preceding analysis indicates, in that they influence future job finding rates and thus future unemployment variability.

To assess the potential quantitative importance of this dynamic channel, we represent the factors du_t^{sr} and du_t^{jfr} in the standard moving average form:

$$du_t^{sr} = \varepsilon_t^{sr} + \sum_{k=1}^{\infty}(a_k \varepsilon_{t-k}^{sr} + b_k \varepsilon_{t-k}^{jfr}), \tag{7}$$

$$du_t^{jfr} = \varepsilon_t^{jfr} + \sum_{k=1}^{\infty}(c_k \varepsilon_{t-k}^{sr} + d_k \varepsilon_{t-k}^{jfr}). \tag{8}$$

where ε_t^{sr} and ε_t^{jfr} are variations in du_t^{sr} and du_t^{jfr} that are uncorrelated over time, but can be correlated contemporaneously. Ignoring the residual term ϵ_t for simplicity, the variance of du_t^{ss} may be written

$$\begin{aligned} Var(du_t^{ss}) &= Var(du_t^{sr} + du_t^{jfr}) \\ &= Var(\varepsilon_t^{sr}) + Var(\varepsilon_t^{jfr}) + 2Cov(\varepsilon_t^{sr}, \varepsilon_t^{jfr}) + \Lambda_t^{sr} + \Lambda_t^{jfr}, \end{aligned} \tag{9}$$

where

$$\begin{aligned} \Lambda_t^{sr} &= \sum_{k=1}^{\infty}[(a_k + c_k)^2 Var(\varepsilon_{t-k}^{sr}) + (a_k + c_k)(b_k + d_k) Cov(\varepsilon_{t-k}^{sr}, \varepsilon_{t-k}^{jfr})], \\ \Lambda_t^{jfr} &= \sum_{k=1}^{\infty}[(b_k + d_k)^2 Var(\varepsilon_{t-k}^{jfr}) + (a_k + c_k)(b_k + d_k) Cov(\varepsilon_{t-k}^{sr}, \varepsilon_{t-k}^{jfr})]. \end{aligned}$$

The decomposition (9) expands on (6) by expressing the variance in terms of intertemporally uncorrelated changes in the factors du_t^{sr} and du_t^{jfr}. The terms Λ_t^{sr} and Λ_t^{jfr} capture the effects of past changes in the separation and job finding rates on current unemployment. The betas are now calculated as

$$\begin{aligned} \beta^{sr} &= \frac{Var(\varepsilon_t^{sr}) + Cov(\varepsilon_t^{sr}, \varepsilon_t^{jfr}) + \Lambda_t^{sr}}{Var(du_t^{ss})}, \\ \beta^{jfr} &= \frac{Var(\varepsilon_t^{jfr}) + Cov(\varepsilon_t^{sr}, \varepsilon_t^{jfr}) + \Lambda_t^{jfr}}{Var(du_t^{ss})}. \end{aligned}$$

We can readily estimate the coefficients of (7) and (8) and the variance-covariance matrix of ε_t^{sr} and ε_t^{jfr}, and thus compute the betas.[9] Results are shown in Table 2. In nearly all cases, the separation rate explains a substantially greater proportion of overall unemployment fluctuations in comparison to the figures given in Table 1. For the full sample of the Fujita-Ramey data, in particular, the past and current movements in the separation rate explain nearly 70 percent of unemployment variability in the HP filtered data, and roughly 60 percent in the first differenced data. This demonstrates that the contemporaneous decomposition may significantly understate the true contribution of the separation rate.

[9] We first estimate a vector autoregression of du_t^{sr} and du_t^{jfr} and then invert it into the infinite-order moving average representation (7) and (8). The lag length of the VAR is set to eight quarters. Varying the lag length has little effect on our findings.

5 Conclusion

Drawing on CPS gross flow data, adjusted for margin error and time aggregation error, we demonstrate that cyclical changes in the separation rate are negatively correlated with changes in labor productivity and tend to move contemporaneously with them, while the job finding rate is positively correlated with and tends to lag productivity by two to three quarters. Moreover, the separation rate accounts for between 40 and 50 percent of unemployment variability when dynamic interactions are not considered. These conclusions are robust to the detrending method, and the basic pattern holds when unemployment is used in place of productivity as an indicator of the business cycle. The conclusions also hold for Shimer (2005a) gross flow-based data. While his duration-based data yield a somewhat smaller contribution of the separation rate when the HP filter is adopted as a detrending method (28 percent), this data set suffers from problems in identifying flows between unemployment and employment. The gross flow-based data, in contrast, provide direct measures of these flows. Finally, accounting for dynamic interactions between the separation and job finding rates substantially increases the importance of the separation rate in explaining unemployment variability.

Our results suggest that in analyzing unemployment adjustment over the business cycle, researchers should consider fluctuations at both the separation and job finding margins. The commonly made assumption of constant separation rates cannot be justified on grounds of empirical realism or quantitative relevance. Moreover, since declines in the job finding rate tend to be preceded by increases in the separation rate, abstracting from cyclical adjustment in the separation rate may distort the analysis of unemployment dynamics in important ways.

References

John Abowd and Arnold Zellner. Estimating gross labor force flows. *Journal of Business and Economic Statistics*, 3:254–83, July 1985.

Olivier Blanchard and Peter Diamond. The Beveridge curve. *Brookings Papers on Economic Activity*, 1:1–60, 1989.

Olivier Blanchard and Peter Diamond. The cyclical behavior of the gross flows of U.S. workers. *Brookings Papers on Economic Activity*, 2:85–155, 1990.

Hoyt Bleakley, Ann Ferris, and Jeffrey Fuhrer. New data on worker flows during business cycles. *New England Economic Review*, July/August:49–76, 1999.

Michael Darby, John Haltiwanger, and Mark Plant. The ins and outs of unemployment: The ins win. NBER Working Paper No. 1997, 1986.

Steven Davis. Fluctuations in the pace of labor reallocation. *Carnegie-Rochester Conference Series on Public Policy*, 27:335–402, 1987.

Steven Davis and John Haltiwanger. Gross job creation, gross job destruction and employment reallocation. *Quarterly Journal of Economics*, 107(3):819–863, 1992.

Steven Davis, John Haltiwanger, and Scott Schuh. *Job Creation and Destruction*. MIT Press, 1996.

Michael Elsby, Gary Solon, and Ryan Michaels. The ins and outs of cyclical unemployment. NBER Working Paper No. 12853, January 2007.

Bruce Fallick and Charles Fleischman. Employer-to-employer flows in the U.S. labor market: The complete picture of gross worker flows. Finance and Economics Discussion Series 2004-34, Board of Governors of the Federal Reserve System, 2004.

Shigeru Fujita and Garey Ramey. The cyclicality of job loss and hiring. Federal Reserve Bank of Philadelphia Working Paper 06-17, UC San Diego Discussion Paper 06-08, November 2006.

Shigeru Fujita and Garey Ramey. Reassessing the Shimer facts. Federal Reserve Bank of Philadelphia Working Paper 07-02, January 2007.

Shigeru Fujita, Christopher Nekarda, and Garey Ramey. The cyclicality of worker flows: New evidence from the SIPP. Federal Reserve Bank of Philadelphia Working Paper 07-05, February 2007.

Robert Hall. Job loss, job finding, and unemployment in the U.S. economy over the past fifty years. *NBER Macroeconomics Annual 2005*, pages 275–310, 2005a.

Robert Hall. Employment fluctuations with equilibrium wage stickiness. *American Economic Review*, 95(1):25–49, March 2005b.

Éva Nagypál. Reallocation over the business cycle: The importance of job-to-job transitions. Draft, Northwestern University, July 2004.

James Poterba and Lawrence Summers. Response variation in the CPS: Caveats for the unemployment analysis. *Monthly Labor Review*, 107(3):37–43, March 1984.

James Poterba and Lawrence Summers. Reporting errors and labor market dynamics. *Econometrica*, 54(6):1319–1338, November 1986.

Robert Shimer. Reassessing the ins and outs of unemployment. Draft, University of Chicago, June 2005a.

Robert Shimer. The cyclical behavior of equilibrium unemployment and vacancies. *American Economic Review*, 95(1):25–49, March 2005b.

Eran Yashiv. Evaluating the performance of the search and matching model. *European Economic Review*, 50(4):909–936, May 2006a.

Eran Yashiv. U.S. labor market dynamics revisited. *IZA dicussion paper 2445*, November 2006b.

Table 1: Contributions to unemployment fluctuations

A. Fujita-Ramey Data

	Full Sample		Post 1985	
	HP filter	First Difference	HP filter	First Difference
β^{sr}	0.405	0.507	0.344	0.457
β^{jfr}	0.587	0.494	0.659	0.543
β^{ϵ}	0.008	-0.001	-0.003	0.000

B. Shimer data

	Full Sample		Post 1985	
	HP filter	First Difference	HP filter	First Difference
Gross flow				
β^{sr}	0.409	0.555	0.274	0.417
β^{jfr}	0.579	0.447	0.729	0.583
β^{ϵ}	0.012	-0.002	-0.003	0.000
Duration				
β^{sr}	0.280	0.400	0.150	0.321
β^{jfr}	0.708	0.603	0.856	0.679
β^{ϵ}	0.012	-0.003	-0.006	0.000

Notes: See text for definitions of β^{sr}, β^{jfr} and β^{ϵ}. Full samples cover 1976Q1-2005Q4 for Fujita-Ramey data, 1967Q2-2004Q4 for Shimer gross flow-based data and 1951Q1-2004Q4 for Shimer duration-based data. Post-1985 results are based on the samples starting at 1985Q1. Fujita-Ramey series are adjusted for margin error, and all series are adjusted for time aggregation error. See Fujita and Ramey (2006) and Shimer (2005a) for data construction details.

Table 2: Dynamic decompositions

A. Fujita-Ramey Data

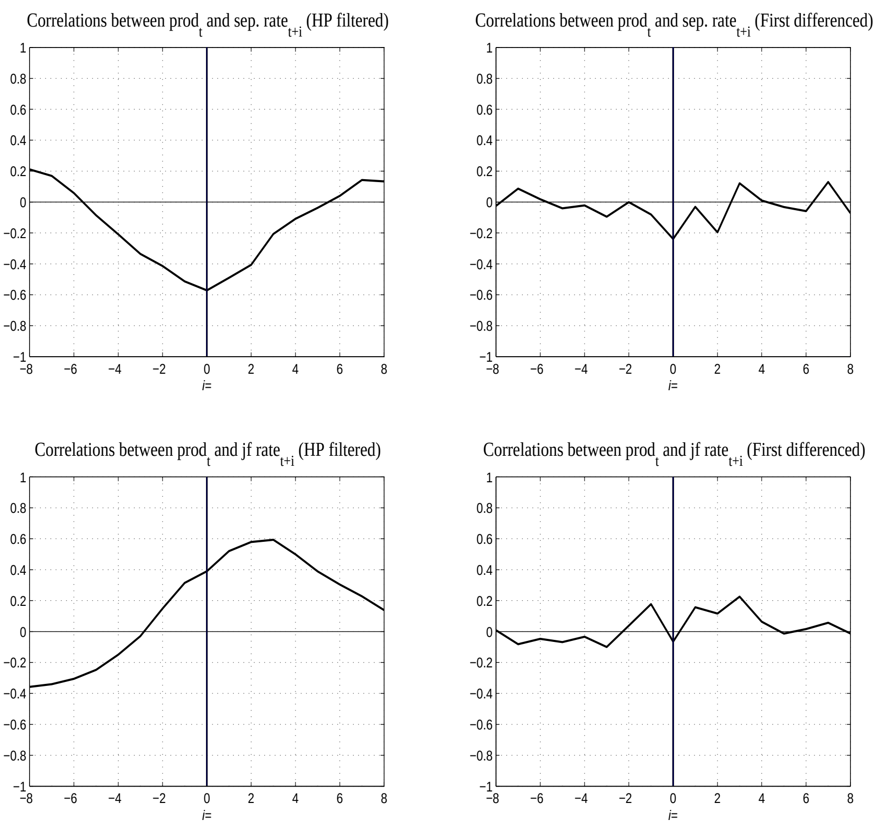
	Full Sample		Post 1985	
	HP filter	First Difference	HP filter	First Difference
β^{sr}	0.669	0.614	0.680	0.516
β^{jfr}	0.331	0.386	0.320	0.484

B. Shimer data

	Full Sample		Post 1985	
	HP filter	First Difference	HP filter	First Difference
Gross flow				
β^{sr}	0.465	0.596	0.709	0.560
β^{jfr}	0.535	0.404	0.291	0.440
Duration				
β^{sr}	0.311	0.405	0.467	0.287
β^{jfr}	0.689	0.596	0.532	0.713

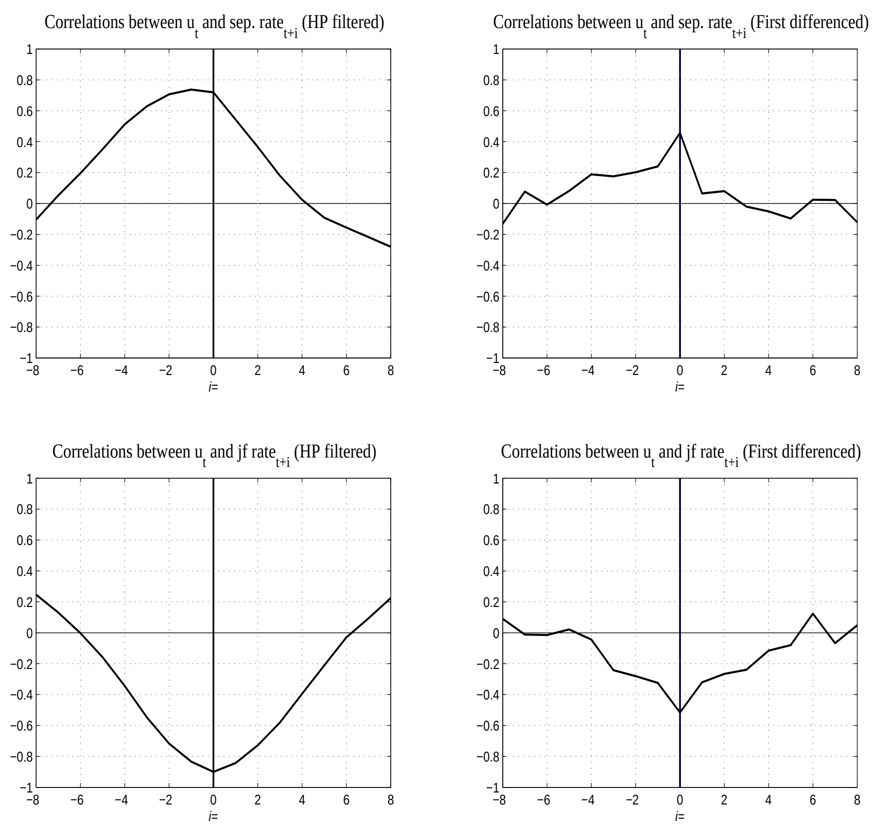
Notes: See text for definitions of β^{sr} and β^{jfr}. Full samples cover 1976Q1-2005Q4 for Fujita-Ramey data, 1967Q2-2004Q4 for Shimer gross flow-based data and 1951Q1-2004Q4 for Shimer duration-based data. Post-1985 results are based on the samples starting at 1985Q1. Fujita-Ramey series are adjusted for margin error, and all series are adjusted for time aggregation error. See Fujita and Ramey (2006) and Shimer (2005a) for data construction details.

Figure 1: Cross correlations between labor productivity and transition hazard rates



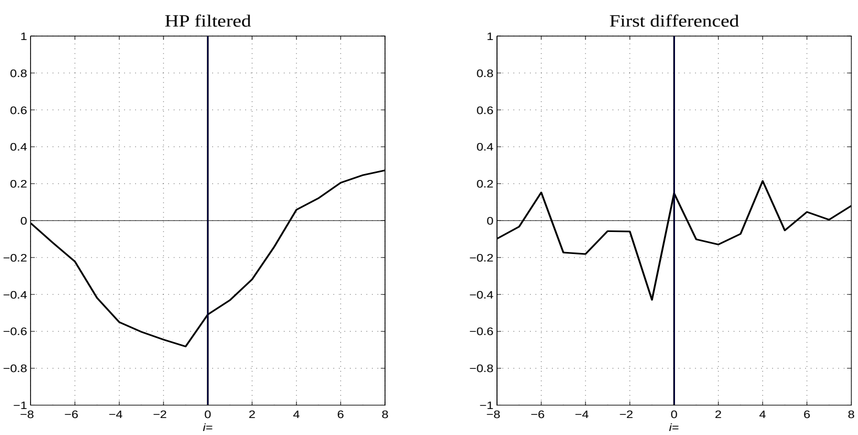
Notes: Sample covers 1976Q1-2005Q4. Transition rate series are adjusted for margin error and time aggregation error. See Fujita and Ramey (2006) for data construction details. Labor productivity is measured as real GDP divided by the number of employed persons reported in the CPS. HP filter uses smoothing parameter of 1600.

Figure 2: Cross correlations between unemployment rate and transition hazard rates



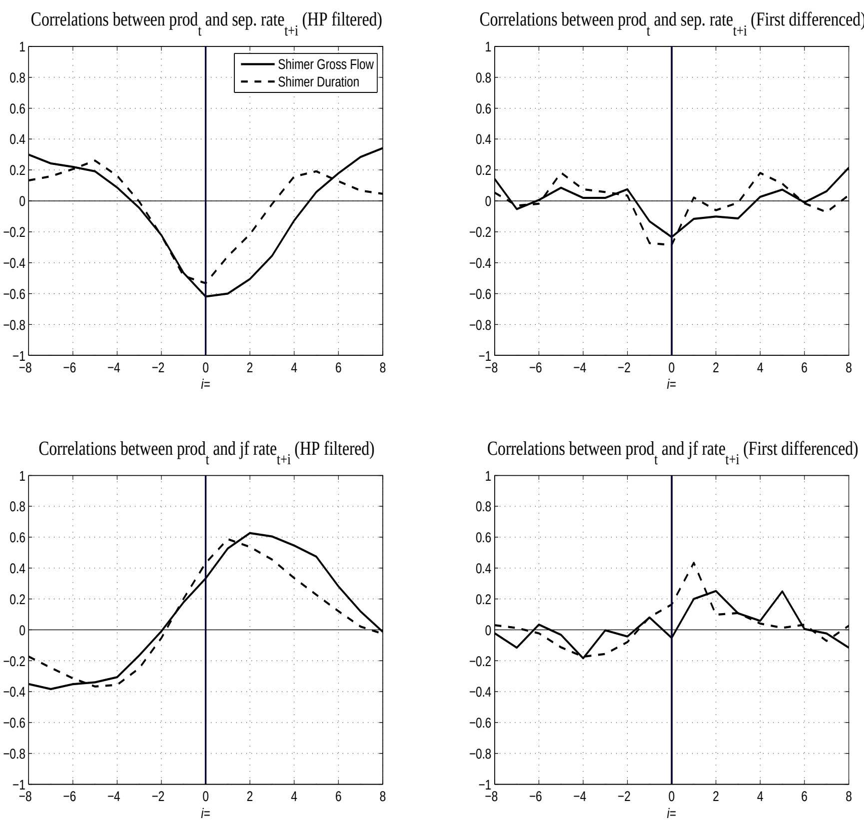
Notes: Sample covers 1976Q1-2005Q4. Series are adjusted for margin error and time aggregation error. See Fujita and Ramey (2006) for data construction details. HP filter uses smoothing parameter of 1600.

Figure 3: Cross correlations between job finding rate at t and separation rate at $t+i$



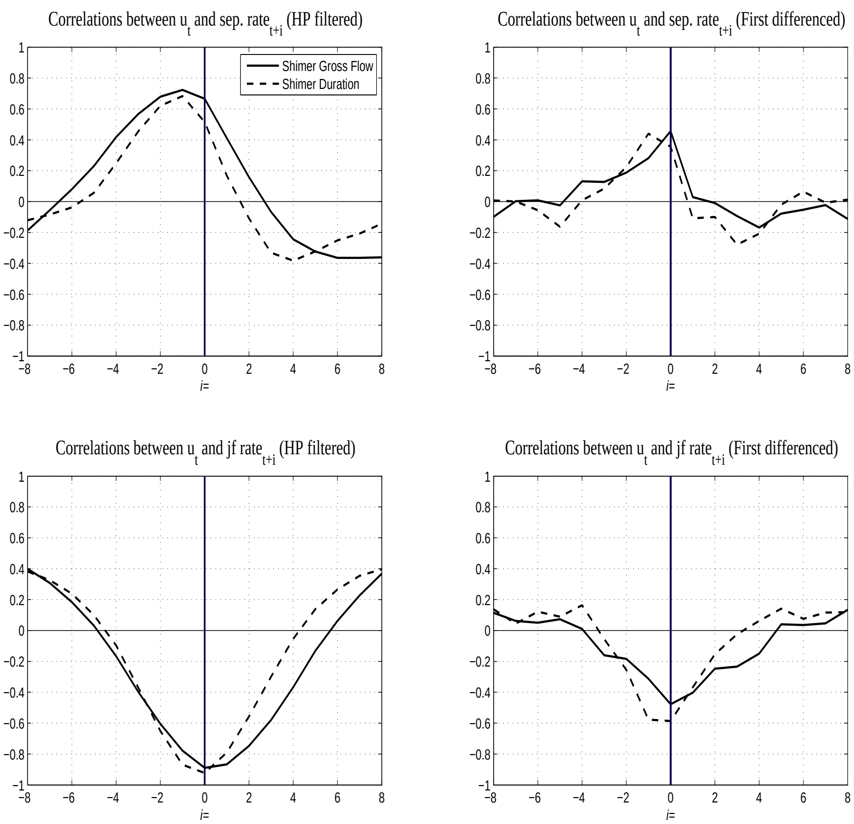
Notes: Sample covers 1976Q1-2005Q4. Series are adjusted for margin error and time aggregation error. See Fujita and Ramey (2006) for data construction details. HP filter uses smoothing parameter of 1600.

Figure 4: Cross correlations between labor productivity and transition hazard rates: Shimer data



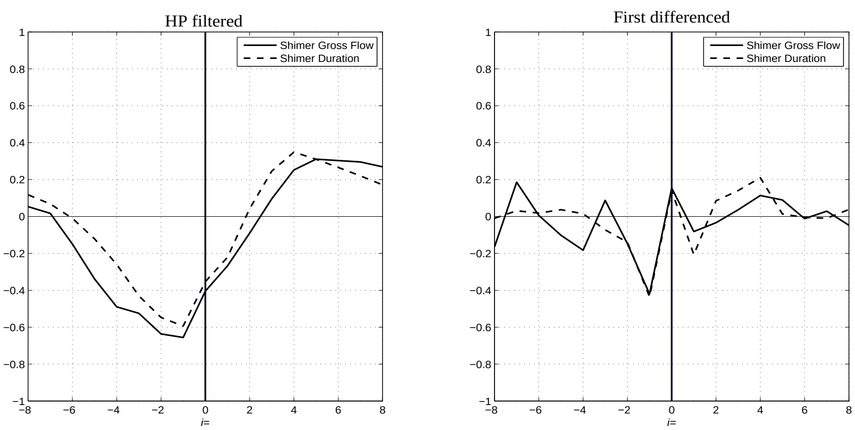
Notes: Samples covers 1967Q2-2004Q4 for Shimer gross flow-based data and 1951Q1-2004Q4 for Shimer duration-based data. Series are adjusted for time aggregation error. See Shimer (2005a) for data construction details. Labor productivity is measured as real GDP divided by the number of employed persons reported in the CPS. HP filter uses smoothing parameter of 1600.

Figure 5: Cross correlations between unemployment rate and transition hazard rates: Shimer data



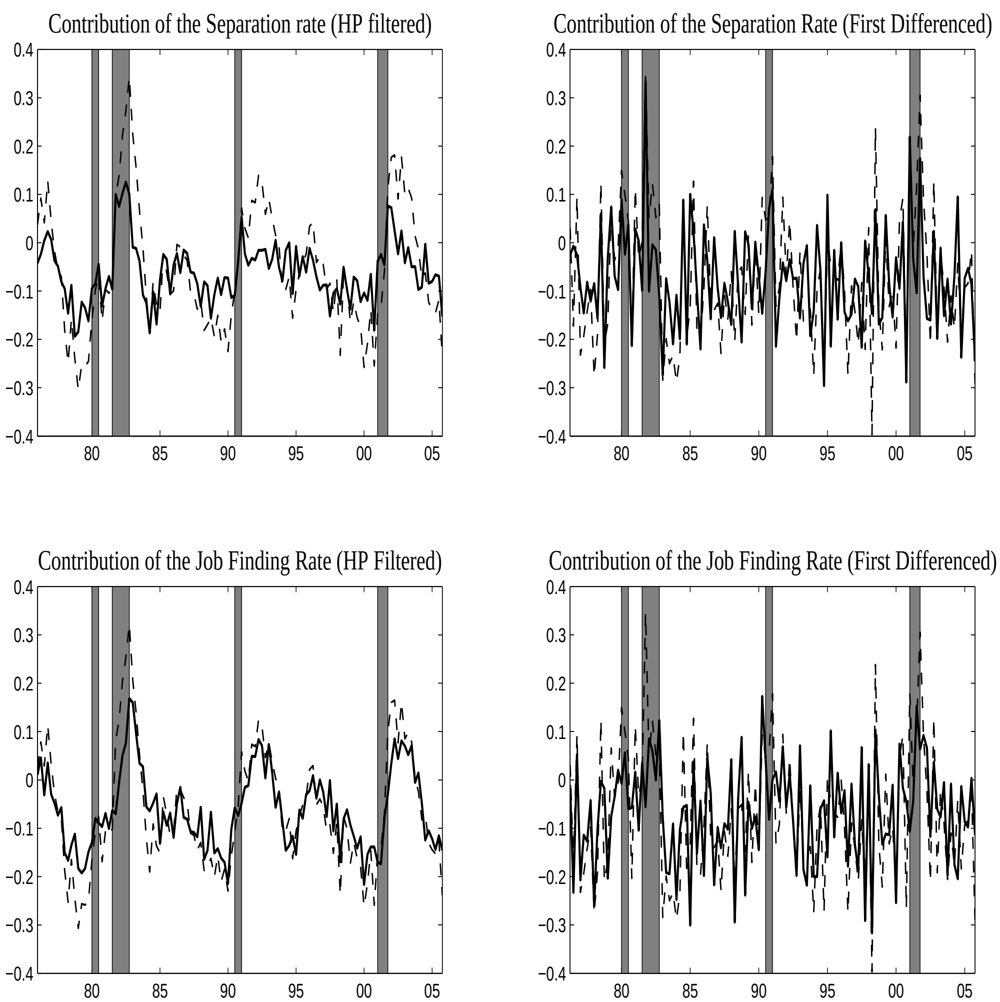
Notes: Samples covers 1967Q2-2004Q4 for Shimer gross flow-based data and 1951Q1-2004Q4 for Shimer duration-based data. Series are adjusted for time aggregation error. See Shimer (2005a) for data construction details.

Figure 6: Cross correlations between job finding rate at t and separation rate at $t + i$: Shimer data



Notes: Samples covers 1967Q2-2004Q4 for Shimer gross flow-based data and 1951Q1-2004Q4 for Shimer duration-based data. Series are adjusted for time aggregation error. See Shimer (2005a) for data construction details.

Figure 7: Contributions of separation and job finding rates to business cycle movements of unemployment rate



Notes: Solid lines indicate du_t^{sr} and du_t^{jfr}. Dashed lines indicate du_t^{ss}. See text for definitions. Sample period is 1976Q1-2005Q4. Shaded areas indicate NBER-dated recessions.