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The Cyclicalities of Job Loss and Hiring

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The Cyclicalities of Job Loss and Hiring

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Abstract

We study the cyclical behavior of job loss and hiring using CPS worker flow data, adjusted for margin error and time aggregation error. The band pass filter is used to isolate cyclical components. We consider both total worker flows and transition hazard rates within a unified framework. Our results provide overwhelming support for a “separation-driven” view of employment adjustment, whereby total job loss and hiring rise sharply during economic downturns, initiated by increases in the job loss hazard rate. Worker flows and transition hazard rates are highly volatile at business cycle frequencies. These patterns are especially strong among prime-age workers. For young workers, job loss and hiring adjust procyclically due to movements into and out of the labor force.

JEL codes: J63, J64

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1 Introduction

The behavior of U.S. job loss and hiring over the business cycle remains an elusive and controversial subject, despite decades of research. Diverse and contradictory conclusions have been drawn from an assortment of data sources, using numerous measures and methodologies. Early work favored a “separation-driven” view of employment adjustment, whereby cyclical downturns are associated with initial waves of job loss, followed by increased hiring activity as the economy recovers.¹ More recent research has focused on job loss and job finding probabilities faced by individual workers. This evidence argues for a “hiring-driven” view, tying employment adjustment to fluctuations in job finding rates, with little role for job loss rates.²

This paper aims to provide a comprehensive picture of job loss and hiring behavior using gross flows data from the Current Population Survey (CPS) over the 1976-2006 period. Our goal is to obtain a definitive reading of the data by dealing carefully with data collection error, time aggregation error, identification of cyclical components, and business cycle comovement. We consider both gross worker flows and transition hazard rates within a unified framework. We also highlight the role of demographic factors underlying the aggregate adjustment process.

Using CPS gross flows data, we construct measures of total U.S. job loss and hiring, including *all* transitions out of and into employment, at monthly frequency. The raw data are adjusted for missing observations (margin error) in a manner that ensures conformity with officially reported stocks of employed, unemployed and not in labor force (NILF) workers. Our method, which builds on the well-known procedure of Abowd and Zellner (1985), is relatively simple to implement, and it includes the standard missing at random specification as a special case.³

While our adjusted CPS data capture month-over-month worker transitions, they miss transitions reversed within the month. To account for possible time aggregation error in

¹Empirical support for the separation-driven view has been provided by Darby, Plant, and Haltiwanger (1985, 1986), Davis (1987), Hall (1995), Davis, Haltiwanger, and Schuh (1996), Bleakley, Ferris, and Fuhrer (1999) and Merz (1999a,b), using unemployment duration data, and Blanchard and Diamond (1990) and Bleakley, Ferris, and Fuhrer (1999), using data on gross worker flows.

²The hiring-driven view has been forcefully advocated by Hall (2005a,b) and Shimer (2005a,b), who draw on both worker flow and unemployment duration data.

³A second source of CPS measurement error, referred to as classification error, derives from misreporting by individuals of employment status and the nature of job search activities. Using available CPS reinterview information, we show below that our results are robust to classification error correction.

measuring total job loss and hiring activity, we link the CPS gross flows data to an underlying continuous-time stock-flow adjustment framework that encompasses all transitions occurring within the month. This procedure, which extends the method of Shimer (2005a), yields estimates of the total job loss and hiring activity. The band pass filter of Baxter and King (1999) is employed to isolate frequencies of adjustment that are relevant for business cycle analysis.

Our results provide overwhelming support for the separation-driven view of cyclical employment adjustment. We first consider total employment-to-unemployment (EU) and unemployment-to-employment (UE) flows. Estimated total job loss and hiring flows exhibit steep increases during all four NBER recessions in the sample. The business cycle component of total job loss, as determined by the band pass filter, displays high negative correlation with the industrial production index, leading the index by about three months. Total hiring also shows sizable negative correlation with the index, lagging it by between one and two months. Both job loss and hiring exhibit high volatility at business cycle frequencies. Moreover, the standard deviation of total job loss is 39 percent greater than that of total hiring.

The estimated transition hazard rates provide further evidence in favor of the separation-driven view. The cyclical component of the job loss hazard rate spikes upward during each of the four NBER recessions, while the job finding hazard rate falls steadily. Correlations with industrial production indicate that the job loss rate rises about three months before a downturn, while the job finding rate declines about two months after. Despite the falling job finding rate, total hiring increases due to the initial upward spike in total job loss. Thus, cyclical employment adjustment is initiated by movements in the job loss rate.

The job finding hazard rate is roughly 30 percent more volatile than the job loss hazard rate, measured in terms of standard deviations of cyclical components. The job loss rate is over twice as volatile as the cyclical component of the industrial production index, however. Thus, both hazard rates are highly volatile in comparison to output.

Finally, worker flows and hazard rates display much greater volatility and counter-cyclicity among prime-age workers, and especially among prime-age males. For the latter workers, in particular, the correlation between the cyclical components of the job loss rate and industrial production is nearly -90 percent at a lag of three months. The standard deviations at business cycle frequencies of the job loss and hiring rates are essentially equal for prime-age males, at over three times the standard deviation of industrial production.

Next we incorporate employment-to-NILF (EN) and NILF-to-employment (NE) transitions into our measurements of worker flows and hazard rates. The expanded measures provide a broader picture of movements out of and into employment over the cycle. When all employment outflows and inflows are considered, the volatilities of total job loss and hiring flows at business cycle frequencies decrease and become roughly equal. Thus, movements between employment and NILF serve to smooth out total flows, particularly for job loss. However, the cyclical components of job loss and hiring flows remain nearly as volatile as the cyclical component of industrial production. Similar comments apply with respect to the cyclical component of the job loss hazard rate.

NILF flows have important implications for employment adjustment among young workers. For these workers, total job loss and hiring, including all employment outflows and inflows, fall sharply during NBER recessions. The cyclical components of total flows exhibit high positive correlation with the cyclical component of industrial production. Moreover, the hiring flows of young workers lead the cycle by about a month, while the job loss flows trail the cycle by four months. Similarly, the job loss and job finding hazard rates for young workers adjust procyclically, with job loss rates trailing the cycle. Among prime-age workers, however, the cyclical behavior of total flows and transition hazard rates is little affected when NILF flows are included, save for reductions in volatility. These findings point to a hiring-driven view of employment adjustment for young workers, strongly tied to movements into and out of the labor force.

Our results bear on recent claims that employment adjustment has become less volatile since the early 1990s and, in particular, that the 2001 recession exhibited little volatility in job loss rates.⁴ Based on fluctuations at business cycle frequencies, however, we find no noticeable differences in any of our measures between the pre- and post-1990 periods, nor does the 2001 recession display meaningful qualitative differences from earlier recessions.

Relation to past research. Blanchard and Diamond (1990) conduct a careful analysis of job loss and hiring flows. Drawing on Abowd and Zellner's gross flow data, they base their key conclusions on a VAR framework identifying aggregate activity shocks as those which move unemployment and vacancies in opposite directions. A negative shock induces a strong increase in EU flows, and a relatively weak response in UE flows. The latter result contrasts with our finding of closely comparable countercyclicality of the EU and UE flows.

Blanchard and Diamond also consider the effects of age on employment adjustment.

⁴This claim has been strongly made by Hall (2005a,b).

They find that older workers experience smaller responses to aggregate shocks than do younger workers, particularly for EU and UE flows and transition rates. We show, however, that these flows and rates exhibit much stronger volatility and countercyclicality among prime-age workers. Moreover, Blanchard and Diamond's aggregate shocks have small effects on the overall transitions between employment and nonemployment for young workers, while we find these transitions to be highly procyclical.

We argue that Blanchard and Diamond's analysis relies on a questionable identification assumption, whereby transitions associated with worker reallocation are excluded. The distinction between aggregate and reallocation shocks is difficult to draw precisely, however. Our analysis adopts a more straightforward approach by tying business cycle fluctuations to an observable output index, rather than an identified structural disturbance. We also clarify the nature of cyclical adjustment by focusing on business cycle frequencies.

Shimer (2005a) uses CPS gross flow data to estimate transition hazard rates using a three-state model that adjusts for time aggregation error. He concludes that job loss rates are acyclic, but this finding appears to be sensitive to the presence of high-frequency noise retained by his filtering method.⁵ Moreover, Shimer does not consider total flows, nor does he isolate the employment adjustment of demographic groups. All other previous work has ignored the possibility of time aggregation error; we show below, however, that the time aggregation correction has little effect on the results.

A large body of research has used CPS unemployment duration data to analyze the cyclicity of EU and UE flows and transition rates.⁶ As a general matter, duration data cannot distinguish whether inflows to unemployment originate from employment or NILF, or whether outflows from unemployment move to employment or NILF. At best, they yield rough approximations of EU and UE flows and transition rates. Moreover, these data are silent with respect to transitions between employment and NILF, and they are subject to

⁵Shimer applies the HP filter, which removes only low frequency components from the data. CPS data contain a great deal of high frequency noise, however. When the band-pass filter at standard frequencies is applied to his quarterly estimates, countercyclical job loss hazard rates emerge. In particular, the peak correlation of Shimer's job loss hazard rate (combining EU and EN hazard rates) with the cyclical component of GDP is -57 percent at a lag of two to three quarters.

⁶Darby, Plant, and Haltiwanger (1985, 1986), Davis (1987), Hall (1995), Davis, Haltiwanger, and Schuh (1996) and Merz (1999a,b) find countercyclical EU and UE flows, while Hall (2005a,b) and Shimer (2005a,b) find acyclic job loss hazard rates and procyclical job finding hazard rates.

serious reporting error.⁷ Gross flow data, which we use, offer more direct measures of the transition information available in the CPS.

Another branch of the previous literature has focused on transitions between jobs, rather than transitions out of and into employment. In particular, Fallick and Fleischman (2004), Nagypál (2004), Hall (2005a,b), and Shimer (2005b) exploit the dependent reinterviewing feature of the CPS, introduced in 1994, to study employment-to-employment (EE) flows. These authors argue that the total separation rate, including all forms of movement out of jobs, did not adjust countercyclically over the post-1994 period.⁸

It is important to note, however, that the CPS data measure month-over-month transitions from one job to another. These include “indirect” EE flows involving transitions between employment and nonemployment occurring within the month. Our time aggregation adjustment picks up these indirect EE flows, so any differences with our findings revolve around the behavior of transitions directly from job to job. In our view, direct EE flows and separations to unemployment or NILF reflect distinctly different aspects of employment adjustment.⁹ Lumping all separations together confuses important distinctions among the sources and implications of labor mobility, particularly as they pertain to business cycles.

The paper proceeds as follows. The margin error correction and measurement procedure are presented in Sections 2 and 3, respectively. Section 4 discusses the findings for cyclical adjustment of total worker flows, and Section 5 covers transition hazard rates. NILF flows are introduced in Section 6. Section 7 considers the necessity of correcting for time aggregation error, and Section 8 assesses the robustness of our results to classification error. An extended discussion is offered in Section 9, and Section 10 concludes.

⁷Poterba and Summers (1984), for example, analyze the problem of misreported unemployment durations in the CPS. Among other findings, they show that a substantial proportion of reported long-duration unemployment spells reflect misreporting of actual short-duration spells.

⁸Hall (2005a,b) also draws on the Survey of Income and Program Participation (SIPP) and the Job Openings and Labor Turnover Survey (JOLTS) to argue for acyclicity of the total separation rate. These data sources have problems of their own, however; see Nagypál (2004) and Faberman (2005).

⁹Drawing on SIPP data, Nagypál shows that EE flows are much less prevalent when separations result from layoffs rather than quits. This is consistent with the idea that direct job-to-job transitions are not closely associated with involuntary job loss. Influential theoretical models have also stressed the essential differences between job-to-job separations and separations to nonemployment; see Mortensen (1994) and Pissarides (2000, ch. 4).

2 Adjusted Worker Flow Data

The CPS surveys a large sample of individual U.S. workers each month, ascertaining whether they are employed and, if nonemployed, whether they engaged in active job search activities over the preceding month.

The CPS data are derived from a sample of physical addresses. After entering the sample, each selected address is surveyed for four consecutive months. Following an eight month hiatus, the address is surveyed again for four consecutive months. Month-over-month transitions between employed, unemployed, and NILF status can be measured by matching individual workers that are in the CPS sample in two consecutive months. Owing to the sample rotation and the eight-month gap, at most 75 percent of individual workers in the sample can be matched.

Further, many locations fail to be surveyed in a given month, for example, because of temporary absence of individuals from the location. Failure to match individual workers is referred to as *margin error*, and it leads to omission of possible transitions from the survey data. The most common correction for margin error uses the *missing at random* (MAR) model, which simply omits the missing observations and reweights the transitions that are measured, effectively imputing the measured population distribution to the missing observations.¹⁰ Frazis et al. (2006) show that stock series generated by the MAR model are inconsistent with the officially measured stocks reported by the BLS, thus invalidating the procedure. Specifically, they show that the gross flows computed under the missing at random assumption for the period December 1994 to December 2004 considerably underestimate the actual changes in the stocks of employed and unemployed individuals based on the official series, and overestimate the actual changes in the stock of NILF individuals.¹¹

This paper employs an extended version of the MAR model that corrects for inconsistencies in the implied stocks. Drawing on the approach of Abowd and Zellner (1985), we specify true gross flows as a log-linear combination of measured flows between employed,

¹⁰The MAR model has been employed by Poterba and Summers (1986), Bleakley, Ferris, and Fuhrer (1999), Fallick and Fleischman (2004), and Shimer (2005a), among others.

¹¹We find similar patterns in our MAR series over a longer sample period of January 1976 through December 2005. Frazis et al. (2006) find rotation group bias to be the most important source of this inconsistency, whereby the proportions of individuals reporting employed and unemployed status are lower in later rotation groups. See also Solon (1986).

unemployed and NILF status.¹² Weights are determined to minimize the squared difference between the stocks implied by the fitted gross flows and the reported BLS stocks. To allow for time variations in the allocation parameters, we run rolling regressions, each of which has a 10-year sample period.¹³ Importantly, our method admits the MAR specification as a special case. The parameter restrictions implied by the MAR model are tested and overwhelmingly rejected for all time periods and all groups of workers considered. See Appendix A for further details.

3 Measurement of Worker Flows

Using the adjusted worker flow data, one can directly measure total month-over-month transitions out of and into jobs. As stressed by Shimer (2005a,b), these measures may provide a misleading picture of total worker mobility, since they miss transitions that are reversed within the month. This problem may be addressed by basing the measurements on a continuous-time adjustment framework.¹⁴

In this section we focus on EU and UE flows. The EU flows correspond closely to the notion of involuntary job loss, while the UE flows reflect the hiring of actively searching workers.¹⁵ Transitions involving NILF workers are considered in Section 6.

Let u_t denote the number of unemployed workers at the end of month t . The size of the labor force is normalized to one for all t , so that $e_t = 1 - u_t$ gives the number of employed workers at the end of month t . Individual worker transitions take place in continuous

¹²Unadjusted gross flows are obtained from the CPS micro data using a standard matching algorithm provided by Shimer (<http://home.uchicago.edu/~shimer/data/flows/>).

¹³Abowd and Zellner (1985) assume fixed allocation parameters, since they have only a very short sample (January 1977 through December 1986). Nevertheless, they find instability of the allocation parameters even within their sample period. This highlights the importance of allowing for time variation in the parameters.

¹⁴Measurement frameworks based on continuous-time adjustment have previously been used by Christiano and Eichenbaum (1987), Jorda (1999), Aadland and Huang (2004) and Jorda and Marcellino (2004). Shimer (2005a) has analyzed transition hazard rates using a three-state version of the method we use.

¹⁵Within the population of unemployed workers, the Bureau of Labor Statistics (BLS) distinguishes job losers, including persons on temporary and permanent layoff and persons completing temporary jobs, from job leavers and labor force entrants. Since the flow of job losers into unemployment is roughly five times the flow of job leavers (see, e.g., Bleakley, Ferris, and Fuhrer (1999)), EU flows predominantly reflect involuntary job loss. Moreover, the population of job leavers includes individuals who quit to search for new work in anticipation of upcoming terminations; these quits should also be considered as involuntary job loss.

time. For measurement purposes, we assume that the continuous-time flow hazard rates for transitions are constant within each month. The *job loss hazard rate*, denoted by λ_t , is the arrival rate of transitions to unemployment for a worker who is employed at any point in month t . Similarly, the *job finding hazard rate*, denoted by p_t , is the arrival rate of transitions to employment for a worker who is unemployed at any point in month t .

Estimates of these hazard rates can be obtained from measured monthly average transition rates. Let $\widehat{\lambda}_t$ indicate the *average job loss rate*, which is the probability that a worker is unemployed at the end of month t , given that he/she is employed at the beginning of the month. Similarly, the *average job finding rate*, \widehat{p}_t , is the probability that a worker is employed at the end of month t , given that he/she is unemployed at the beginning of the month. In Appendix B, we demonstrate that the average transition rates are related to the hazard rates according to the following formulas:

$$\widehat{\lambda}_t = \beta_t(1 - e^{-\alpha_t}), \quad (1)$$

$$\widehat{p}_t = (1 - \beta_t)(1 - e^{-\alpha_t}), \quad (2)$$

where

$$\alpha_t = \lambda_t + p_t, \quad \beta_t = \frac{\lambda_t}{\lambda_t + p_t}. \quad (3)$$

Using the estimated hazard rates, it is possible to calculate total gross flows, including *all* of the movements of individual workers into and out of employment during the month. *Total job loss* and *total hiring*, denoted by l_t and f_t , respectively, are given by:

$$l_t = \lambda_t \left(-(u_{t-1} - \beta_t) \frac{1 - e^{-\alpha_t}}{\alpha_t} + (1 - \beta_t) \right), \quad (4)$$

$$h_t = p_t \left((u_{t-1} - \beta_t) \frac{1 - e^{-\alpha_t}}{\alpha_t} + \beta_t \right). \quad (5)$$

In Appendix B it is verified that the change in employment equals total job finding minus total job loss:

$$e_t - e_{t-1} = h_t - l_t. \quad (6)$$

Thus, the two total flow measures serve to decompose employment adjustment in terms of all hiring and job loss events occurring within the month. This captures the totality of worker mobility between employment and unemployment, including movements that are subsequently reversed within the month.

Average transition rates are calculated from our adjusted CPS data in the following way:

$$\hat{\lambda}_t = \frac{eu_t}{e_{t-1}}, \quad \hat{p}_t = \frac{ue_t}{u_{t-1}}, \quad (7)$$

where eu_t indicates measured flows from employment to unemployment, and ue_t denotes measured flows from unemployment to employment, during month t . These measures are substituted into (1)-(3) to obtain estimates of the hazard rates λ_t and p_t ; the latter are in turn substituted into (4) and (5) to estimate the total flows l_t and h_t .

4 Cyclical Behavior of Worker Flows

Estimated total job loss and total hiring, derived from (4) and (5), are presented in Figures 1 and 2; here we report 12-month backward moving averages in order to screen out high-frequency noise. Vertical reference bands indicate NBER recession dates. Results for all workers and for three demographic categories are reported. Among all workers, total job loss and total hiring exhibit steep increases during all four recessions in the sample period. These recessionary increases are particularly strong for prime-age and prime-age male workers, while they are much less apparent for young workers.

Observe that the volumes of total job loss and hiring among young workers, as a percent of population, are roughly twice the volumes experienced by prime-age workers. Secular declines in both job loss and hiring, beginning in the early 1990s, may also be noted. This finding suggests that “job churning” has decreased in the U.S. economy.¹⁶

Figures 3 and 4 present cyclical components extracted by applying the band-pass filter to the estimated series. The band is restricted to the standard business-cycle frequencies of 15 to 96 months (Baxter and King (1999)). Thus, components having frequencies less than 15 months, or greater than eight years, are eliminated. Recessionary spikes in job loss and hiring flows show up clearly in all four recessions. The spikes are especially prominent for prime-age and prime-age male workers. Note further that the post-1990 period does not differ from the earlier period in any important way, nor does the 2001 recession notably differ from earlier recessions.

Standard deviations of total job loss and hiring are reported in Table 1. The standard deviation of total job loss, at 4.66 percent, is 39 percent greater than the standard deviation of 3.35 percent for total hiring. Thus, employment adjustment at business cycle frequencies

¹⁶This point is made by Bleakley, Ferris, and Fuhrer (1999).

relies more on changes in job loss than on changes in hiring. Moreover, the standard deviation of the cyclical component of industrial production, used as our output measure, is only 2.35 percent.¹⁷ It follows that both measures of total worker flows are significantly more volatile than output.

Cross correlations between cyclical components of total job loss and total hiring are given in Figure 5. For all workers, the flows exhibit a contemporaneous correlation of nearly 75 percent at business cycle frequencies. This remains true for the two prime-age categories, while job loss and hiring flows are essentially uncorrelated for young workers.

To assess the business cycle comovement of worker flows, we consider the cross correlations of the total flows series with the industrial production index. Figure 6 depicts the cross correlations for total job loss. Among all workers, and within each of the three demographic categories, job losses are highly countercyclical. The correlation of total job loss with industrial production peaks at about -80 percent at a lag of three months. Thus, job losses lead the business cycle by about three months. Again, the prime-age groups closely mimic the pattern for all workers. Countercyclicity is somewhat attenuated for young workers, reaching a peak correlation with industrial production of -50 percent at a lag of about eight months.

Business cycle variation in total hiring is considered in Figure 7. For all workers, total hiring is strongly countercyclical, with a contemporaneous correlation with industrial production of about -75 percent. Thus, the hiring of unemployed workers tends to rise during economic downturns. A slight rightward phase shift may be noted, indicating that total hiring lags the cycle by one to two months. The results are essentially the same for the two prime-age categories, while total hiring for young workers does not exhibit important business cycle comovement.

These results demonstrate that downturns are preceded by waves of job loss, followed by rebounds in hiring. This pattern is especially prominent among prime-age workers. Importantly, employment reductions during economic downturns are *not* driven by declines in total hiring.

¹⁷The monthly index of industrial production approximates well the cyclicity of aggregate output. In particular, the cyclical component of the time-averaged industrial production index is highly correlated with the cyclical component of the real GDP series, with a correlation coefficient of over 90 percent.

5 Cyclical Behavior of Hazard Rates

Gross worker flows are determined by transition hazard rates in combination with levels of employment and unemployment. Since the levels adjust gradually, sharp adjustments in gross flows must be initiated by changes in hazard rates. Thus, to understand employment adjustment, it is important to consider the cyclical behavior of hazard rates.

Recall that the estimated job loss and job finding hazard rates, denoted by λ_t and p_t , respectively, are obtained from equations (1)-(3) using the adjusted CPS data. Figures 8 and 9 report the values of the hazard rates for all workers and within the demographic subgroups. The four NBER recessions in the sample period are each accompanied by steep increases in the job loss hazard and steep declines in the job finding hazard. Job loss rates for young workers are over twice as large as those of prime-age workers, while job finding rates for the two groups are comparable.

Cyclical components at business-cycle frequencies are shown in Figures 10 and 11. The cyclical components of the job loss hazard rates display sharp recessionary spikes, particularly for the prime-age groups, while the job finding hazard rates decline steadily over the course of each recession. Again, the pre- and post-1990 periods display qualitatively similar behavior, and the 2001 recession shows no important differences relative to earlier recessions.

Standard deviations of the cyclical components are given in Table 2. The standard deviation of the job finding rate, at just under 7 percent, is 32 percent greater than the standard deviation of the job loss rate. Note, however, that the job loss rate is over twice as volatile as the cyclical component of industrial production; thus, both transition rates are highly volatile relative to output.

The results for all workers mask important differences across demographic groups. For young workers, the job finding rate is nearly twice as volatile as the job loss rate. It is only 12 percent more volatile among prime-age workers, however, and the volatilities are roughly equal among prime-age males. Prime-age workers experience significantly greater variability in transition hazard rates relative to young workers, particularly for job loss rates. Notably, job loss and job finding rates for prime-age males are roughly 350 percent more volatile than industrial production. This contrasts with the findings of Blanchard and Diamond (1990), who argue that hazard rate volatilities are greater among young workers.

Figure 12 reports cross correlations of the job loss and job finding hazard rates. Among

all workers, the two hazard rates exhibit a strong negative correlation of roughly -80 percent. Further, the job loss rate leads the job finding rate by about six months. The pattern is similar for the three demographic categories.

Cross correlations of the job loss and job finding rates with industrial production are shown in Figures 13 and 14, respectively. The job loss rate is highly negatively correlated with industrial production, with peak correlation of -80 percent at a lag of three months. The comovement is somewhat attenuated for young workers, while prime-age males display the strongest negative correlation, at nearly -90 percent. The correlation of the job finding rate with industrial production is about 80 percent at a lead of two months. The results are similar across the demographic groups.

In summary, both the job loss and job finding hazard rates exhibit high variability over the business cycles, with the job loss rate rising roughly three months before a downturn in output, and the job finding rate falling about two months after. Thus, cyclical employment adjustments are initiated by movements in the job loss rate. The job finding rate is somewhat more volatile than the job loss rate, but both rates are highly volatile relative to output. Patterns of comovement are surprisingly similar across the three demographic categories considered.

6 Not In Labor Force Flows

Our analysis has thus far abstracted from EN and NE flows. These flows are highly significant, however, both in their volume and cyclical variability. It is therefore important to assess the role of transitions between employment and NILF in the cyclical adjustment of employment.

The EN flows encompass many job leavers who exit the labor force voluntarily, while the NE flows bring in workers who did not actively search for work in the preceding month. Importantly, the sum of all employment outflows, consisting of the EU and EN flows, combines involuntary job losers with large numbers of voluntary job leavers; thus, the measure is less closely associated with the notion of involuntary job loss. Although we will maintain the terminology of the preceding section, the job loss flows and rates of this section should be interpreted as measures of overall transitions to unemployment and NILF.

Measurement. The continuous-time adjustment framework is easily extended to incorporate flows between employment and NILF. Let $a(s)$ indicate the number of *nonemployed* workers, i.e., persons who are not employed at time s , but who want a job at some point during the next month. According to this definition, the pool of nonemployed workers includes officially designated unemployed workers and NILF workers who “want a job” at the start of the month, along with workers who become new entrants or reentrants at some point during the month. The nonemployed population is normalized to one for each s , and employment is given by $e(s) = 1 - a(s)$.¹⁸

The hazard rate λ_t now represents the arrival rate of transitions from employment to nonemployment, and p_t gives the arrival rate of transitions from nonemployment to employment. Note that the extended framework accounts for *all* transitions out of and into employment. Similarly, $\hat{\lambda}_t$ and \hat{p}_t now indicate the average transition rates between employment and nonemployment. Formulas (1)-(3) carry over directly to the extended framework, while (4) and (5) hold when u_{t-1} is replaced by a_{t-1} .

The average job loss rate is measured as

$$\hat{\lambda}_t = \frac{eu_t + en_t}{e_{t-1}},$$

where en_t indicates measured flows from employment to NILF in month t . The corresponding measure of the average job finding rate \hat{p}_t would capture employment inflows relative to the total nonemployed population, i.e.:

$$\hat{p}_t = \frac{ue_t + ne_t}{a_{t-1}},$$

where ne_t indicates measured flows from NILF to employment in month t . Implementation of this formula is hampered, however, by the absence of any satisfactory measure of the total population of nonemployed persons in a given month.¹⁹

¹⁸Note that we abstract from flows between unemployment and NILF. Including the latter population as a separate state variable is not useful, however, since there are no reliable measures of the subpopulation of NILF workers who either want a job at the start of the month, or enter the unemployment pool during the month.

¹⁹The large volume of monthly flows from NILF to employment indicates that the pool of workers who want to work over the course of a month greatly exceeds the officially reported labor force at the beginning of the month. Moreover, NILF workers who claim to “want a job” amount to roughly two-thirds of the unemployed population. At the same time, it is likely that most NILF workers do not wish to work in any given month. See Blanchard and Diamond (1990) and Castillo (1998) for further discussion of this issue.

We resolve this issue by imputing the size of the nonemployed population in a manner that equates job finding rates across all nonemployed workers:

$$\frac{ue_t}{u_{t-1}} = \frac{ne_t}{a_{t-1} - u_{t-1}}. \quad (8)$$

Equation (8) states that the average job finding rate for unemployed workers is equal to the rate for NILF workers who want a job during month t . This assumption is reasonable to the extent that the latter population combines new entrants and reentrants, likely to have relatively high job finding rates, with marginally attached or “discouraged” workers having relatively low rates.²⁰

Cyclicity of worker flows. Figures 15 and 16 report the estimated total job loss and hiring series, incorporating flows from the NILF population. Including the latter flows greatly increases the total volume of job loss and hiring: in comparison with Figures 1 and 2, total flows are increased by about half for prime-age males, roughly doubled for all prime-age workers, and nearly tripled for young workers. This demonstrates the greater importance of movements into and out of the labor force for female and young workers.

The cyclicity of total flows for young workers is also affected. With the inclusion of NILF flows, total job loss and hiring among young workers decline sharply during recessions, in contrast to the acyclic behavior observed when only unemployment flows are considered. The cyclical adjustment of total flows is not affected for the prime-age groups. Cyclical components extracted via the band-pass filter, shown in Figures 17 and 18, reinforce these findings.

Standard deviations of the cyclical components of total flows are given in Table 3. Relative to the figures in Table 1, the standard deviations of total job loss and hiring flows decline significantly and become roughly equal among all workers. This reflects strong declines in volatility for prime-age workers, while volatility actually rises slightly for young workers. Thus, movements between employment and NILF raise the variability of employment adjustment for young workers, while smoothing it for prime-age workers. Prime-age males have a significantly higher standard deviation of total job loss, however.

²⁰The assumption of equal job-finding rates may be directly motivated by a constant-returns-to-scale matching function, in which net employment inflows depend on job vacancies and total “efficiency units” of worker search. Each unemployed worker contributes one efficiency unit, while $a_t - u_t$ gives the total efficiency units of search contributed by nonemployed workers who are not in the unemployment pool at the beginning of the month.

According to Figure 19, inclusion of NILF flows generates a large positive correlation between total job loss and total hiring among young workers, peaking at nearly 90 percent. This contrasts with the essentially zero correlations seen in Figure 5. Correlations for prime-age and prime-age males are affected only slightly. Moreover, job loss and hiring flows become highly procyclical for young workers, as reported in Figures 20 and 21. For these workers, total job loss and total hiring have peak correlations with industrial production of nearly 70 percent. Hiring flows lead the cycle by a month, while job loss flows lag the cycle by about four months. For prime-age and prime-age male workers, in contrast, the inclusion of NILF flows does not alter the qualitative behavior of total flows over the cycle, although the quantitative magnitudes are somewhat reduced, particularly for hiring flows.

Overall, NILF flows have important implications for the cyclical employment adjustment of young workers. Total job loss and hiring increase in both volume and volatility, and they become highly procyclical. Broadly speaking, employment adjustment for these workers is driven largely by fluctuations in labor force participation, with inflows from NILF leading outflows to NILF. For prime-age and prime-age male workers, in contrast, allowing for NILF flows does not significantly alter the earlier findings, save for changes in levels and reductions in the variability of total flows.

Cyclicity of hazard rates. Estimated job loss and job finding hazard rates are shown in Figures 22 and 23. Our method for imputing the total number of nonemployed workers, based on formula (8), yields estimated job finding hazard rates very close to the rates obtained by ignoring NILF flows. Thus, the earlier results for job finding rates carry over to the present case.

Important differences emerge for job loss hazard rates. Comparing Figures 8 and 22, it may be seen that the estimated job loss rate rises by about 50 percent for prime-age male workers when NILF flows are introduced. The rate more than doubles for all prime-age workers, however, and it nearly triples for young workers. These findings further highlight the looser labor force attachment of female and young workers.

Figure 24 establishes that the cyclical component of the job loss rate for young workers declines during three of the four NBER recessions, while Figure 26 shows that it exhibits a positive correlation with the job finding rate at business cycle frequencies. As seen in Figure 27, the job loss rate displays mild procyclicality among young workers, with the industrial production correlation peaking at 50 percent at a lead of eight months.

Thus, countercyclical movements in the rate of transitions to unemployment, observed in Figure 13, are outweighed by procyclical movements in the rate of transitions to NILF.

For prime-age and prime-age male workers, on the other hand, the earlier results continue to hold when NILF flows are introduced, excepting level changes and reductions in the volatility of the job loss rate. Importantly, the small contemporaneous correlation between the job loss rate and industrial production for all workers, observed in Figure 27, masks very strongly countercyclical job loss rates among prime-age workers.

7 Time Aggregation Effects

Previous studies of worker flows have relied on measures of month-over-month transitions as proxies for gross flows into and out of employment. Owing to omitted transitions within the month, these measures in fact reflect *net* transitions, since a transition out of or into employment is picked up only when the worker's status remains unchanged at the end of the month. Our measures of total flows, which adjust for these omitted transitions, may be compared with the net measures to assess the importance of time aggregation error in gross flow measurement.

In each of the figures, the results for net job loss and net hiring, or average job loss and job finding rates, are shown as dashed lines. Due to time aggregation, net flows underestimate the total volume of worker transitions, as indicated by the differences between the solid and dashed lines in Figures 1 and 2. The net and total series exhibit very similar cyclical properties, however. Adjustments during NBER recessions are quite similar, and the fluctuations at business cycle frequencies, shown in Figures 3 and 4, are nearly identical.

As seen in Table 1, the standard deviations of net flows for the various demographic categories tend to be somewhat higher than their total flow counterparts, but the major results are unchanged. None of the cross correlations displayed in Figures 5 through 7 are altered in any significant way when net flows are considered.

Similar conclusions hold for the estimated transition rates. Table 2 demonstrates that the standard deviations of the hazard rates are roughly similar to those of the measured average transition rates $\hat{\lambda}_t$ and \hat{p}_t , which ignore time aggregation error. It may be observed in Figures 8 through 14 that the time aggregation correction has virtually no effect on the cyclical properties of job loss and job finding rates.

Time aggregation error does have some effect when NILF flows are considered. Fig-

ures 19 through 21 show that the unadjusted flows tend to understate the correlations for all workers, while Figures 24 and 25 reveal distortions in the phasing. Ignoring time aggregation error would not alter the major conclusions in any important way, however.²¹

These findings bear on the claim of Hall (2005a,b) and Shimer (2005a,b) that high procyclicality of job finding rates may induce spuriously measured countercyclicality of job loss rates. There is an alternate possibility, however: spurious procyclicality of job finding rates might emerge from strongly countercyclical job loss rates. The measurement procedure of Section 3 accounts for both of these possibilities. Our results show that the potential measurement errors do not matter for the cyclicity of either total worker flows or hazard rates. Time aggregation errors may be important in other contexts, however, and as a general rule it is necessary to assess whether these errors distort the results in any particular application.

8 Classification Error Adjustment

In the CPS, individuals may misreport their employment status and the nature of their job search activities, causing transitions to be mismeasured. This is referred to as *classification error*. To assess the robustness of our results to classification error, we make use of error probabilities estimated by Poterba and Summers (1986) using CPS reinterview data.²² This information allows us to make a standard classification error correction, which we apply to the raw CPS data in conjunction with our margin error correction; see Appendix C for details.

We find that the classification error correction has a negligible effect on our results concerning the cyclical behavior of EU and UE flows and transition rates. We do not, however, have sufficient reinterview information to obtain a sensible correction for the EN and NE series. The robustness of our EU-UE results nonetheless suggests that our findings for the NILF case are likely to be reasonably accurate.

²¹Note also that net job loss, net hiring, and the average job loss rate are by definition unrelated to our imputation of the number of nonemployed workers. It follows that most of our findings are insensitive to the imputation procedure.

²²As part of its survey procedures, BLS interviewers return to a subset of sampled households each month to conduct a further interview. The reinterviews can be used to check for classification errors, and for a portion of the sample period these data were used to estimate classification error probabilities.

9 Discussion

Two broad conclusions emerge from our analysis of job loss and hiring activity. First, every measure of job loss and hiring, considered in terms of either total flows or transition hazard rates, exhibits high volatility at business cycle frequencies. In particular, the standard deviations of the various job loss and hiring measures never fall below 70 percent of the standard deviation of output, as measured by the index of industrial production. No dimension of job loss or hiring activity can be plausibly viewed as acyclic.²³

Second, aggregate adjustment is marked by important differences based on worker demographics. Among prime-age workers, and especially prime-age males, economic downturns are times of significantly increased job loss and hiring activity. Job loss flows and hazard rates are strongly countercyclical for these workers, and they lead the cycle. Among young workers, in contrast, total job loss and hiring flows decrease during downturns, and job loss activity trails the cycle. Movements in labor force participation play a key role for these workers.

Based on these results, a clear stylized picture of recessionary employment adjustment may be drawn. For prime-age workers, economic downturns are preceded by waves of job loss, associated with spikes in the job loss hazard rate. These waves tend to occur about three months prior to the downturns. The job finding rate plunges soon thereafter, but total hires nevertheless rise sharply. This highlights the role of unemployment as a springboard to new jobs following a negative shock: although individual workers face greater difficulty finding jobs, the expanded pool of unemployed workers drives up total hiring activity on balance. Thus, employment adjustment for prime-age workers entails large and rapid movements into and then out of the unemployment pool.

Recessionary job loss has significant implications for the welfare of prime-age workers. These workers tend to be in long-term, high-wage jobs. Displacement leads to large wage declines in subsequent jobs, along with heightened probabilities of subsequent displacement (Ruhm (1991), Jacobson, LaLonde, and Sullivan (1993), Stevens (1997)). Loss of industry-specific human capital, associated with sectoral shifts, exacerbates these losses (Topel (1990), Neal (1995)). Moreover, wage losses appear to be greater when displacements occur during recessions (Barlevy (2001)). This suggests policymakers ought to closely

²³In particular, our results invalidate the hypothesis of acyclic job loss rates, recently advanced by Hall (2005a,b) and Shimer (2005a,b). It is worth reiterating that, among prime-age males, the correlation of the job loss hazard rate with industrial production is roughly -90 percent, leading industrial production by about three months.

consider the ramifications of recessionary job loss among prime-age workers.

The stylized picture is much different among young workers. Economic downturns are accompanied by sharp declines in hiring flows and job finding rates, with job loss flows and rates falling over six months later. The welfare implications are also much different. Young workers typically have low-wage, low-tenure jobs, and they move into and out of the labor force at high rates. Turnover reflects a process of “job shopping,” whereby workers pass rapidly through multiple jobs in order to find more favorable matches (Topel and Ward (1992)). Recessions constrain this process by suppressing the hiring of young workers, thus limiting opportunities for them to work their way upward. These effects show up most prominently in the movements between employment and NILF: when a downturn hits, movements of unattached young workers into jobs decline sharply. For these workers, policy should focus on the limited job opportunities available during downturns.

More broadly, recessions are pernicious for each group of workers, but for different reasons: prime-age workers suffer waves of job loss and harmful effects of displacement; young workers experience depressed job opportunities and reduced prospects for advancement. There is little evidence that either group of workers obtains benefits from recessions, at least in the short term.

Our results have important implications for theoretical models of aggregate employment adjustment. Models in the Keynesian and Schumpeterian traditions conform to the separation-driven view of cyclical adjustment, wherein downturns are associated with initial phases of heightened job loss followed by increased hiring activity as the economy recovers. Mortensen and Pissarides (1994), Caballero and Hammour (1996), Ramey and Watson (1997), Merz (1999a), and Den Haan, Ramey, and Watson (2000a), among others, exemplify this class of models. An alternative class of models adopts the hiring-driven view, suggesting that downturns are initiated by declines in hiring activity. This class includes Pissarides (1985), Merz (1995), and Andolfatto (1996).

Our findings strongly validate the separation-driven view, particularly among prime-age workers. Keynesian- or Schumpeterian-style models, with their predictions of counter-cyclical job loss hazard rates, fit the facts most closely. Models that follow the hiring-driven view are incapable of explaining key aspects of the data. Notably, models in both classes typically abstract from movements into and out of the labor force. Our results provide particularly strong support for the separation-driven view when NILF flows are omitted.

To explain the evidence fully, theoretical models must incorporate two essential features. First, workers must be heterogeneous: low-wage, high-turnover workers should co-

exist with high-wage, low-turnover workers. Den Haan, Ramey, and Watson (2000b) and Den Haan, Haefke, and Ramey (2005) show that models along these lines can help explain numerous important facts about aggregate employment. Second, labor force participation must be explicitly considered. Veracierto (2004) demonstrates that cyclical variations in the participation margin have significant implications for employment dynamics. Future theoretical work should seek to explain the close connections between worker heterogeneity and movements in labor force participation that our results uncover.

10 Conclusion

Gross flow data from the CPS, adjusted for margin error and corrected for time aggregation, show that total worker flows and transition hazard rates are highly volatile at business cycle frequencies. Total job loss flows and job loss hazard rates are highly countercyclical and lead the cycle. Total hiring flows and job finding hazard rates lag the cycle, with total hiring adjusting countercyclically and job finding rates adjusting procyclically. Prime-age workers conform strongly to this pattern, whether or not NILF flows are considered. For young workers, in contrast, the inclusion of NILF flows largely reverses the pattern, reflecting the importance of movements in labor force participation.

Our results suggest that composition effects based on age may be key factors in accounting for the cyclical behavior of wages and productivity. Highly countercyclical adjustment of prime-age workers, with their high-wage, high-productivity jobs, contrasts with the procyclical adjustment of young workers, having low-wage, low-productivity jobs. Future research should focus on how these dynamics interact to influence the behavior of aggregate wages and productivity.

Appendix A Margin Error Correction

Let the populations of employed, unemployed and NILF individuals at the reference week of month t be denoted by $E(t)$, $U(t)$ and $N(t)$, respectively. These populations are based on CPS survey results, appropriately weighted to reflect aggregate U.S. characteristics. The number of individuals in population i in month $t - 1$ and population j in month t , for $i, j = E, U, N$, is denoted $z_{ij}(t)$. Note, however, that not all individual workers can be fully classified due to the rotation of the CPS; some workers' status is missing in either the current month or the previous month. This occurs mainly due to the sample rotation

of the CPS, as explained in Section 2.²⁴

Our procedure applies time-varying weights to the fully measured transitions. We obtain a normalized measure of these transitions, denoted $\mu_{ij}(t)$, $i, j = E, U, N$, by reweighting the raw flows in the following manner:

$$\mu_{ij}(t) = \frac{z_{ij}(t)}{\sum_i \sum_j z_{ij}(t)}. \quad (9)$$

Note that (9) gives the corrected flows generated by the MAR method.

Adjusted gross flows, denoted $\gamma_{ij}(t)$, are determined by

$$\gamma_{ij}(t) = \frac{\mu_{ij}(t)^{\theta_{ij}(t)}}{\Delta(t)}, \quad (10)$$

where $\theta_{ij}(t)$ are weights to be estimated for each month t , and $\Delta(t)$ is a normalization factor:

$$\Delta(t) = \sum_i \sum_j \mu_{ij}(t)^{\theta_{ij}(t)}.$$

Using the functional form (10), we can estimate the following system of six nonlinear equations:

$$x_{i*}(t) = \sum_j \gamma_{ij}(t) + \varepsilon_{i*}(t), \quad i = E, U, N, \quad (11)$$

$$x_{*j}(t) = \sum_i \gamma_{ij}(t) + \varepsilon_{*j}(t), \quad j = E, U, N, \quad (12)$$

where $x_{i*}(t)$ and $x_{*j}(t)$ indicate the official BLS stocks at the beginning of months $t - 1$ and t , respectively. Note that the estimated weights capture the degree to which the normalized gross flow data must be inflated or deflated (in elasticity form) in each month in order to achieve the optimal fit with the measured stock data. The missing at random model emerges as a special case of this specification, in which $\theta_{ij}(t) = 1$ for all i, j and t .

Bleakley, Ferris, and Fuhrer (1999) show that gender composition has important effects on margin error correction, while further disaggregation has small effects. Thus, to estimate aggregate gross flow series, we first construct flow MAR series for males and females

²⁴In addition to rotation, entry into and exit from the civilian non-institutional population generates partially classified observations. Entry occurs when a worker turns 16, leaves the army, leaves an institution, or immigrates. Similarly, exit occurs when a worker dies, enters the military, enters an institution, or emigrates. However, as Abowd and Zellner (1985) show, the flows associated with population entry and exit are very small relative to flows between the three states.

separately and average them using the population weights. These aggregated series are used to estimate (11) and (12).²⁵

Observations for January 1976, January 1978, July 1985, October 1985, January 1994, and June-September 1995 are missing from the sample. Further, the MAR series $\mu_{ij}(t)$ exhibit several temporary but unusually large jumps that appear unrelated to the underlying true series. Most notably, in January 2002 the values of $\mu_{EE}(t)$ and $\mu_{NN}(t)$ show unusually large upward and downward jumps, respectively.

To deal with the missing value and outlier problems, we use the procedure called TRAMO (Time Series Regression with ARIMA Noise, Missing Observations and Outliers) developed by Victor Gómez and Augustín Maravall; see its manual (Gómez and Maravall (1997)) for instructions. This procedure parameterizes each series as an ARIMA process. Estimation of the missing observations is performed by a “skipping” approach. This carries out a maximum likelihood estimation of the process by skipping the missing observations, and then uses the fixed point smoother for interpolation of the missing values (see Gómez and Maravall (1999) for details). To detect outliers, TRAMO applies an algorithm similar to the one developed by Chen and Liu (1993). We let TRAMO detect two types of outliers, additive and transitory. Additive outliers are characterized by an immediate and one-shot effect on the series. Transitory outliers produce an initial jump, dying out gradually over time. For each observation, t -tests determine the presence of these two types of outliers; observations having absolute t -values greater than a pre-specified critical level (which is set to 4, as recommended by Gómez and Maravall (1997)) are chosen to be outliers.

After correcting the gross flow series for missing observations and outliers, we estimate (10)-(12) by the seemingly unrelated regression (SUR) method. To allow for time-varying weight coefficients, we run rolling regressions to estimate $\theta_{ij}(t)$ for each t with the sample length for each regression set to 10 years. More specifically, the estimated $\theta_{ij}(t)$ for $t = 61, \dots, 300$ are obtained from regressions that use the data for the period $t - 60$ to $t + 59$ (note that our data span 360 months from January 1976 through December 2005). For $t = 1, \dots, 60$ and $t = 301, \dots, 360$ we estimate fixed weights based on the first and last 10 years of data, respectively. Finally, the estimated values $\hat{\theta}_{ij}(t)$ are used to calculate adjusted gross flow series $\hat{\gamma}_{ij}(t)$ according to the formula (10).

²⁵For the three subgroups of workers (young, prime-age, and prime-age male), we estimate (11) and (12) after obtaining $\mu_{ij}(t)$'s for those three subgroups. The $\mu_{ij}(t)$'s for young and prime-age workers are again computed as a weighted average of the male and female series.

Appendix B Hazard Rates and Total Flows

Let s denote continuous time, and suppose measurements are made at times $s = 1, 2, \dots$. The labor force at each instant s is normalized to unity, and $u(s) \in [0, 1]$ indicates the number of unemployed workers at time s . Employment is therefore given by $e(s) = 1 - u(s)$. The arrival rates for worker transitions out of and into employment for each $s \in [t - 1, t)$ are given by λ_t and p_t , respectively. Thus, the law of motion for $u(s)$ over the interval $[t - 1, t)$ is

$$\dot{u}(s) = \lambda_t e(s) - p_t u(s). \quad (13)$$

The number of unemployed workers at the end of month t is $u_t = u(t)$. It follows that the solution to (13) is

$$u(s) = (u_{t-1} - \beta_t) e^{-\alpha_t(s - \tau_{t-1})} + \beta_t, \quad (14)$$

where α_t and β_t are defined in (3).

Formulas (1) and (2) derived as follows. Let e_t^n denote the number of employed workers at the end of month t who were either unemployed or employed in *different* jobs at the beginning of the month (the latter transitions constitute the indirect EE flows). Using (14), e_t^n can be expressed as

$$\begin{aligned} e_t^n &= \int_{t-1}^t p_t u(s) e^{-\lambda_t(\tau_t - s)} ds \\ &= (u_{t-1} - \beta_t) e^{-\lambda_t} (1 - e^{-p_t}) + (1 - \beta_t) (1 - e^{-\lambda_t}). \end{aligned} \quad (15)$$

Alternatively, e_t^n may be expressed in terms of average transition rates. First, each worker who starts the month unemployed and ends it employed is included in e_t^n . There are $u_{t-1} \hat{p}_t$ of these workers. Second, some of the workers who are employed at both the start and end of the month experienced spells of unemployment within the month, and these workers must also be included in e_t^n . By definition, $1 - \hat{\lambda}_t$ gives the probability that a worker who begins the month employed is also employed at the end of the month, while $e^{-\lambda_t}$ gives the probability that a worker who begins the month employed does not experience any separation during the month. Thus, $1 - \hat{\lambda}_t - e^{-\lambda_t}$ is the probability that such a worker ends the month in a different job. There are $(1 - u_{t-1})(1 - \hat{\lambda}_t - e^{-\lambda_t})$ of these workers. It follows that e_t^n satisfies

$$e_t^n = u_{t-1} \hat{p}_t + (1 - u_{t-1})(1 - \hat{\lambda}_t - e^{-\lambda_t}). \quad (16)$$

Matching the coefficients of (15) and (16) gives (1) and (2).

Equations (4) and (5) are determined by

$$l_t = \int_{t-1}^t \lambda_t(1 - u(s))ds = \lambda_t \left(-(u_{t-1} - \beta_t) \frac{1 - e^{-\alpha t}}{\alpha_t} + (1 - \beta_t) \right),$$

$$h_t = \int_{t-1}^t p_t u(s)ds = p_t \left((u_{t-1} - \beta_t) \frac{1 - e^{-\alpha t}}{\alpha_t} + \beta_t \right).$$

Equation (6) may be verified as follows. Using (14), the change in employment may be expressed as

$$1 - u_t - (1 - u_{t-1}) = (u_{t-1} - \beta_t)(1 - e^{-\alpha t}).$$

Equation (6) then follows from (4), (5) and the definition of β_t .

Appendix C Classification Error Correction

In modeling classification error, we make the standard assumption that classification errors are independent over time, i.e., the probability of a particular error for a particular respondent does not depend on whether the respondent was previously misclassified. Let $\beta_{i|j}(t)$ be the probability that a person in state j is classified as being in state i in period t , and let $\gamma_{ij}(t)$ and $\pi_{ij}(t)$ denote the margin error adjusted and true transitions, respectively, from state i to state j in month t . Define the matrices $B(t) = \{\beta_{i|j}(t)\}$, $\Gamma(t) = \{\gamma_{ij}(t)\}$ and $\Pi(t) = \{\pi_{ij}(t)\}$ for $i, j = E, U, N$. Then the adjusted flows are related to the true ones according to the following matrix equation:

$$\Gamma(t) = B(t-1)' \Pi(t) B(t). \quad (17)$$

The error rate matrix $B(t)$ can be estimated using CPS reinterview data. By using the interview-reinterview data over December 1976 through December 1982, Abowd and Zellner (1985) estimate an error rate matrix that varies at quarterly frequency. Since we have no access to such high frequency reinterview data, we use the fixed error rates estimated by Poterba and Summers (1986). They estimate the reporting error rates for all workers and for demographic subgroups by using the reinterview data for the period January through June 1981.²⁶

²⁶There are other recent attempts estimating the reporting error rates in the CPS; see for example Sinclair and Gastwirth (1998). None of them, however, estimate the error rates for demographic subgroups. Note also that these more recent estimates for all workers roughly agree with Poterba and Summers' estimates.

Using the estimated fixed error rate matrix \widehat{B} , our final gross flow series, corrected for both margin and classification error, are determined by

$$\widehat{\Pi}(t) = (\widehat{B}')^{-1}\widehat{\Gamma}(t)\widehat{B}^{-1}, \quad (18)$$

where the matrix $\widehat{\Gamma}(t)$ is composed of the series $\widehat{\gamma}_{ij}(t)$ that have been previously adjusted for margin error. Despite the time-invariant error rate matrix, it should be clear that the cyclical properties of the gross flow series $\widehat{\pi}_{ij}(t)$ may well differ from those of the corresponding series $\widehat{\gamma}_{ij}(t)$, since the former are linear combinations of the latter.

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Table 1: Standard deviations of cyclical components of worker flows ($E \Leftrightarrow U$)

	total flows		net flows	
	job loss	hiring	job loss	hiring
all workers	0.0466	0.0335	0.0531	0.0396
young	0.0287	0.0277	0.0306	0.0295
prime	0.0630	0.0503	0.0694	0.0557
prime male	0.0770	0.0702	0.0845	0.0786

Notes: based on logged and band-pass filtered series by Baxter and King's (1999) method. Periodicities of 15 months through 96 months are passed.

Table 2: Standard deviations of cyclical components of transition rates ($E \Leftrightarrow U$)

	hazard rates		average rates	
	job loss	job finding	job loss	job finding
all workers	0.0525	0.0693	0.0595	0.0591
young	0.0358	0.0677	0.0405	0.0583
prime	0.0679	0.0758	0.0745	0.0652
prime male	0.0827	0.0793	0.0904	0.0678

Notes: based on logged and band-pass filtered series by Baxter and King's (1999) method. Periodicities of 15 months through 96 months are passed.

Table 3: Standard deviations of cyclical components of worker flows ($E \Leftrightarrow U, N$)

	total flows		net flows	
	job loss	hiring	job loss	hiring
all workers	0.0239	0.0206	0.0204	0.0168
young	0.0323	0.0318	0.0237	0.0233
prime	0.0311	0.0214	0.0337	0.0240
prime male	0.0431	0.0378	0.0492	0.0488

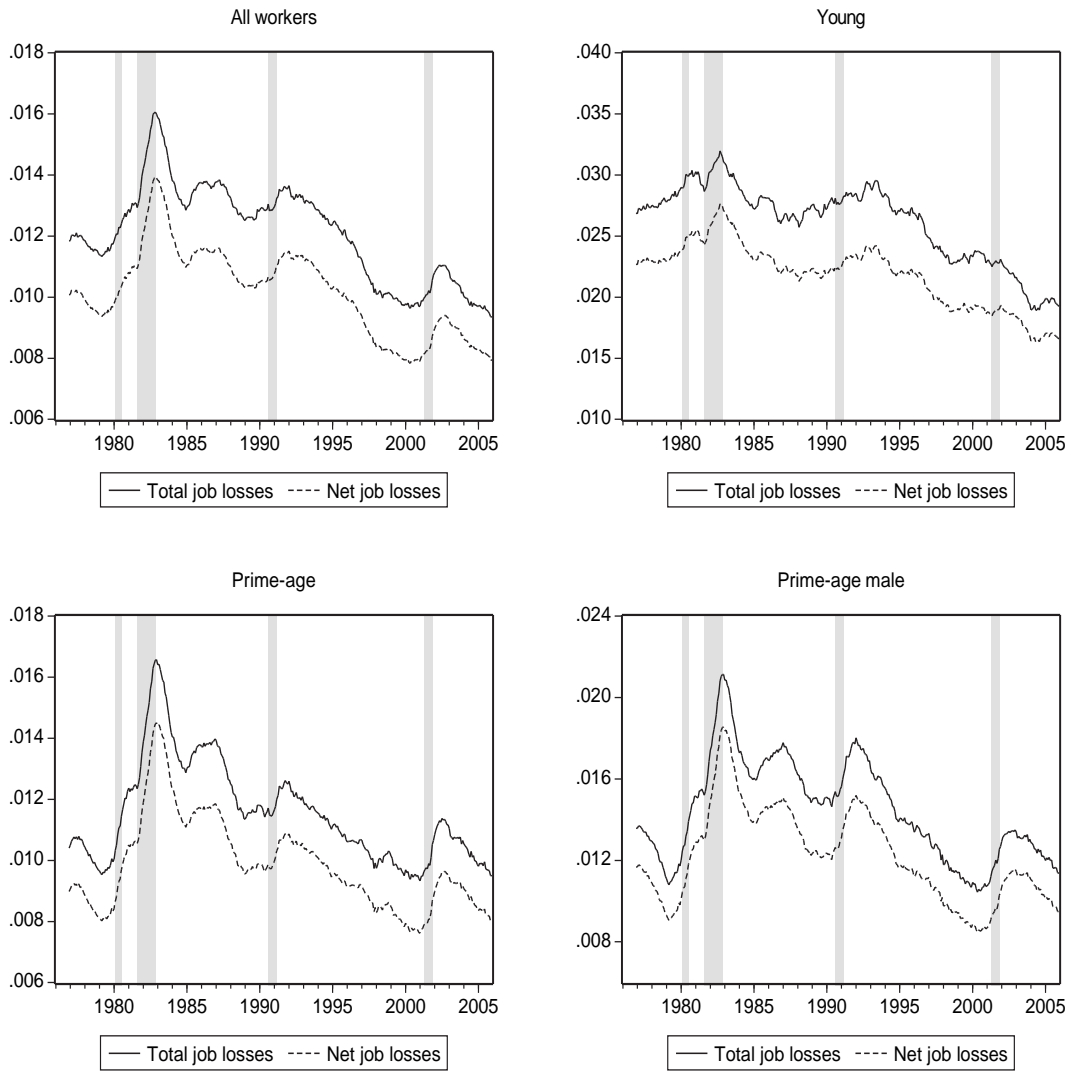
Notes: based on logged and band-pass filtered series by Baxter and King's (1999) method. Periodicities of 15 months through 96 months are passed.

Table 4: Standard deviations of cyclical components of transition rates ($E \Leftrightarrow U, N$)

	hazard rates		average rates	
	job loss	job finding	job loss	job finding
all workers	0.0217	0.0701	0.0219	0.0591
young	0.0233	0.0693	0.0189	0.0583
prime	0.0333	0.0761	0.0372	0.0652
prime male	0.0478	0.0795	0.0546	0.0678

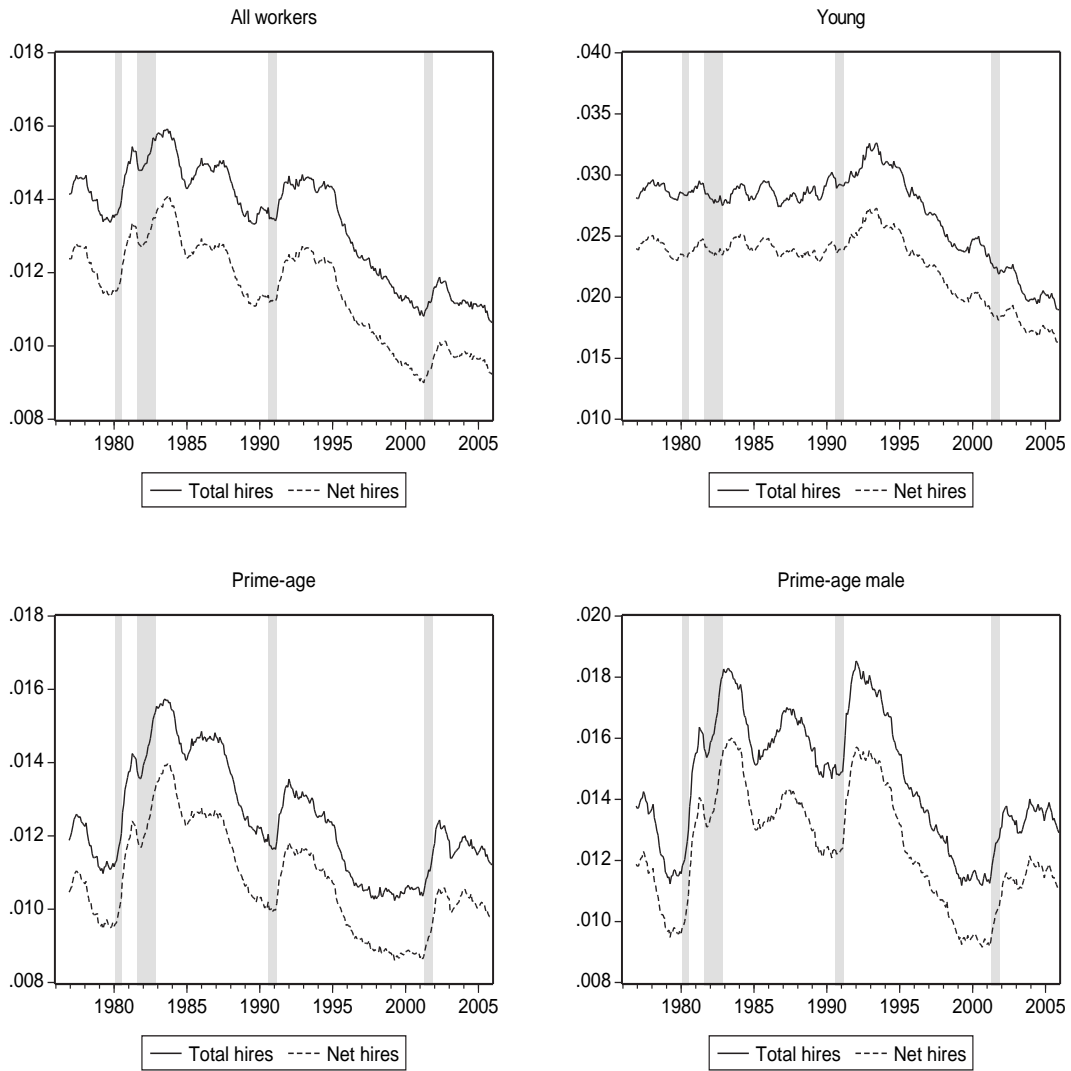
Notes: based on logged and band-pass filtered series by Baxter and King's (1999) method. Periodicities of 15 months through 96 months are passed.

Figure 1: Job loss flows ($E \rightarrow U$)



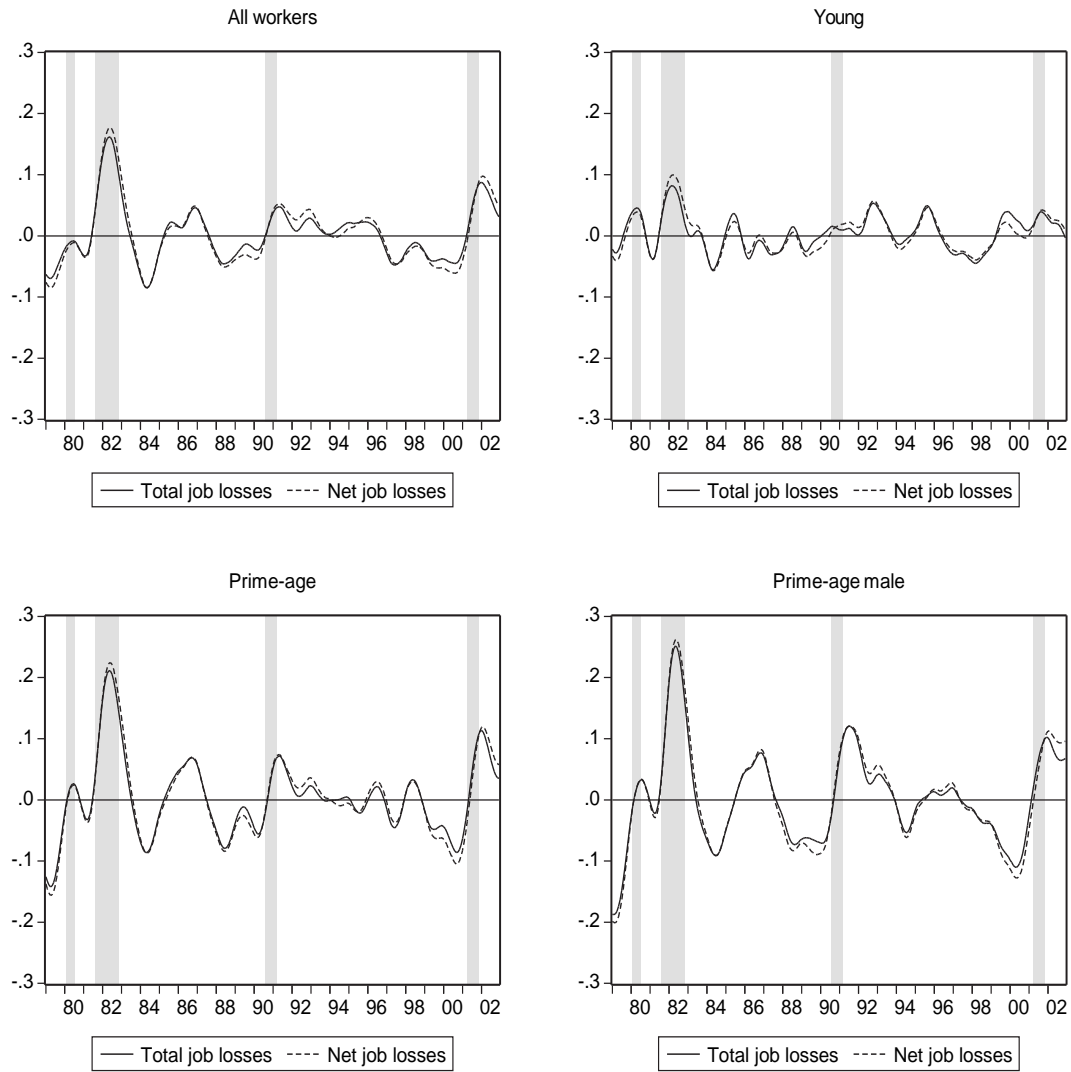
Notes: 12-month backward moving averages of nonseasonally adjusted data. Expressed as a fraction of civilian noninstitutional population. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 2: Hiring flows ($U \rightarrow E$)



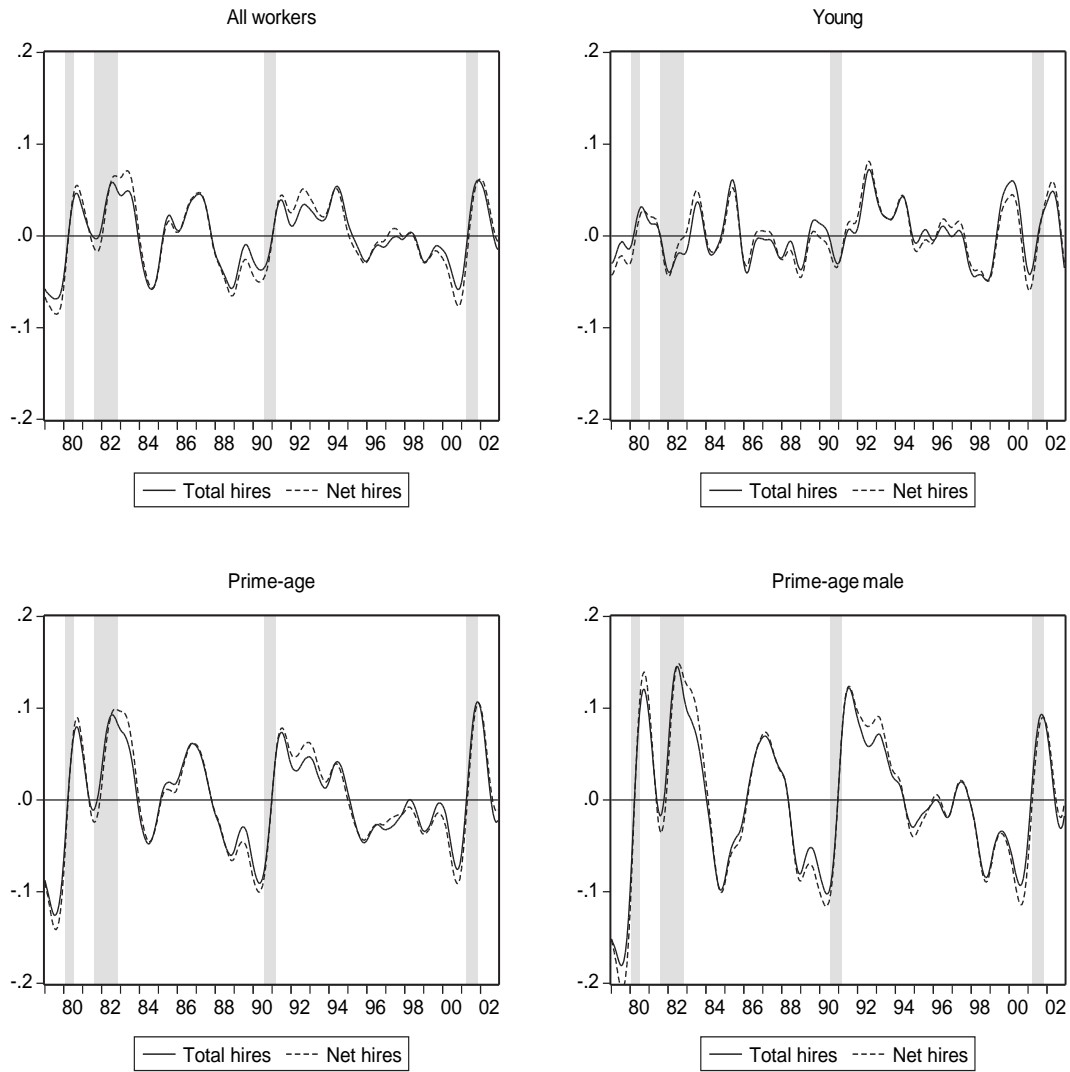
Notes: 12-month backward moving averages of nonseasonally adjusted data. Expressed as a fraction of civilian noninstitutional population. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 3: Cyclical components of job loss flows ($E \rightarrow U$)



Notes: Logged and band-pass filtered by Baxter and King's (1999) method. Periodicities of 15 months through 96 months are passed. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 4: Cyclical components of hiring flows ($U \rightarrow E$)



Notes: Logged and band-pass filtered by Baxter and King's (1999) method. Periodicities of 15 months through 96 months are passed. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 5: Cross correlations of cyclical components: job loss flows at t and hiring flows at $t + i$ ($E \rightleftharpoons U$)

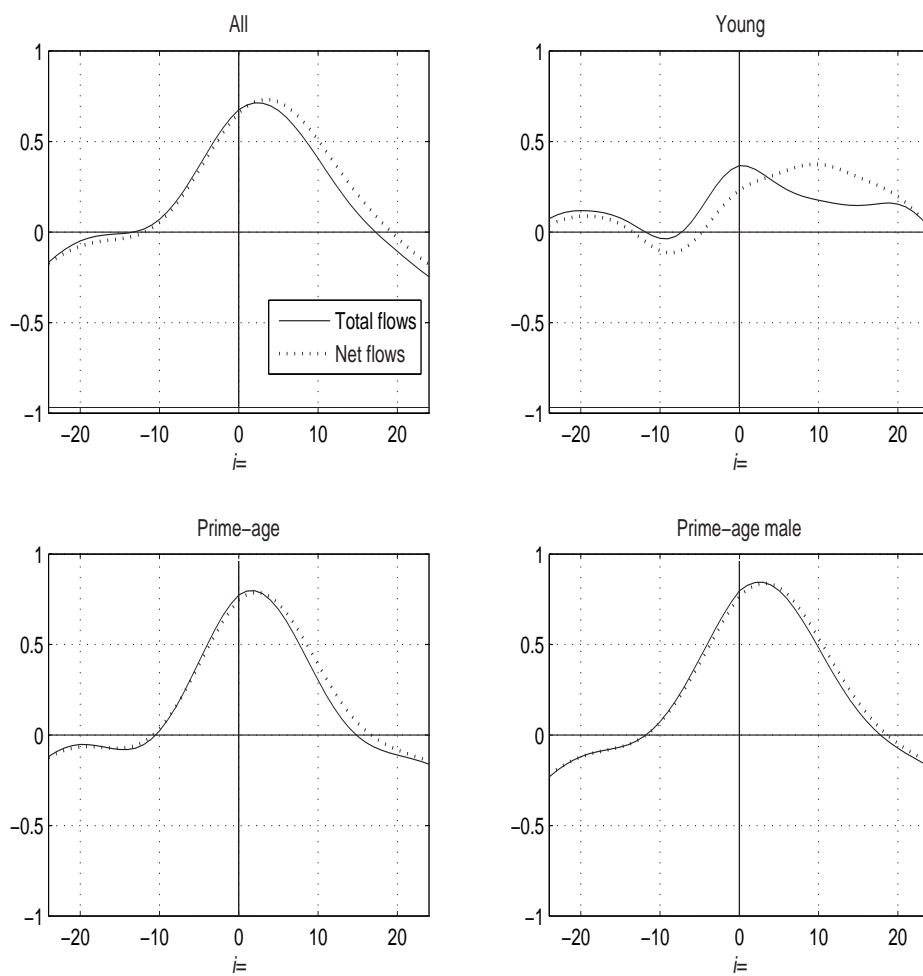


Figure 6: Cross correlations of cyclical components: industrial production at t and job loss flows at $t + i$ ($E \rightarrow U$)

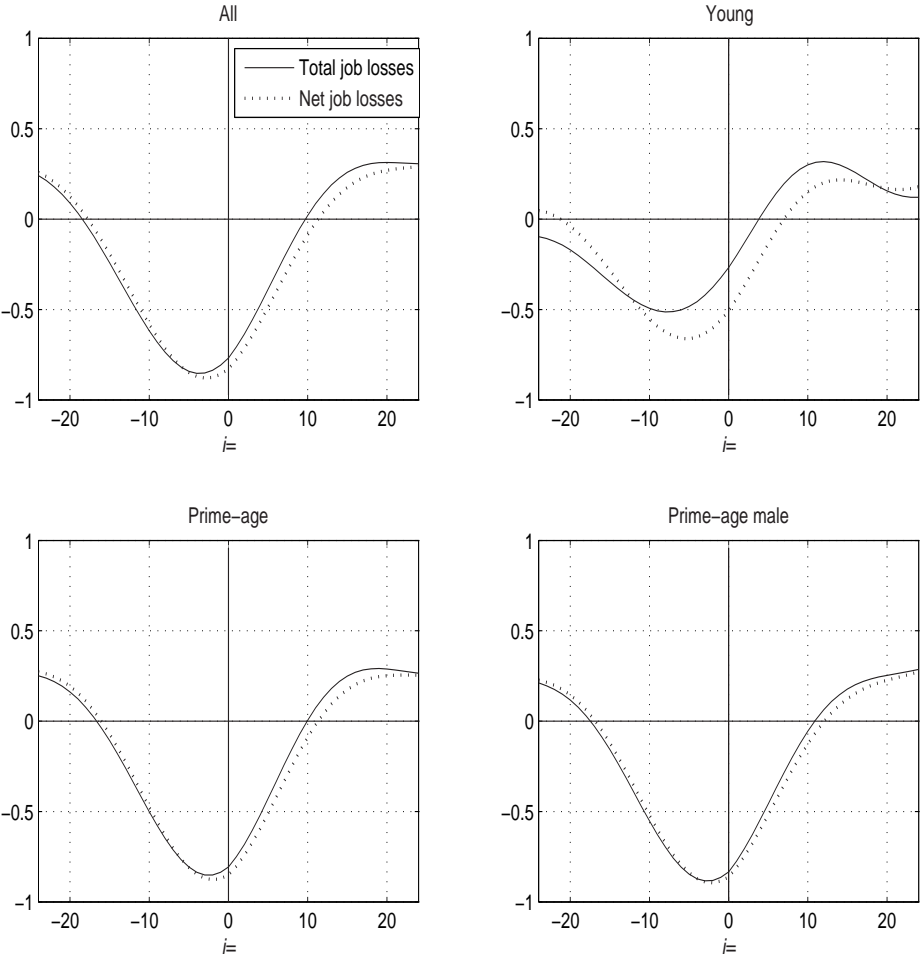


Figure 7: Cross correlations of cyclical components: industrial production at t and hiring flows at $t + i$ ($U \rightarrow E$)

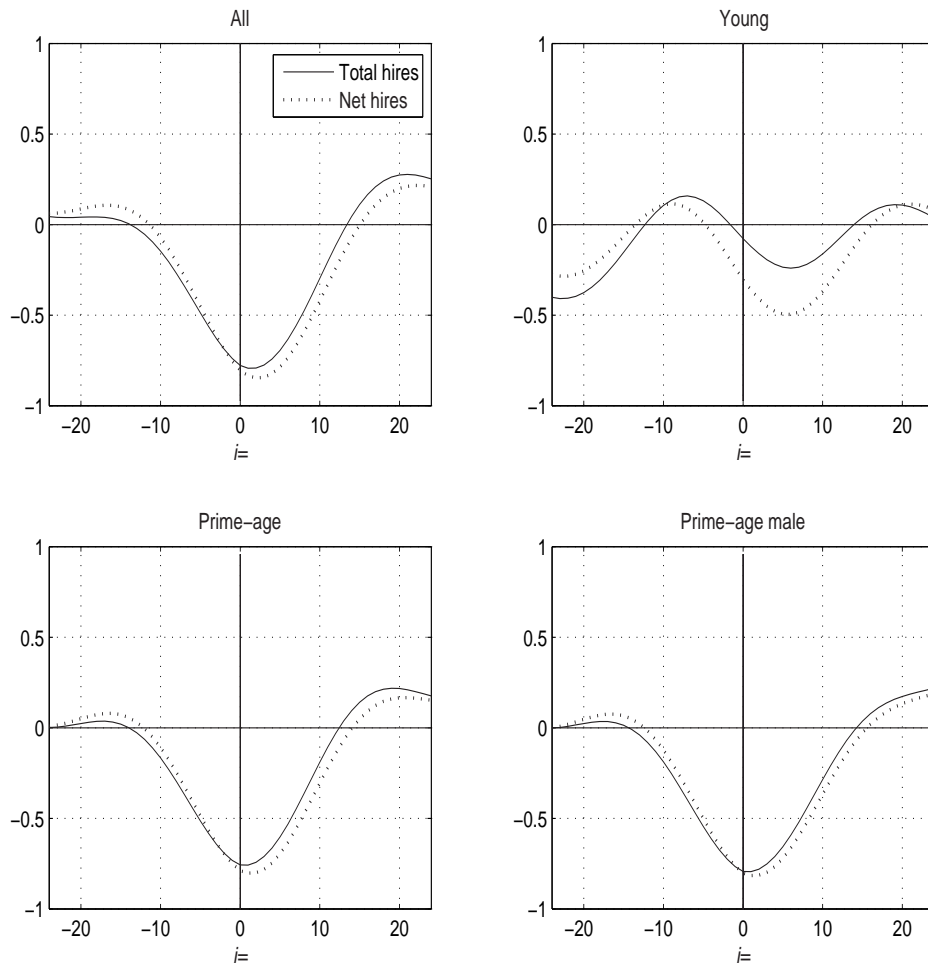
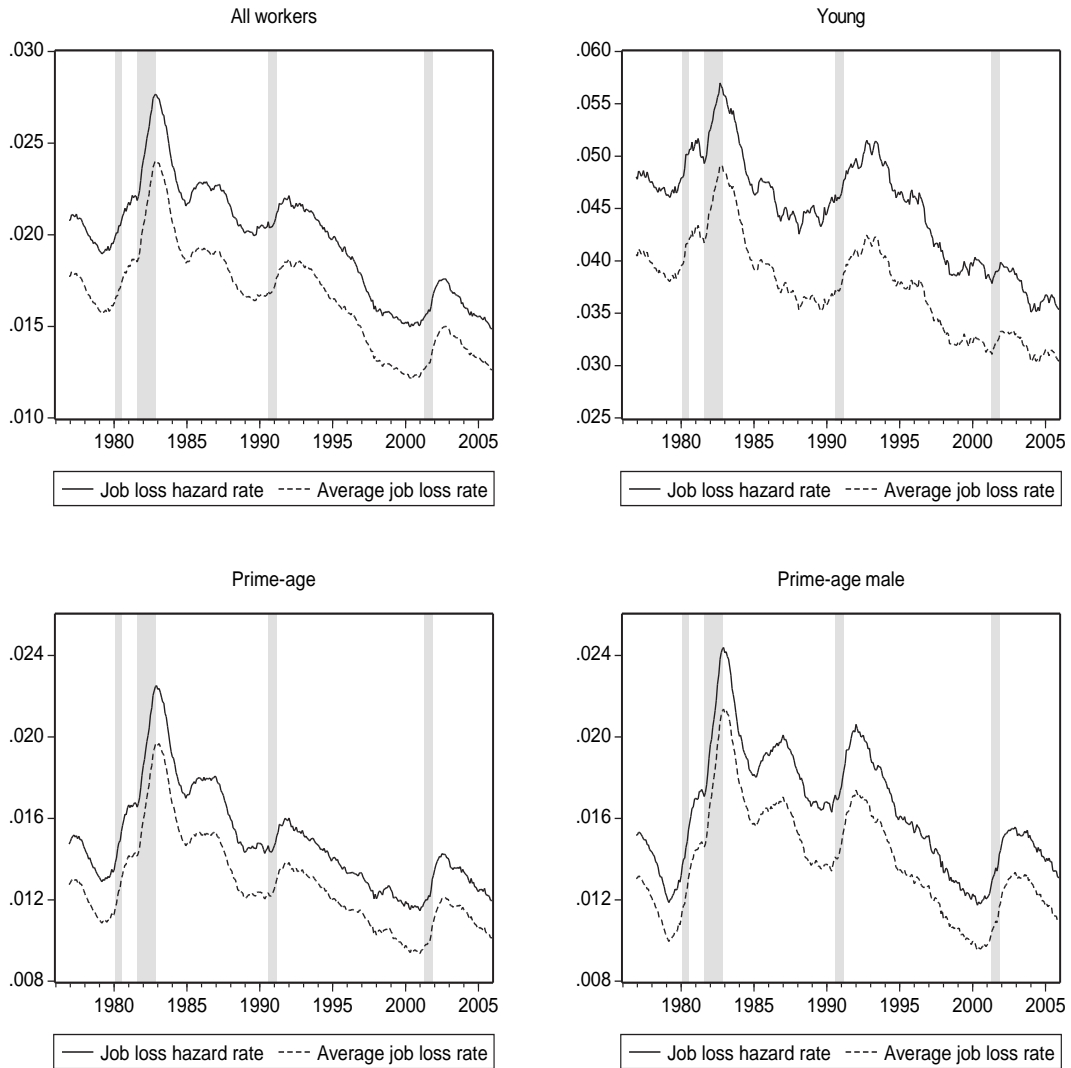
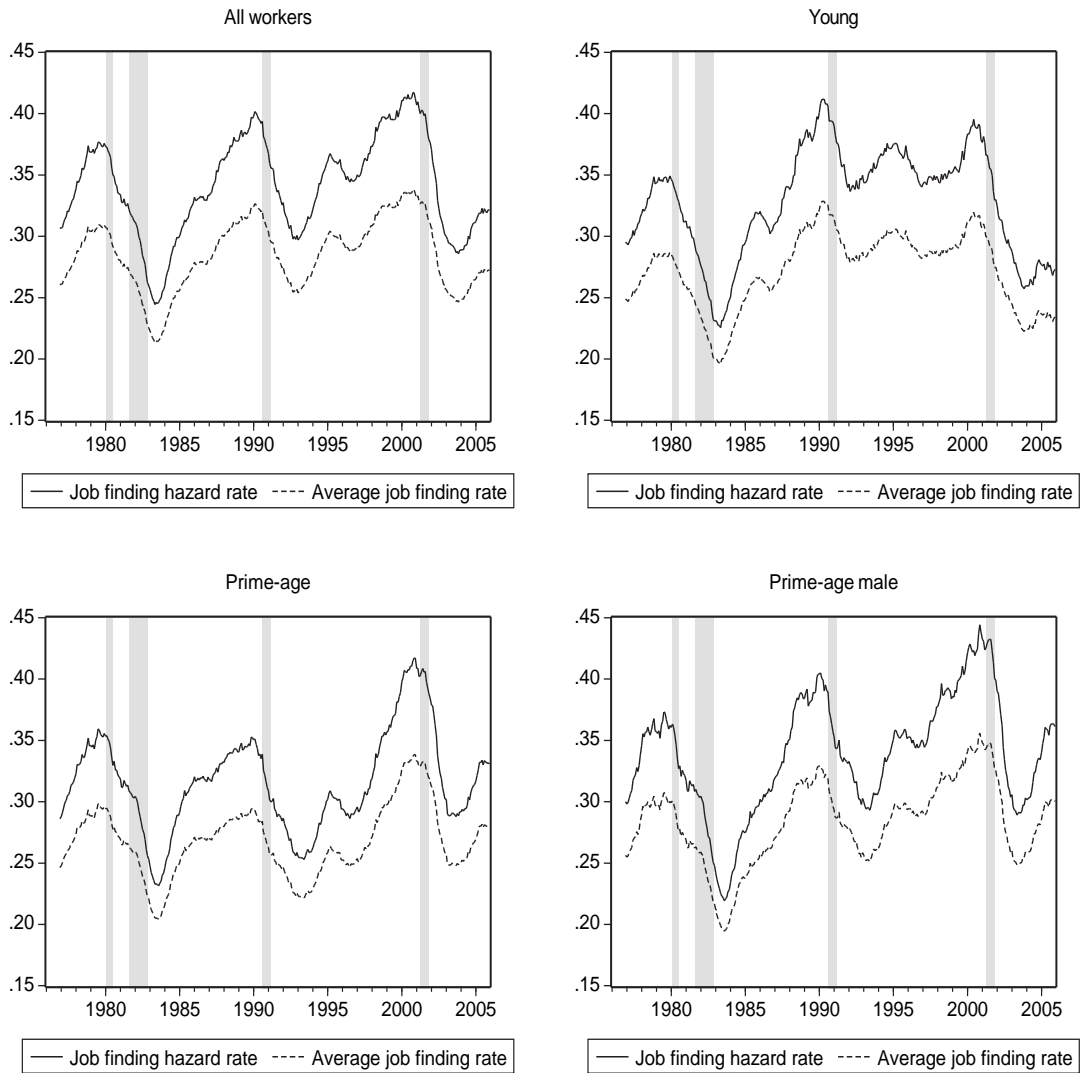


Figure 8: Job loss transition rates ($E \rightarrow U$)



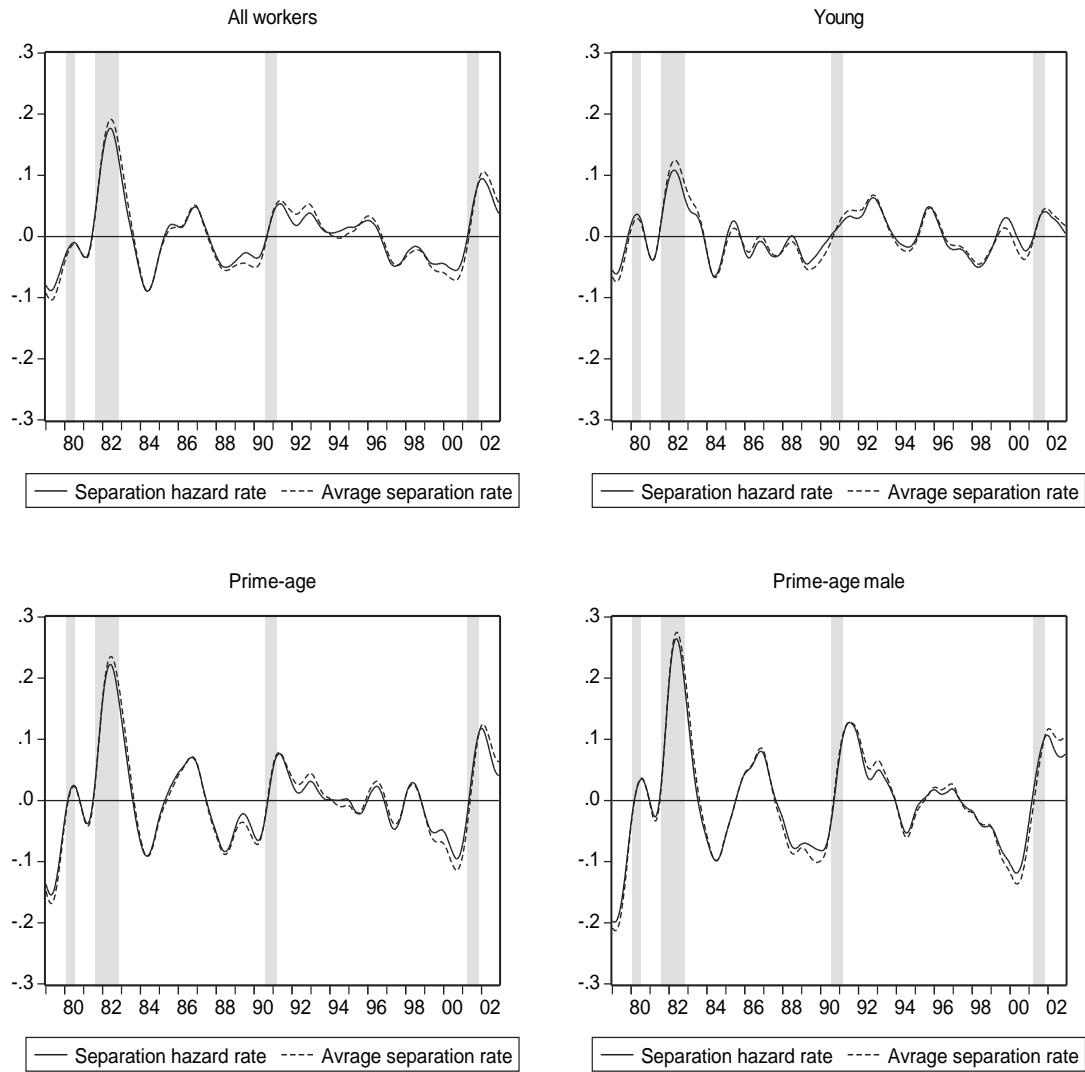
Notes: 12-month backward moving averages of nonseasonally adjusted data. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 9: Job finding transition rates ($U \rightarrow E$)



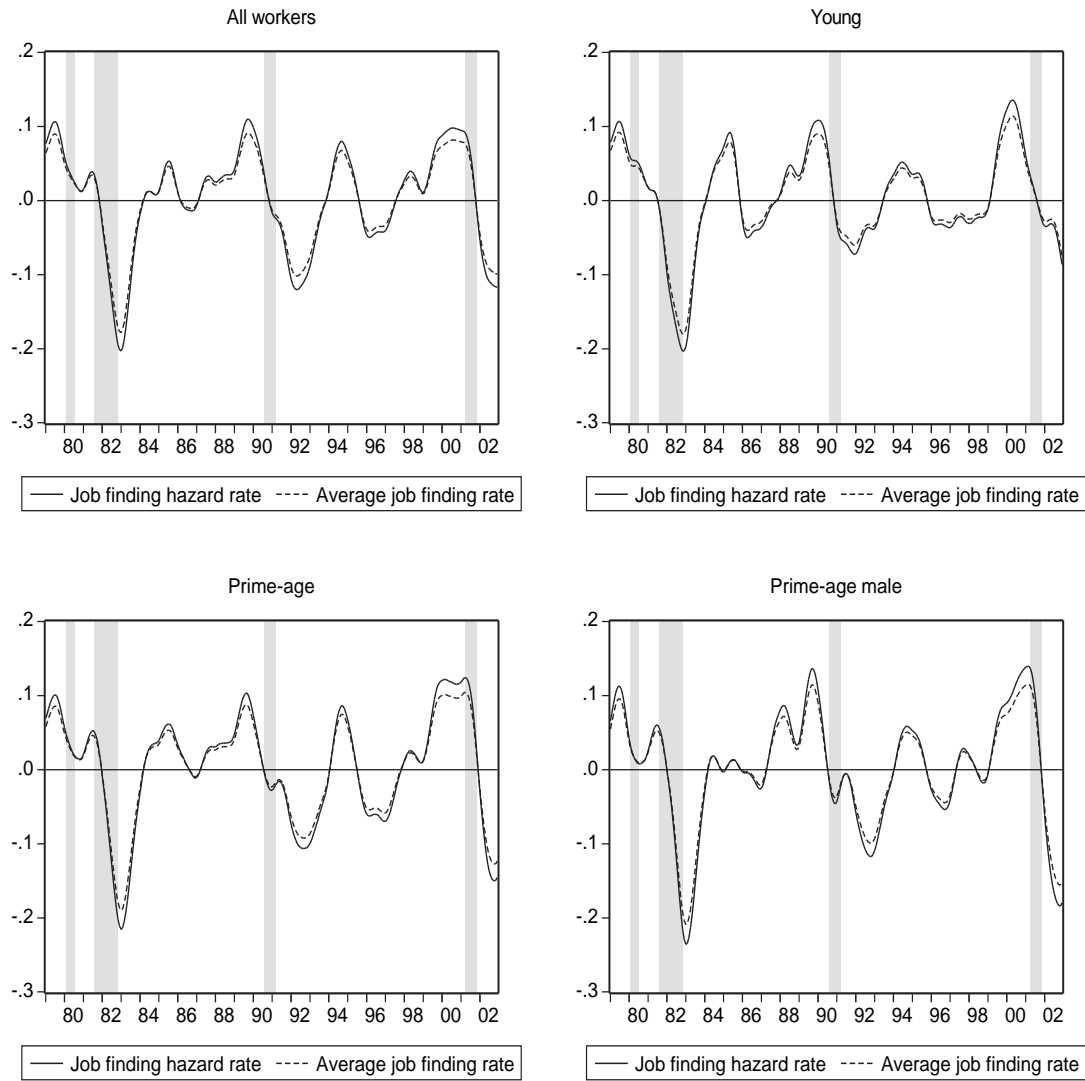
Notes: 12-month backward moving averages of nonseasonally adjusted data. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 10: Cyclical components of job loss transition rates ($E \rightarrow U$)



Notes: Logged and band-pass filtered by Baxter and King's (1999) method. Periodicities of 15 months through 96 months are passed. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 11: Cyclical components of job finding transition rates ($U \rightarrow E$)



Notes: Logged and band-pass filtered by Baxter and King's (1999) method. Periodicities of 15 months through 96 months are passed. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 12: Cross correlations of cyclical components: job loss rates at t and job finding rates at $t + i$ ($E \leftrightarrow U$)

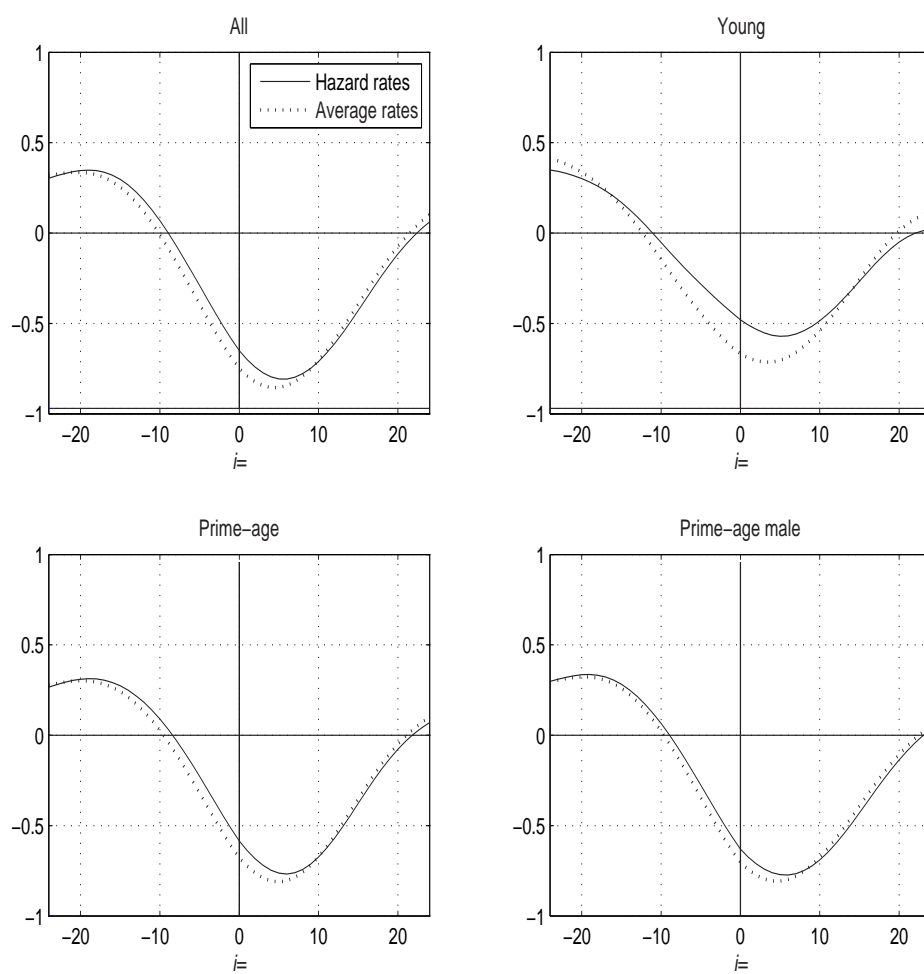


Figure 13: Cross correlations of cyclical components: industrial production at t and job loss rates at $t + i$ ($E \rightarrow U$)

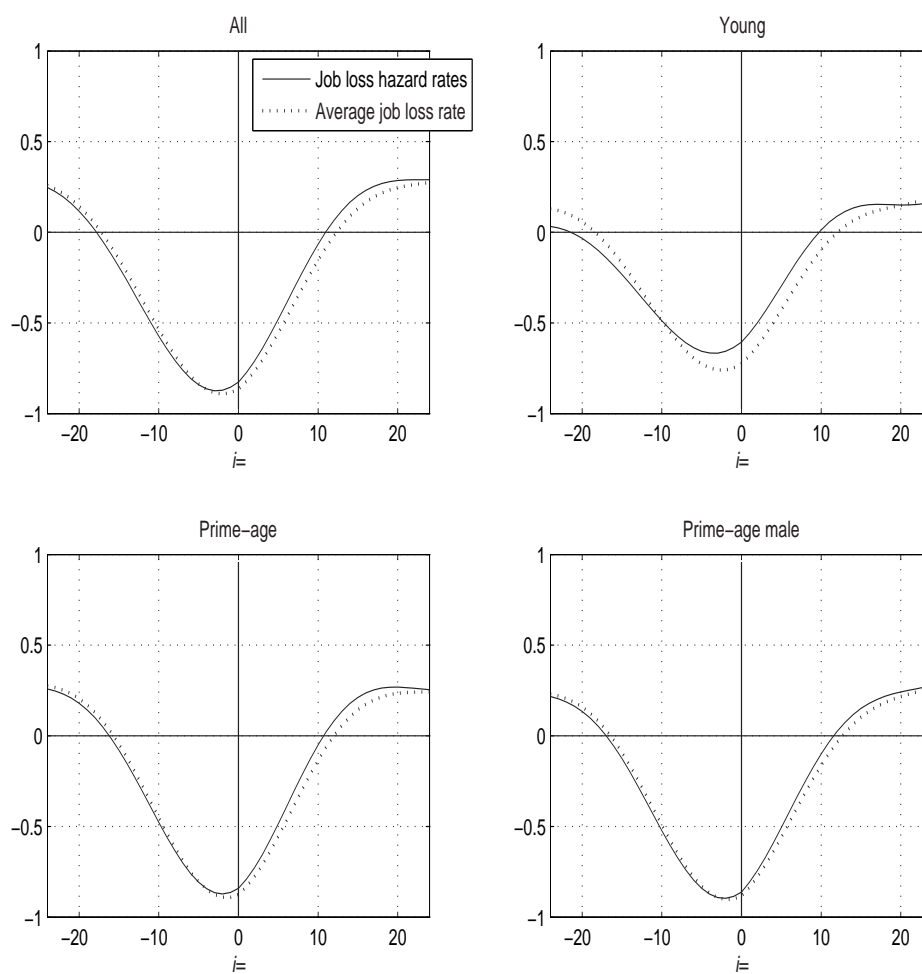


Figure 14: Cross correlations of cyclical components: industrial production at t and job finding rates at $t + i$ ($U \rightarrow E$)

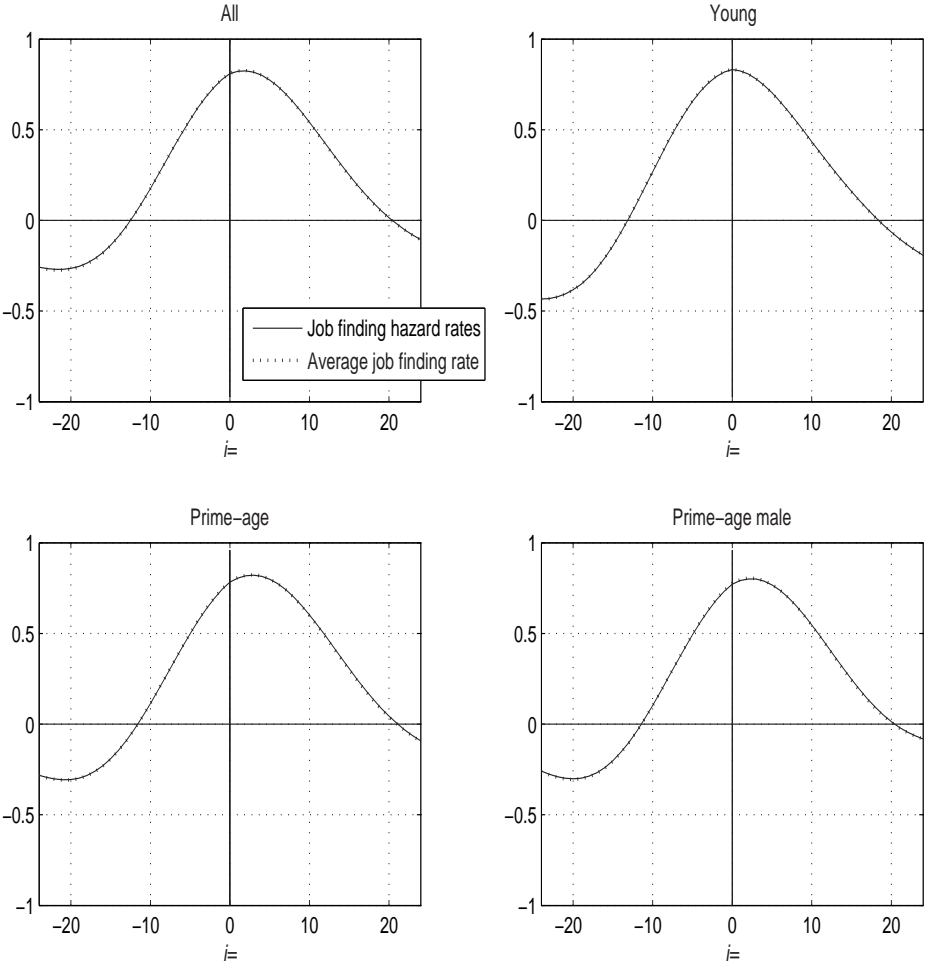
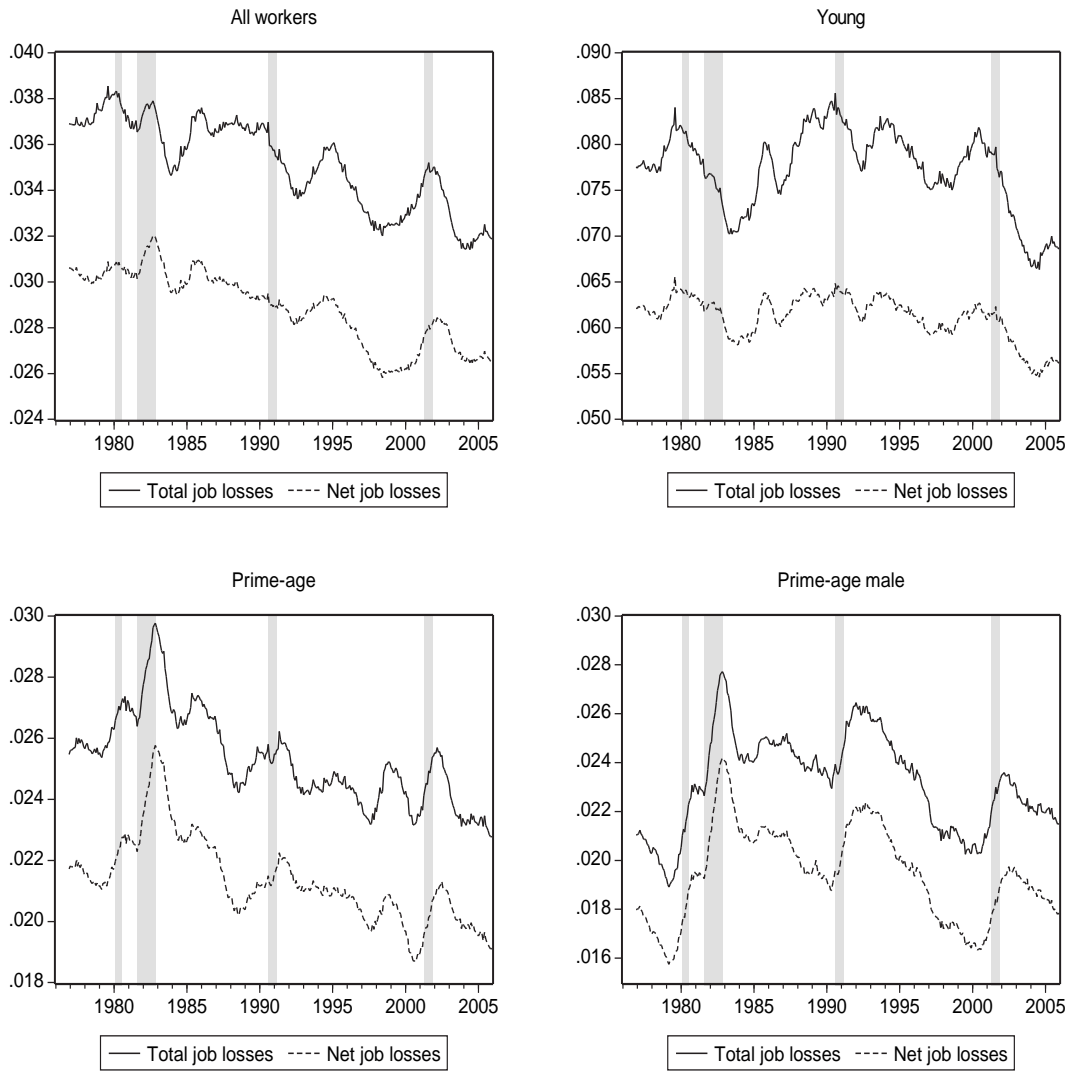
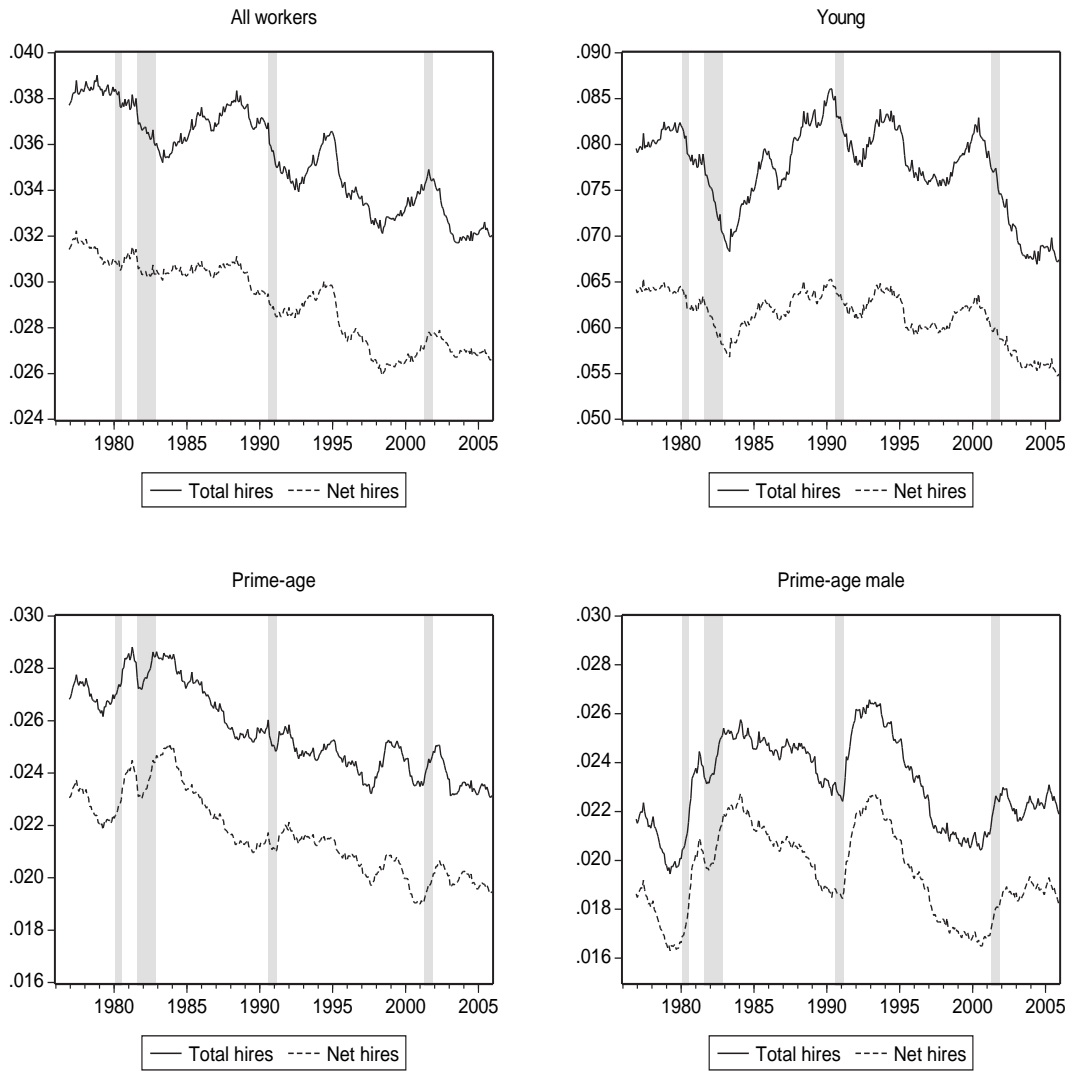


Figure 15: Job loss flows ($E \rightarrow N\&U$)



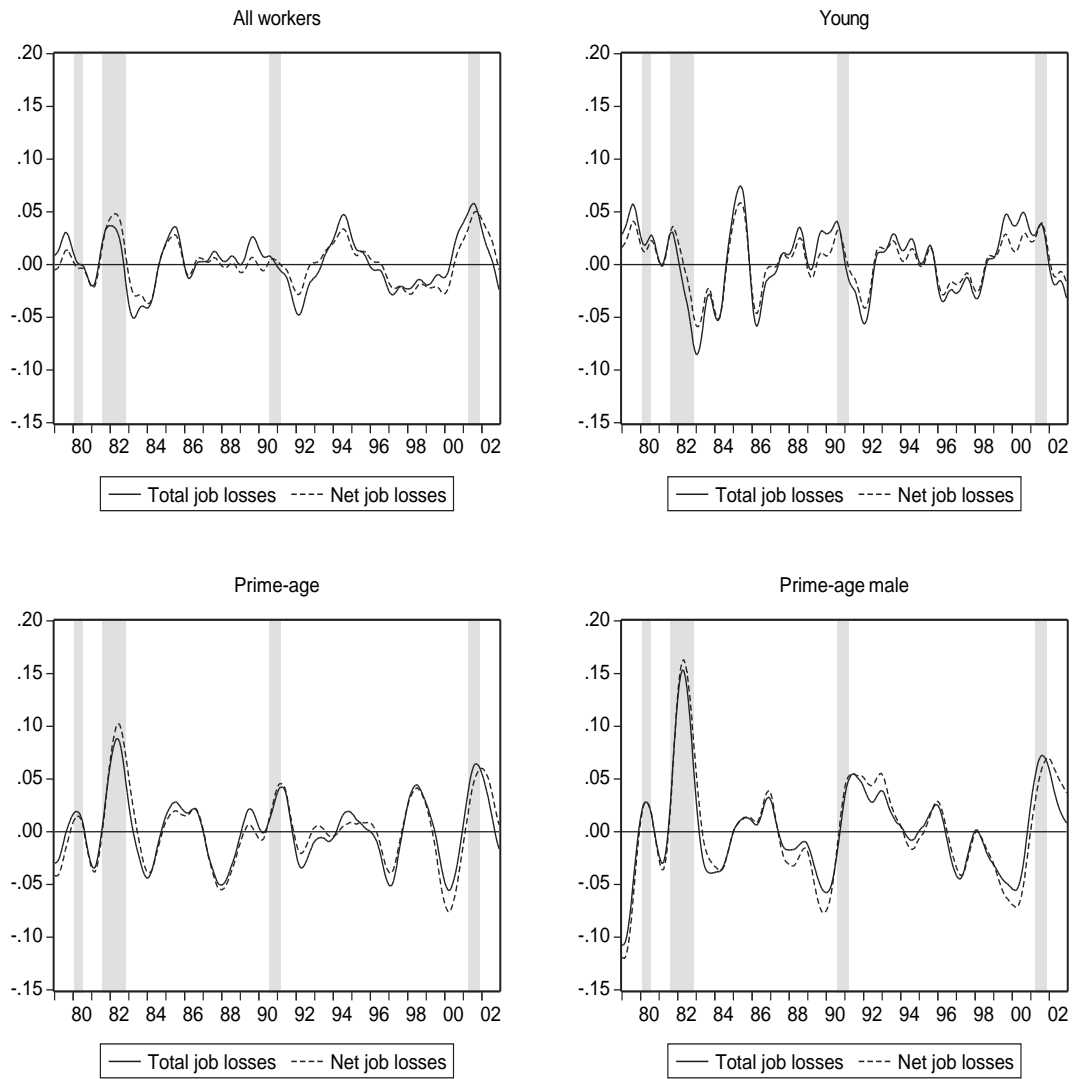
Notes: 12-month backward moving averages of nonseasonally adjusted data. Expressed as a fraction of civilian noninstitutional population. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 16: Hiring flows ($N\&U \rightarrow E$)



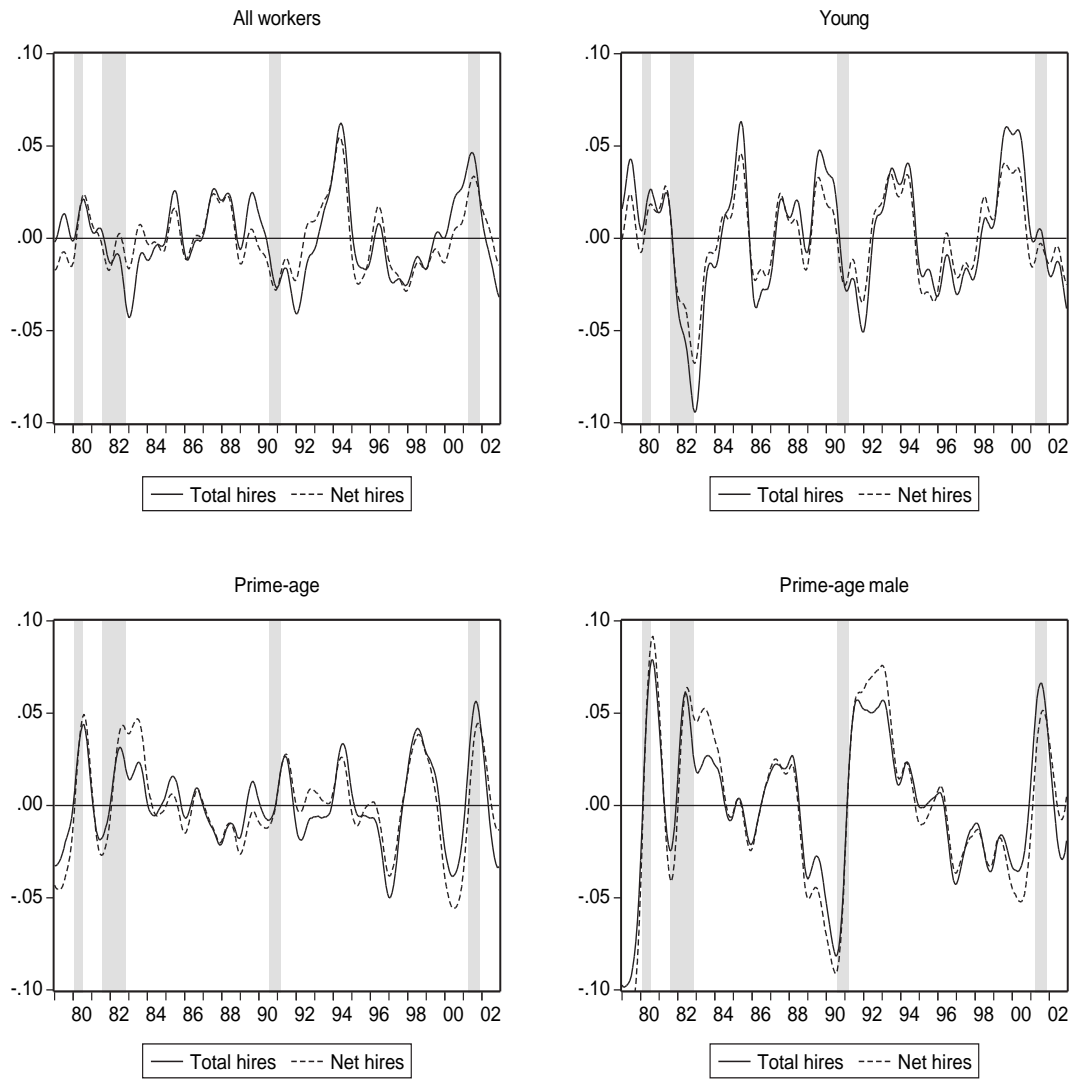
Notes: 12-month backward moving averages of nonseasonally adjusted data. Expressed as a fraction of civilian noninstitutional population. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 17: Cyclical components of job loss flows ($E \rightarrow N&U$)



Notes: Logged and band-pass filtered by Baxter and King's (1999) method. Periodicities of 15 months through 96 months are passed. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 18: Cyclical components of hiring flows ($N \& U \rightarrow E$)



Notes: Logged and band-pass filtered by Baxter and King's (1999) method. Periodicities of 15 months through 96 months are passed. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 19: Cross correlations of cyclical components: job loss flows at t and hiring flows at $t + i$ ($E \rightleftharpoons N\&U$)

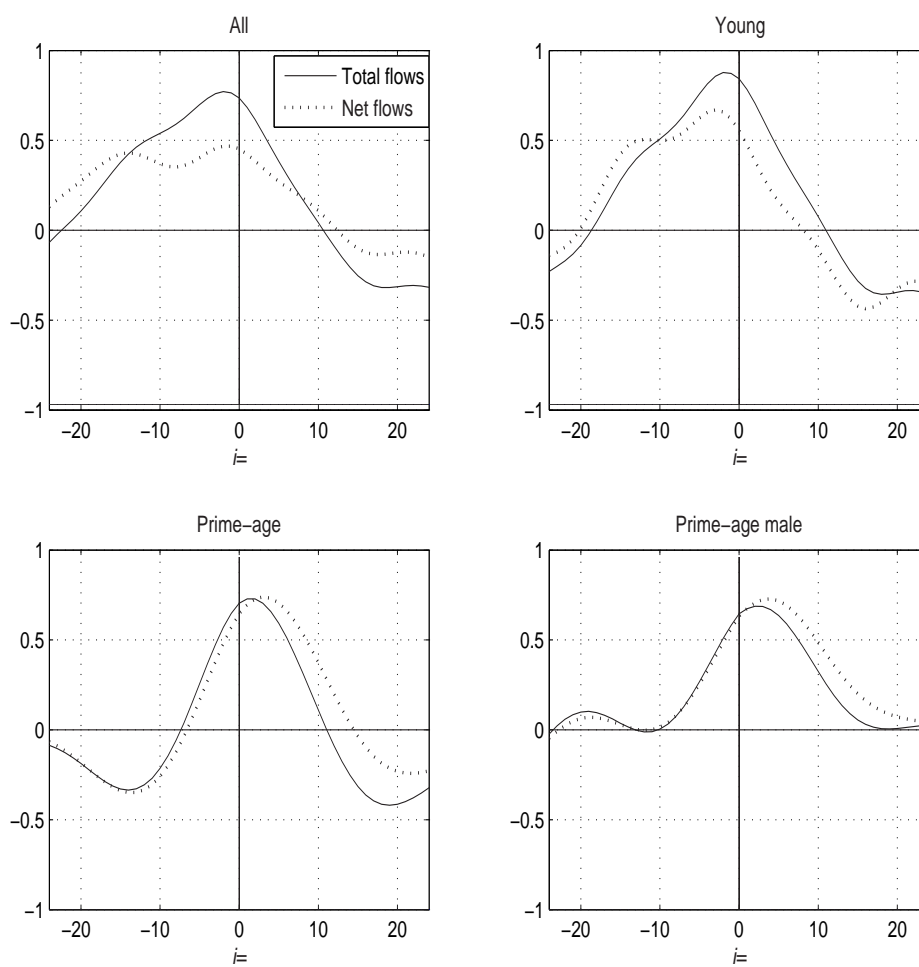


Figure 20: Cross correlations of cyclical components: industrial production at t and job loss flows at $t + i$ ($E \rightarrow N\&U$)

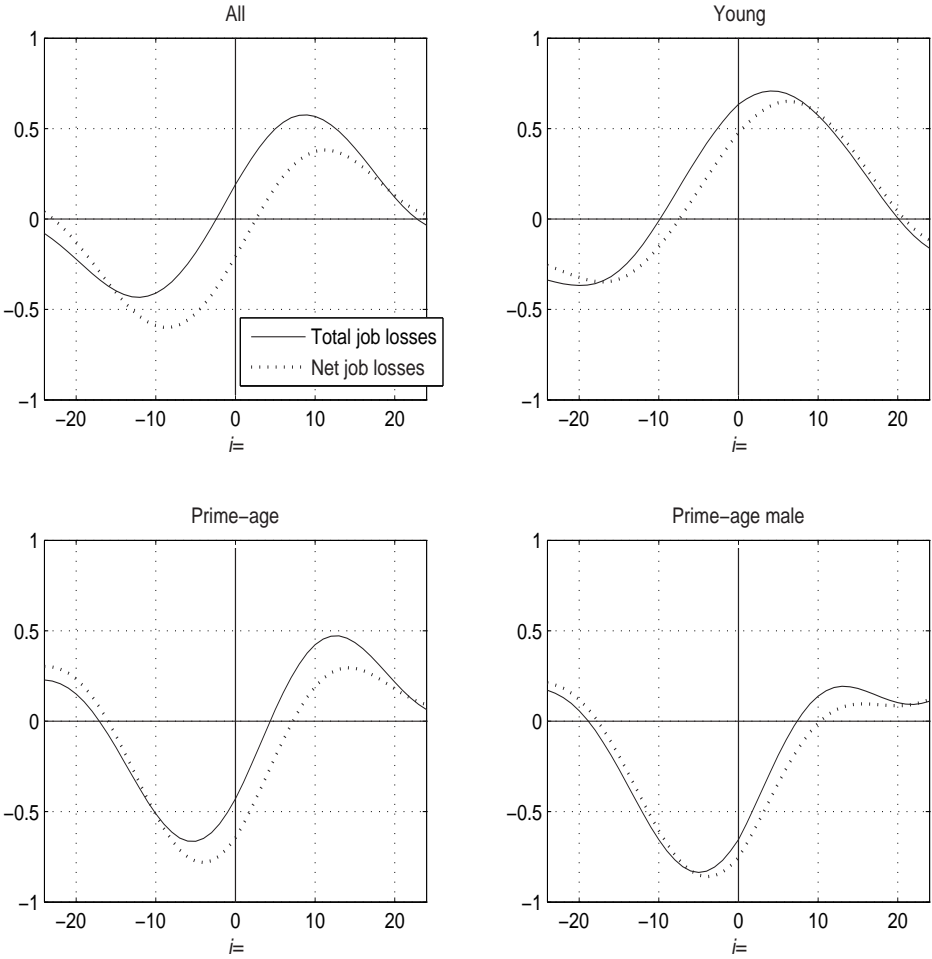


Figure 21: Cross correlations of cyclical components: industrial production at t and hiring flows at $t + i$ ($N\&U \rightarrow E$)

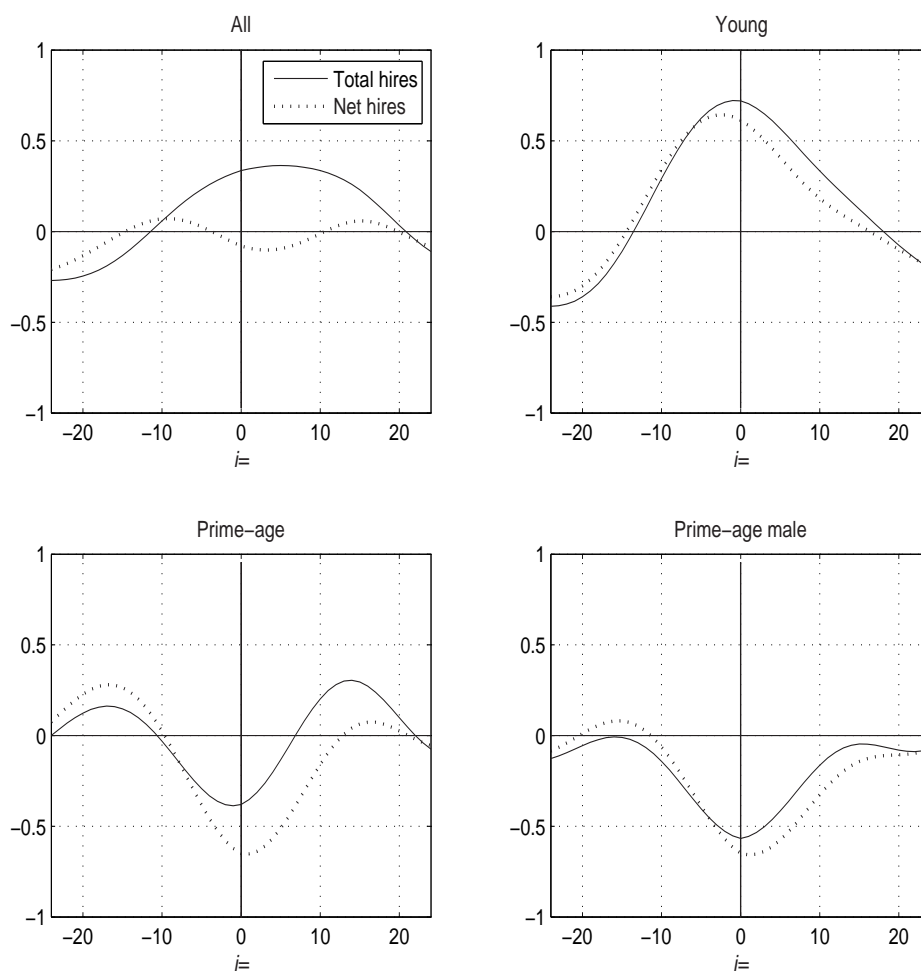
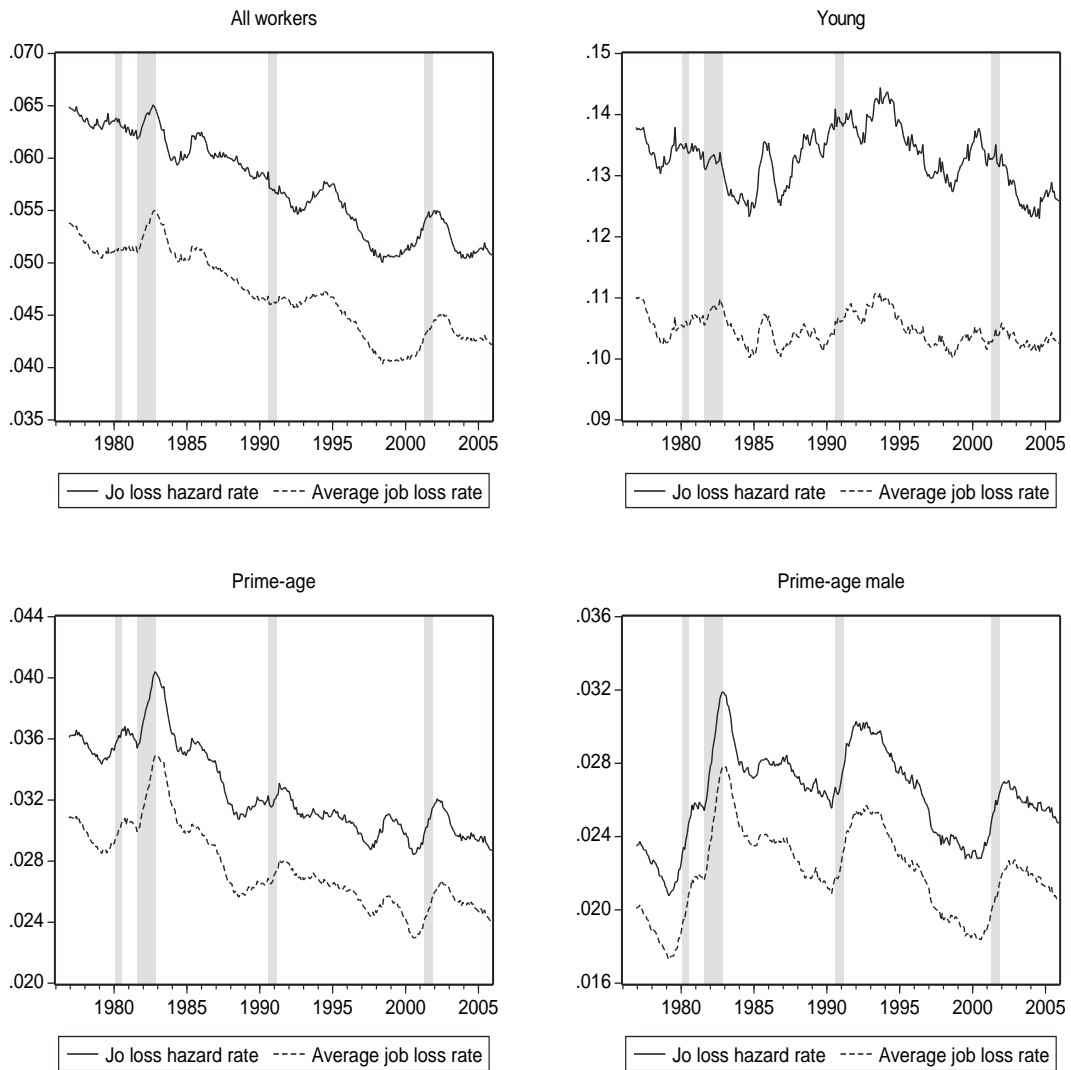
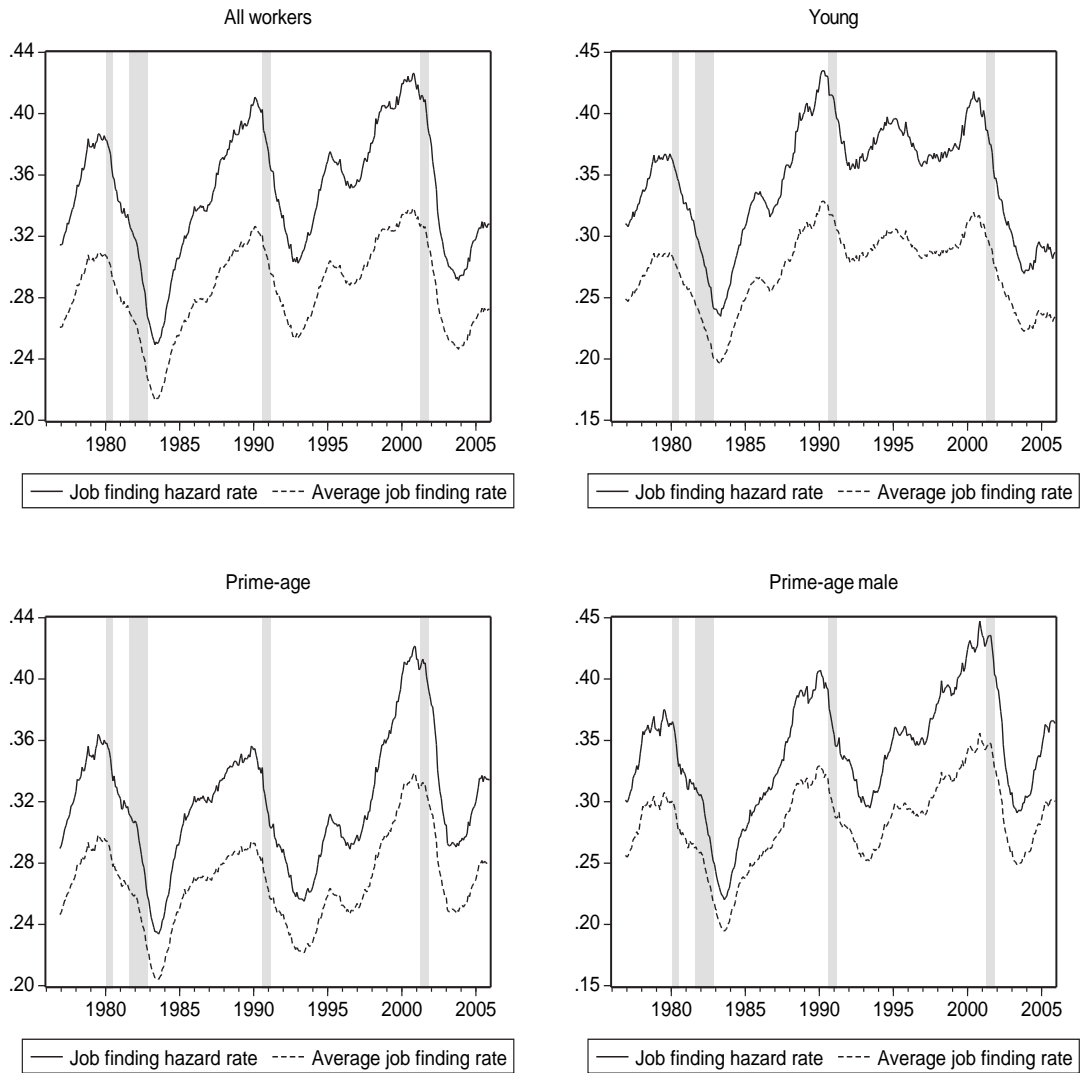


Figure 22: Job loss transition rates ($E \rightarrow N\&U$)



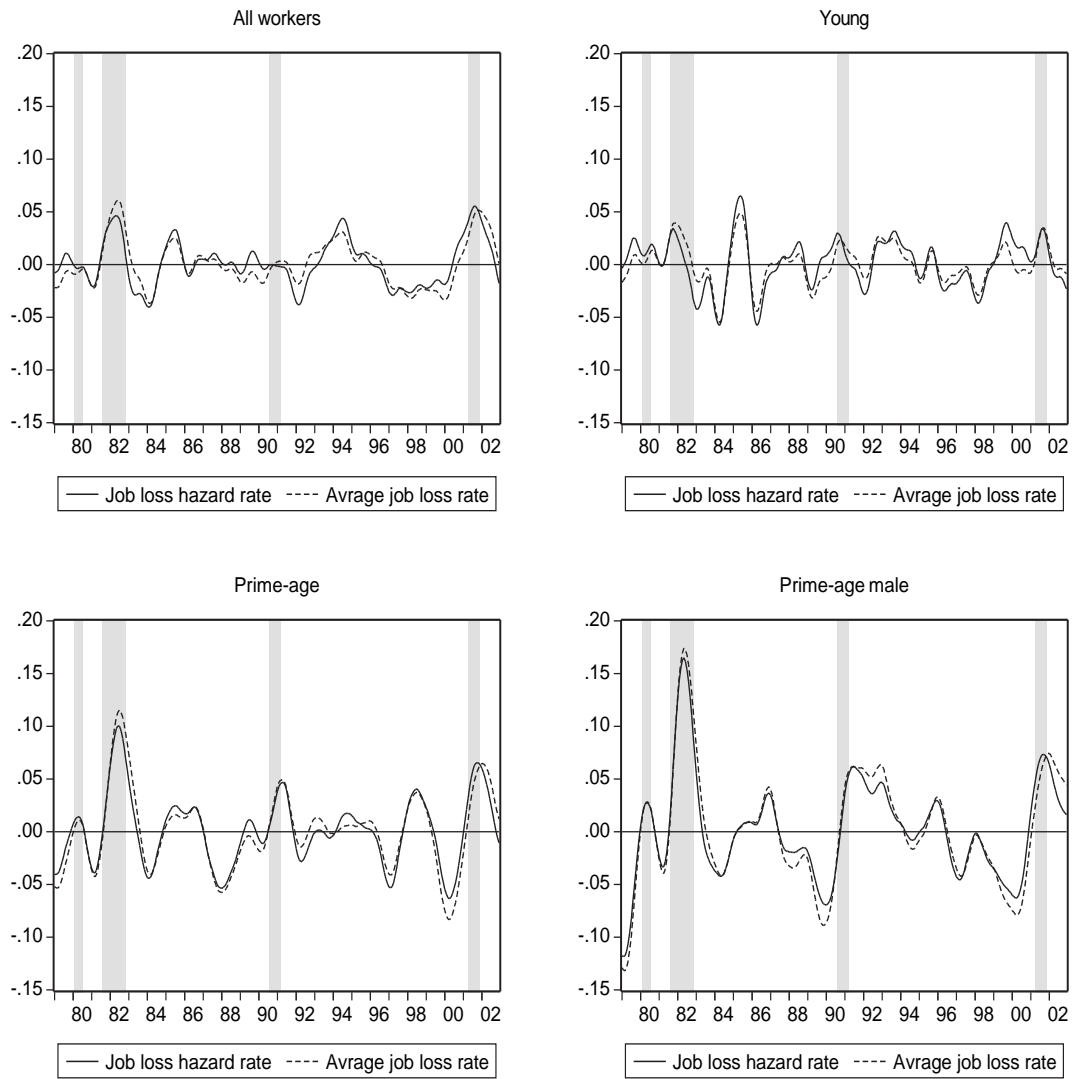
Notes: 12-month backward moving averages of nonseasonally adjusted data. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 23: Job finding transition rates ($N\&U \rightarrow E$)



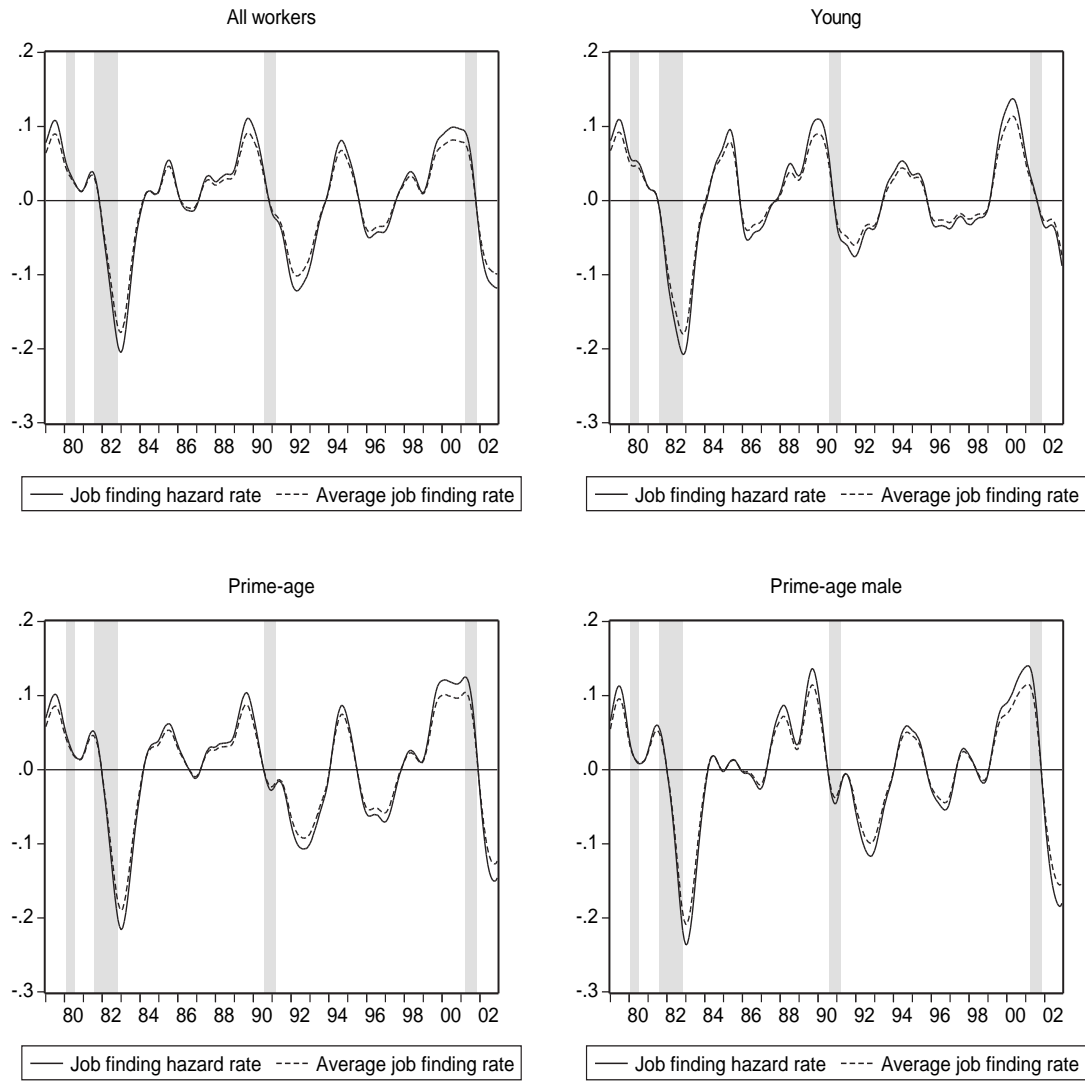
Notes: 12-month backward moving averages of nonseasonally adjusted data. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 24: Cyclical components of job loss transition rates ($E \rightarrow N&U$)



Notes: Logged and band-pass filtered by Baxter and King's (1999) method. Periodicities of 15 months through 96 months are passed. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 25: Cyclical components of job finding transition rates ($N\&U \rightarrow E$)



Notes: Logged and band-pass filtered by Baxter and King's (1999) method. Periodicities of 15 months through 96 months are passed. All workers: 16 or older. Young: 16-24. Prime-age: 25-54. Shaded areas indicate the NBER-dated recessions.

Figure 26: Cross correlations of cyclical components: job loss rates at t and job finding rates at $t + i$ ($E \leftrightarrow N\&U$)

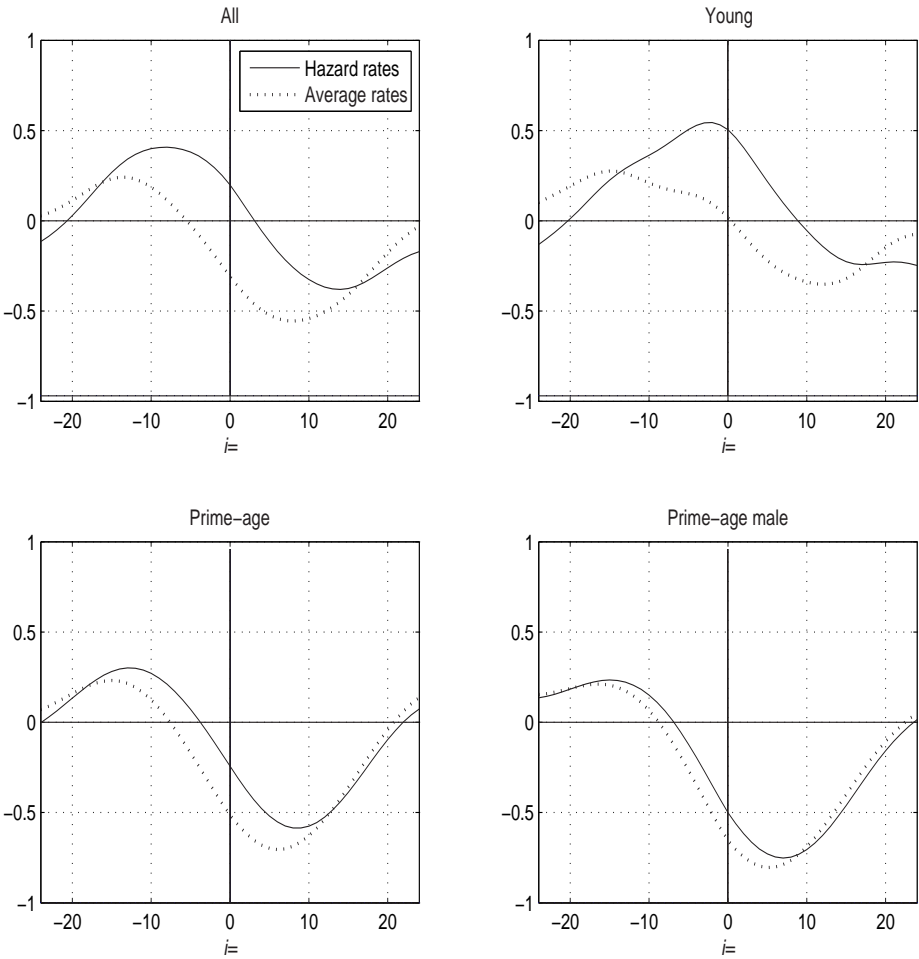


Figure 27: Cross correlations of cyclical components: industrial production at t and job loss rates at $t + i$ ($E \rightarrow N\&U$)

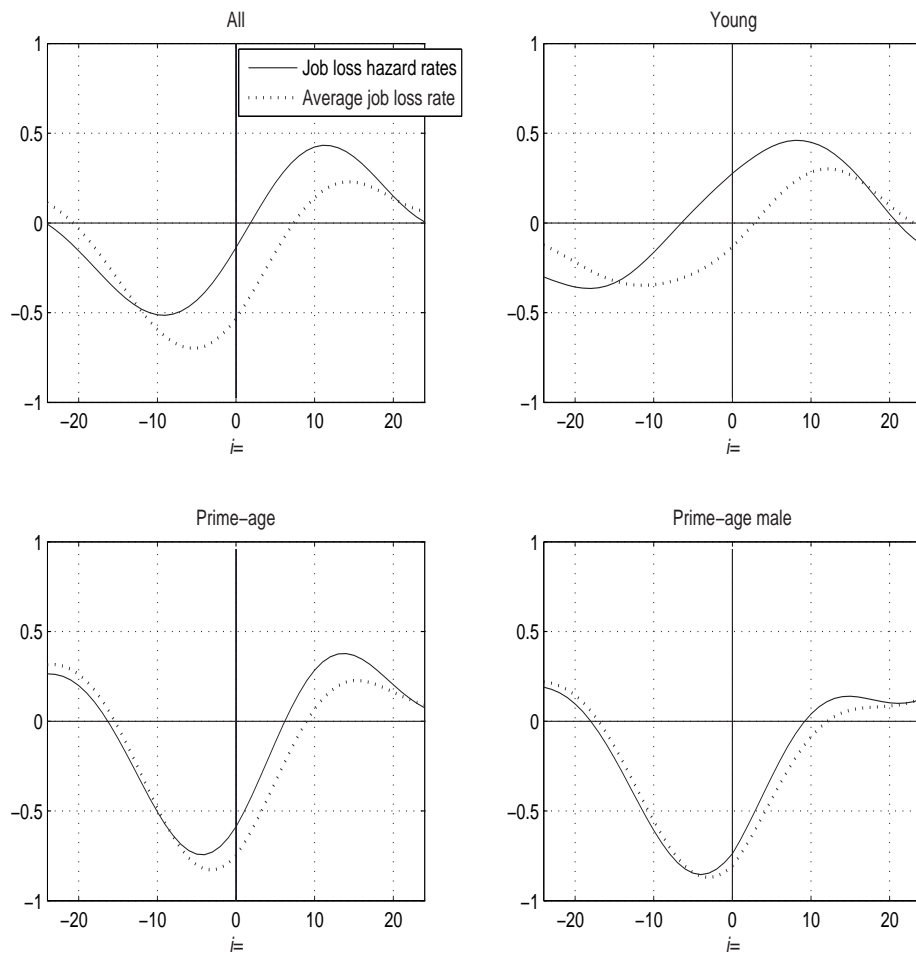


Figure 28: Cross correlations of cyclical components: industrial production at t and job finding rates at $t + i$ ($N\&U \rightarrow E$)

