Understanding Unemployment Dynamics: The Role of Time Aggregation

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First version: 8 August 2008
Current version: 19 June 2009

Abstract

This paper uses weekly data from the Survey of Income and Program Participation (SIPP) to estimate the role of time aggregation in measuring gross labor force flows and unemployment dynamics. Time aggregation is substantial: gross flows estimated from monthly data understate the true number of transitions by 15–24 percent. Time aggregation in both separations to unemployment and accessions from unemployment comoves positively with the business cycle. The effect from time aggregation on separations is roughly offset by its effect on accessions, however, creating no meaningful cyclical bias in measured gross flows or hazard rates. Contrary to claims by Hall (2006) and Shimer (2007), separation hazard rates calculated from the SIPP and the Current Population Survey are strongly countercyclical and remain so after adjusting for time aggregation. In addition, the separation hazard rate contributes fully one-half of the cyclical variance of the steady-state unemployment rate after adjusting for time aggregation.

JEL codes: J63, J64, E32, C22, C42
Keywords: time aggregation, gross flows, separation, accession, hazard rate, SIPP, CPS, cyclicality

1 Introduction

Understanding how unemployment changes over the business cycle is an important and controversial topic in economics. Although on the surface unemployment dynamics appear straightforward—unemployment rises when workers lose jobs and falls when unemployed persons find jobs—the behavior of its components over the business cycle and their relative importance continues to be an active and contentious area of research.

Beginning with Darby et al. (1986), and later Blanchard and Diamond (1990) and Davis and Haltiwanger (1990), researchers identified higher separation rates—inflows to unemployment—as the primary determinant of higher unemployment during recessions. Recently, Hall (2005, 2006) and Shimer (2005) have challenged this conventional wisdom, arguing that separations are not important for the cyclical dynamics of unemployment.[1] They claim that the separation rate is unaffected by the business cycle and that declines in job finding alone lead to increased unemployment during recessions.

There is considerable evidence that separations move countercyclically: the number of separations and the probability that an employed worker loses his job both increase during a recession.[2] To reconcile the constant-separation view with this evidence, Shimer (2007) argues that the countercyclicality in measured gross flows and hazard rates arises from time aggregation.

Problems of time aggregation arise when attempting to estimate a continuous-time relationship, such as unemployment duration, using data only available at discrete intervals.[3] In the context of gross flows, time aggregation arises because transitions among labor force states, for example from employment to unemployment, are measured by the change in a person's labor force status from one month to the next. If transitions occur at frequencies higher than a month, the monthly measurement may combine multiple transitions into a single "aggregate" transition. In particular, researchers worry about missing short spells of employment or unemployment. If these unmeasured spells occur with different propensity during a recession, then the measured gross flows will have a cyclical bias.

Shimer (2007) argues that the observed countercyclical movement of separations is the result of a bias from time aggregation: a decrease in the job finding probability during a recession indirectly raises the measured transition rate from employment to unemployment because workers who lose their jobs

1. Shimer released an updated version of his 2005 paper, hereafter Shimer (2007).

2. Blanchard and Diamond (1990); Bleakley et al. (1999); Fujita and Ramey (2006, 2007, 2009); Fujita et al. (2007); Elsby et al. (2009).

3. See Kaitz (1970); Kiefer (1988); Petersen (1991); Petersen and Koput (1992).

are more likely to experience measured spells of unemployment. Put differently, measured separations during a boom are too low because workers who lose their jobs quickly rematch with a new employer and are not recorded as unemployed. This implies a procyclical bias in separations due to time aggregation.

Shimer (2007) uses a theoretical model to relate measured monthly transition rates to underlying continuous-time hazard rates. Since this development, it has become standard practice to adjust for time aggregation.[4] Yet there is no way to observe or measure time aggregation using the standard source for labor market data, the Current Population Survey (CPS). Instead, corrections for time aggregation rely on the mechanical relationship between measured stocks and flows to adjust for time aggregation implicitly.[5]

I use high-frequency labor force data from the Survey of Income and Program Participation (SIPP) to identify and measure time aggregation and assess its implications for measured gross flows and hazard rates. The SIPP provides information about labor force status and job search behavior at a weekly frequency. Using this information I construct weekly measures of labor force status and week-over-week transitions.[6] Comparing the weekly transitions with a measure of month-over-month transitions that replicates the CPS, I can identify intramonth transitions that would not be observed in the CPS. This allows me to quantify time aggregation: the difference in the number of transitions in the weekly and the monthly measures.

Time aggregation in gross flows is substantial. Gross flows estimated from monthly data understate the true number of transitions by between 15 and 24 percent. Although monthly measures of gross flows capture a majority of labor market activity, roughly 20 percent of it occurs between measurement points. This speaks to the large level of time aggregation in gross flows, but not whether it contributes a cyclical bias.

The degree of time aggregation changes over time. Over the business cycle, time aggregation comoves positively with unemployment, especially for flows between employment and unemployment. This validates Shimer's (2007) hypothesis that measured separations appear too high during recessions. How-

4. See Shimer (2005, 2007); Fujita and Ramey (2006, 2009); Yashiv (2007); Elsby et al. (2009).

5. Shimer (2007) uses unemployment duration data to capture "short-term" unemployment in a 2-state model. There are no data available from the CPS that allow measuring time aggregation in a 3-state model.

6. At least since Perry (1972), many models of the labor market have taken the week as the fundamental unit of time. Indeed, the weekly frequency has become the modeling vanguard for discrete-time search and matching models. See Hagedorn and Manovskii (2008); Ramey (2008); Elsby et al. (2009).

ever, time aggregation is equally procyclical in accessions (job finding), implying that the CPS misses accessions when the job finding is high (or, alternatively, that job finding appears too high during recessions). The cyclical effect of time aggregation on separations is thus roughly offset by its affect on accessions. Time aggregation does not impart a cyclical bias to measured gross flows. Contrary to the Hall-Shimer claim, the separation hazard rate calculated from the SIPP is strongly countercyclical and remains so after adjusting for time aggregation.

Because the SIPP sample does not cover the entire period for which CPS data are available, I estimate adjustment factors for CPS gross flows using the relationship between time aggregation measured in the SIPP and the unemployment rate. This regression is then used to predict a adjustment factors for the entire CPS sample period. In the CPS, separations to unemployment are strongly countercyclical. Adjusting for time aggregation reduces the cyclical correlation with unemployment by less than 10 percent. In addition, the separation hazard rate calculated from the CPS is strongly countercyclical and contributes fully one-half of the cyclical variance in the steady-state unemployment rate, both before and after adjusting for time aggregation.

Section 2 discusses how weekly SIPP data are used to estimate time aggregation. It also describes the method, unique to this literature, used to isolate components of the time series that move at business cycle frequency. Section 3 reports the estimates of time aggregation, highlighting both the average and cyclical behavior. Section 4 studies the effect of time aggregation on CPS gross flows and hazard rates.

2 Estimating Time Aggregation

This section describes the method used to estimate time aggregation. I first briefly describe the Survey of Income and Program Participation (SIPP); for a detailed description of the SIPP and additional comparisons with the Current Population Survey (CPS), see Nekarda (2008b). I then describe how information from the SIPP is used to create a weekly labor force measure. I next explain the algorithm for identifying time aggregation by comparing these two measures for the same person. The section concludes with econometric details of the aggregation and how cyclical components are isolated.

2.1 Survey of Income and Program Participation

The SIPP is an ongoing longitudinal survey of U.S. households. 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. Each panel is randomly divided into 4 *rotation groups*, one of which is interviewed each month. At each interview respondents are asked to provide information about the previous four months. Unlike the CPS, the SIPP follows original household members who move.

The initial SIPP survey design called for each panel to last thirty-two months and have a target sample size of 20,000 households. A new panel was to begin each year, with multiple panels active at the same time to improved accuracy. In 1996 the SIPP underwent a substantial redesign; the overlapping panel structure was eliminated in favor of a substantially larger sample size and target panel length was increased to forty-eight months.

This paper uses data from 12 SIPP panels: 1984, 1985, 1986, 1987, 1988, 1990, 1991, 1992, 1993, 1996, 2001, and 2004.[7] The time coverage of the SIPP panels begins in June 1983 and ends in December 2006, however there is an eight-month gap from March to October 2000, during which the SIPP did not conduct interviews for budgetary reasons. Together, the 12 SIPP panels yield longitudinal data on over 610,000 persons and cover more than twenty years. Table 1 presents basic statistics on the SIPP data.

In the CPS, individuals are interviewed 8 times over sixteen months, with an eight month break in between the fourth and fifth interview. Because of this break only 2 sets of 3 month-over-month labor force transitions can be measured for any person.[8] In contrast, the SIPP longitudinal data are continuous over an individual's duration in the panel, leaving only 1 unmeasurable transition. The average longitudinal duration in the SIPP sample is twenty-five months. Thus, although the SIPP has fewer people than the CPS, it contains substantially more longitudinal information about its respondents. In addition, because the SIPP follows movers it does not suffer from geographic mobility bias.[9]

7. The 1989 panel contains only 3 interview waves and is not used.

8. The discrepancy between measured stocks and flows arising from unmeasurable transitions is known as "margin error" in the CPS matching literature. See Abowd and Zellner (1985); Poterba and Summers (1984, 1986); Chua and Fuller (1987); Fujita and Ramey (2006).

9. Moscarini and Thomsson (2008) discuss geographic mobility as a source of bias in CPS gross flows.

2.2 Synthetic CPS Labor Force Measures

I use weekly information from the SIPP to construct 2 measures of labor market transitions that, together, allow me to estimate time aggregation. One replicates how an individual from the SIPP would be classified if she was surveyed by the CPS.[10] The other adapts the CPS labor force definitions to the weekly frequency and records all weekly transitions. By comparing these two measures for the same person, I can identify and measure intramonth transitions that are not captured by the CPS.

The CPS determines an individual's labor force status for a month based on his experience during that month's *reference week*, the week of the month containing the twelfth.[11] The SIPP asks respondents to identify whether they were employed, on layoff, or searching for work in each week of the reference period. I use this information to construct a weekly measure of labor force status using CPS definitions.

Classification as employed (E) follows directly from the CPS definitions; unemployment and not in the labor force (NILF) are not as straightforward. The CPS classifies a person as unemployed if he has searched for a job within the last four weeks. I apply this definition on a rolling basis to determine a person's weekly labor force status. That is, a person without a job would be considered unemployed (U) 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 have elapsed, a person is classified as NILF (N).

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.

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.[12] Some difference between the two data sources is expected due to sampling variation and minor differences in survey design and definitions. For the

10. See Nekarda (2008b) for details.

11. The week containing the fifth is used as the reference week for December, provided that it falls entirely within the month; otherwise the week of the twelfth is used.

12. Nekarda (2008b) compares in detail the stocks and gross flows derived from the two data sources.

most part, the SIPP and the CPS capture the same dynamics of the U.S. labor market.

The estimated population in the SIPP and in the CPS are not statistically different and the time-series correlation between the two population levels is 0.9967. The correlation of the stock of employed persons measured from the two data sources is high (0.91) as is the correlation for unemployed persons (0.94). Gross flows calculated from the CPS and the SIPP also behave similarly: the correlation for `EU` transitions is 0.83 and for `UE` transitions is 0.73. Although the SIPP and CPS agree less on measures involving persons NILF, particularly for `UN` flows, the dynamics involving unemployment are closely related in the two data sources.

2.3 Identifying Time Aggregation

Before describing how the parallel labor force transition series are used to identify and estimate time aggregation, it is instructive to see an example of the two measures. Table 2 shows the labor force history for a SIPP respondent. The first two columns show the month and week within the month. The next column shows the weekly labor force status, according to CPS definitions, for each week. The final two columns report the monthly and weekly labor force transitions. Shaded rows indicate CPS reference weeks; information would only be available for these weeks if this person was surveyed by the CPS.

This individual begins March 1990 with a job after being employed in February (not shown). He remains employed through the month of March; the monthly and weekly measures are identical. In the second week of April he becomes unemployed and because that week is the CPS reference week, the CPS would classify him unemployed in April. Both the weekly and monthly measures record this transition as `eu`.

The period between the April and May reference weeks illustrates a situation where the measures differ. The monthly measure records a `ue` transition, reflecting his change from the previous reference week. The weekly transition measure also records a `ue` transition. However it also records 2 additional transitions not captured by the monthly measure. Because the CPS does not have information about the period between interviews, the `ue`, `eu`, and `ue` transitions would be "aggregated" into a single `ue` transition.

The next five weeks provides a dramatic illustration of time aggregation. Because this individual was employed in the reference weeks for May and June, the monthly measure records no transition (`ee`). Although the monthly measure records a nontransition, in fact 4 unique transitions occurred. The CPS would miss the short spells of employment, unemployment, and nonparticipation and their associated transitions.

The transitions in July and August illustrate situations where both the monthly and weekly measures record the same transition, but the week in which the transition is identified differs. Since both measures agree at some point over the period between CPS reference weeks, these cases are *not* measured as time aggregation.

2.3.1 Identification Algorithm

The principal objective is to measure intramonth transitions that are missed by traditional month-over-month measures. This is achieved by searching the period in between reference weeks to identify missed transitions.

The algorithm uses two sets of counters for each person. There are 9 counters $C(\mathtt{ij})$ in each set, one for each possible transition from state $\mathtt{i} \in \{\mathtt{e}, \mathtt{n}, \mathtt{u}\}$ to state $\mathtt{j} \in \{\mathtt{e}, \mathtt{n}, \mathtt{u}\}$. The first set records the traditional month-over-month labor force transition—that is, the change in labor force status from the previous CPS reference week to the current one. Only 1 counter in this first set takes on a value of 1 in a month.

The second set of counters, $C(\mathtt{ij})^*$, records all weekly transitions, including those that occur between CPS reference weeks. Transitions starting from the current month's reference week up to, but not including, the previous reference week are considered a part of the *current* month. In the example, the 5 transitions between week 3 of May 1990 and week 2 of June 1990 are counted in June. When the same type of transition occurs more than once in the period, each unique instance is counted; `ee`, `nn`, and `uu` transitions must be interrupted by another transition to be counted more than once. In the example from table 2, in May 1990 the starred counters would be: $C(\mathtt{uu})^* = 1$, $C(\mathtt{ue})^* = 2$, and $C(\mathtt{eu})^* = 1$.

Upon completion, each person has two parallel measures of her transitions for each month. The first is the traditional month-over-month labor force transition (synthetic CPS). The second records all transitions that occur between the CPS reference weeks. Differences between the two measures for the same person identify time aggregation at the individual level. However, because there is no sensible metric for time aggregation at the individual level—it is generally either zero or infinite—I study time aggregation using aggregated data.

2.4 Aggregation and Estimation

The aggregation of all individual $\mathtt{ij}$ transitions is called the $\mathtt{IJ}$ *flow*, where capital letters indicate the aggregate quantity. Thus $\mathtt{IJ}$ is the number of persons who move from state I in month $t-1$ to state J in month t as measured by the CPS. Similarly, $\mathtt{IJ}^*$ is the number of persons who make the same transition, accounting for all weekly transitions over the month. Time aggregation is defined as the ratio:

$$T_t^{\mathtt{IJ}} = \frac{\mathtt{IJ}_t^*}{\mathtt{IJ}_t}. \tag{1}$$

The ratio $T^{\mathtt{IJ}}$ gives the relative increase in the $\mathtt{IJ}$ flow resulting from measuring all intramonth transitions—that is, from time aggregation. If there were no intramonth transitions, then both transition measures would be the same and $T^{\mathtt{IJ}} = 1$. However if $\mathtt{IJ}^*$ identifies transitions not captured by $\mathtt{IJ}$ then $T^{\mathtt{IJ}} > 1$, indicating positive time aggregation. It is also possible to have $T^{\mathtt{IJ}} < 1$; this could occur, for example, if transitions are misclassified by time aggregation.

This ratio is an appealing metric for several reasons. First, it is scale free, allowing the bias in flows with different magnitudes to be uniformly compared. Second, the ratio construction eliminates the "seam effect" and any panel- or rotation group–specific measurement error that causes problems when comparing aggregate estimates.[13]

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.

Time aggregation is estimated using a ratio estimator for population totals. The month t estimator for time aggregation in the $\mathtt{IJ}$ flow is

$$\widehat{T}_t^{\mathtt{IJ}} = \frac{\widehat{\mathtt{IJ}}_t^*}{\widehat{\mathtt{IJ}}_t} = \frac{\sum_{p=1}^{P_t} \sum_{r=1}^{R_{pt}} \sum_{j=1}^{m_{prt}} \omega_{prt} w_{prjt}\, C(\mathtt{ij})_{prjt}^*}{\sum_{p=1}^{P_t} \sum_{r=1}^{R_{pt}} \sum_{j=1}^{m_{prt}} \omega_{prt} w_{prjt}\, C(\mathtt{ij})_{prjt}}, \tag{2}$$

13. See Nekarda (2008b) for a discussion of these problems.

where $C(\texttt{ij})$ and $C(\texttt{ij})^*$ are the transition counters for person prj (discussed in section 2.3). Each individual's observations are weighted by their monthly sampling weight w_{prjt}. Each rotation group is weighted by its contribution to the total number of observations in a month:

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

The pooled estimates are found by further aggregating over time:

$$\widehat{T}^{\texttt{IJ}} = \frac{\sum_{t=1}^{T} \widehat{\texttt{IJ}}_t^*}{\sum_{t=1}^{T} \widehat{\texttt{IJ}}_t}. \tag{4}$$

Equations 2 and 4 are estimated separately for each IJ transition. The variance of the pooled-sample estimate is calculated to reflect survey sampling uncertainty; see the appendix for details.

2.5 Identifying Cyclical Components

Analyzing the cyclical behavior of a time series requires isolating the elements of the time series with periodic variation at a certain frequency. The traditional technique in macroeconomics is to filter the series to extract the cyclical component: the lowpass Hodrick-Prescott (HP) filter and bandpass Baxter-King (BK) filter are common methods.[14]

A drawback of such ad hoc filters is that they can lead to spurious cycles and other distortions.[15] Instead, I employ the structural time series modeling approach developed by Harvey (1989).[16] This approach views the time series as the sum of distinct unobserved components, each with an economic interpretation.

Such models are very flexible and can optimally replicate the gain properties of the HP and BK filters; in recent work, Harvey and Trimbur (2003) derive optimal lowpass and bandpass filters as the joint solution to a signal extraction problem in an unobserved-components model. An additional benefit of this approach is that missing values can be estimated directly from the structural model.

I model the times series behavior of time aggregation, and later of gross flows and hazard rates, using a structural time series model. I model the observed time series as the sum of four independent, unobserved components: a

14. Hodrick and Prescott (1997); Baxter and King (1999).
15. Harvey and Jaeger (1993); Cogley and Nason (1995); Murray (2003).
16. See also Durbin and Koopman (2001).

trend, a cycle, a seasonal, and an irregular component. The trend represents low-frequency movements that, when extrapolated, give the clearest indication of the future long-term movements in the series.[17] The cyclical component is a 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 non-systematic variation.

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

$$y_t = \mu_t + \psi_t + \gamma_t + \varepsilon_t \, , \tag{5}$$

where μ_t is the trend, ψ_t the cyclical, γ_t the seasonal, and ε_t the irregular component. Details of the econometric specification of the components are provided in the appendix.

Equation 5 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 structural time series analyzer, modeller, and predictor (STAMP) program written by Koopman et al. (2007). The state space form and the details of the estimation appear in the appendix.

3 Results

I first present estimates from a pooled sample of all months. These results establish the quantitative importance of time aggregation. I then examine the cyclicality of time aggregation and explore its implications for the cyclicality of hazard rates in the SIPP.

3.1 Pooled-Sample Estimates of Time Aggregation

The long-term level of time aggregation in each `IJ` flow is estimated with equation 4 using a pooled sample of all 273 months. The pooled sample contains 15.9 million observations covering July 1983–December 2006.

Table 3 reports summary statistics from the pooled estimation, grouped by type of flow. One can interpret the values in table 3 as the percentage increase in the `IJ` flow resulting from measuring all weekly transitions. The central result is that many transitions are missed because of time aggregation. Among

17. Harvey (1989), p.284

transitions between different labor force states, the smallest increase is 14.5 percent while the largest is 24.4 percent. These values are very precisely estimated, with standard errors of 0.36 percent or less. Thus failing to account for time aggregation substantially understates the true magnitude of gross flows.

Focusing on flows between employment and unemployment, I estimate that time aggregation in separations (23 percent) is about equal to that in accessions (24 percent). Although the large degree of time aggregation in separations is consistent with Shimer (2007), the equally large degree of time aggregation in accessions sharply conflicts; Shimer claims that time aggregation causes little bias in the job finding rate.[18] This claim is not supported by the data.

It is instructive to examine how intramonth transitions—which would not be observed in the CPS— are classified by the synthetic CPS measure. This exercise considers only cases where the weekly measure identifies a transition that the monthly measure does not. Figure 1 shows the distribution of the monthly classifications for each type of unrecorded weekly transition. The panel title identifies the unrecorded transition; the 9 possible monthly classifications are listed along the abscissa and their relative frequencies are plotted vertically.

The `UE` panel shows that unrecorded separations would be classified primarily as `EE` transitions in the CPS. Close to 60 percent of intramonth separations are classified as continuous employment.[19] Observations at monthly frequency miss primarily short spells of nonemployment. However, over a quarter of `EU` separations are incorrectly classified as `UU`, indicating that the CPS misses short spells of *employment* as well. The remaining nondiagonal transitions represent a combination of misclassification and multiple intramonth transitions; collectively they represent about 20 percent of transitions.

The pattern for unrecorded `UE` transitions, also shown in figure 1, is similar to that for separations to unemployment. Although about 20 percent are classified as `UU`, compared to 26 percent for `EU` transitions, only 46 percent are originally classified as `EE`. The difference comes from the 21 percent of `UE` transitions classified as `NE`. The misclassification hypothesis is explored below.

3.1.1 Misclassification from Time Aggregation

Although time aggregation in separation flows to nonparticipation (`EN`) has the same magnitude as in those to unemployment (table 3), time aggregation

18. Shimer (2007) p. 6.

19. I do not identify transitions directly from one employer to another without an intervening spell of unemployment. Fallick and Fleischman (2004) report that such direct employment-to-employment transitions are more than twice the magnitude of flows from employment to unemployment.

in accessions from nonparticipation (NE)is considerably lower than from unemployment. The 0.5-point difference in time aggregation between the two accession flows results from classification errors due to time aggregation.

Such a misclassification can arise because the CPS does not inquire about job search behavior for persons classified as employed. Thus, if a person was NILF during the previous reference week but searched for and found a job by the current reference week, the CPS would incorrectly record the transition as NE.

I employ a search procedure similar to that used to identify time aggregation to test this hypothesis. For each NE transition, I search backwards up to the previous reference week for active job search. If any job search is identified, the person must have experienced NU and UE transitions that were time-aggregated to NE.

This procedure confirms that about 5 percent of NU–UE transitions are incorrectly classified as NE. That is, the CPS incorrectly identifies too few UE transitions. Time aggregation in UE flows is 4.5 percent higher than in NE flows, consistent with the evidence that the CPS undercounts UE transitions. In addition, timing-related classification error also explains much of the difference in measured time aggregation in participation flows. If 5 percent of NE flows are actually UE flows, the CPS also misses the NU transition when the person began searching for a job.

The UE and NU panels of figure 1 corroborates the timing hypothesis. The bulk of unrecorded NU transitions are counted as NE, indicating that the CPS missed a short spell of unemployment in between nonparticipation and employment. Also, the UN panel shows that 36 percent of UN transitions were recorded as UE flows. These are missed UN–NE transitions, possibly arising from cessation of search after finding a job but before starting employment.

3.1.2 Short-Duration Spells

The existence of short spells is implied by the frequent and regular misclassification of labor force transitions using monthly data. The data show that most intramonth accessions and separations are incorrectly classified as a nontransition by the CPS. This is confirmed by the large proportion of unmeasured short spells recorded in the diagonal transitions, particularly spells of unemployment.

Table 3 also reports time aggregation in diagonal flows—"flows" between the same labor force state. These nontransitions comprise most of the labor market activity recorded, together accounting for 96 percent of all transitions. Time aggregation measured in these flows has the interpretation as an unrecorded short spell in that state. Time aggregation increases EE flows by about

5 and NN flows by roughly 8 percent. The striking result, however, is the 60 percent increase in UU flows due to time aggregation.

An important finding uncovered in the weekly SIPP data is that short spells of employment and unemployment occur considerably more frequently that previously thought. This finding is important for understanding time aggregation but also the dynamics of the U.S. labor market more broadly.

3.2 Cyclical Behavior of Time Aggregation

The previous section demonstrated the quantitative importance of time aggregation on average over 1983–2006. However important questions involve the time-series behavior of time aggregation. In particular, Shimer (2007) argues that failure to account for time aggregation imparts a countercyclical bias to measured UE flows. This point is central to his claim that the separation hazard rate is acyclical. Examining the cyclical behavior of time aggregation can inform about this claim.

3.2.1 Time-Series Behavior

Before analyzing the cyclical component, I first plot time-series behavior of time aggregation. A time series of the level of time aggregation is estimated separately for each of the 6 nondiagonal flows using equation 2. Figures 2–4 plot the time series of time aggregation along with the combined trend-cycle component estimated from the structural model (5), $\widehat{\mu}_t^{\mathtt{IJ}} + \widehat{\psi}_t^{\mathtt{IJ}}$. This is conceptually similar to plotting smoothed, seasonally-adjusted data. Shaded bars indicate recessions as dated by the National Bureau of Economic Research (NBER).

Figure 2 shows the degree of time aggregation in separation flows. Although there are several large outliers in the EN series, time aggregation in both separation series exhibits low time-series volatility: the ratio of the standard deviation to the mean is 0.08 for EU and 0.09 for EN. For comparison, the same volatility measure in gross flows is 0.19 for EU and 0.20 for EN. Time-series volatility in time aggregation is less than half as large as in gross flows. Time aggregation in EU flows exhibits a secular decline over the sample, while that in EN flows declines only through the mid-1990s.

Time aggregation in accession flows is shown in figure 3. The evolution of time aggregation for each accession flow follows its counterpart separation flow closely. The time-series variation of time aggregation in UE flows (0.08) is slightly lower than its separation counterpart and it exhibits the same downward trend. Time aggregation in NE flows is equally as volatile (0.11) as in EN flows, although the trend-cycle component is smoother. As with separations, time aggregation in accessions is about half as volatile as in gross flows.

Finally, time aggregation in participation flows is shown in figure 4. Unlike time aggregation in separations and accessions, there is no secular trend in the series. Both series exhibit low time-series volatility.

3.2.2 Cyclicality of Time Aggregation

Shimer (2007) argues that ignoring time aggregation will bias a researcher towards finding countercyclical separations to unemployment.[20] Shimer's argument implies that time aggregation in EU flows is procyclical. On the other hand, Fujita and Ramey (2006) find little evidence of cyclicality in their theory-based time aggregation adjustment. This section evaluates the cyclicality of time aggregation estimated from the SIPP data.

I use as cyclical indicators the civilian unemployment rate published by the Bureau of Labor Statistics (BLS) and the index of industrial production published by the Board of Governors of the Federal Reserve. Although I focus on the unemployment rate, I also present results using industrial production as an alternate indicator of the business cycle as a robustness check against the possibility that the unemployment rate is directly affected by time aggregation. In addition, industrial production is a measure of output, rather than employment, and thus its cyclical dynamics are not directly related to the *measurement* of labor market activity. That said, the correlation between cyclical components of industrial production and of the unemployment rate is very strong (-0.91). The cyclical components of the cyclical indicators are estimated from the structural model described in section 2.5.

Table 4 reports the contemporaneous correlation between the cyclical component of time aggregation and the cyclical component of each cyclical indicator. Significance of the correlation is calculated using Fisher's transformation.[21]

Focusing on EU and UE flows, the cyclical correlation of time aggregation with unemployment is negative, indicating that time aggregation in these flows is procyclical. The cyclical correlation of EU separations is -0.33, demonstrating moderate procyclicality. Although Shimer (2007) does not report cyclicality directly, this result is consistent with the direction of bias implied by his claims of acyclical separations.

The procyclical pattern of time aggregation in separations can be thought

20. Shimer (2007), p. 3.

21. Pearson's product-moment correlation coefficient, r, is not normally distributed but can be transformed by $z = \frac{1}{2}\ln\left(\frac{1+r}{1-r}\right)$ to be asymptotically normal; see Fisher (1915).

of as follows. Recessions are characterized by an increase in the number of separations to unemployment; the true number of separations, $\mathtt{EU}^*$, increases. However because the likelihood of quickly finding a new job declines in a recession—increasing the likelihood of experiencing a measured spell of unemployment—the CPS records a greater share of the true number of separations. That is, EU increases by *more* than $\mathtt{EU}^*$. Therefore the ratio $T^{\mathtt{EU}} = \mathtt{EU}^*/\mathtt{EU}$ declines during a recession, even though separations are increasing.

Unlike Shimer, however, I find that time aggregation in UE accessions is strongly procyclical (−0.42), in fact more procyclical than in separations. Procyclicality in accessions is a natural consequence of greater time spent in unemployment. During a boom, workers who lose jobs and find new jobs quickly experience EU and UE transitions which are aggregated into an EE transition. As job finding slows during a recession and there are more measured spells of unemployment, those EU and UE transitions are now more likely to be observed separately by the CPS.

Thus, on balance, one should expect time aggregation to contribute little bias to the cyclicality of gross flows or hazard rates. This offsetting effect helps explain why Fujita and Ramey (2006) found little cyclical effect from their mechanical time aggregation correction.

Richer dynamics in the cyclical correlation are revealed by a plot of the cross-correlations between the cyclical components of time aggregation and the cyclical indicators. 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 indicator in month t and $j = 0, 1, \ldots, 24$ leads and lags of time aggregation, $\operatorname{corr}\left(\widehat{\psi}_t^{cyc}, \widehat{\psi}_{t+j}^{\mathtt{IJ}}\right)$, where $\widehat{\psi}_t$ is the cyclical component estimated from the structural times series model and $cyc = \{UR, IP\}$ is the cyclical indicator. Confidence intervals for the correlation are calculated using Fisher's transformation.

The cross-correlation of time aggregation with the unemployment rate is plotted in figure 5. The cross-correlation for time aggregation in EU flows has a hump shape, with peak correlation of −0.39 at $j = -4$. This confirms that time aggregation in EU flows is moderately procyclical and indicates that changes in time aggregation lead changes in unemployment by four months.

Time aggregation in UE accessions also has a hump shape, but it is less pronounced than for EU flows. The peak correlation of −0.43 occurs at a lag of three months, with a dynamic response roughly symmetric about the peak. This means that an increase in unemployment today is associated with a decline in time aggregation three months later. The peak correlation is stronger for accessions than separations.

The cross-correlations of time aggregation with the index of industrial production are shown in figure 6. These cross-correlations exhibit very similar patterns to those with unemployment, albeit reflected about the abscissa. The relationship with industrial production is more muted than with unemployment, with lower correlations at all leads and lags. The general patterns remain evident: a peak countercyclical correlation leading the cycle and the response of accessions shifted forward in time relative to separations. The correlations of time aggregation in `EU` and `UE` flows with industrial production are similar to those with unemployment. Both exhibit a hump shape, although the peak correlations are shifted forward in time, consistent with the cyclical component of unemployment lagging the cyclical component of industrial production.

3.2.3 Nonparticipation

The picture of time aggregation is less clear for flows into and out of labor force nonparticipation. `NE` flows are weakly procyclical when unemployment is used as a cyclical indicator but no significant relationship is found when using industrial production (table 4). `EN` flows are weekly countercyclical using either indicator. The large and similar cyclical correlations for `UN` and `NU` suggest that time aggregation in these flows arises from unmeasured short spells of unemployment.

This suggestion is confirmed by moderately procyclical time aggregation in `UU` flows. Procyclical short spells of unemployment is consistent with the evidence of time aggregation in `EU` and `UE` flows and with the hypothesis of increasing chance of experiencing a measurable spell of unemployment during a recession.

Time aggregation in flows between employment and nonparticipation has little significant cyclical variation when using either unemployment (figure 5) or industrial production (figure 6). Time aggregation in the participation flows is procyclical and lags the cycle. The peak correlation for `NU` is -0.55 at $j = 10$ while the peak correlation for `UN` is -0.47 at $j = 12$. The cyclical pattern of time aggregation in the participation flows is essentially the same when the index of industrial production is used as a cyclical indicator.

3.3 Cyclical Behavior of Hazard Rates

The previous section shows that time aggregation is procyclical in separations to unemployment but also in accessions from unemployment, confounding Shimer's (2007) claim that time aggregation leads to a cyclical bias in the separation hazard rate. Next I directly assess the impact of time aggregation on the separation and job finding hazard rates calculated from the SIPP. This analysis also addresses the Hall-Shimer claim of a constant separation hazard rate.

I calculate monthly separation and job finding hazard rates

$$\widehat{s}_t = \frac{\mathtt{EU}_t}{\mathtt{E}_{t-1}} \quad \text{and} \quad \widehat{f}_t = \frac{\mathtt{UE}_t}{\mathtt{U}_{t-1}} \tag{6}$$

from the unadjusted SIPP gross flows and

$$\widehat{s}^*_t = \frac{\mathtt{EU}^*_t}{\mathtt{E}_{t-1}} \quad \text{and} \quad \widehat{f}^*_t = \frac{\mathtt{UE}^*_t}{\mathtt{U}_{t-1}} \tag{7}$$

from the time aggregation–adjusted gross flows, where $\mathtt{E}$ and $\mathtt{U}$ are the stock of employed and unemployed persons. I estimate equation 5 for each of the four hazard rates.

Figure 7 graphs the cyclical component (in logarithms) of the separation and job finding hazard rate against the cyclical component of the unemployment rate. The solid colored lines show hazard rates adjusted for time aggregation (equation 7) while dashed lines show the unadjusted hazard rates (equation 6). The gray line is the unemployment rate.

Looking first at the unadjusted series, it is clear from figure 7 that the separation hazard rate is not constant over the business cycle. Indeed, it tracks the rise in unemployment closely in each of the 2 recessions in the sample. Adjusting for time aggregation (solid line) does not alter this conclusion. The separation hazard rate is 92 percent as volatile as unemployment, falling to 79 percent after adjusting for time aggregation.

The separation hazard rate is countercyclical. The contemporaneous correlation between the cyclical components of the separation rate and unemployment is 0.43, falling slightly to 0.38 after adjusting for time aggregation. The peak correlation with unemployment, however, is strongly countercyclical, 0.71, and is basically unchanged after adjusting for time aggregation. The full cross-correlation is shown in figure 8.

Figure 7 confirms that the cyclical behavior of the job finding hazard rate closely mirrors that of unemployment. Adjusting for time aggregation does not significantly affect job finding. Consistent with previous evidence, the job finding hazard rate is more volatile than the separation hazard rate. The job finding rate is 25 percent more volatile than unemployment, *rising* to 28 percent after adjusting for time aggregation. The cross-correlation in the bottom panel of figure 8 shows strongly procyclical comovement with the business cycle. The contemporaneous correlation is −0.82 in the unadjusted data and −0.83 in the adjusted data; peak correlations are essentially coincident.

Motivated by Fujita and Ramey (2009), I next examine how much of the variance in the unemployment rate is attributable to variations in the separation hazard rate and the job finding hazard rate. Shimer (2007) approximates the steady state unemployment rate, ur^{ss} implied by his continuous-time model by

$$ur_t \approx \frac{s_t}{s_t + f_t} \equiv ur_t^{ss}, \tag{8}$$

where s_t is the separation hazard rate and f_t is the job finding hazard rate.

Fujita and Ramey (2009) decompose the variation in ur_t^{ss} into factors that depend on separations and accessions plus an error term. Log linearizing ur_t^{ss} about its trend $\overline{ur}_t^{ss}$ yields the linear decomposition

$$ln\left(\frac{ur_t^{ss}}{\overline{ur}_t^{ss}}\right) = \left(1 - \overline{ur}_t^{ss}\right) ln\left(\frac{s_t}{\bar{s}_t}\right) - \left(1 - \overline{ur}_t^{ss}\right) ln\left(\frac{f_t}{\bar{f}_t}\right) + \epsilon_t, \tag{9}$$

where an overbar indicates a variable's trend component. Fujita and Ramey express this linearization generically as $dur_t^{ss} = dur_t^{sr} + dur_t^{jfr} + dur_t^{\epsilon}$, allowing them to decompose the total variance of dur_t^{ss} as[22]

$$\text{var}\left(dur_t^{ss}\right) = \text{cov}\left(dur_t^{ss}, dur_t^{sr}\right) + \text{cov}\left(dur_t^{ss}, dur_t^{jfr}\right) + \text{cov}\left(dur_t^{ss}, \epsilon_t\right). \tag{10}$$

Employing the concept of beta used in finance, they define the share of total variation, both direct and indirect, attributable to the separation rate, the job finding rate, and the residual as

$$\beta^{sr} = \frac{\text{cov}\left(dur_t^{ss}, dur_t^{sr}\right)}{\text{var}\left(dur_t^{ss}\right)} \tag{11}$$

$$\beta^{jfr} = \frac{\text{cov}\left(dur_t^{ss}, dur_t^{jfr}\right)}{\text{var}\left(dur_t^{ss}\right)} \tag{12}$$

$$\beta^{\epsilon} = \frac{\text{cov}\left(dur_t^{ss}, \epsilon_t\right)}{\text{var}\left(dur_t^{ss}\right)}. \tag{13}$$

I estimate these contributions using unadjusted and time aggregation–adjusted SIPP hazard rates. The trend components in equation 9 are estimated using the time series model (i. e., μ_t in equation 5). The results of the SIPP variance decomposition are reported in table 5.

22. Fujita and Ramey (2009), p. 7.

In the unadjusted SIPP data, variations in the separation hazard rate account for 43 percent of the variance of the steady-state unemployment rate. As suggested by figure 7, adjusting for time aggregation reduces the contribution of the separation rate; it contributes 38 percent of the variance in unemployment. The contribution of the separation hazard rate to the cyclical variance of unemployment is large and remains so after adjusting for time aggregation.

3.4 Discussion

The evidence in this section provides a clear picture that time aggregation is quantitatively important. Recording all weekly transitions in separation and accession flows increases recorded monthly flows by about 20 percent on average over 1983–2006. Although the level is high, the time series of time aggregation are roughly half as volatile as gross flows. Time aggregation exhibits more substantial volatility at business cycle frequencies. It is most pronounced for transitions into and out of unemployment, where time aggregation is moderately procyclical. Time aggregation in flows between employment and labor force nonparticipation, on the other hand, are weakly and distantly involved with the business cycle.

Although these results confirm Shimer's (2007) argument that time aggregation in EU flows is procyclical, it is not possible to directly compare our findings because he does not report statistics about his time aggregation correction. Also, his conclusions about the cyclicality of time aggregation are based on a visual inspection of a counterfactual theoretical experiment, not on actual data. In addition, my findings about time aggregation in UE flows are sharply at odds with Shimer (2007). Whereas Shimer asserts that "time aggregation causes relatively little bias in the job finding rate," I find that, not only is the magnitude of time aggregation in UE flows higher than in EU flows, but that the cyclical correlation with unemployment is greater.[23] Therefore a researcher should be at least as concerned about time aggregation when measuring job *finding* as with job loss.

Examining separation and job finding hazard rates in the SIPP fully refutes Shimer's (2007) claim that time aggregation imparts a countercyclical bias to the separation hazard rate. The data also refute Hall's (2006) claim that the separation rate is constant over the business cycle. These sharply contrasting conclusions follow from two results. First, time aggregation in UE accessions is also procyclical and has a stronger contemporaneous correlation with unemployment than do EU separations. Any potential bias arising from unmeasured

23. Shimer (2007), p. 6.

separations is offset by unmeasured accessions. Second, the overall volatility of time aggregation is small. Even if there were large cyclical variations in time aggregation, there is little room for time aggregation to have a dramatic effect on the cyclicality of gross flows or hazard rates.

The next section assesses the cyclical behavior of time aggregation–adjusted gross flows and hazard rates estimated from the CPS. This robustness exercise has a longer sample (1976–2007) and allows for direct comparison with pervious studies of time aggregation in the CPS.[24]

4 Adjusting the CPS for Time Aggregation

In this section I construct time aggregation–adjusted CPS gross flows and hazard rates and study their cyclical properties. Because the SIPP sample does not cover the entire period for which CPS data are available, I first estimate the relationship between time aggregation and the unemployment rate. This relationship is then used to predict an adjustment factor for the entire CPS sample period.

4.1 Time Aggregation–Adjusted CPS Gross Flows

For each flow, I regress the log of $\widehat{T}_t^{\mathtt{IJ}}$ on the trend, cycle, and seasonal components of the unemployment rate (also expressed in logarithms),[25]

$$\ln\left(\widehat{T}_t^{\mathtt{IJ}}\right) = \theta_0 + \theta_\mu \,\widehat{\mu}_t^{UR} + \theta_\psi \,\widehat{\psi}_t^{UR} + \theta_\gamma \,\widehat{\gamma}_t^{UR} + \epsilon_t. \tag{14}$$

The time series $\widehat{T}^{\mathtt{IJ}}$ used as the dependent variable is estimated directly from the SIPP data using equation 2. The cyclical components of the unemployment rate are estimated using the structural time series model in section 2.5. The regressions use data for July 1983–November 2006.

The results of the time aggregation adjustment factor regressions are reported in table 6. The coefficient on the cyclical component, θ_ψ, is negative in all regressions, consistent with the correlations in column 1 of table 4. I calculate time aggregation adjustment factors as the fitted values from the regression (14) taken over the full time series of the unemployment rate. Figure 9 graphs the time series of the time aggregation adjustment factor for each of the 6 flows over 1976–2007.

24. Shimer (2007); Fujita and Ramey (2006, 2009); Elsby et al. (2009).

25. A specification including the irregular component was rejected by a likelihood ratio test; there is little reason to believe that the irregular component has predictive power.

The final step is to apply the time aggregation adjustment to gross flows estimated from the CPS. CPS gross flows are first adjusted for margin error; see the appendix for details. For the remainder of the paper "unadjusted" CPS flows refer to flows not adjusted for time aggregation. The margin error-adjusted gross flows are then adjusted for time aggregation using the factors shown in figure 9. I then estimate the structural time series model (equation 5) separately for unadjusted and adjusted CPS gross flows.[26]

Figure 10 graphs the combined trend and cycle components of the CPS gross flows, with and without adjusting for time aggregation, reported as a percentage of the population. Although a level shift is readily apparent from looking at the data in figure 10, nothing of consequence can be determined about how time aggregation affects cyclicality by visual inspection.

4.2 Cyclical Behavior of CPS Gross Flows

To properly assess the effect of time aggregation on the cyclicality of gross flows I focus on only the cyclical components estimated from equation 5.

Adjusting for time aggregation reduces the time-series volatility of the cyclical component of CPS gross flows. The cyclical volatility of EU flows and UE flows decreases by 3 and 8 percent, respectively. The volatility of gross flows relative to unemployment or industrial production is largely unchanged by time aggregation. In the unadjusted data, gross flows are 54 percent as volatile as unemployment and 2.2 times as volatile as industrial production. After adjusting for time aggregation, gross flows are 50 percent as volatile as unemployment and 2 times more volatile than industrial production.

In unadjusted gross flows separations to unemployment are 38 percent more volatile than accessions from unemployment, qualitatively consistent with Fujita and Ramey's (2006) findings. After adjusting for time aggregation EU flows are 47 percent more volatile than UE flows. Adjusting for time aggregation *increases* cyclical volatility of separations relative to accessions—exactly the opposite conclusion from Shimer (2007).

Table 7 reports the contemporaneous correlation of the cyclical component of gross flows with the cyclical components of the unemployment rate and the index of industrial production. Looking first at the relationship between unadjusted gross flows and the unemployment rate, two things are apparent. First, the relationships are very strong; the weakest correlation is 0.82. Second, EU

26. It is well documented that changes in the CPS identification records prohibit matching for several months in the CPS sample. See Bleakley et al. (1999); Fallick and Fleischman (2004); Nagypál (2008); Fujita and Ramey (2006, 2007); Shimer (2007). These missing observations are estimated directly from the structural model.

separation flows are strongly countercyclical; its contemporaneous correlation with unemployment is 0.84. The correlation for UE accessions is even stronger (0.91).

Gross flows adjusted for time aggregation yield the same conclusions as with the unadjusted data. The cyclical correlation of the time aggregation–adjusted EU separation flow with unemployment falls, from 0.84 to 0.77, but still indicates strongly countercyclical comovement. Adjusting for time aggregation lowers the correlation of UE accession flows with unemployment from 0.91 to 0.82. After adjusting gross flows for time aggregation, they still remain strongly countercyclical. One draws the same conclusions when industrial production is used as a cyclical indicator.

The minimal impact of time aggregation is clear in the cross-correlations of gross flows. Figures 11 and 12 show the cross-correlations between the cyclical component of CPS gross flows and the cyclical component of the two cyclical indicators. Each panel plots 2 series, one using data not adjusted for time aggregation (dashed line) and the other using time aggregation–adjusted data (solid line). This figure informs both upon the cyclical behavior of CPS gross flows (the solid line) and the contribution of time aggregation (the difference between the dashed and solid lines).

In figure 11 the peak correlation of unadjusted EU separations is strongly countercyclical (0.95) and leads the cycle by five months. Adjusting for time aggregation reduces the peak correlation to 0.90 at a lead of six months. Accessions from unemployment are strongly countercyclical (0.91) and lag unemployment by one month. Adjusting for time aggregation reduces the cyclicality of UE flows (0.83) at a lag of two months. Separations to and accessions from unemployment are strongly correlated with the business cycle and remain so after adjusting for time aggregation.

Consistent with findings by Blanchard and Diamond (1990) and Fujita and Ramey (2006), the comovement of flows to and from unemployment is almost exactly opposite that of movement to and from NILF over the business cycle: separations to NILF are strongly procyclical while accessions from NILF are strongly countercyclical. Unadjusted separations to NILF are procyclical and lag the cycle by two months. Adjusting for time aggregation reduces the peak correlation slightly, from -0.86 to -0.83, but does not affect the phasing. Job finding from NILF is strongly procyclical (-0.82) and is coincident with the business cycle; it remains procyclical (-0.79) after adjusting for time aggregation.

Participation flows are countercyclical and lag unemployment by one to two months. Adjusting for time aggregation lowers the peak correlation of NU flows from 0.84 to 0.79 and reduces it from 0.85 to 0.82 for UN flows. Both remain roughly coincident with unemployment after adjusting for time aggregation.

Figure 12 plots the cross-correlations of gross flows with the index of industrial production. The general pattern is the same as with unemployment. Separations to and accessions from unemployment are strongly countercyclical and become slightly less so after adjusting for time aggregation. Similarly, separations to and accessions from NILF are strongly procyclical; adjusting for time aggregation reduces the cyclical comovement negligibly. The phasing of the correlations with industrial production is shifted slightly forward in time relative to unemployment, consistent with unemployment lagging industrial production.

Although adjusting CPS gross flows for time aggregation reduces their contemporaneous and peak cyclical correlations, it does not meaningfully affect their degree or pattern of comovement with unemployment or industrial production. This finding is sharply at odds with Shimer (2007).

4.3 Cyclical Behavior of CPS Hazard Rates

This final section explores the effect of time aggregation on CPS hazard rates. It also explores the relationship between the data-based time aggregation correction and the mechanical correction employed by previous researchers.

As in section 3.3, I calculate monthly separation and job finding hazard rates from CPS gross flows with and without adjusting for time aggregation. In addition, I evaluate the mechanical correction suggested by Shimer (2007) that links month-over-month gross flows to underlying continuous-time adjustment equations. The separation hazard rate $\tilde{s}_t$ and the job finding hazard rate $\tilde{f}_t$ will satisfy[27]

$$\tilde{s}_t = \frac{s_t\left(1 - \mathrm{e}^{-\left(s_t + f_t\right)}\right)}{s_t + f_t} \quad \text{and} \quad \tilde{f}_t = \frac{f_t\left(1 - \mathrm{e}^{-\left(s_t + f_t\right)}\right)}{s_t + f_t}, \tag{15}$$

where s_t and f_t are given by equation 6.

Figure 13 graphs the cyclical component (in logarithms) of the hazard rates against the cyclical component of the unemployment rate. The gray line is the unemployment rate. The short dashed line is the monthly hazard rate calculated from the CPS gross flows using equation 6. The long dashed line is the theoretical adjustment for time aggregation (equation 15). Finally, the solid colored line is the hazard rate adjusted for time aggregation using the data (equation 7).

27. See Fujita and Ramey (2009), p. 4.

As with the SIPP data, the separation hazard rate is obviously not constant over the business cycle. Adjusting for time aggregation using either method does not change this conclusion. The separation hazard rate is strongly countercyclical. The contemporaneous correlation between the cyclical components of the separation rate and unemployment is 0.88 and the peak correlation is 0.95 at a lead of four months (figure 14).

Also like the SIPP data, the job finding hazard rate comoves closely with unemployment and time aggregation has virtually no effect on measured cyclicality. The cross-correlation in the bottom panel of figure 14 shows strongly procyclical comovement coincident with the unemployment.

Adjusting for time aggregation makes little difference for the cyclicality of the separation and job finding hazard rates. The cross-correlations shown in figure 14 indicate that the theoretical time-aggregation adjustment does remarkably little to the cyclical relationships. This is consistent with the mechanical nature of the correction; it uses no new information. The data-based adjustment for time aggregation slightly reduces the cyclical correlation of the separation hazard rate and slightly increases the correlation of the job finding hazard rate.

I also perform the unemployment variance decomposition using the CPS data; table 8 reports the results. In the unadjusted data, variations in the separation hazard rate and job finding rate each account for one-half of the variance of the steady-state unemployment rate. Adjusting for time aggregation using the SIPP data makes virtually no difference in the variance decomposition. After adjusting for time aggregation, fully one-half of steady-state unemployment volatility results from separations to unemployment.

Shimer's (2007) theoretical correction for time aggregation, however, reduces the contribution of fluctuations in the separation rate to 42 percent of the variance of unemployment. His correction spuriously reduces the contribution of the separation hazard rate by almost 20 percent. Thus, rather than improve estimates by adjusting for time aggregation, Shimer's (2007) correction *biases* them toward finding lower separation volatility.

5 Conclusion

This paper uses high-frequency data from the SIPP to estimate the degree to which measured CPS gross flows are biased due to the monthly sampling frequency of the survey. Economists worry—correctly—that a month may be too long an interval over which to measure the change in labor force states. By identifying and measuring transitions that happen in the weeks between interviews, I can empirically quantify and evaluate time aggregation.

Using the SIPP's weekly information on labor force status, I measure labor force transitions that are missed when information is available only once a month. I quantify time aggregation as the increase in gross flows resulting from measuring transitions that occur between interviews.

I find that the level of time aggregation is substantial. Gross flows estimated from monthly data understate the true number of transitions by between 15 and 24 percent. Although monthly measures of gross flows capture a majority of labor market activity, roughly 20 percent of it occurs between measurement points. Although the level is high, it has comparatively low time-series volatility.

Time aggregation varies over the business cycle, especially in transitions into and out of unemployment. Time aggregation in these flows is procyclical: as spells of unemployment become longer and more frequent during a recession, flows into and out of unemployment that are recorded by the CPS increase by *more* than the true flows do because more short spells of unemployment are captured by the CPS. Time aggregation in flows between employment and labor force nonparticipation, on the other hand, is weakly and distantly involved with the business cycle.

This paper also makes a methodological contribution to the cyclical analysis of labor market behavior. Whereas previous research has extracted business-cycle frequencies using an ad hoc mix of seasonal adjustment and filtering, I isolate cyclical components in a unified model that jointly identifies unobserved components of a time series as the optimal solution to a signal-extraction problem.

There has been substantial debate in the literature about the cyclical pattern and relative importance of job separations and accessions over the business cycle.[28] Recently, Shimer (2005) has emphasized the importance of time aggregation for assessing cyclical patterns, arguing that failing to adjust for time aggregation causes separations to appear spuriously countercyclical.

The evidence presented in this paper refutes this claim. Time aggregation in separations to unemployment comoves positively with the business cycle, consistent with Shimer's claims. Contrary to Shimer's claim, not only is the magnitude of time aggregation in job finding higher than in separations, but the cyclical correlation with unemployment is greater. After adjusting for time aggregation, the monthly separation hazard rate is strongly countercyclical and is 79 percent as volatile as unemployment over the business cycle.

28. Darby et al. (1986); Hall (2006); Shimer (2005); Fujita and Ramey (2006, 2007, 2009); Fujita et al. (2007); Yashiv (2007); Elsby et al. (2009).

Estimates from the SIPP are used to construct a dynamic time aggregation adjustment factor for CPS gross flows over 1976–2007. Adjusting for time aggregation generally reduces the cyclical volatility of CPS gross flows but *increases* the volatility of separations relative to accessions. Although adjusting for time aggregation does reduce the contemporaneous and peak cyclical correlation of gross flows, it does not meaningfully affect the degree or pattern of comovement with unemployment or industrial production. Separations are strongly countercyclical after adjusting for time aggregation.

Additionally, properly adjusting for time aggregation does not alter the contribution of the separation hazard rate. Adjusting for time aggregation using Shimer's (2007) theoretical correction, however, spuriously reduces the contribution of the separation hazard rate. The time aggregation–adjusted CPS separation hazard rate is strongly countercyclical and contributes one-half of the cyclical variance in the steady-state unemployment rate.

Shimer (2007) argues that "ignoring time aggregation will bias a researcher towards finding a countercyclical employment exit probability."[29] This paper refutes Shimer's claim: time aggregation imparts no meaningful cyclical bias to either gross flows or hazard rates. Nevertheless, although time aggregation is not important for cyclical dynamics, researchers must account for time aggregation in levels, such as when calibrating a weekly matching model.

Appendix

Variance Estimation

The SIPP is a multistage stratified survey and, accordingly, estimating the variance requires special consideration. Ignoring the survey design and assuming that observations are selected under simple random sampling understates the true variance.

The SIPP microdata include variables that identify the stratum and primary sampling unit (PSU) from which a person was selected.[30] Because assignment of households to rotation groups is random, the strata from different rotation

29. Shimer (2007), p. 3.

30. The original PSU and strata codes are not included in the SIPP public use data to maintain confidentiality. Instead, sets of PSUs are combined across strata to produce variance units and variance strata that may be treated as PSUs and strata for variance estimation. See Westat (2001), p. 7–2.

groups can be thought of as separate strata.

As in the text, 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. For the variance estimation, let $h = 1, 2, \ldots, L_{pr}$ index strata and $i = 1, 2, \ldots, n_{prh}$ index PSUs within rotation group pr. Finally, let $j = 1, 2, \ldots, m_{prhit}$ index persons from rotation group pr within stratum h, PSU i in month t.

The variance estimator for the population ratio (2) is

$$\text{(A.1)} \quad \widehat{V}\left(\widehat{T}_t^{\mathtt{IJ}}\right) = \frac{1}{V\left(\widehat{\mathtt{IJ}}_t^2\right)} \left\{ \widehat{V}\left(\widehat{\mathtt{IJ}}_t^*\right) - 2\,\widehat{T}_t^{\mathtt{IJ}} \text{cov}\left(\widehat{\mathtt{IJ}}_t^*, \widehat{\mathtt{IJ}}_t\right) + \left(\widehat{T}_t^{\mathtt{IJ}}\right)^2 \widehat{V}\left(\widehat{\mathtt{IJ}}_t\right) \right\}.$$

where the survey variance estimator $\widehat{V}\left(\widehat{Y}_t\right)$ is

$$\text{(A.2)} \qquad \widehat{V}\left(\widehat{Y}_t\right) = \sum_{p=1}^{P_t} \sum_{r=1}^{R_{pt}} \sum_{h=1}^{L_{pr}} \frac{n_{prh}}{n_{prh} - 1} \sum_{i=1}^{n_{prh}} (z_{prhit} - \overline{z}_{prht})^2,$$

and where $z_{prhit} = \sum_{j=1}^{m_{prhit}} w_{prhijt}\, y_{prhijt}$ is the population estimate for stratum h, PSU i in month t and $\overline{z}_{prht} = \frac{1}{n_{prh}} \sum_{j=1}^{m_{prht}} z_{prhit}$ is the mean estimate over stratum h. Finally, the survey covariance estimator is

$$\text{(A.3)} \quad \widehat{\text{cov}}\left(\widehat{Y}_t, \widehat{X}_t\right) = \sum_{p=1}^{P_t} \sum_{r=1}^{R_{pt}} \sum_{h=1}^{L_{pr}} \frac{n_{prh}}{n_{prh} - 1} \sum_{i=1}^{n_{prh}} (z_{prhit}^x - \overline{z}_{prht}^x)(z_{prhit}^y - \overline{z}_{prht}^y).$$

The 1984–1991 SIPP panels each have 72 variance strata, divided equally among the 4 rotation groups. The 1992 and 1993 panels have 99 strata, the 1996 and 2001 panels have 105, and the 2004 panel has 114. Taken together the pooled SIPP panels contain 1,025 variance strata, each with 2 variance PSUs per stratum.

Structural Time Series Model

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

$$[5] \qquad y_t = \mu_t + \psi_t + \gamma_t + \varepsilon_t,$$

where μ_t is the trend, ψ_t the cyclical, γ_t the seasonal, and ε_t the irregular component.

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

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{A.4}$$

$$\Delta\beta_t = \zeta_t, \tag{A.5}$$

where $\Delta = (1 - L)$ and L is the lag operator. The disturbances η_t and ζ_t are independent and identically distributed (i. i. d.) normal random variables with mean zero and variances σ^2_η and σ^2_ζ.

The cyclical component is modeled as a second-order stochastic cycle with frequency λ, where[31]

$$\begin{bmatrix} \psi_t^{(j)} \\ \psi_t^{*(j)} \end{bmatrix} = \rho \begin{bmatrix} \cos\lambda & \sin\lambda \\ -\sin\lambda & \cos\lambda \end{bmatrix} \begin{bmatrix} \psi_{t-1}^{(j)} \\ \psi_{t-1}^{*(j)} \end{bmatrix} + \begin{bmatrix} \psi_t^{(j-1)} \\ \psi_t^{*(j-1)} \end{bmatrix} \tag{A.6}$$

for $j = 1, 2$ and $\psi_t^{(0)} = \kappa_t$ and $\psi_t^{*(0)} = \kappa_t^*$. The disturbances κ_t and κ_t^* are i. i. d. normal each with mean zero and variance σ^2_κ. Note that for $j = 1$ and $\rho = 1$ equation A.6 reduces to a deterministic cycle

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

where ψ_0 and ψ_0^* are i. i. d. zero-mean random variables with variance σ^2_ψ.

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

$$\gamma_t = -\sum_{j=1}^{s-1} \gamma_{t-j} + \omega_t, \tag{A.7}$$

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

The model given by equations 5 and A.4–A.7 is represented by a state space system relating observed data y_t to unobserved state vector $\boldsymbol{\alpha}_t$ through measurement vector $\mathbf{z}$:

$$y_t = \mathbf{z}'\boldsymbol{\alpha}_t + \varepsilon_t \tag{A.8}$$

$$\boldsymbol{\alpha}_t = \mathbf{T}\boldsymbol{\alpha}_{t-1} + \boldsymbol{\eta}_t. \tag{A.9}$$

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

The unobserved state evolves according to a first-order Markov process with transition matrix $\mathbf{T}$. The state equation (A.9) is

$$
\text{(A.10)} \quad \begin{bmatrix} \mu_t \\ \beta_t \\ \psi_t \\ \psi_t^* \\ \gamma_{t-1} \\ \gamma_{t-2} \\ \vdots \\ \gamma_{t-s+2} \end{bmatrix} = \begin{bmatrix} \mathbf{T}_{\text{trend}} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{T}_{\text{cycle}} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{T}_{\text{seasonal}} \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \beta_{t-1} \\ \psi_{t-1} \\ \psi_{t-1}^* \\ \gamma_{t-2} \\ \gamma_{t-3} \\ \vdots \\ \gamma_{t-s+1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ \zeta_t \\ \kappa_t \\ \kappa_t^* \\ \omega_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}
$$

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

$$
\text{(A.11)} \quad z = \begin{bmatrix} 1 & 0 & 1 & 0 & 1 & 0 & \dots & 0 \end{bmatrix}'.
$$

The unknown parameters σ_ε^2, σ_η^2, ρ, λ, σ_κ^2, and σ_ω^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 HP trend.[32] This variance is $\sigma_\zeta^2 = \sigma_\varepsilon^2/129{,}600$.[33] The cycle frequency λ is fixed at sixty months; this

32. 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.

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

corresponds roughly with the center of Burns and Mitchell's (1946) 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.

Constructing CPS Gross Flows

Because of the CPS's rotating sample design, at most 75 percent of observations can be matched across succeeding months. The simplest approach is to assume that the unmatched observations are simply missing at random; calculations are performed on the population of matched observations. This assumption has been shown to be a poor one.[34] In particular, the missing-at-random (MAR) correction significantly undercounts the unemployed.

The conditional MAR model is a simple but powerful extension of the MAR model. Given the timing convention for flows, a person's month t labor force status is always observed, even if the previous month's status is unknown. The MAR model throws this information away. Similar to the corrections of Abowd and Zellner (1985) and Fujita and Ramey (2006), the conditional MAR correction makes use of partially-classified observations. In particular, it assumes that a person missing in month $t-1$ with state $\mathtt{J}$ in month t is drawn randomly from the population of persons with state $\mathtt{J}$ in month t. That is, a person is missing at random conditional on having state $\mathtt{J}$ in month t.

The BLS performs much of its second-stage analysis separately by demographic group.[35] In particular, the distinction between male and female and between white and nonwhite are most important. I adjust for margin error separately by these 4 sex-race groups.

Let $\mathtt{IJ}_{srt}$ be the number of persons with sex $s \in \{M, F\}$ and race $r \in \{W, NW\}$ who had labor force status $\mathtt{i}$ in month $t-1$ and status $\mathtt{j}$ in month t. Let $\mathtt{MJ}_{srt}$ be the number of persons with missing labor force status in month $t-1$ and status $\mathtt{j}$ in month t. The ratio

$$R^{\mathtt{J}}_{srt} = \frac{\mathtt{EJ}_{srt} + \mathtt{NJ}_{srt} + \mathtt{UJ}_{srt}}{\mathtt{EJ}_{srt} + \mathtt{NJ}_{srt} + \mathtt{UJ}_{srt} + \mathtt{MJ}_{srt}} \tag{A.12}$$

is the number of observed transitions into state $\mathtt{J}$ (flows into $\mathtt{J}$) relative to the total number persons who had status $\mathtt{J}$ in month t (stock of $\mathtt{J}$). The MAR correction normalizes the entire population to the sum of all observed transitions

34. See Abowd and Zellner (1985) and Nekarda (2008a).
35. Bureau of Labor Statistics (2002).

in each state:

$$R^{MAR}_{srt} = \frac{\texttt{IJ}_{srt}}{\sum_{\texttt{i}\in\{\texttt{E,N,U}\}} \sum_{\texttt{j}\in\{\texttt{E,N,U}\}} \texttt{ij}_{srt}}. \tag{A.13}$$

Define the margin error–adjusted IJ flow, denoted with a tilde, for sex s and race r in month t as

$$\widetilde{\texttt{IJ}}_{srt} = \frac{\texttt{IJ}_{srt}}{R^{\texttt{J}}_{srt}}. \tag{A.14}$$

The table below, reporting the average of monthly adjustment factors over 1976–2007, shows that conditioning on month t labor force status makes a large difference. Averaging across demographic groups, the MAR model (equation A.13) would inflate each measured flow by a factor of 1.43. The conditional MAR model, in contrast, inflates flows ending in employment by 1.43 but flows ending unemployment by 1.51. The difference is about 6 percent more flows into unemployment than partially-classified transitions are ignored.

		Status in month t		
Demographic group	*MAR*	E	U	N
Male, white	1.4235	1.4245	1.4995	1.4081
Male, nonwhite	1.4569	1.4583	1.5303	1.4371
Female, white	1.4178	1.4215	1.5161	1.4075
Female, nonwhite	1.4463	1.4485	1.5393	1.4314

The population margin error–adjusted IJ flow in month t is the sum over sex and race categories:

$$\widetilde{\texttt{IJ}}_{t} = \sum_{s} \sum_{r} \widetilde{\texttt{IJ}}_{srt}. \tag{A.15}$$

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Table 1. The Survey of Income and Program Participation

			Number of		
Panel	*Begin*	*End*	*Months*	*Persons*	*Observations*[a]
1984	Jun 1983	Apr 1986	35	48,498	1,077,059
1985	Oct 1984	Jul 1987	34	33,231	730,946
1986	Oct 1985	Mar 1988	30	27,215	588,511
1987	Oct 1986	Apr 1989	31	27,262	618,268
1988	Oct 1987	Dec 1989	27	26,895	516,829
1990	Oct 1989	Aug 1992	35	52,220	1,321,940
1991	Oct 1990	Jul 1993	35	33,438	848,159
1992	Oct 1991	Dec 1994	39	46,747	1,307,685
1993	Oct 1992	Dec 1995	39	46,659	1,296,200
1996	Dec 1995	Feb 2000	51	88,798	2,892,975
2001	Oct 2000	Dec 2003	39	79,834	1,948,077
2004	Oct 2003	Dec 2006	39	99,877	2,527,403
All	Jun 1983	Dec 2006	276	610,674	15,674,052

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

a. Monthly.

Table 2. Example Labor Force History[a]

Month	Week	Labor force status	Transition: Monthly	Transition: Weekly
1990:3	1	e		ee
1990:3	2	e	ee	ee
1990:3	3	e		ee
1990:3	4	e		ee
1990:4	1	e		ee
1990:4	2	u	eu	eu
1990:4	3	u		uu
1990:4	4	e		ue
1990:5	1	u		eu
1990:5	2	e	ue	ue
1990:5	3	n		en
1990:5	4	e		ne
1990:5	5	u		eu
1990:6	1	u		uu
1990:6	2	e	ee	ue
1990:6	3	e		ee
1990:6	4	u		eu
1990:7	1	u		uu
1990:7	2	u	eu	uu
1990:7	3	u		uu
1990:7	4	u		uu
1990:8	1	e		ue
1990:8	2	e		ee
1990:8	3	e	ue	ee
1990:8	4	e		ee
1990:8	5	e		ee
1990:9	1	e		ee
1990:9	2	e	ee	ee
1990:9	3	e		ee
1990:9	4	e		ee

Source: SIPP microdata, 1990 panel.
a. Shading indicates CPS reference week.

Table 3. Time Aggregation, Pooled Estimates, 1983–2006 [a]

Flow	$\widehat{T}^{\mathtt{IJ}}$	*Standard error* [b]	*95 percent confidence interval*	
Separation				
EU	1.2298	0.0036	1.2228	1.2368
EN	1.2330	0.0025	1.2281	1.2379
Accession				
UE	1.2438	0.0031	1.2378	1.2498
NE	1.1902	0.0026	1.1851	1.1952
Participation				
UN	1.1455	0.0025	1.1407	1.1504
NU	1.2119	0.0026	1.2067	1.2171
Diagonal				
EE	1.0525	0.0002	1.0522	1.0529
UU	1.5991	0.0030	1.5933	1.6050
NN	1.0786	0.0004	1.0779	1.0794

Source: Author's calculations using SIPP microdata for 1983:7–2006:12.

a. Measure of time aggregation, $\widehat{T}^{\mathtt{IJ}} = \widehat{\mathtt{IJ}}^{*}/\widehat{\mathtt{IJ}}$, estimated using pooled sample of 15,947,129 observations over 273 months.

b. Linearized standard error estimated from survey data. See appendix for details.

Table 4. Contemporaneous Correlation of Time Aggregation with Cyclical Indicators[a]

Flow	*Unemployment rate*	*Industrial production*
Separation		
EU	−0.3258***	0.2454***
EN	−0.1006**	0.0128
Accession		
UE	−0.4158***	0.2154***
NE	0.0822*	−0.1098**
Participation		
UN	−0.2563***	0.1928***
NU	−0.4152***	0.2878***
Diagonal		
EE	0.3606***	−0.2653***
UU	−0.4836***	0.4597***
NN	0.1394**	−0.0674

Source: Author's calculations using data from the SIPP, the BLS, and the Board of Governors of the Federal Reserve System.

a. Cyclical components estimated using equation 5. *** indicates significance at 1 percent, ** at 5 percent, and * at 10 percent.

Table 5. Contributions to Unemployment Fluctuations, SIPP, 1983–2002 [a]

Component	*Unadjusted*	*Adjusted* [b]
Separation hazard rate (β^{sr})	0.4345	0.3820
Job finding hazard rate (β^{jfr})	0.5696	0.6207
Residual (β^{ϵ})	−0.0041	−0.0027

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

a. Share of variance of steady-state unemployment rate; see text for details.

b. Adjusted for time aggregation.

Table 6. Time Aggregation Adjustment Factor Regressions[a]

	Flow					
Coefficient	EN	EU	NE	UE	NU	UN
θ_0	0.8603***	1.0040***	0.7467***	0.8869***	0.1206	0.2022***
	(0.0774)	(0.0592)	(0.0747)	(0.0556)	(0.0778)	(0.0639)
θ_μ	0.2274***	0.2824***	0.2002***	0.2368***	−0.0257	0.0219
	(0.0270)	(0.0207)	(0.0261)	(0.0194)	(0.0272)	(0.0223)
θ_ψ	−0.1245***	−0.1637***	−0.0386	−0.1532***	−0.1237***	−0.0887**
	(0.0444)	(0.0339)	(0.0428)	(0.0319)	(0.0446)	(0.0366)
θ_γ	0.3579***	0.0554	0.3048***	0.2799***	0.1968***	0.3479***
	(0.0743)	(0.0565)	(0.0717)	(0.0534)	(0.0747)	(0.0614)
Summary statistic						
No. obs.	281	280	281	281	281	281
R^2	0.2575	0.4150	0.2176	0.3999	0.0563	0.1213

Source: Author's regressions using data from the SIPP and the BLS.

a. Regression of $\ln\left(\widehat{T}_t^{\mathtt{IJ}}\right) = \theta_0 + \theta_\mu \widehat{\mu}_t^{UR} + \theta_\psi \widehat{\psi}_t^{UR} + \theta_\gamma \widehat{\gamma}_t^{UR} + \epsilon_t$, where $\widehat{\mu}_t^{UR}$, $\widehat{\psi}_t^{UR}$, and $\widehat{\gamma}_t^{UR}$ are the estimated trend, cycle, and seasonal components of the unemployment rate (see section 2.5). Regressions use data from 1983:7–2006:11. Standard errors are reported in parentheses. * indicates significance at 10 percent, ** at 5 percent, and *** at 1 percent.

Table 7. Contemporaneous Correlation of Gross Flows with Cyclical Indicators, 1976–2007 [a]

	Unemployment rate		Industrial production	
Flow	*Unadjusted*	*Adjusted* [b]	*Unadjusted*	*Adjusted* [b]
Separation				
EU	0.8426	0.7694	−0.8630	−0.8175
EN	−0.8404	−0.8173	0.7316	0.6893
Accession				
UE	0.9055	0.8147	−0.8574	−0.7946
NE	−0.8237	−0.7881	0.7747	0.7227
Participation				
UN	0.8201	0.7874	−0.7662	−0.7394
NU	0.8320	0.7783	−0.7776	−0.7314

Source: Author's calculations using data from the SIPP, the BLS, and the Board of Governors of the Federal Reserve System.

a. Cyclical components estimated using equation 5.

b. Adjusted for time aggregation using the adjustment factors in figure 9.

Table 8. Contributions to Unemployment Fluctuations, CPS, 1976–2007[a]

		Adjusted	
Component	*Unadjusted*	*Data*[b]	*Theoretical*[c]
Separation hazard rate (β^{sr})	0.4982	0.5021	0.4224
Job finding hazard rate (β^{jfr})	0.5090	0.5046	0.5850
Residual (β^{ϵ})	−0.0073	−0.0068	−0.0073

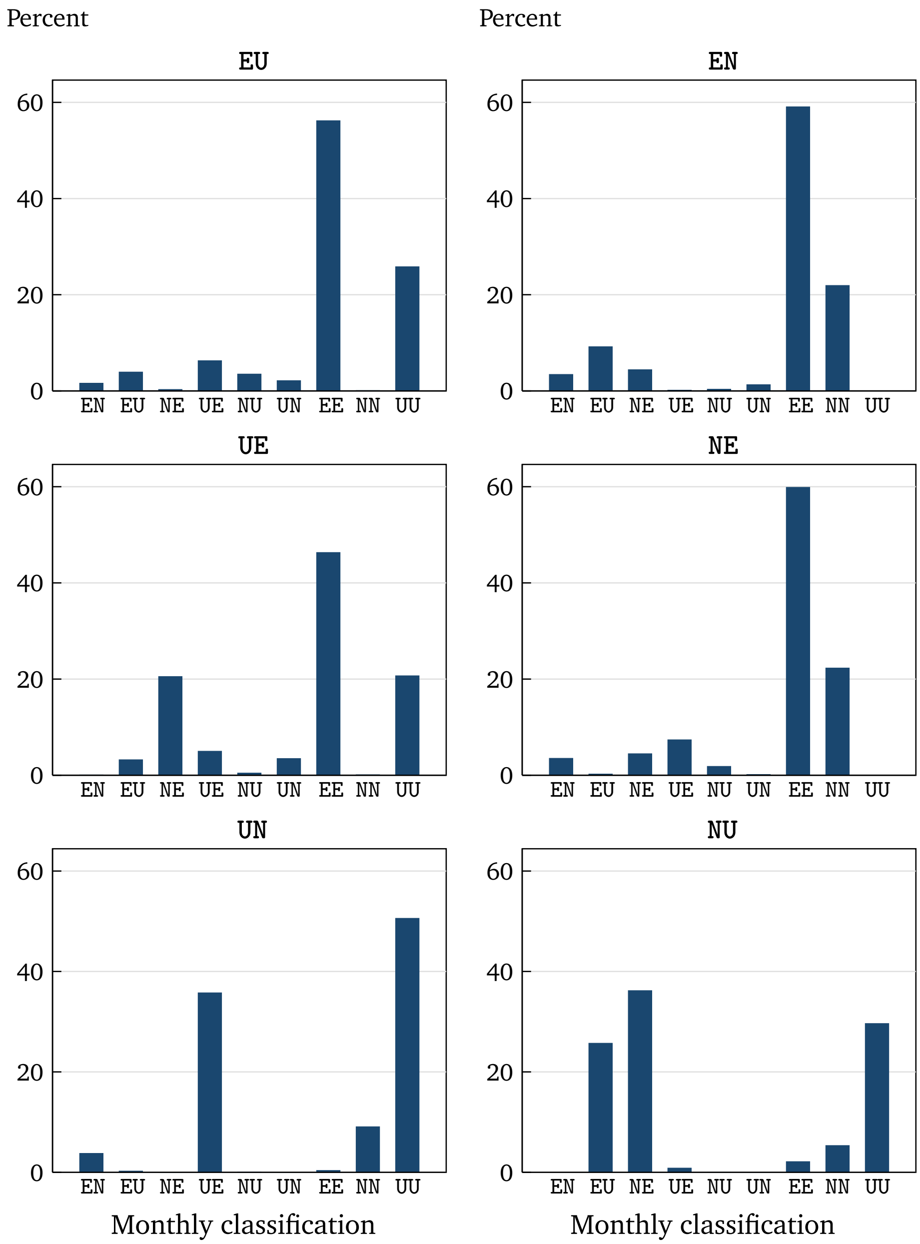
Source: Author's calculations using data from the SIPP and the CPS.

a. Share of variance of steady-state unemployment rate; see text for details.

b. Adjusted for time aggregation using the adjustment factors in figure 9.

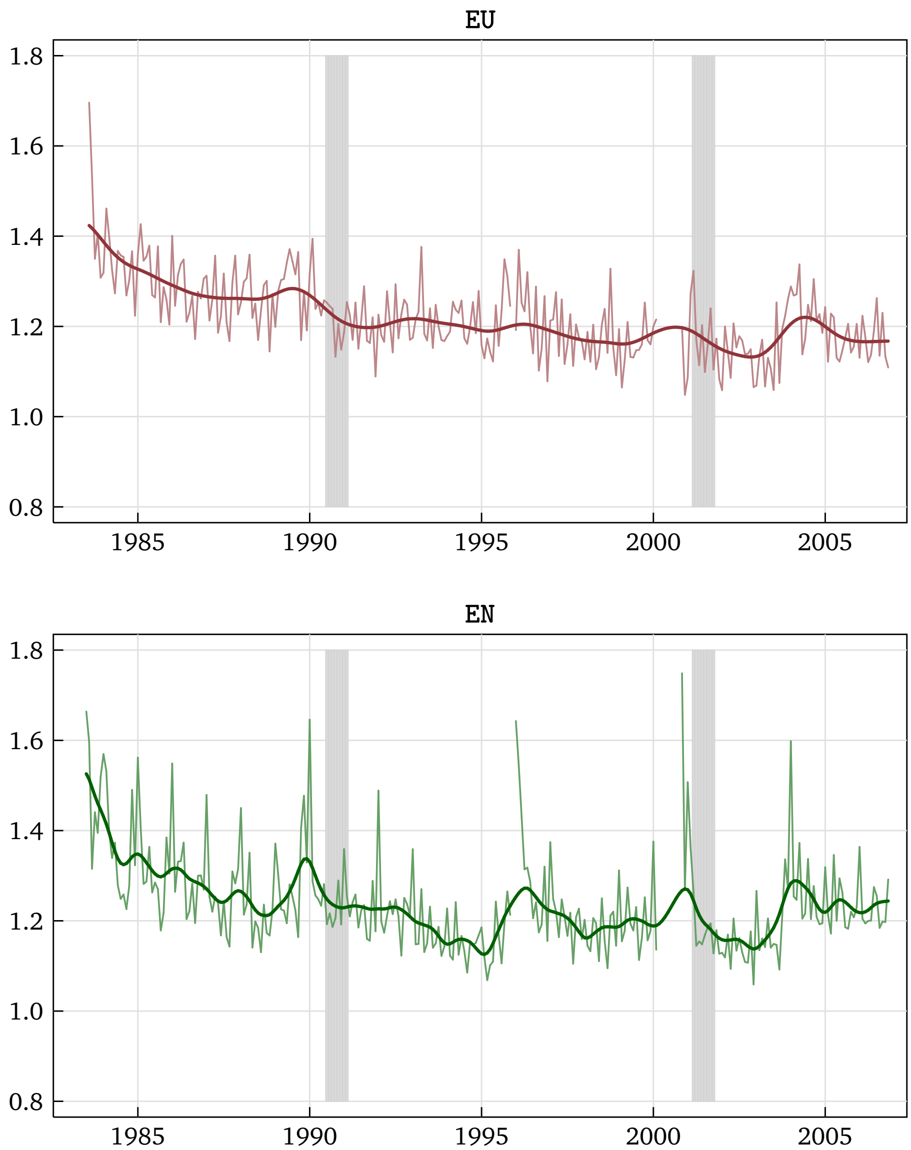
c. Adjusted for time aggregation using Shimer (2007)'s theoretical model.

Figure 1. Origins of Time Aggregation[a]



Source: Author's calculations using weekly SIPP data for 1983:6–2006:12.
a. Distribution of monthly classification for unrecorded weekly transitions.

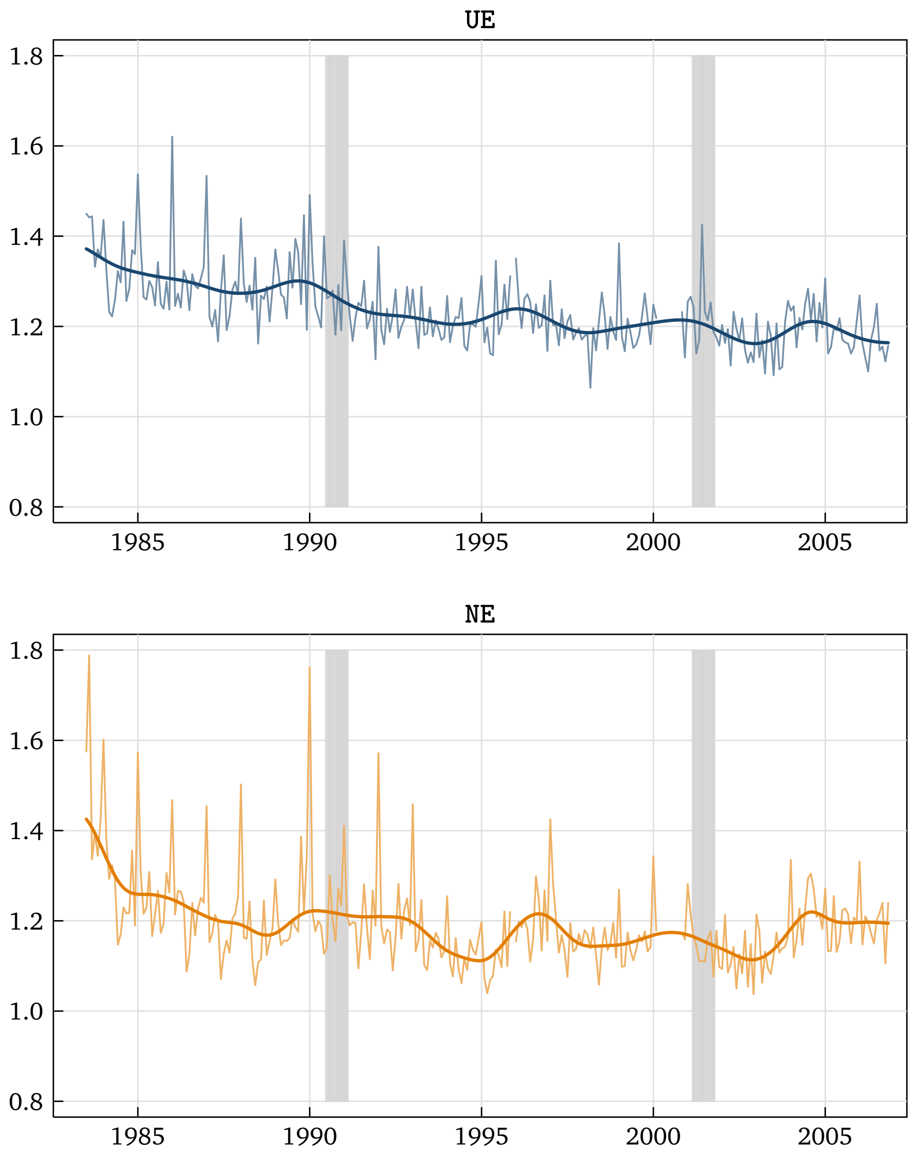
Figure 2. Time Aggregation, Separation Flows, 1983–2006[a]



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

a. Graph of $\widehat{T}_t^{\mathtt{IJ}} = \widehat{\mathtt{IJ}}_t^{*}/\widehat{\mathtt{IJ}}_t$ shown with combined trend-cycle component estimated using equation 5. Shaded bars indicate NBER-dated recessions.

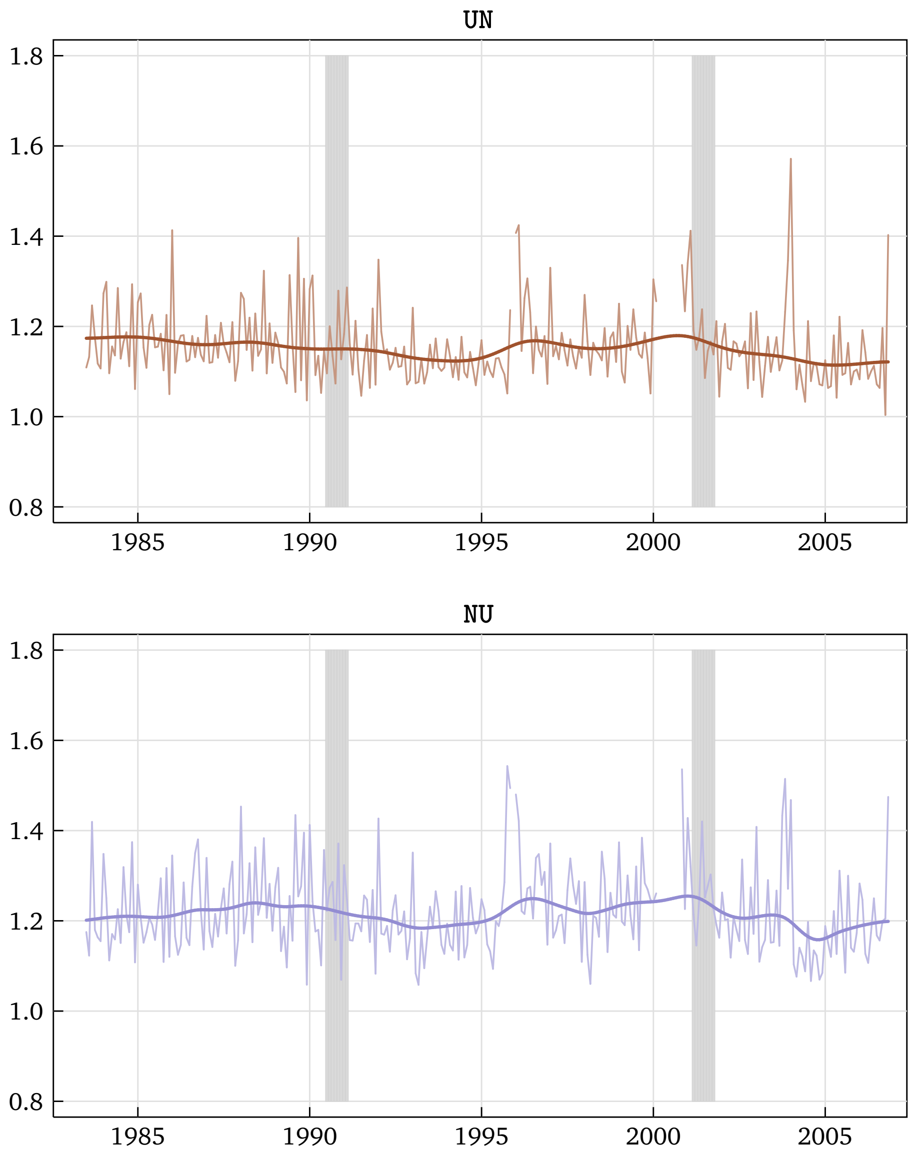
Figure 3. Time Aggregation, Accession Flows, 1983–2006[a]



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

a. Graph of $\widehat{T}_t^{\mathtt{IJ}} = \widehat{\mathtt{IJ}}_t^{*}/\widehat{\mathtt{IJ}}_t$ shown with combined trend-cycle component estimated using equation 5. Shaded bars indicate NBER-dated recessions.

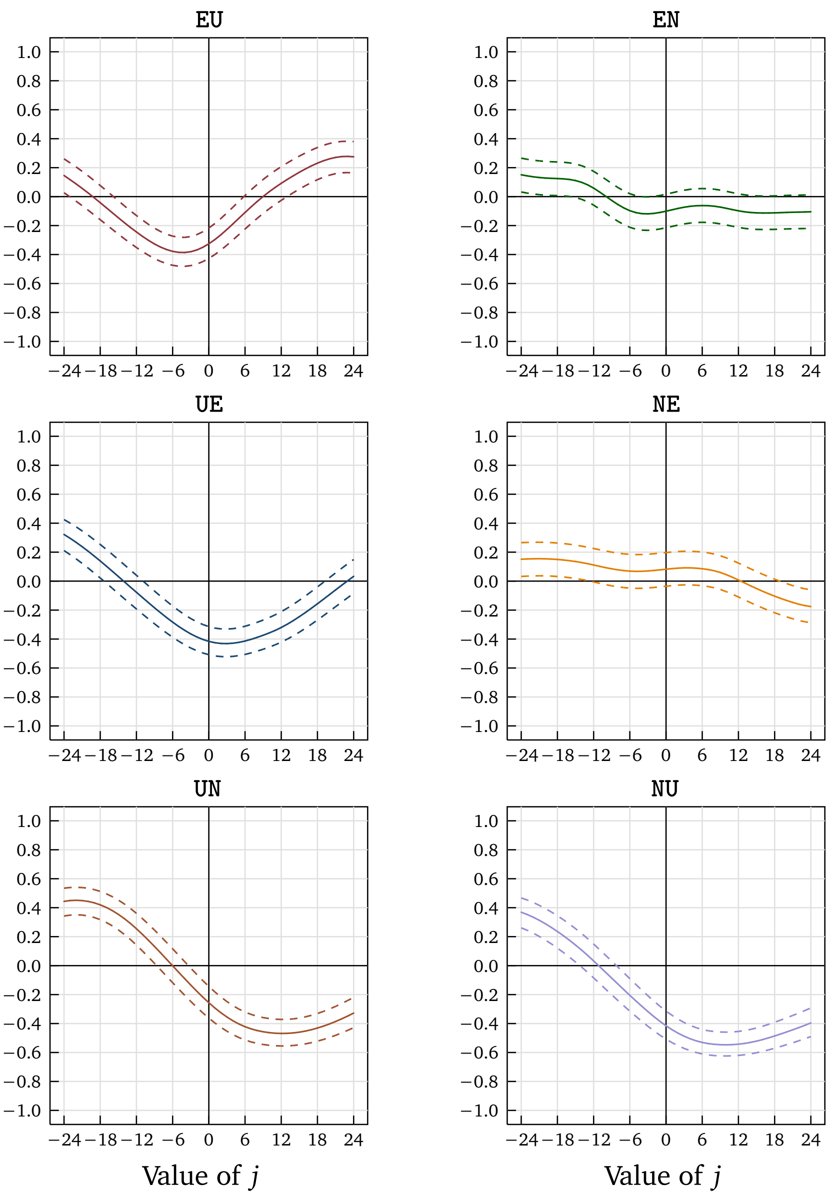
Figure 4. Time Aggregation, Participation Flows, 1983–2006[a]



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

a. Graph of $\widehat{T}_t^{\mathtt{IJ}} = \widehat{\mathtt{IJ}}_t^{*}/\widehat{\mathtt{IJ}}_t$ shown with combined trend-cycle component estimated using equation 5. Shaded bars indicate NBER-dated recessions.

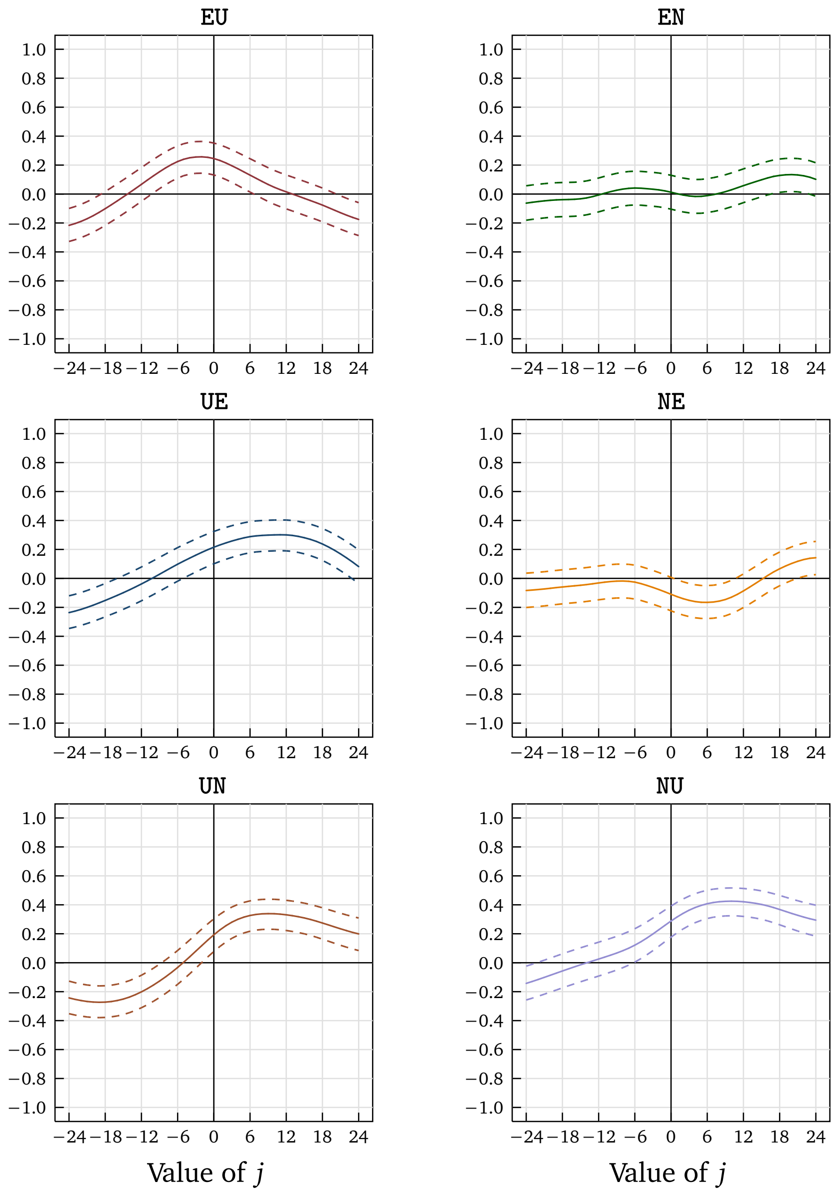
Figure 5. Cross-Correlations of Time Aggregation with Unemployment Rate, 1983–2006[a]



Source: Author's calculations using data from the SIPP and the BLS.

a. Correlation of $\widehat{\psi}_t^{UR}$ with $\widehat{\psi}_{t+j}^{IJ}$. Cyclical components, $\widehat{\psi}$, are estimated using equation 5. Dashed lines indicate 95 percent confidence interval.

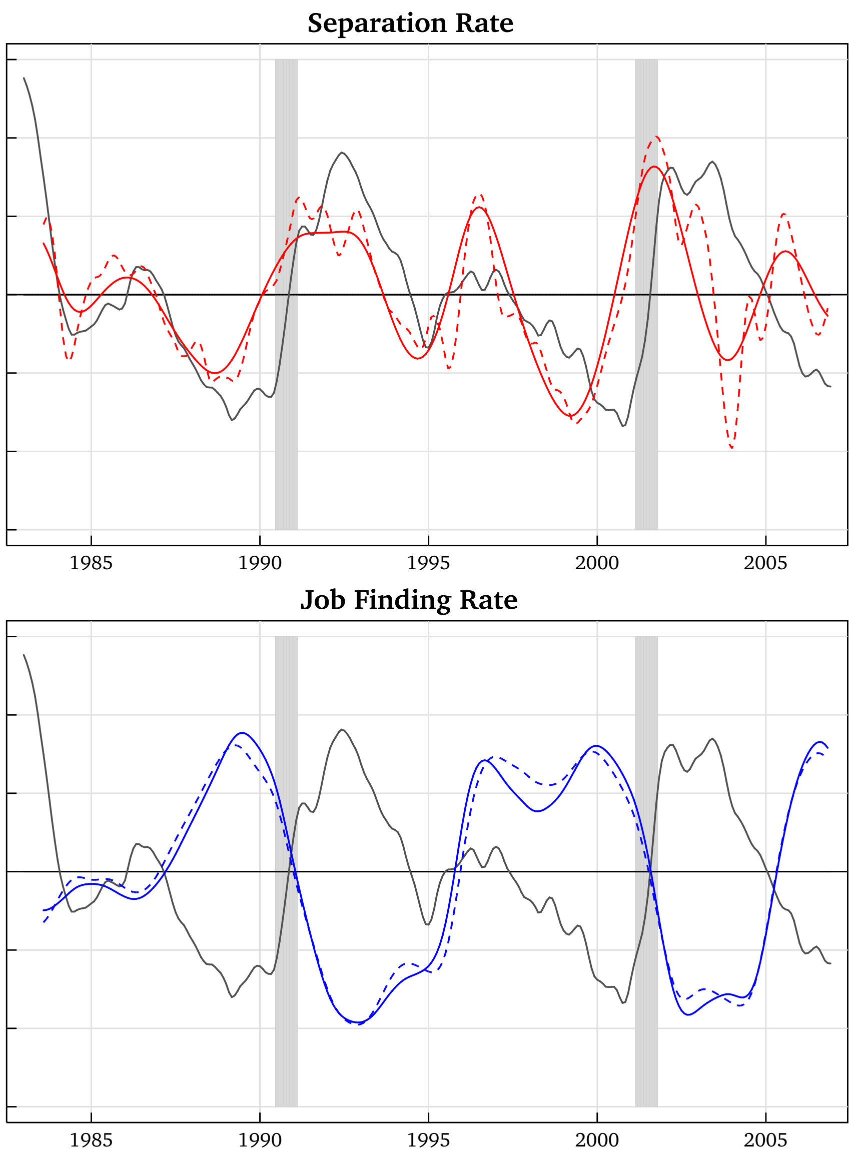
Figure 6. Cross-Correlations of Time Aggregation with Industrial Production, 1983–2006[a]



Source: Author's calculations using data from the SIPP and the Board of Governors of the Federal Reserve.

a. Correlation of $\widehat{\psi}_t^{IP}$ with $\widehat{\psi}_{t+j}^{\mathtt{IJ}}$. Cyclical components, $\widehat{\psi}$, are estimated using equation 5. Dashed lines indicate 95 percent confidence interval.

Figure 7. Cyclical Component of Separation and Job Finding Hazard Rates, SIPP, 1983–2006[a]



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

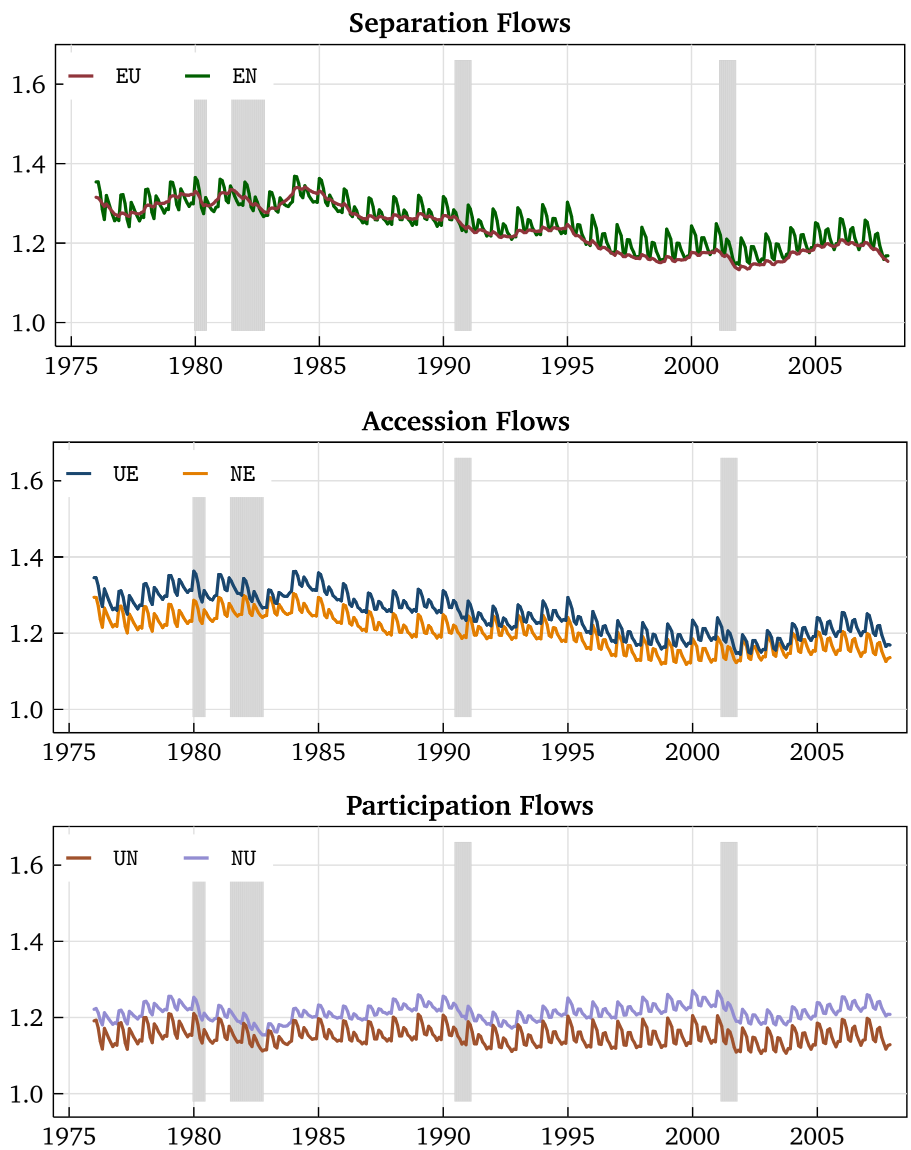
a. Cyclical components estimated using equation 5. Dark gray line is cyclical component of unemployment rate. Solid colored lines are adjusted for time aggregation; dashed lines are unadjusted. Shaded bars indicate NBER-dated recessions.

Figure 8. Cross-Correlations of Separation and Job Finding Hazard Rates with Unemployment, SIPP, 1983–2006[a]

Source: Author's calculations using data from the SIPP and the BLS.

a. Correlation of $\widehat{\psi}_t^{UR}$ with $\widehat{\psi}_{t+j}^{sr}$ and $\widehat{\psi}_{t+j}^{jfr}$. Cyclical components, $\widehat{\psi}$, are estimated using equation 5. Solid line is adjusted for time aggregation; dashed line is unadjusted.

Figure 9. Time Aggregation Adjustment Factors, 1976–2007[a]

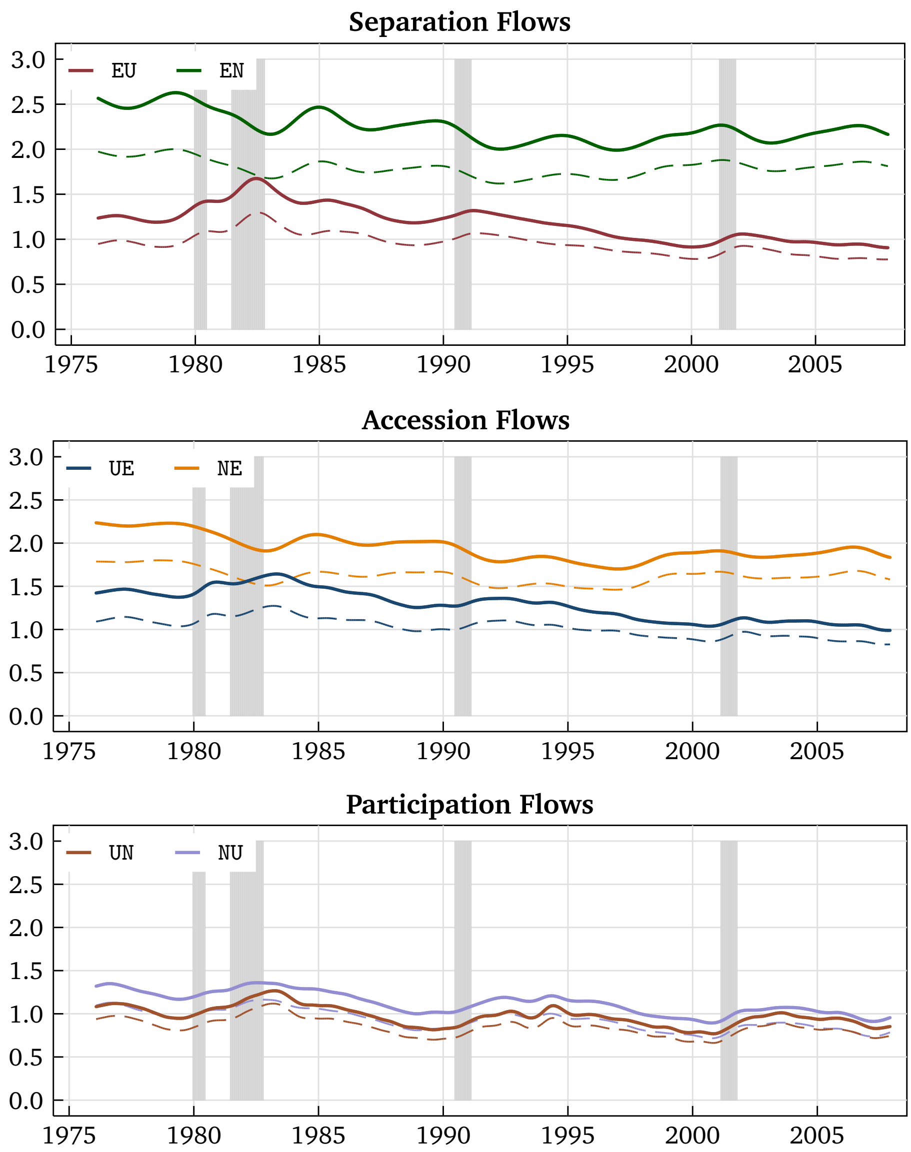


Source: Author's regressions using data from the SIPP and the BLS.

a. Predicted $\widehat{T}^{IJ}$ from regressions in table 6. Shaded bars indicate NBER-dated recessions.

Figure 10. Adjusted and Unadjusted CPS Gross Flows, 1976–2007[a]

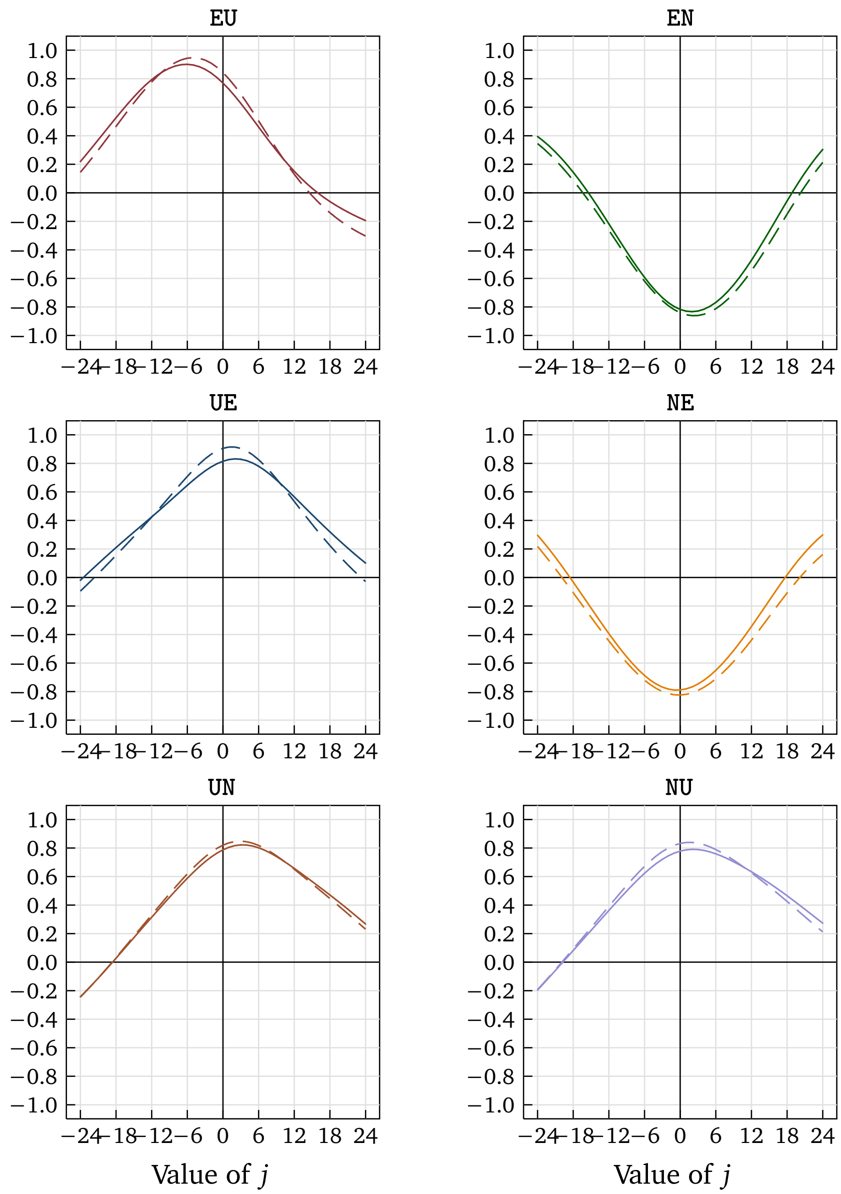
Percent of population



Source: Author's calculations using data from the SIPP, the CPS, and the BLS.

a. Trend-cycle component of CPS gross flows. Solid line is adjusted for time aggregation using SIPP data; dashed line is unadjusted. Components estimated using equation 5. Shaded bars indicate NBER-dated recessions.

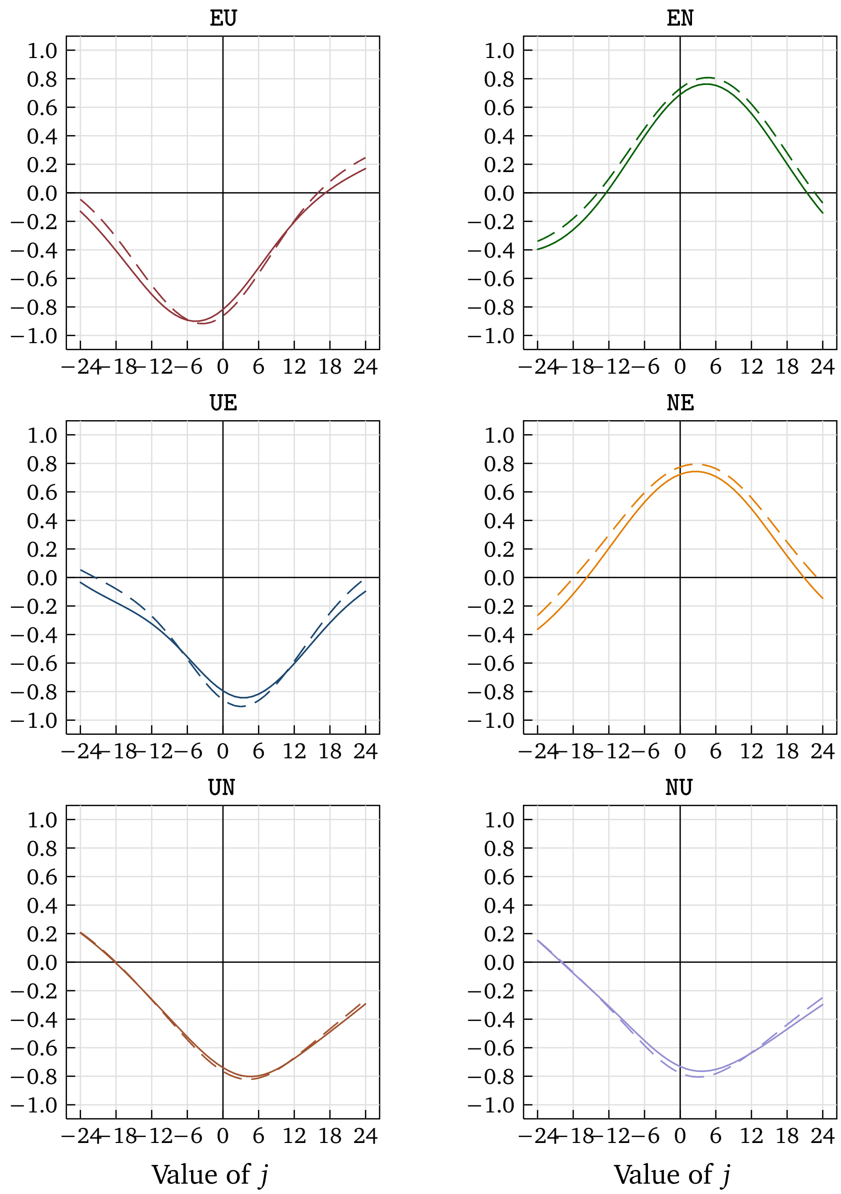
Figure 11. Cross-Correlations of Gross Flows with Unemployment Rate, 1976–2007[a]



Source: Author's calculations using data from the CPS and the BLS.

a. Correlation of cyclical components of unemployment rate at t with gross flow at $t+j$, corr$\left(\widehat{\psi}^{UR}_{t}, \widehat{\psi}^{\mathrm{IJ}}_{t+j}\right)$. Cyclical components, $\widehat{\psi}$, estimated using equation 5. Solid line is adjusted for time aggregation using SIPP data; dashed line is unadjusted.

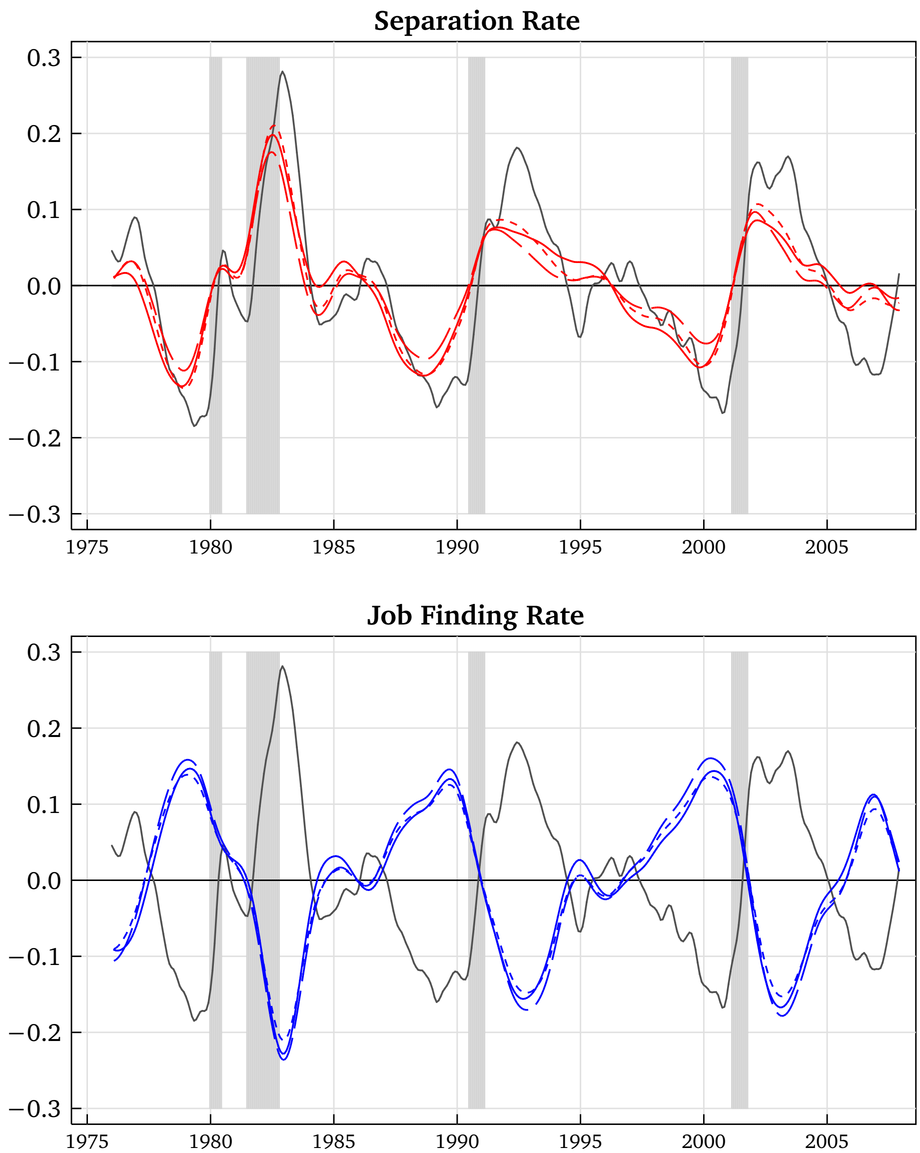
Figure 12. Cross-Correlations of Gross Flows with Industrial Production, 1976–2007[a]



Source: Author's calculations using data from the CPS and Board of Governors of the Federal Reserve System.

a. Correlation of cyclical components of unemployment rate at t with gross flow at $t+j$, $\text{corr}\left(\widehat{\psi}_t^{IP}, \widehat{\psi}_{t+j}^{\text{IJ}}\right)$. Cyclical components, $\widehat{\psi}$, estimated using equation 5. Solid line is adjusted for time aggregation using SIPP data; dashed line is unadjusted.

Figure 13. Cyclical Component of Separation and Job Finding Hazard Rates, CPS, 1976–2007[a]



Source: Author's calculations using CPS microdata for 1976:2–2007:12.

a. Cyclical components, $\widehat{\psi}$, estimated using equation 5. Dark gray line is cyclical component of unemployment rate. Solid colored line is adjusted for time aggregation using SIPP data (equation 7); long-dashed line adjusted using theoretical correction (equation 15) and short-dashed line is unadjusted.

Figure 14. Cross-Correlations of Separation and Job Finding Hazard Rates with Unemployment, CPS, 1976–2007[a]

Source: Author's calculations using data from the SIPP, CPS, and BLS.

a. Correlation of $\widehat{\psi}_t^{UR}$ with $\widehat{\psi}_{t+j}^{sr}$ and $\widehat{\psi}_{t+j}^{jfr}$. Cyclical components, $\widehat{\psi}$, estimated using equation 5. Solid line is adjusted for time aggregation using SIPP data (equation 7); long-dashed line adjusted using theoretical correction (equation 15) and short-dashed line is unadjusted.