# Weekly Time Series of the U.S. Labor Market

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**Abstract**

Data from the Survey of Income and Program Participation (SIPP) are used to create a new data set of U.S. labor market behavior at weekly frequency, including the number of direct employment-to-employment (EE) transitions. The paper documents difficulties encountered creating the weekly series and discusses the strengths and weaknesses of the SIPP data relative to the CPS. Overall the SIPP labor force stocks, gross flows, and cyclical dynamics compare favorably with those from the Current Population Survey (CPS). Abstracting from labor force participation, direct EE transitions account for one-half of all separations from employment. Although CPS–based estimates of EE flows are nearly twice as high, the CPS overstates EE flows because of time aggregation. Separations to a new job are strongly procyclical while separations to unemployment are strongly countercyclical. The combination yields a nearly acyclical total separation rate.

JEL codes:
Keywords:

# 1 Introduction

At least since Kaitz (1970) and Perry (1972), many models of the labor market have taken the week as the fundamental unit of time. Recently, there has been increasing interest in using the weekly frequency for discrete-time search and matching models.[1] Previously, information needed to calibrate a matching model has only been available based on monthly estimates of labor market behavior.

This paper uses data from the Survey of Income and Program Participation (SIPP) over 1983–2006 to create a new data set of U.S. labor market behavior at weekly frequency. Unlike the Current Population Survey (CPS), which only collects data about a specific week of the month, the SIPP collects information for every week. By applying CPS labor force definitions to these data I can construct weekly time series of the U.S. labor market, including the number of direct employment-to-employment transitions.

Because the SIPP is not designed for aggregate time series analysis, several obstacles must be overcome to create the weekly series. In particular, the SIPP data suffer from a phenomenon known as the "seam effect," whereby transitions tend to be concentrated at the seam between two waves of interviewing. I devise a correction for the seam effect that allows for consistent estimates of aggregate series. The paper documents these difficulties and provides a detailed description of how the weekly data are constructed from the SIPP microdata.

I then assess how the labor force measures constructed from the SIPP compare with a known benchmark, the CPS. However, because the weekly SIPP data are not strictly comparable to the CPS, I construct "synthetic" CPS measures within the SIPP that replicate, to the best extent possible, how a SIPP respondent would be classified if surveyed by the CPS. I then compare the SIPP with the CPS along three dimensions: labor force stocks, gross flows, and cyclical dynamics.

The labor force stocks estimated from the SIPP and CPS are very similar in level and are highly correlated. However, the number of transitions among labor force states measured in the SIPP is substantially lower than in the CPS.[2] SIPP gross flows are between one-third and one-half as large as those estimated from the CPS. However, the volatility of gross flows is similar to that in the CPS and the time-series correlation between series from the two data sources is high.

The cyclical dynamics captured by the SIPP are quite similar to those in

1. See Hagedorn and Manovskii (2008); Ramey (2008); Elsby et al. (forthcoming).
2. This is similar to findings by Nagypál (2004) and Bils et al. (2007).

the CPS. The estimated cyclical components of the separation and job finding hazard rates in the SIPP and CPS have similar time-series behavior and correlation coefficients of 0.6 or higher. The SIPP exhibits significantly larger cyclical volatility. In both data sources the separation hazard rate is strongly countercyclical and the job finding hazard rate is strongly procyclical, although the relationship is weaker in the SIPP.

Thus, at a monthly frequency the SIPP and CPS have similar cyclical dynamics. An advantage of the SIPP over the CPS is that it provides more detailed information about labor market dynamics. In particular, the SIPP data can be used to construct weekly time series of the U.S. labor market. There is concern among researchers that measuring transitions using monthly data may lead to bias from time aggregation.[3] Nekarda (2008b) shows that time aggregation does not lead to cyclical bias in gross flows or hazard rates. However, gross flows estimated from monthly data understate the true number of transitions by approximately 20 percent when all weekly transitions are measured.

Another benefit is that the SIPP includes information on job changes by workers who remain employed. Fallick and Fleischman (2004) estimate that roughly twice as many workers separate direct to another job without an intervening spell of unemployment. These employment-to-employment (EE) separations do not directly affect unemployment. More recently, Moscarini and Thomsson (2008) argue that the EE rate is even higher.

However, the CPS may overstate direct EE transitions due to time aggregation. In the CPS since 1994, when a person is determined to be employed during the reference week they are asked whether they are employed with the same employer. If they answer no, this is identified as a direct EE transition. However, the CPS does not contain information about her labor market behavior outside the previous week. It may, however, be the case that a person was employed in consecutive reference weeks and with a new employer the second month but did *not* make a direct EE transition.

Using the SIPP allows me to identify direct EE transitions at the weekly level, eliminating time aggregation. Abstracting from labor force participation, I construct new measures of the EE and EU transition rates at weekly frequency. I find that employment-to-employment transitions account for one-half of all separations from employment. This estimate is 50 to 60 percent smaller than estimates of direct EE transitions using the CPS.[4]

Finally, I examine the cyclical behavior of the labor market at weekly frequency. The EE and EU rates have roughly the same volatility as unemployment

3. Shimer (2007).

4. Fallick and Fleischman (2004); Moscarini and Thomsson (2008).

at business cycle frequencies. In contrast, the total separation rate, the sum of the EE and EU rates, is substantially less variable than either of its components and only 60 percent as volatile as output. The EU rate is strongly countercyclical, leading unemployment by ten months, while the EE rate has a strong negative correlation and leads unemployment by five months. The combination yields a nearly acyclical total separation rate. Thus, the apparently weak cyclical movements of the total separation rate mask strong movements in underlying separation activity at the EE and EU margins. The weekly job finding rate is almost twice as volatile as unemployment over the business cycle. It is strongly procyclical and coincident with unemployment.

The paper proceeds as follows. Section 2 discusses the SIPP and the technical aspects of how the weekly data set is constructed. In particular, section 2.5 describes the seam effect and the correction I devise. In section 3 I compare the labor force measures constructed from the SIPP with the CPS. Section 4 analyzes weekly hazard rates and the cyclical behavior of total separations at weekly frequency. The final section concludes.

## 2 Survey of Income and Program Participation

The Survey of Income and Program Participation (SIPP) is an ongoing longitudinal survey of U.S. households. It is similar in many respects to the CPS, allowing for concurrent analysis, yet the SIPP offers researchers additional information and richness not available in the CPS. This section describes the SIPP survey, focusing on elements important for estimating aggregate time series.

The largest organizational unit of the SIPP is the *panel*. Each panel is formed from a nationally-representative sample of individuals fifteen years of age and older selected from households in the civilian noninstitutional population. These sampled individuals, along with others who subsequently live with them, are interviewed once every four months over the duration of the panel. Unlike the CPS, original sample members who move from their original address are interviewed at their new address.

The SIPP survey design calls for one-quarter of the sample to be interviewed in each month. Each household in the panel is randomly assigned to one of these four *rotation groups*. A set of interviews conducted for each of the 4 rotation groups constitutes 1 interview *wave*. At each interview respondents are asked to provide information about the previous four months. Table 1 shows the relationship between rotation group, calendar month, and survey wave for the 1985 panel. For instance, the first column of table 1 shows that rotation group 1 had its wave 1 interview in January 1985. At that interview respondents provided information about the previous four months, beginning with October 1984.

Each rotation group is interviewed the same number of times in each panel. However because each rotation group enters the survey universe in a different month, each rotation group spans a different set of calendar months. This can be seen clearly in table 1. Note that the first and last three months of every panel do not have observations from all 4 rotation groups; this becomes important when considering the seam effect (discussed below).

Each panel was originally designed to have 8 waves of interviews and a target initial sample size of 20,000 households. In practice, however, insufficient funding led to the early termination of several panels and frequent shortfalls in the target size. The original SIPP survey design also called for a new panel to begin each year, giving an overlapping design to improve accuracy.

The SIPP survey underwent a substantial redesign in 1996 to improve the quality of longitudinal estimates. The overlapping panel structure was eliminated in favor of a substantially larger sample size and panel length was increased from thirty-two months to forty-eight months. In addition, computer-assisted survey techniques, such as dependent interviewing, were introduced.[5]

Currently there are data available for 13 SIPP panels. The 1989 panel, which only lasted 3 waves, is not used. The time series coverage of each panel is shown in figure 1. Each of the 12 SIPP panels used in this paper is shown on the vertical axis. Each month a panel contributes data is indicated by a solid line.

The first panel is the 1984 panel, although data from the first interview go back to June 1983. A new panel is added each year until 1993. The 1996 panel is the first selected under the new survey design; data begin in December 1995. There is a seven month period from March 2000 to September 2000 where no interviews were conducted because of insufficient funding. Data from the 2001 panel begin in October 2000.

## 2.1 Survey Design

Each SIPP panel is formed from a nationally-representative sample of individuals fifteen years of age and older selected from households in the civilian noninstitutional population. These sampled individuals, along with others who subsequently live with them, are interviewed once every four months over the life of the panel. Each panel is randomly divided into 4 rotation groups, with each rotation group interviewed in a separate month. For a given panel, a set of

5. Similar improvements were implemented in the CPS following its redesign in 1994. See Bureau of Labor Statistics (2002).

interviews conducted for each of the 4 rotation groups constitutes 1 interview wave. At each interview respondents are asked to provide information about the previous four months.

Original sample members fifteen years or older who move from their original address to another address are interviewed at the new address. If persons not previously in the survey join a respondent's household, they are interviewed for as long as they live with the original respondent.

Although the pre-1996 panels were designed to have 8 waves of interviews, a number of panels were terminated early because of insufficient funding. In addition, the intended initial sample size of 20,000 households was rarely achieved.

The SIPP survey underwent a substantial redesign in 1996 to improve the quality of longitudinal estimates. The overlapping panel structure was eliminated in favor of a substantially larger sample size and panel length was increased from thirty-two months to forty-eight months. In addition, computer-assisted survey techniques, such as dependent interviewing, were introduced.[6]

## 2.2 Survey Content

The core content of the survey consists of questions asked at every interview, covering demographic characteristics; labor force participation; program participation; amounts and types of earned and unearned income received, including transfer payments; noncash benefits from various programs; asset ownership; and private health insurance.[7] Most core data are measured on a monthly basis. Some core items are recorded only once per wave (e.g. race), while others are measured on a weekly basis (e.g. labor force status).

The information necessary to calculate gross flows is contained in 2 types of microdata files: full panel files and core wave files. Core wave files are released following the completion of a survey wave and contain the core labor force data and individual sampling weights. Wave files generally contain one record for each person in each month of the wave (e.g. up to four records per wave for each sample member).

Full panel files are released after interviewing for an entire panel is completed. They contain one record for each person interviewed at any time during the panel.

The full panel files are the best choice for longitudinal analysis. They contain demographic information for each person in the sample that has been

6. Similar improvements were implemented in the CPS following its redesign in 1994.
7. Westat (2001), p. 1-4.

edited to ensure longitudinal consistency. Missing observations from persons who were not interviewed for 1 or more months are either imputed or are identified as not in the sample.

Unfortunately, the full panel files have two major drawbacks for constructing gross labor flows. First, individuals' records are indexed by reference month, not calendar date of the interview. Because each rotation group begins in a different month there is not a one-to-one correspondence between reference month and calendar month within each panel file. Second, the full panel files do not contain sufficiently detailed information on labor force classification and sampling weight. These issues are addressed in section 3.

## 2.3 SIPP Data Sources

As discussed above, the SIPP data come in two forms: full panel files and core wave data. The full panel files contain edited and longitudinally-consistent demographic information. They form the basis for defining a person's observations in the SIPP. The necessary labor force and sample weight information from the core wave files is then merged into the full-panel file.

Individuals are matched longitudinally using 3 variables: the sample unit identifier (`SSUID`), the entry address identifier (`EENTAID`), and the person number (`EPPPNUM`).[8]

There are three groups of SIPP panels over which the data structures and procedures are consistent: 1984–1988, 1990–1996, 2001. I discuss each period in turn.

### 2.3.1 Panels 1984–1988

The Census Bureau publishes full panel files for each of the 5 panels in this period (1984, 1985, 1986, 1987, 1988). A full panel file was not produced for the dramatically-shortened 1989 panel; few usable observations are lost by excluding it. The following variables are taken from the full panel files: the three identification variables, rotation group, interview status, sex, and age. The ID, rotation group, and sex variables are constant across the panel for each person but interview status and age can change in each month. Note that no information about the calendar date is contained in the full panel file.

The core wave files for this period have a "rectangular" structure (i.e. 1 observation per person per wave) and must be reshaped to a person-month format (i.e. 4 observations per person per wave). For each person, the fol-

8. All variables are named using the 1996 panel definitions.

lowing variables are taken from the core wave files: the three identification variables, date, sampling weight, and 3 labor force variables.

Because the labor force recode is not available on a weekly basis prior to the 1990 panel, it must be constructed using the answers to 3 weekly questions:

1. Did this person have a job or business during this week of the reference period? (WKWJOB)
2. Was this person with a job or business but without pay for this week of the reference period? (WKWABS)
3. Was this person looking for work or on layoff during this week of the reference period? (WKLOOK)

A weekly labor force recode consistent with CPS definitions is constructed by the following rules:

1. A person is *employed* if WKWJOB $= 1$ or if WKWJOB $= 0$ and WKWABS $= 1$;
2. A person is *unemployed* if WKWJOB $= 0$ and WKLOOK $= 1$; and,
3. A person is *not in the labor force* if WKWJOB $= 0$ and WKLOOK $= 0$.

The constructed labor force recode variable and all other variables from the core wave files are then merged into the full panel file to create the dated time series for each person.

### 2.3.2 Panels 1990–1993

The full panel files are available for the 1990, 1991, 1992, and 1993 panels. The same 8 variables are extracted from the full panel files as for the previous period. The core wave files for this period are published in person-month format and require no reshaping. The same 5 non-labor force variables are taken from the core wave files. A change in the weekly labor force coding allows for direct extraction of the weekly labor force recode.

The weekly labor force recode for week $w$ (WKESR$w$) classifies persons into 5 states. The CPS-equivalent labor force status is given by:

1. A person is *employed* if WKESR$w = 1, 2$, or 3;
2. A person is *unemployed* if WKESR$w = 4$; and,
3. A person is *not in the labor force* if WKESR$w = 5$.

The constructed labor force recode variable and all other variables from the core wave files are then merged into the full panel file to create the dated time series for each person.

### 2.3.3 Panels 1996, 2001, and 2004

No full panel files are published for the panels after 1993. For 1996, "panel longitudinal" core wave files, which have undergone longitudinal editing similar to full panel files, are published. Only core wave files are available for the 2001 and 2004 panels. All variables are taken from these core wave files. The labor force classification follows that for the previous period.

## 2.4 Constructing Aggregate Time Series

When estimating a longitudinal object such as gross flows, each rotation group should be thought of as its own separate panel—where here "panel" has its traditional econometric meaning: a collection of repeated observations on the same cross-section of individuals. Because each SIPP panel is nationally representative and because households are randomly assigned to rotation groups, the SIPP data can be viewed as 48 smaller, overlapping panels.

Let $p = 1, 2, \ldots, 12$ index SIPP panels and $r \in \{1, 2, 3, 4\}$ index the rotation group within a SIPP panel. An individual rotation group is uniquely identified by $pr$. In month $t$ there are observations from $P_t$ panels, each with $R_{pt}$ rotation groups. Let $j = 1, 2, \ldots, m_{prt}$ index persons from rotation group $pr$ in month $t$.

The estimator of a population total for some data object $Y$ from rotation group $pr$ for month $t$ is given by

$$\widehat{Y}_{prt} = \sum_{j=1}^{m_{prt}} w_{prjt}\, y_{prjt}\,, \tag{1}$$

where $y_{prjt}$ is the individual's response for object $Y$ and $w_{prjt}$ is his sampling weight for month $t$.[9] The population estimator for rotation group $pr$ is the weighted sum of responses for all persons in that rotation group. The aggregate estimate for month $t$ is taken across all panels and rotation groups:

$$\widehat{Y}_t = \sum_{p=1}^{P_t} \sum_{r=1}^{R_{pt}} \sum_{j=1}^{m_{prt}} \omega_{prt} w_{prjt}\, y_{prjt}\,. \tag{2}$$

Each rotation group is weighted by its contribution to the total number of observations in a month:

$$\omega_{prt} = \frac{N_{prt}}{\sum_{p=1}^{P_t} \sum_{r=1}^{R_{pt}} N_{prt}}. \tag{3}$$

9. Individual sampling weights reflect a person's weight in the entire SIPP panel. These are multiplied by 4 to make each rotation group nationally representative.

The pooled estimates are found by further aggregating over time:

$$\widehat{Y} = \sum_{t=1}^{T} \widehat{Y}_t. \tag{4}$$

Equations 1 and 4 are estimated separately for each of the 3 labor force stocks and 9 transitions. For stocks, the object $Y$ is an indicator for having labor force status `I` in month $t$. For example, when estimating the stock of employed $y_{prjt} = I(\mathtt{LFS}_{prjt} = \mathtt{E})$. For labor force transitions, the aggregation of all individual `ij` transitions is called the `IJ` *flow*, where capital letters indicate the aggregate quantity. Thus `IJ` is the number of persons who move from state $I$ in month $t-1$ to state $J$ in month $t$.

## 2.5 The Seam Effect

A phenomenon known as the "seam effect" is a well-documented but little-understood problem in the SIPP.[10] A *seam* in the SIPP is the boundary between four-month reference periods in successive waves of a panel.[11] The seam effect is characterized by observing significantly more changes in survey variables from the last month of the previous wave to the first month of the next wave (i. e., at the seam) than between any two months within a wave. The seam effect is prevalent in measures of labor force behavior, particularly in identifying a change of employer.

Exactly why the SIPP suffers from seam effects have not been definitively identified. Westat (1998) finds that research on the seam phenomenon in recipiency items has no association with the characteristics of respondents, edits and imputations, proxy versus self-response, or changes in interviewer assignments.[12] This suggests that the seam effect may be the product of inertia in reporting or recall bias.

Figures 2 and 3 illustrate the seam effect in two labor force transition measures estimated from the 1996 panel. Each panel graphs the flow estimated separately for each rotation group (thin line) together with the average across all rotation groups (thicker line) that excludes rotation groups on a seam. All panels share common time- and y-axes to facilitate comparison. Dashed vertical lines indicate the seam between waves.

Figure 2 plots the gross flows from employment to unemployment. There are obvious and sizable jumps in separations to unemployment estimated at the

10. See Westat (1998), chapter 6.
11. Westat (1998), p. 63.
12. Westat (1998), p. 64.

seam compared with non-seam months, although the seam effect is somewhat obscured by seasonal variation. Comparing the separation flow estimated from rotation group 3 to the average across all rotation groups illustrates the large deviations occurring at seams.

The seam effect is particularly severe for employment-to-employment transitions (figure 3). The observation on the seam records 2 to 4 times as many flows as the nonseam observations. Job-to-job transitions occur when a person reports working for a different employer without a change in labor force status. The survey instrument asks respondents for the date of the change in employer ID, so it is surprising that dramatically more employment-to-employment changes are reported at the seam. This indicates that the SIPP measure of direct employment-to-employment (EE) flows will be sensitive to correcting for the seam effect.

Although the seam effect is typically described as a monthly phenomenon, it manifests itself at the first transition between waves, regardless of frequency. For measures calculated at monthly frequency, the seam occurs at the first month of the wave. Thus, because of the SIPP's rotation pattern, only one-fourth of the sample is on a seam for any pair of calendar months within a rotation group. For the weekly SIPP data, the seam phenomenon affects only the first week of each wave.

I test for the presence of the seam effect using a fixed-effects regression on data aggregated at the rotation group–level. Let $s_{prt} = 1$ if rotation group $pr$ is on a seam at week $t$ and $s_{prt} = 0$ otherwise. To test for the seam effect in object $Y$, I regress $\ln(Y_{prt})$ on $s_{prt}$ and fixed effects for panel, rotation group, and time:

$$(5) \qquad \ln\left(Y_{prt}\right) = \alpha_0 + \alpha_{1p} I(p) + \alpha_{2r} I(r) + \alpha_{3m} I(m) + \beta s_{prt} + \xi_{prt}\,,$$

where $Y_{prt}$ is the stock- or flow-population ratio and where $I(p)$, $I(r)$, and $I(m)$ represent fixed effects for panel, rotation group, and month. The omitted groups are $p = 1984$, $r = 1$, and $m =$ June 1986. Table 3 reports the estimated coefficient $\widehat{\beta}$ for the SIPP labor force stocks and gross flows.

Looking first at stocks (upper panel), the presence of a seam effect is rejected in all 3 stocks. As suggested by Westat (1998), response variance on the seam does not affect cross-sectional estimates such as labor force stocks. The seam affects the *composition* of the transitions that cumulate to the period $t$ stock.

The lower panel of table 3 confirms the visual evidence of the large seam effects from the earlier figures. All coefficient are positive, indicating more transitions recorded on a seam, and highly statistically significant. Direct EE flows are 3.6 times higher on a seam than in nonseam weeks. The same pattern holds for the other flows, with coefficients indicating 2–3 times greater flows on a seam.

Although the seam effect occurs regularly, it still is necessary to correct for it in aggregate estimates because of periods when no seams occur. This occurs in the first 3 months of each panel and at any time a rotation group is missing from the sample. During the months when no seam is present, such as a junction between two panels, a dramatic decline in measured flows is observed when using uncorrected data. There are four periods in the SIPP where a non-overlapping junction between panels produces no seams: in 1990, 1996, 2000, and 2004.

### 2.6 Seam Effect Correction

The previous sections shows large and statistically significant seam effects in all flows. To mitigate the effect on aggregate estimates, I correct the data for the seam effect.

Because the SIPP's rotation pattern places only one-fourth of the sample on a seam for any month, it is possible to infer the true behavior using the rotation groups not on a seam. Consider an alternate estimate of object $Y$ that is calculated excluding any rotation groups on a seam:

$$Y_t^{ns} = \sum_{p=1}^{P_t} \sum_{r=1}^{R_{pt}} \omega_{prt}^{ns} (1 - s_{prt}) Y_{prt}\,, \tag{6}$$

where $s_{prt} = 1$ if rotation group $pr$ is on a seam at date $t$ and equals zero otherwise and weight $\omega_{prt}^{ns}$ is defined analogously to equation 3 for nonseam observations. In a sufficiently large sample, equations 6 and 1 are both consistent estimators for $Y_t$.

I use equation 6 to calculate aggregate estimates, in effect replacing observations at a seam with the average of all nonseam observations for that date. Because seams occur at fixed intervals and are uncorrelated with the sample selection, this missing-at-random (MAR) correction is consistent.

## 3 Comparing SIPP and CPS Labor Force Measures

This section assess how the labor force measures constructed from the SIPP compare with a known benchmark, the CPS. I first compare the SIPP with the CPS along three dimensions: labor force stocks, gross flows, and cyclical dynamics. However, because the weekly SIPP data are not strictly comparable to the CPS, I first discuss constructing "synthetic" CPS measures within the SIPP; these measures replicate to the best extent possible, how a SIPP respondent would be classified if surveyed by the CPS. CPS data are from Nekarda (2008a).

### 3.1 Synthetic CPS Labor Force Classification

The CPS determines an individual's labor force status for a month based on his experience during that month's *reference week*. The SIPP monthly labor force recode is not strictly comparable to the CPS measure. However, it is possible to construct a "synthetic" CPS labor force classification using weekly labor force classification described in section 2.3.[13] This labor force classification is the closest possible measure to what the person would have been classified were he surveyed by the CPS.

The SIPP core wave files contain questions pertaining to labor force status for each week of the reference period. The first step in constructing the synthetic CPS labor force classification is to identify the CPS reference week within each wave file.

The CPS reference week is defined as the 7-day period, Sunday through Saturday, that includes the 12th of the month. In December, the week of the 5th is used as the reference week, provided that the week falls entirely within the month; otherwise the week containing the 12th is used as the reference week.

After identifying the CPS reference week for each month the weekly SIPP labor force information can be used to determine the individual's CPS labor force classification. The correspondence between the SIPP weekly labor force recode (`WKESR`)—or the constructed weekly labor force recode—and the CPS labor force definitions is provided in the previous section. A person's CPS labor force classification is defined as the corresponding labor force recode in the CPS reference week.

The synthetic CPS recode is harder to construct for the pre-1990 panels. The core wave files before 1990 organize the weekly information chronologically by week (i.e. `WKESR1`, `WKESR2`, `WKESR4`, ..., `WKESR18`). However because each rotation group begins in a different month, `WKESR1` for rotation group 1 does not represent the same calendar week as `WKESR1` for rotation group 2. Thus a correspondence between SIPP reference week and calendar week must be determined separately for each rotation group.[14]

13. This is the same procedure developed in Fujita et al. (2007).

14. Identifying this correspondence is further complicated because several waves have only 3 rotation groups and the 1984 panel wave 8 file does not contain data for rotation group 3.

This is best illustrated with an example. In wave 1 of the 1986 panel, the first observation for rotation group 2 is for January 1986. The CPS reference week for this month was week three, so the synthetic CPS labor force status for January 1986 is determined by `WKESR3`. The reference week for February was the second week and the corresponding CPS reference week is `WKESR7` (January 1986 has five weeks plus the two weeks until the reference week). The remaining reference weeks are calculated similarly.

Classification as employed and not in the labor force (NILF) follows directly from the CPS definitions; unemployment requires an additional step. The CPS classifies a person as unemployed if he has searched for a job within the last four weeks. For this section only I apply this definition on a rolling basis to determine a person's weekly synthetic CPS labor force status. That is, a person without a job would be considered unemployed this week if he had searched for work during any of the previous four weeks, even if he did not search this week. After four weeks without search has elapsed, a person is classified as NILF. For the weekly labor force measures used in section 4, a person is only considered unemployed in a week where he is searching for a job.

Labor force transitions are measured by comparing a person's labor force status in two successive time periods. I define a transition from state `i` in period $t-1$ to state `j` in period $t$ as an `ij` transition observed at $t$. Transitions are identified at two different frequencies. A person's *weekly* labor force transition is the change in labor force status from one week to the next week. A person's *monthly* labor force transition is the change in labor force status from one CPS reference week to the next CPS reference week. This "synthetic" CPS labor force transition records how a person would have been classified by the CPS.

### 3.2 Stocks

The starting point for comparison is the estimates of the civilian noninstitutional population aged sixteen and older derived from both data sources. The time averages of the estimated population in the SIPP and the CPS are virtually identical and the correlation between the two population levels is 0.9966. For the rest of the analysis, I compare population ratios for the objects of interest rather than absolute levels.

Table 4 reports the labor force stocks, expressed as a share of population, for the CPS and the SIPP. All statistics are calculated for the SIPP sample period (June 1983–December 2006) from seasonally unadjusted data. The sample averages for all three stocks are very similar. The two data sets agree on employment, with nearly identical averages and similar volatility. The SIPP data have about 7 percent fewer unemployed and correspondingly more persons NILF.

In addition, the SIPP unemployed stock is over 40 percent more volatile than the CPS stock. However, the correlation between the SIPP and CPS stocks is highest for unemployment (0.95). Employment is similarly strongly correlated in the two data sets (0.91) although the correlation for NILF is weaker (0.73).

Figure 4 plots the stocks estimated from the SIPP and CPS. The figure shows CPS data for 1976–2007 (dashed line) together with SIPP data (solid line). The upper panel confirms the similarity of employment in the SIPP and CPS. The unemployment series (middle panel) also both track each other closely. The SIPP reports more unemployed than the CPS over 1983–1990 and slightly fewer during 1996–2001. Both show a similar increase during periods surrounding the 1991 and 2001 recessions.

The stocks of persons NILF do not agree as well as those for employment and unemployment. In particular, the SIPP series is too high in the 1990–1993 panels, although it returns to the CPS level with the 1996 panel. There is also a significant disagreement in the `N` stock at the start of the 2004 panel; there is a corresponding jump in employment.

### 3.3 Gross Flows

Table 5 compares the gross flows measured from SIPP and CPS. The first 2 columns report the mean and standard deviation of the CPS gross flows, expressed as a percent of the population. Labor force transitions are relatively rare events, accounting for only about 7 percent of all observations; the remaining 93 percent of observations record no change in labor force state.

The next 3 columns report data for the SIPP gross flows. For comparison, the level and volatility are expressed relative to the CPS values. As discussed in section 2.5, it is important to correct the SIPP gross flows for seam effects. The gross flows reported in table 5 using the seam effect correction from section 2.6.

As has been noted elsewhere, the SIPP records fewer labor force transitions than the CPS.[15] The SIPP gross flows from employment to unemployment are only 43 percent as large as those from the CPS while flows from unemployment to employment are just over one-half as large. Although the SIPP levels are substantially lower, the volatility is similar to the CPS and the correlation of the series in the two data sources is much higher (columns 4 and 5 of table 5).

Despite the SIPP having a larger measured `N` stock, the gross flows between employment and nonparticipation are lower relative to the CPS than for unemployment. Flows to and from nonparticipation are roughly one-third as large in the SIPP as in the CPS. As with transitions involving unemployment, the rel-

15. Nagypál (2004); Bils et al. (2007); Fujita et al. (2007); Moscarini and Thomsson (2008).

ative volatility is similar and the gross flows tend to move together in two data sets.

Although the number of transitions measured in the SIPP is only one-third to one-fifth as large as in the CPS, the time-series behavior of the series are similar. Although the time-series correlation of EU and UE flows between the SIPP and CPS is high, the implications for the cyclical dynamics must be assessed using a more sophisticated method.

### 3.4 Cyclical Dynamics

To compare the cyclical dynamics of the SIPP and CPS, I focus on the dynamics of the separation and job finding hazard rates. The monthly separation and job finding hazard rates are calculated by

$$s_t = \frac{\mathtt{EU}_t}{\mathtt{E}_{t-1}} \quad \text{and} \quad f_t = \frac{\mathtt{UE}_t}{\mathtt{U}_{t-1}} \tag{7}$$

where E and U are the stock of employed and unemployed persons.

The mean of the separation and job finding hazard rates in the CPS, expressed in percent, is reported in column 1 of table 6. Consistent with the lower level of gross flows, the mean of the SIPP hazard rates (column 3) is lower than in the CPS. The SIPP separation rate is 55 percent of that in the CPS while the mean job finding hazard rate is 70 percent as large as in the CPS.

Again, although the levels are quite different, the principal concern is how the *cyclical* behavior of hazard rates compares. To assess the cyclical dynamics, I first must isolate the component of the time series that moves at business cycle frequencies. I model the observed time series as the sum of four independent, unobserved components: a trend, a cycle, a seasonal, and an irregular component.[16] The trend represents low-frequency movements in the series. The cyclical component is a stochastic periodic function of time with a frequency at that of the business cycle. The seasonal component represents fluctuations that repeat annually and the irregular component captures the remaining nonsystematic variation.

The unobserved-components model for the natural logarithm of a time series $Y_t$, denoted $y_t$, is

$$y_t = \mu_t + \psi_t + \gamma_t + \varepsilon_t\,, \tag{8}$$

where $\mu_t$ is the trend, $\psi_t$ the cyclical, $\gamma_t$ the seasonal, and $\varepsilon_t$ the irregular component. Details of the econometric specification of the components are provided in appendix 5.

16. This follows the general method described in Harvey (1989).

Equation 8 is recast as a state space model where the unobserved components are represented by the state of the system. The unknown parameters are estimated by maximum likelihood using the Kalman filter to update and smooth the unobserved state. The estimation is performed using the STAMP program written by Koopman et al. (2007). The state space form and the details of the estimation appear in appendix 5.

Figure 5 plots the estimated cyclical components of the separation and job finding hazard rate. The cyclical component of the civilian unemployment rate published by the Bureau of Labor Statistics (BLS) is shown (thick gray line) as an indicator of the business cycle. The solid line shows the estimated cyclical component of the SIPP hazard rate and the dashed line shows the analogous CPS series.

Several features are apparent. First, except for two periods, the cyclical components of the two data sources track each other reasonably well. In the upper panel, both separation rates rise with unemployment during both the 1991 and 2001 recessions. The cyclical component of the job finding rate (lower panel) in the SIPP and CPS track very closely until 1996.

Two significant disruptions in the cyclical component of both SIPP series are readily apparent. The first occurs at the junction of the 1993 and 1996 panels (October 1995–February 1996) and the second occurs at the junction of the 2001 and 2004 panels (October 2003–February 2004). In both cases, these periods feature incomplete overlap between the panels, resulting in fewer than 4 rotation groups in any month. Although the effects are more abstruse than a discrete jump in the series, the time series model allows for a level shift in the trend component in January 1996 and January 2003 to help mitigate this effect in the cyclical component.[17]

The estimated cyclical components show a substantial oscillation in 1996 and a smaller one in 2003. If one visually smoothes over those two periods, however, the overall relationship between the cyclical dynamics in the SIPP and the CPS are similar. Largely because of these two periods, the standard deviation of the cyclical component of the SIPP hazard rates are nearly twice those of the CPS hazard rates (table 6). Nevertheless, the cyclical components of the CPS and SIPP series still have a high correlation: 0.62 for separation hazard rate and 0.82 for the job finding hazard rate.

The final assessment of the cyclical dynamics of SIPP is the correlation of the separation and job finding hazard rates with the business cycle. I use the

17. Interestingly, the period between the 1996 and 2001 panels (March 2000–October 2000) does not suffer from such a disturbance. The cyclical component for this period is estimated directly from the unobserved state of the model using the Kalman smoother.

civilian unemployment rate as in indicator of the business cycle. I estimate the cyclical component of the unemployment (shown in figure 5) rate using equation 8.

A richer picture of the cyclical dynamics are revealed by a plot of the cross-correlations between the cyclical component of the hazard rate and the cyclical indicator. This shows not only the contemporaneous correlation but also how time aggregation relates to the business cycle at other horizons. I calculate the cross-correlation between the cyclical component of the unemployment rate in month $t$ and $j = 0, 1, \ldots, 24$ leads and lags of the hazard rate, $\text{corr}\left(\widehat{\psi}_t^{UR}, \widehat{\psi}_{t+j}^{hr}\right)$, where $\widehat{\psi}_t^{hr}$ is the cyclical component of the hazard rate.

$$\text{corr}\left(\widehat{\psi}_t^{UR}, \widehat{\psi}_{t+j}^{hr}\right),$$

where $\widehat{\psi}_t^{hr}$ is the cyclical component of the separation or job finding rate.

The cross-correlations of the SIPP and CPS hazard rates are shown in figure 6. The cross-correlations confirm the strong visual relationship between the cyclical components of SIPP and CPS hazard rates. The contemporaneous correlation ($j = 0$) of the separation hazard rate with unemployment in the CPS data is 0.89. Despite the two visible disruptions in the SIPP series, the contemporaneous correlation of the SIPP hazard rate with unemployment is 0.55, about 38 percent lower. Both data sources find countercyclical separation hazard rates.

The SIPP and CPS agree more closely on the job finding rate. The contemporaneous correlation in the CPS is $-0.93$ and about 17 percent lower ($-0.78$) in the SIPP. Job finding is strongly procyclical in both the SIPP and CPS.

### 3.5 Discussion

The stocks of employed and unemployed estimated from the SIPP and CPS are very similar in level and are highly correlated. The number of transitions measured in the SIPP is substantially lower than in the CPS: SIPP gross are between one-third and one-half as large as those estimated from the CPS. However, the volatility of gross flows is similar to that in the CPS and the time-series correlation between series from the two data sources is high.

The cyclical dynamics captured by the SIPP are quite similar to those in the CPS. Although the SIPP time series are obscured by two periods where incomplete overlap between the panels results in significant instability, this disruption can be minimized using the unobserved-components model. The estimated cyclical components of the separation and job finding hazard rates in the SIPP and CPS have similar time-series behavior. In both data sources the separation hazard rate is strongly countercyclical and the job finding hazard rate is strongly procyclical, though the relationship is weaker in the SIPP.

Although the SIPP is designed for different purposes than the CPS, the labor force statistics calculated from the SIPP match those from the CPS remarkably well. Some difference between the two data sources is expected due to sampling variation and minor differences in survey design and definitions. Broadly speaking, however, the SIPP and the CPS capture similar dynamics of the U.S. labor market.

# 4 Weekly Time Series

Thus, at monthly frequency the SIPP and CPS have similar cyclical dynamics. An advantage of the SIPP over the CPS is that it provides more detailed information about labor market dynamics. In particular, the SIPP data can be used to construct weekly time series of the U.S. labor market. I use the SIPP to construct weekly hazard rates.

The SIPP allows me to identify direct $\mathtt{EE}$ transitions at the weekly level, eliminating time aggregation. Abstracting from labor force participation, I construct new measures of the $\mathtt{EE}$ and $\mathtt{EU}$ transition rates at weekly frequency. I find that employment-to-employment transitions account for one-half of all separations from employment, about 50 to 60 percent smaller than estimates using the CPS.

## 4.1 Constructing Hazard Rates

For the hazard rate analysis, I restrict attention to the employed and unemployed only. I construct hazard rate series at weekly frequency and normalize by stocks implied by those flows. This construction is necessary to normalize by stocks that are consistent with the population of interest.

I first estimate weekly gross flows from the SIPP and take a monthly average. I then construct stocks of employed and unemployed from the measured transitions. Given the timing convention for measuring gross flows, the period $t$ stock, $\mathtt{J}_t$, is the sum of flows of persons who end period $t$ in state $j$.

$$\tilde{\mathtt{E}}_t = \mathtt{EE}_t^{same} + \mathtt{EE}_t^{new} + \mathtt{UE}_t \tag{9}$$

$$\tilde{\mathtt{U}}_t = \mathtt{UU}_t + \mathtt{EU}_t \tag{10}$$

I define the four hazard rates below in relation to these stocks:

$$EER_t = \frac{\mathtt{EE}_t^{new}}{\tilde{\mathtt{E}}_{t-1}} \tag{11}$$

$$EUR_t = \frac{\mathtt{EU}_t}{\tilde{\mathtt{E}}_{t-1}} \tag{12}$$

$$TSR_t = \frac{\mathtt{EE}_t^{new} + \mathtt{EU}_t}{\tilde{\mathtt{E}}_{t-1}} \tag{13}$$

$$JFR_t = \frac{\mathtt{UE}_t}{\tilde{\mathtt{U}}_{t-1}}. \tag{14}$$

These data and hazard rate measures are also used by Nekarda and Ramey (2007) to evaluate a discrete-time weekly matching model with on-the-job search and direct employment-to-employment transitions.

## 4.2 Results

The first column of table 7 reports the average weekly hazard rate over 1983–2006. The EU and EE separation rates both average 0.16 percent a week, indicating that direct job change accounts for one-half of all separations from employment. This is considerably at odds with previous estimates from the CPS.

To put the weekly figures into more comparable terms, multiply by 52/12 to get 0.70 percent a month. This rate is considerably lower than the monthly rates for either EU (1.57 percent, table 5) or EE separations (2.7–3.2 percent, Fallick and Fleischman (2004) and Moscarini and Thomsson (2008)). However, as tables 5 and 6 indicate, the SIPP undercounts the number of transitions by roughly 50 percent. I adjust for this systematic undercounting by dividing each weekly hazard rate by the relative mean for the hazard rates reported in table 6.[18]

After adjusting for the systematic undercounting of transitions in the SIPP, the monthly separation implied by the adjusted weekly data rate is 1.27 percent, quite close to the CPS estimate. The implied monthly rate of direct EE separations is also 1.27 percent, about 50 to 60 percent lower than those of Fallick and Fleischman (2004) and Moscarini and Thomsson (2008). Thus, even after adjusting for the level of transitions, the SIPP finds considerably less direct employment-to-employment change than in the CPS, suggesting substan-

18. Both the EU and EE rates are adjusted by the separation hazard rate.

tial time aggregation in the CPS measures of direct employment-to-employment separations.

The second column of table 7 reports the standard deviation of the cyclical component of the four hazard rates. The EE and EU rates have roughly the same volatility as unemployment at business cycle frequencies. The EE rate is slightly more volatile than employment (1.12) while the EU rate is slightly less volatile (0.96). In contrast, the total separation rate is substantially less variable than either of its components and only 60 percent as volatile as output.

Figure 7 plots the cyclical components of the four hazard rates together with the cyclical component of unemployment rate. The two separation rates in the upper panel move sharply opposite each other, except for the period in 1996 associated with the panel disruption. Both series appear equally as volatile as unemployment.

The lower panel of figure 7 plots the total separation and job finding hazard rates. The total separation rate is considerably less volatile than either unemployment or the job finding rate, and has little clear association with the unemployment rate. The job finding rate mirrors the unemployment rate and displays considerably higher volatility.

The last column of table 7 reports the contemporaneous correlation of each hazard rate with unemployment while figure 8 plots the cross-correlation. The EU rate is strongly countercyclical and leads unemployment by ten months, while the EE rate has a strong negative correlation and leads unemployment by five months. The combination yields a nearly acyclical total separation rate. Thus, the apparently weak cyclical movements of the total separation rate mask strong movements in underlying separation activity at the EE and EU margins. The weekly job finding rate is almost twice as volatile as unemployment over the business cycle. It is strongly procyclical and coincident with unemployment.

# 5 Conclusion

This paper uses data from the SIPP to create a new data set of U.S. labor market behavior, including the number of direct employment-to-employment transitions, at weekly frequency. When the weekly data are analyzed in a manner that mimics the CPS, the SIPP data replicate many of the features of the U.S. labor market observed in the CPS. The labor force stocks estimated from the SIPP closely match the CPS stocks. The gross flows estimated from the SIPP, however, are at least 50 percent lower than those in the CPS. It is likely that this difference is a by-product of correcting the SIPP data for the "seam effect." Although its sources are not well understood, the seam effect describes the tendency for transitions in the SIPP to be concentrated at the seam between two waves of interviews. Because these seams do not occur in all months, they must be removed to construct a consistent time series; doing so necessarily reduces the level of gross flows. However, the time-series correlation between gross flows from the two surveys is high.

In addition, the cyclical dynamics captured by the SIPP are similar to the CPS. The cyclical components of the separation and job finding hazard rates have similar time-series behavior in both surveys and exhibit the same cyclical patterns: a strongly countercyclical separation hazard rate and a strongly procyclical job finding hazard rate. The notable difference in the cyclical dynamics is the SIPP's significantly larger cyclical volatility. A significant share of the higher volatility comes from two periods where the SIPP series have large oscillations in the cyclical component not seen in the CPS series. These periods, in 1996 and 2004, arise from incomplete overlap between the junction of two panels. Although the univariate structural time series model can partially compensate for this disturbance, a more comprehensive treatment requires panel structural time series estimation. This will also allow for a more sophisticated treatment of the seam effect, improving estimated gross flows.

Analyzing weekly the time series, I find that the rate of separations to unemployment (EU) and of direct employment-to-employment separations (EE) each account for one-half of the rate of total separations from employment. The cyclical volatility of the EU and EE rates is comparable to unemployment, however the total separation rate is substantially less variable. The EU rate is strongly countercyclical while the EE rate is strongly procyclical, yielding a nearly acyclical total separation rate. The apparently weak cyclical movement of the total separation rate masks strong movements in underlying separation activity. The weekly job finding rate is strongly procyclical and almost twice as volatile as unemployment over the business cycle.

My estimates, adjusted for the SIPP's systematic undercounting of transitions, imply a monthly EE separation rate that is 50 to 60 percent smaller than estimates from the CPS.[19] This suggests that as many as half of employment-to-employment transitions recorded by the CPS may not, in fact, have been direct. Because the CPS does not contain information about labor market behavior outside the reference week, it is not possible to differentiate true EE transitions from separate EU and UE transitions that are aggregated into a direct EE transition. Thus, the CPS will overstate direct EE transitions. Indeed, Nekarda (2008a) shows that most unrecorded EU and UE transitions are classified in the CPS as continuous employment. An implication of these results

19. Fallick and Fleischman (2004); Moscarini and Thomsson (2008).

for policymakers is that, although direct employment-to-employment transitions are important, the traditional channel of cyclical employment adjustment (unemployment) is equally important.

Much of this literature abstracts from labor force participation. Yet about 60 percent of the flows into and out of employment involve nonparticipation and the cyclical dynamics of NILF flows are distinct from those involving unemployment. Two rich avenues for future research are understanding the cyclical dynamics of the labor force participation decision and modeling high-frequency movements into and out of the labor force.

# Appendix

## Structural Time Series Model

The structural time series model for the natural logarithm of each series, denoted $y_t$, is

$$y_t = \mu_t + \psi_t + \gamma_t + \varepsilon_t, \tag{8}$$

where $\mu_t$ is the trend, $\psi_t$ the cyclical, $\gamma_t$ the seasonal, and $\varepsilon_t$ the irregular component.

I model the trend component as a smooth first-order local linear trend:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{A.1}$$

$$\Delta\beta_t = \zeta_t, \tag{A.2}$$

where $\Delta = (1 - L)$ and $L$ is the lag operator. The disturbances $\eta_t$ and $\zeta_t$ are independent and identically distributed (i. i. d.) normal random variables with mean zero and variances $\sigma^2_\eta$ and $\sigma^2_\zeta$.

The cyclical component is modeled as a second-order stochastic cycle with frequency $\lambda$, where[20]

$$\begin{bmatrix} \psi_t^{(j)} \\ \psi_t^{*(j)} \end{bmatrix} = \rho \begin{bmatrix} \cos\lambda & \sin\lambda \\ -\sin\lambda & \cos\lambda \end{bmatrix} \begin{bmatrix} \psi_{t-1}^{(j)} \\ \psi_{t-1}^{*(j)} \end{bmatrix} + \begin{bmatrix} \psi_t^{(j-1)} \\ \psi_t^{*(j-1)} \end{bmatrix} \tag{A.3}$$

for $j = 1, 2$ and $\psi_t^{(0)} = \kappa_t$ and $\psi_t^{*(0)} = \kappa_t^*$. The disturbances $\kappa_t$ and $\kappa_t^*$ are i. i. d. normal each with mean zero and variance $\sigma^2_\kappa$. Note that for $j = 1$ and $\rho = 1$ equation A.3 reduces to a deterministic cycle

$$\psi_t = \psi_0 \cos\lambda t + \psi_0^* \sin\lambda t,$$

20. Harvey and Trimbur (2003) find that, in practice, a second-order cycle provides a good approximation of the gain function of the Baxter-King (BK) bandpass filter.

where $\psi_0$ and $\psi_0^*$ are i. i. d. zero-mean random variables with variance $\sigma_\psi^2$.

The stochastic seasonal component is constructed so that the $s$ seasonal effects sum to zero in expectation. This is modeled as

$$\gamma_t = -\sum_{j=1}^{s-1} \gamma_{t-j} + \omega_t, \tag{A.4}$$

where $\omega_t \sim N(0, \sigma_\omega^2)$. Finally, the irregular component $\varepsilon_t$ is i. i. d. normal with zero mean and variance $\sigma_\varepsilon^2$. All disturbances are mutually uncorrelated.

The model given by equations 8 and A.1–A.4 is represented by the state space system relating observed data $y_t$ to the unobserved state vector $\boldsymbol{\alpha}_t$ through a measurement vector $\mathbf{z}$:

$$y_t = \mathbf{z}'\boldsymbol{\alpha}_t + \varepsilon_t \tag{A.5}$$

$$\boldsymbol{\alpha}_t = \mathbf{T}\boldsymbol{\alpha}_{t-1} + \boldsymbol{\eta}_t. \tag{A.6}$$

The unobserved state evolves according to a first-order Markov process with transition matrix $\mathbf{T}$. The state equation (A.6) is

$$\begin{bmatrix} \mu_t \\ \beta_t \\ \psi_t \\ \psi_t^* \\ \gamma_{t-1} \\ \gamma_{t-2} \\ \vdots \\ \gamma_{t-s+2} \end{bmatrix} = \begin{bmatrix} \mathbf{T}_{\text{trend}} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{T}_{\text{cycle}} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{T}_{\text{seasonal}} \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \beta_{t-1} \\ \psi_{t-1} \\ \psi_{t-1}^* \\ \gamma_{t-2} \\ \gamma_{t-3} \\ \vdots \\ \gamma_{t-s+1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ \zeta_t \\ \kappa_t \\ \kappa_t^* \\ \omega_t \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{A.7}$$

where

$$\mathbf{T}_{\text{trend}} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$$

$$\mathbf{T}_{\text{cycle}} = \begin{bmatrix} \rho\cos\lambda & \rho\sin\lambda \\ -\rho\sin\lambda & \rho\cos\lambda \end{bmatrix}$$

$$\underset{(s-1 \times s-1)}{\mathbf{T}_{\text{seasonal}}} = \begin{bmatrix} -1 & -1 & \dots & -1 & -1 \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ & & \vdots & & \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix}$$

This system represents a system with a first-order cycle. The extension to second-order cycles is straightforward.

The state vector enters the measurement equation by the $(4+s-1 \times 1)$ vector

$$z = \begin{bmatrix} 1 & 0 & 1 & 0 & 1 & 0 & \dots & 0 \end{bmatrix}'. \tag{A.8}$$

The unknown parameters $\sigma_\varepsilon^2$, $\sigma_\eta^2$, $\rho$, $\lambda$, $\sigma_\kappa^2$, and $\sigma_\omega^2$ are estimated by maximum likelihood using the Kalman filter. For consistency across all series, I fix the variance of the trend so as to reproduce the Hodrick-Prescott (HP) trend.[21] This variance is $\sigma_\zeta^2 = \sigma_\varepsilon^2/129,600$.[22] The cycle frequency $\lambda$ is fixed at sixty months; this corresponds roughly with the center of Burns and Mitchell (1946)'s period of business cycle frequencies. With these restrictions, the estimated trend and cyclical components correspond to a HP lowpass filtered trend and a BK bandpass filtered cyclical component.

21. Harvey and Jaeger (1993) show that the HP trend can be replicated in a structural time series model by a smooth local linear trend with signal-to-noise ratio equal to the inverse of the HP smoothing parameter.

22. Ravn and Uhlig (2002) find the optimal HP smoothing parameter for monthly data is 129,600.

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**Table 1. Relationship between Survey Wave, Rotation Group, and Calendar Date[a]**

| | *Rotation group* | | | |
|---|---|---|---|---|
| *Date* | *1* | *2* | *3* | *4* |
| 1984m10 | 1–1 | | | |
| 1984m11 | 1–2 | 1–1 | | |
| 1984m12 | 1–3 | 1–2 | 1–1 | |
| 1985m1 | 1–4 | 1–3 | 1–2 | 1–1 |
| 1985m2 | 2–1 | 1–4 | 1–3 | 1–2 |
| 1985m3 | 2–2 | 2–1 | 1–4 | 1–3 |
| 1985m4 | 2–3 | 2–2 | 2–1 | 1–4 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| 1987m1 | 8–1 | 7–4 | 7–3 | 7–2 |
| 1987m2 | 8–2 | 8–1 | 7–4 | 7–3 |
| 1987m3 | 8–3 | 8–2 | 8–1 | 7–4 |
| 1987m4 | 8–4 | 8–3 | 8–2 | 8–1 |
| 1987m5 | | 8–4 | 8–3 | 8–2 |
| 1987m6 | | | 8–4 | 8–3 |
| 1987m7 | | | | 8–4 |

Source: Author's calculations.
a. Cell entry gives the interview wave number and month number within each wave.

**Table 2. The Survey of Income and Program Participation**

| | | | *Number of* | | | |
|---|---|---|---|---|---|---|
| *Panel* | *Begin* | *End* | *Months* | *Weeks* | *Persons* | *Observations*[a] |
| 1984 | Jun 1983 | Apr 1986 | 35 | 153 | 48,934 | 5,031,872 |
| 1985 | Oct 1984 | Jul 1987 | 34 | 148 | 33,457 | 3,330,820 |
| 1986 | Oct 1985 | Mar 1988 | 30 | 131 | 27,330 | 2,681,937 |
| 1987 | Oct 1986 | Apr 1989 | 31 | 135 | 27,401 | 2,797,571 |
| 1988 | Oct 1987 | Dec 1989 | 27 | 117 | 27,145 | 2,432,822 |
| 1990 | Oct 1989 | Aug 1992 | 35 | 152 | 52,256 | 5,747,440 |
| 1991 | Oct 1990 | Jul 1993 | 35 | 152 | 33,473 | 3,689,173 |
| 1992 | Oct 1991 | Dec 1994 | 39 | 170 | 46,756 | 5,694,370 |
| 1993 | Oct 1992 | Dec 1995 | 39 | 169 | 46,747 | 5,669,515 |
| 1996 | Dec 1995 | Feb 2000 | 51 | 221 | 89,013 | 12,727,920 |
| 2001 | Oct 2000 | Dec 2003 | 39 | 170 | 80,026 | 8,499,728 |
| 2004 | Oct 2003 | Dec 2006 | 39 | 170 | 100,105 | 11,022,347 |
| All | Jun 1983 | Dec 2006 | 276 | 1,200 | 612,643 | 69,325,515 |

Source: Author’s tabulations using SIPP microdata for 1983:6–2006:12.

a. Weekly.

**Table 3. Testing for Seam Effects in Weekly SIPP Data**

| *Dependent variable* | *Seam effect* | *t statistic* | *No. obs.* | $R^2$ |
| --- | --- | --- | --- | --- |
| *Stocks* | | | | |
| E | 0.0008<br>(0.0005) | 1.56 | 6,851 | 0.8630 |
| U | 0.0028<br>(0.0040) | 0.69 | 6,851 | 0.9246 |
| N | −0.0017<br>(0.0012) | −1.44 | 6,852 | 0.5458 |
| *Gross flows* | | | | |
| EE | 3.5939***<br>(0.0562) | 63.98 | 5,790 | 0.4563 |
| EU | 2.0073***<br>(0.0314) | 63.91 | 6,793 | 0.4734 |
| EN | 2.6444***<br>(0.0319) | 82.82 | 6,820 | 0.5781 |
| UE | 1.8967***<br>(0.0307) | 61.83 | 6,825 | 0.4710 |
| NE | 2.7729***<br>(0.0307) | 90.46 | 6,817 | 0.6225 |
| UN | 2.6005***<br>(0.0292) | 89.08 | 6,793 | 0.6305 |
| NU | 2.5885***<br>(0.0315) | 82.11 | 6,804 | 0.5875 |

Source: Author's regressions using weekly SIPP microdata for 1983:6–2006:12.

a. Reports coefficient $\hat{\beta}$ from regression of $\ln(Y_{prt}) = \alpha_0 + \alpha_{1p}I(p) + \alpha_{2r}I(r) + \alpha_{3m}I(m) + \beta s_{prt} + \xi_{prt}$, where $s_{prt}$ is an indicator for panel $p$, rotation group $r$ being on a seam at week $t$; $\alpha$s are fixed effects for panel, rotation group, and month.

**Table 4. Comparison of SIPP and CPS Labor Force Stocks, 1983–2006[a]**

Percent of population

| *Stock* | *Mean* | *Standard deviation* | *Correlation with CPS* |
|---|---|---|---|
| *CPS* | | | |
| E | 62.46 | 1.51 | 1.0000 |
| U | 3.87 | 0.74 | 1.0000 |
| N | 33.67 | 0.94 | 1.0000 |
| *SIPP* | | | |
| E | 62.38 | 1.63 | 0.9143 |
| U | 3.59 | 1.04 | 0.9487 |
| N | 34.03 | 0.73 | 0.7252 |

Source: Author's calculations using SIPP microdata for 1983:6–2006:12 and CPS data from Nekarda (2008a).

a. Statistics and correlations are based on 276 monthly observations.

**Table 5. Comparison of SIPP and CPS Labor Force Gross Flows, 1983–2006[a]**

Percent of population

| | CPS | | SIPP | | |
|---|---|---|---|---|---|
| | | | Relative[b] | | |
| *Flow* | *Mean* | *Standard deviation* | *Mean* | *Standard deviation* | *Correlation with CPS* |
| *Separation* | | | | | |
| EU | 0.94 | 0.16 | 0.4255 | 0.7500 | 0.8167 |
| EN | 1.80 | 0.33 | 0.3111 | 0.7576 | 0.8695 |
| *Accession* | | | | | |
| UE | 1.03 | 0.17 | 0.5146 | 0.8824 | 0.7250 |
| NE | 1.61 | 0.24 | 0.3416 | 1.0000 | 0.7442 |
| *Participation* | | | | | |
| NU | 0.90 | 0.14 | 0.2444 | 0.7143 | 0.6023 |
| UN | 0.84 | 0.11 | 0.1786 | 0.7273 | 0.4254 |

Source: Author's calculations using SIPP microdata for 1983:6–2006:12 and CPS data from Nekarda (2008a).

a. Statistics and correlations are based on 276 monthly observations.

b. SIPP estimate divided by CPS estimate.

**Table 6. Comparison of SIPP and CPS Hazard Rates, 1983–2006[a]**

| | | | *SIPP* | | |
|---|---|---|---|---|---|
| | *CPS* | | *Relative*[b] | | |
| *Flow* | *Mean* | *Standard deviation*[c] | *Mean* | *Standard deviation*[c] | *Correlation with CPS*[c] |
| Separation | 1.51 | 5.58 | 0.5497 | 1.9373 | 0.6166 |
| Job finding | 26.97 | 6.99 | 0.6963 | 1.6896 | 0.8181 |

Source: Author's calculations using SIPP microdata for 1983:6–2006:12 and CPS data from Nekarda (2008a).

a. Using fully-aggregated data; see text for details. Statistics and correlations are based on 276 monthly observations.

b. SIPP estimate divided by CPS estimate.

c. Cyclical component estimated using equation 8.

**Table 7. Weekly Transition Rates and Unemployment Rate, 1983–2006** [a]

| | | *Cyclical component* [b] | | |
|---|---|---|---|---|
| *Rate* | *Mean* | *Standard deviation* | *Relative standard deviation* [c] | *Correlation with UR* |
| EER | 0.16 | 0.1043 | 1.1167 | −0.6563 |
| EUR | 0.16 | 0.0900 | 0.9636 | 0.5476 |
| TSR | 0.33 | 0.0558 | 0.5974 | −0.1944 |
| JFR | 4.29 | 0.1693 | 1.8126 | −0.7885 |
| UR | 5.82 | 0.0934 | 1.0000 | 1.0000 |

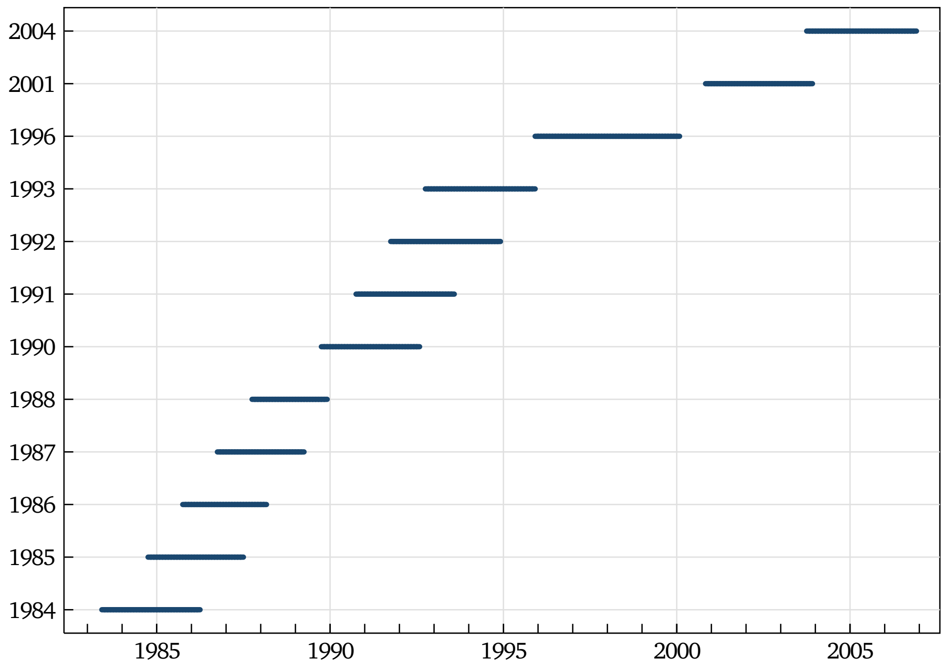
Source: Author's calculations using BLS data and SIPP microdata for 1983:7–2006:11.

a. Monthly average of weekly hazard rates.

b. Cyclical component estimated using equation 8.

b. Relative to standard deviation of unemployment rate.

**Figure 1. SIPP Panel Coverage, 1983–2006**[a]

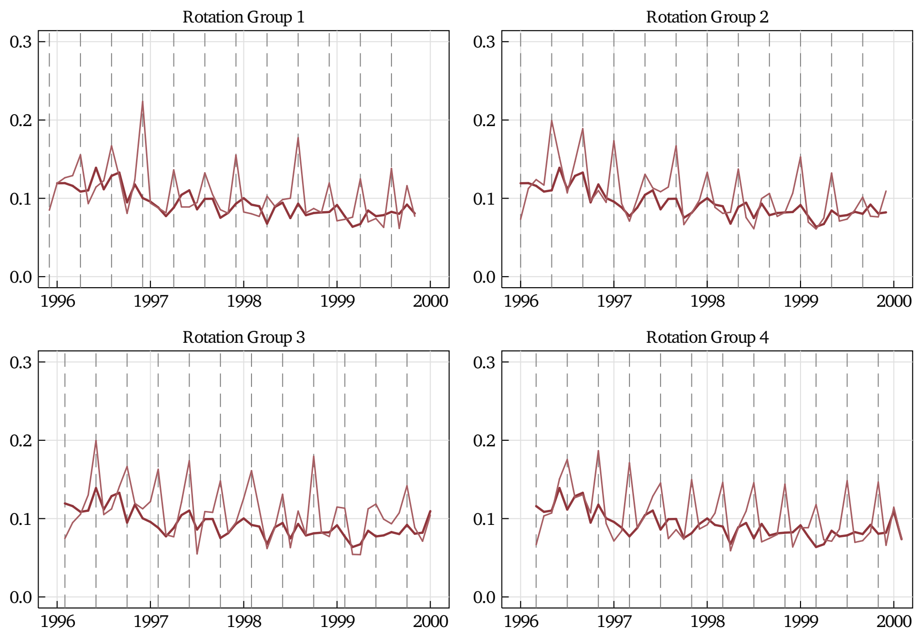



Source: Author's tabulations using SIPP microdata for 1983:6–2006:12.

a. Vertical axis indexes SIPP panels; horizontal lines indicate time coverage of panel.

**Figure 2. The Seam Effect in Separations to Unemployment, 1996 Panel[a]**

Percent of population

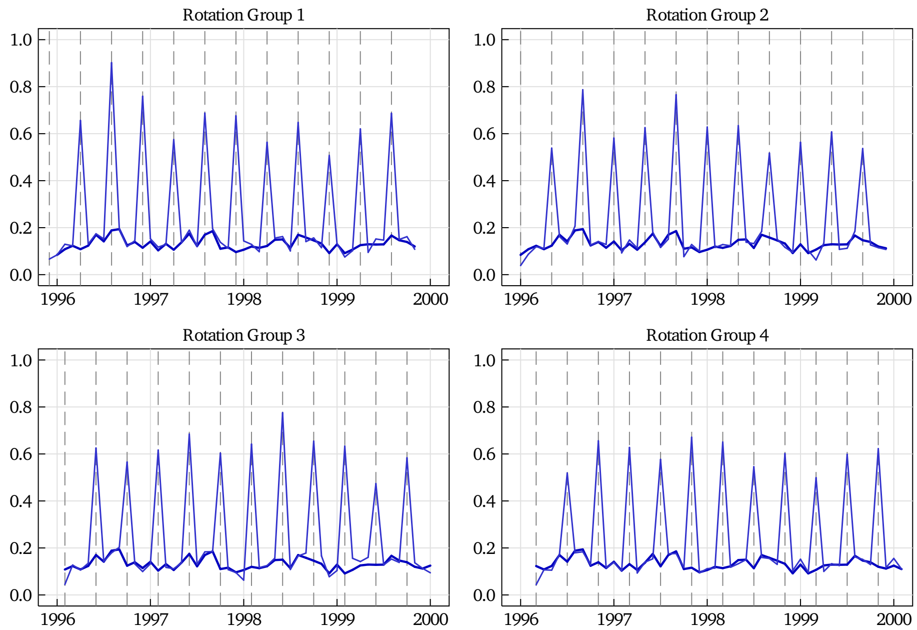



Source: Author's calculations using SIPP microdata from the 1996 panel.

a. Depicts the flow of persons as a share of the population calculated for each rotation group (solid line) and the seam-corrected average (thick line). Vertical dashed lines indicate wave boundaries.

**Figure 3. The Seam Effect in Job to Job Transitions, 1996 Panel[a]**

Percent of population




Source: Author's calculations using SIPP microdata from the 1996 panel.

a. Depicts the flow of persons as a share of the population calculated for each rotation group (solid line) and the seam-corrected average (thick line). Vertical dashed lines indicate wave boundaries.

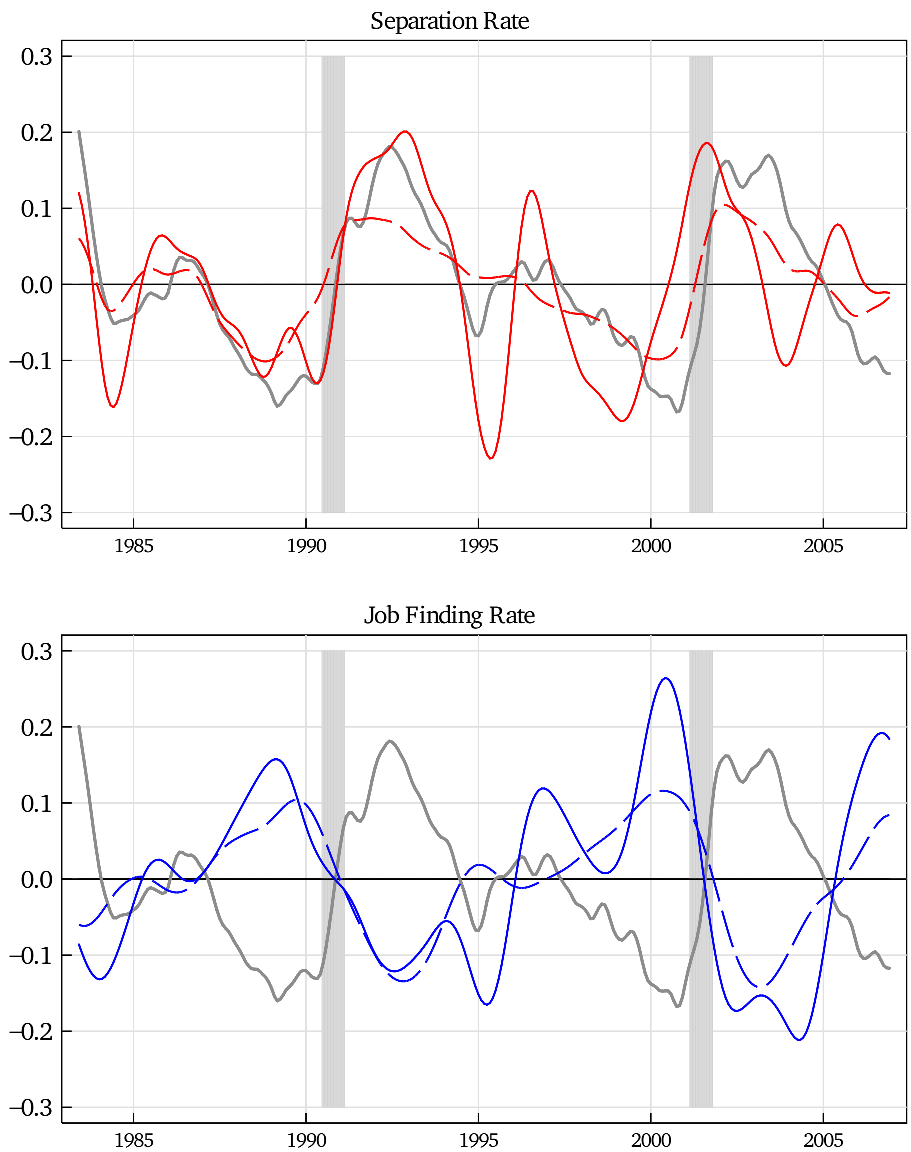
**Figure 4. Comparison of SIPP and CPS Labor Force Stocks, 1976–2007[a]**

Percent of population


Source: Author's calculations using SIPP microdata for 1983:6–2006:12 and CPS data from Nekarda (2008a).

a. Data are not seasonally adjusted.

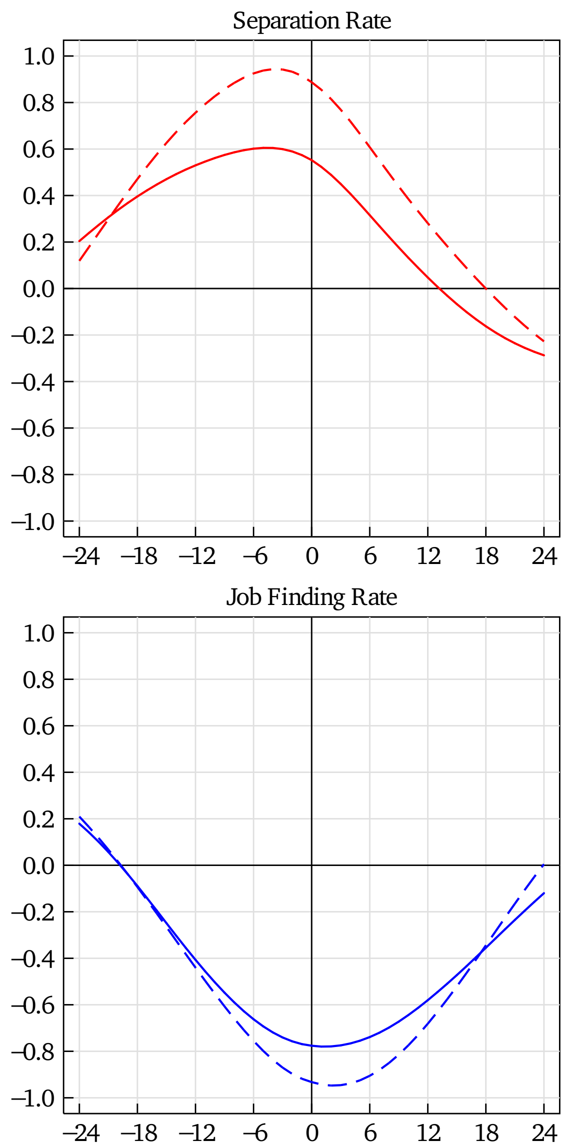
**Figure 5. Cyclical Component of SIPP and CPS Hazard Rates, 1983–2006[a]**




Source: Author's calculations using SIPP and CPS microdata for 1983:6–2006:12.

a. Cyclical component estimated using equation 8. Gray line is cyclical component of unemployment rate. Thin solid line is SIPP data; dashed line is CPS data. Shaded regions indicate recessions as dated by the National Bureau of Economic Research (NBER).

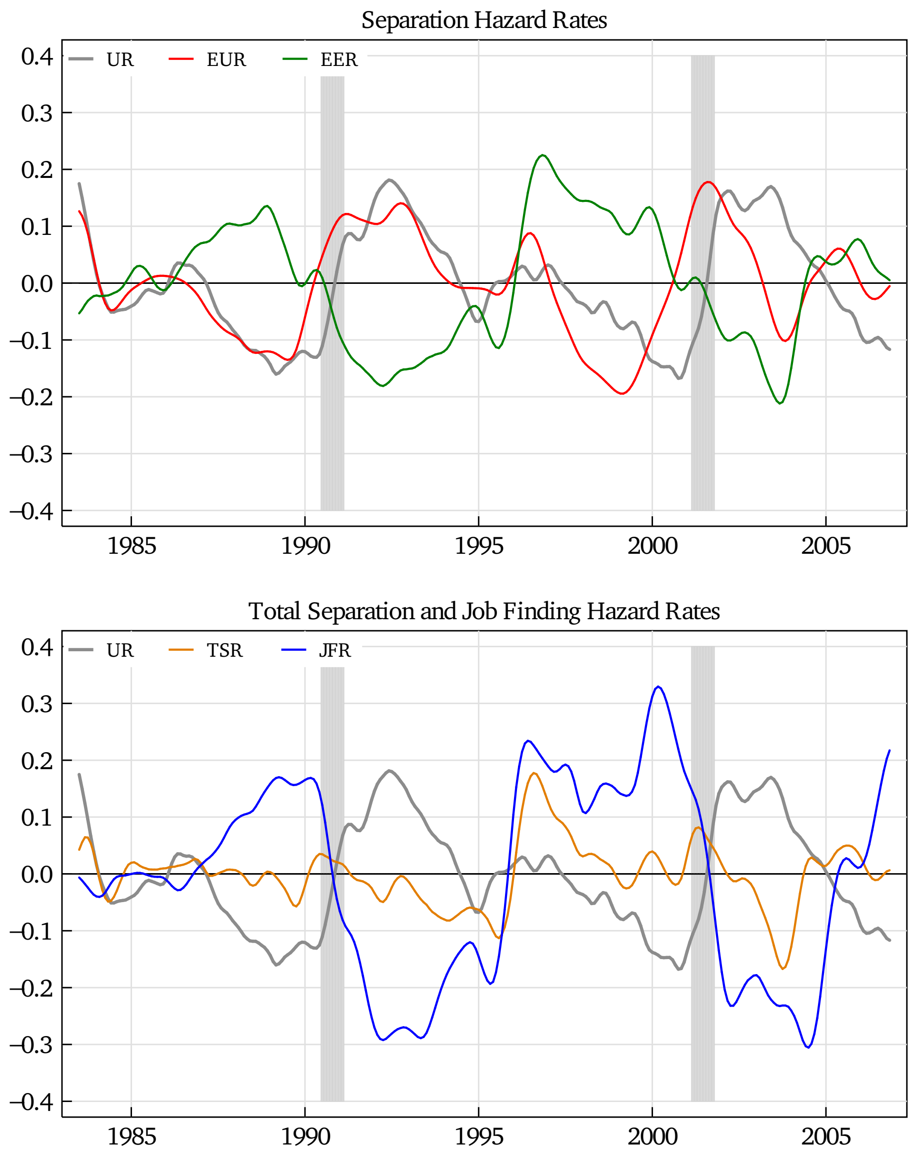
**Figure 6. Cross-Correlation of Cyclical Components of SIPP and CPS Hazard Rates with Unemployment, 1983–2006[a]**




Source: Author's calculations using SIPP and CPS microdata for 1983:6–2006:12.

a. Cyclical component estimated using equation 8. Gray line is cyclical component of unemployment rate. Thin solid line is SIPP data; dashed line is CPS data. Shaded regions indicate recessions as dated by the NBER.

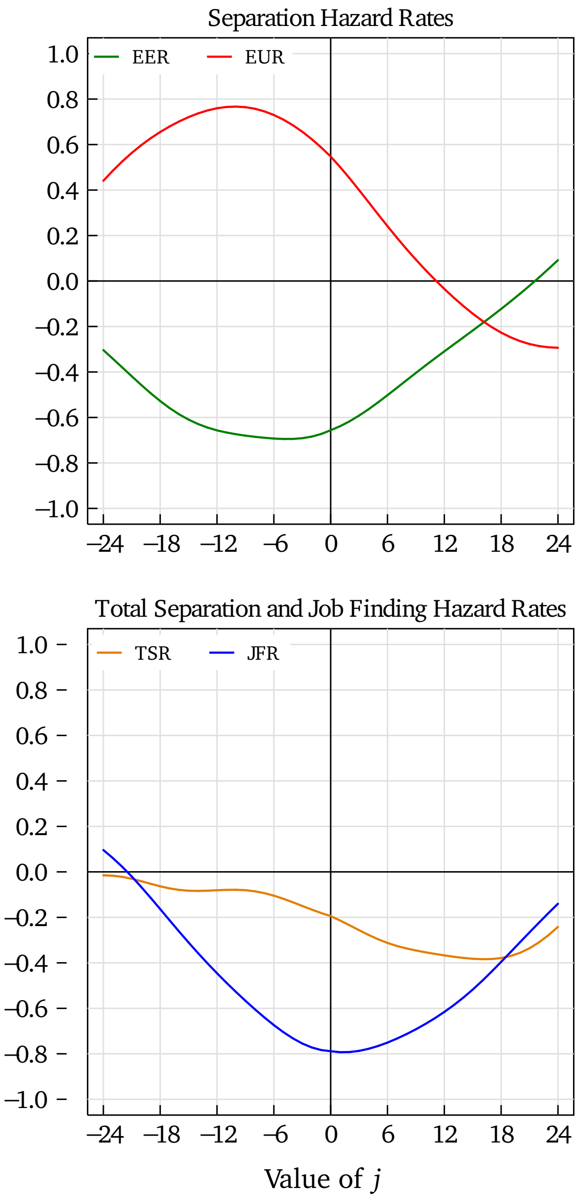
**Figure 7. Cyclical Component of Weekly Hazard Rates, 1983–2006**[a]




Source: Author's calculations using BLS data and SIPP microdata for 1983:7–2006:11.

a. Monthly averages of weekly hazard rates. Cyclical component estimated using equation 8. Shaded areas indicate recessions as dated by the NBER.

**Figure 8. Cross-Correlations of Weekly Hazard Rates with Unemployment, CPS, 1983–2006**[a]




Source: Author's calculations using BLS data and SIPP microdata for 1983:7–2006:11.

a. Monthly averages of weekly hazard rates. Correlation of $\widehat{\psi}_t^{UR}$ with $\widehat{\psi}_{t+j}^{hr}$, where $hr$ is the appropriate hazard rate. Cyclical component, $\widehat{\psi}$, estimated using equation 8.