WORKER REALLOCATION OVER THE BUSINESS CYCLE: THE IMPORTANCE OF EMPLOYER-TO-EMPLOYER TRANSITIONS

ÉVA NAGYPÁL

Abstract. In this paper, I show that employer-to-employer transitions are not only pervasive in the U.S. labor market, making up 49% of all separations from employers over the past decade, but also are a critical component in understanding worker turnover over the business cycle. In fact, the shift in the composition of separations from employer-to-employer transitions to employment-to-unemployment transitions explains all of the rise in the incidence of unemployment during the 2001 recession. In addition, the contribution of the change in the employer-to-employer transition probability to unemployment volatility was almost as large as that of the change in the job-finding probability.

A parsimonious model of worker turnover with on-the-job search and stochastic unemployment risk can explain the cyclical features of employer-to-employer transitions in response to the observed variation in the job-finding probability. The model also can account for all of the rise in unemployment incidence without any change in the separation hazard faced by different jobs, although it cannot fully explain the speed of the rise.

Keywords: Labor-market dynamics, employer-to-employer transitions, business-cycle dynamics, worker flows

JEL codes: E24, J63, J64

Department of Economics, Northwestern University, 2001 Sheridan Road, Evanston, IL 60208-2600, USA. E-mail: nagypal@northwestern.edu.
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1. Introduction

Employer-to-employer transitions are a pervasive feature of the U.S. labor market. Each month, 2.2% of employed workers leave for a job with a different employer. This flow makes up 49% of all exits from employers, versus 20% of separations that are employment-to-unemployment transitions and 31% that are transitions from employment to being out of the labor force. Employer-to-employer (EE) transitions also play a key role in our understanding of worker turnover over the business cycle. That is because the rise in unemployment incidence that occurs during a recession can be accounted for fully by the shift in the composition of separations from EE transitions towards transitions into unemployment.

In this paper, I document these facts using two microdata sets covering the period between 1994 and 2007. I also show that a parsimonious model of worker turnover with on-the-job search and stochastic unemployment risk can explain the time-series properties of EE transitions and the shift in the composition of separations that occurred in the 2001 recession.

To establish the cyclical properties of worker transitions, I decompose the cyclical volatility of unemployment into four components: the change in the exit rate from employers; the change in the propensity of exiting workers to stay in the labor force; the change in the composition of exits between employment-to-unemployment transitions and employer-to-employer transitions; and, the change in the job-finding rate of unemployed workers. I find that the first component has a negative contribution to unemployment volatility: the exit rate from employment is somewhat procyclical, which would imply a procyclical unemployment rate, holding all else equal. The second component is close to acyclical: the propensity to stay in the labor force upon exit does not change with the business cycle. What leads to the countercyclicality of unemployment incidence, therefore, is the fact that the share of exits resulting in an EE transition drops substantially in a recession. In fact, this component explains 50 to 60% of cyclical unemployment volatility, with the variation in the job-finding rate of unemployed workers explaining the rest. This conclusion does not change significantly if one controls for the cyclical change in the composition of workers making labor-market transitions, or if one takes into account the cyclical effect of time aggregation on monthly turnover data.

Given employer-to-employer transitions are strongly procyclical, how much of this procyclicality is driven by quits? Using data from the SIPP on the reason for separation, I find that the contribution of procyclical quits (which are indeed more likely to be followed by an EE transition) is only around 20% when it comes to explaining the drop in EE transition rates; the remaining 80% comes from the decline in EE transition rates within the different types of separations. This result — together with those on the breakdown of EE transitions by reason for separation — establishes that the correspondence between quits and EE transitions is far from perfect. Because earlier studies using indirect measures of EE transitions assumed that they were simply a share of all quits, measuring the EE transitions directly allows one to decouple the behavior of quits from those transitions.

To explain these facts, I construct a simple and parsimonious model of worker turnover that can explain the level and cyclical properties of employer-to-employer transitions over the past decade in response to observed variation in the job-finding probability. The model also can account for the rise in unemployment incidence during the 2001 recession without resorting to changes in the underlying risk of unemployment in different jobs. In the model, workers with different employers face different unemployment risk, so jobs can be either stable or unstable. The stability of a job is stochastic during the employment relationship (due to, say, demand shocks affecting the employer's profitability, or variation in and learning about the worker's productivity). When a worker experiences a shock that makes her job unstable, she undertakes on-the-job search to locate a stable job. According to the view of cyclical worker turnover captured in the model, jobs with a high unemployment risk always exist in an economy, but during good times these jobs are easy to leave for more stable jobs. Therefore, during good times, not many employed workers will go through a spell of unemployment before locating a more attractive stable job, and most exits will result in an EE transition. During bad times, though, it becomes harder for workers to "escape" unemployment by leaving unstable jobs for stable ones. Correspondingly, during bad times fewer exits result in an EE transition, and the share of employment-to-unemployment transitions among all exits rises. In this view, job search does not start when a worker becomes unemployed but rather before, in the face of increased unemployment risk. So both the employment-to-unemployment and the unemployment-to-employment flows respond to a slowdown in the rate at which workers can find jobs.

This model also highlights that the decomposition of cyclical changes in the unemployment rate into the rate of entry into and exit from unemployment[1] misses one important component of labor-market dynamics. In the presence of employer-to-employer transitions, such a decomposition is not clearcut, because these transitions represent a simultaneous separation and job-finding.[2]

These findings have several important implications. First, models of the labor market aiming to explain the cyclical variation in the unemployment rate cannot abstract from employer-to-employer transitions as has commonly been done.[3] Second, these findings suggest a view of worker reallocation over the business cycle that puts more of the emphasis on the role of declining job-finding rates in a recession than is found in decompositions of the cyclical variation in the unemployment rate into distinct separation and job-finding rate margins, abstracting from employer-to-employer transitions. Thus, in order to explain the cyclical variation in the unemployment rate, one needs to explain why jobs are becoming harder to find, both for unemployed and employed workers, in a recession. (This conclusion is reminiscent of those of Shimer (2007), although he does not take EE transitions into account and he underestimates the countercyclicality of the employment-to-unemployment transition rate.)

Job search theory has been criticized for not taking employer-to-employer transitions into account at least since Tobin (1972). While there have been many theoretical advances in search theory allowing for on-the-job search and EE transitions,[4] it has been difficult to

[1] Recently undertaken by Shimer (2007), Fujita and Ramey (2007a), or Elsby, Michaels, and Solon (2007).
[2] The view of worker turnover that emphasizes the shift in the composition of exits also has been espoused by Perry (1972) and more recently by Hall (2005), whose conclusions have been influenced by results in a previous version of this paper.
[3] See, for example, Mortensen and Pissarides (1994), or more recently Shimer (2005a).
[4] Most notably Burdett (1978), Mortensen (1994), Pissarides (1994), and Burdett and Mortensen (1998).

assess the empirical magnitude and cyclicality of such transitions in the U.S. because of the lack of datasets representative of the entire workforce that allow for the measurement of these transitions. Most studies have inferred the extent of EE transitions using indirect information on the quit rate (measured as the manufacturing quit rate prior to 1981) and on the fraction of quitters who have a job lined up.[5] The few studies that have attempted to directly measure the extent of EE transitions have relied either on non-representative data or on low-frequency (annual) data.[6] For example, Royalty (1998) uses the NLSY1979 data to measure EE transitions. She estimates an annual EE transition rate of 16% for women and 20% for men in her sample of young workers. Blanchard and Diamond (1990), and Stewart (2002), use the Current Population Survey March Supplements to measure EE transitions based on the number of jobs and unemployment spells that a worker reports in the previous year. Blanchard and Diamond's best guess measure of the annual rate of EE transitions averages 12% between 1975 and 1985, while Stewart's measure implies that the rate rose from 8.6% to 13.7% between 1975 and 2000. It is not possible to construct reliable EE transition measures at higher than annual frequency using the PSID data (see Polsky (1999)).

In contrast to these studies, I use two large micro datasets, the Current Population Survey (CPS) and the Survey of Income and Program Participation (SIPP), which allow me to identify workers who move from one job to another without an intervening spell of unemployment. While the CPS is not explicitly a panel data set, it does have a longitudinal component that can be used to study worker flows, including EE flows, since 1994. While the worker flow data derived from the CPS is useful, they suffer from important measurement problems, I argue. Therefore, I use the SIPP to validate my findings from the CPS. Reassuringly, after accounting for measurement issues, the findings from the two studies correspond reasonably well to each other, both in terms of levels and in terms of cyclical characteristics. In addition, the SIPP allows me to directly measure the time aggregation problem in worker flows that Shimer (2007) has pointed out.

[5]For example, Akerlof, Rose, and Yellen (1988), Blanchard and Diamond (1989), and Mortensen (1994)

[6]See the discussion in Farber (1999) on sources of data on job mobility.

Fujita and Ramey (2007b) use the SIPP data to study the cyclicality of worker flows without taking into account EE transitions. Mazumder (2007) presents estimates of EE transition rates using SIPP data. He uses different concepts to measure EE transitions (which allows him to construct a longer time series than what is used in this paper) without correcting for time aggregation, or studying the reason for separation, and without establishing a formal cyclical measurement procedure or theoretical model for the study of worker turnover. Like the current study, Fallick and Fleischmen (2004) use CPS data to assess the importance of EE transitions in the U.S. economy for the period between 1994 and 2003.[7] In contrast to their study, though, I provide an econometric decomposition of cyclical unemployment volatility. I also present a theoretical framework for interpreting my findings. Finally, I address the problem of measurement error arising from non-matching and from classification error in the CPS; I also cross-validate my CPS findings using the SIPP data and a second measure of EE transitions in the CPS.

2. Data and measurement

2.1. **Current Population Survey.** I use the Current Population Survey (CPS) for January 1994 to August 2007. The CPS is the largest survey of U.S. households and the source of official unemployment statistics. It contains about 60,000 households (56,000 prior to 1996 and 50,000 until June 2001); it is collected by the Bureau of the Census for the Bureau of Labor Statistics. Although the Current Population Survey is not an explicit panel survey, it does have a longitudinal component that allows for the measurement of monthly labor-market transitions. Specifically, a sample unit is interviewed for four consecutive months; then, after an eight-month rest period, interviewed for the same four months one year later. Households in the sample are replaced on a rotating basis, with one-eighth of the households introduced to the sample each month.

Since its inception, the CPS has been used to categorize individuals as employed, unemployed, and out of the labor force. The longitudinal component thus allows for the measurement of transitions between these states, and this has been the source of many studies looking

[7] Shimer (2005b) also follows their and my work and uses this measure of employer-to-employer transitions.

at the characteristics of worker flows.[8] However, the transition of workers between employers could not be measured directly, which meant that studies of worker flows abstracted from employer-to-employer (EE) transitions.

In January 1994, a major redesign of the CPS was implemented. The primary objective was to improve the quality of the data from the survey by introducing a new questionnaire and computerizing data collection methods. A computer-assisted interviewing environment was adopted, which in turn permitted the introduction of dependent interviewing.[9] Alon with dependent interviewing, several new questions were introduced, including one that asks whether respondents are still working for the same employer as in the previous month. This information allows for the measurement of employer-to-employer transitions in the CPS data. These transitions are measured as the fraction of workers who are employed in the first month and report being employed by a different employer in the second month. Of course, this definition does not preclude the existence of an intervening short spell of non-employment, which leads to a time aggregation bias in the measurement of EE transitions in the CPS data. To assess the size of this bias, I later use the SIPP data, which provides weekly labor force information.

Given this design of the CPS, the sample overlap between two consecutive months is theoretically 75%, but the actual matching rate in the data pooled from 1994 to 2007 is 71.12% because of changes in the sample size and attrition from the sample due to moving[10], temporary absence, or refusal to respond to the survey. Examining the non-matched observations indicates that they are not missing at random. In particular, workers without a match in the second month are: more likely to be unemployed in the first month; male; in their 20s; less educated; in the first month in the sample; unmarried; and non-white. Non-matching rates also increase in the summer and in December, and increase over time, with the non-match rate being highest in 2005-2007. Because of this non-random matching, assuming that these

[8] For example Blanchard and Diamond (1990).

[9] Dependent interviewing is the term used to describe the practice of using information obtained in a previous month's interview in the current month's interview, which is generally considered to improve the consistency of the data from one month to the next while reducing respondent burden. I am not aware of any studies, however, that systematically evaluate the effects of dependent interviewing techniques on measurement error.

[10] The CPS is an address-based survey, so individuals moving are not followed.

individuals are missing at random, and therefore simply dropping the non-matched observations (as is done by Fallick and Fleischmen (2004) or Shimer (2007)), can lead to biased estimates. Instead, I allocate the missing observations based on a conditional missing-at-random procedure whereby I condition on demographic characteristics, labor-force status in the first month, month in sample, and calendar month and year.[11]

In addition to the problem of non-random attrition from the sample, measuring turnover in the CPS is made more difficult because of classification error. That is, some workers are incorrectly categorized into a labor-market state in a given month, which gives rise to spurious measured labor-market transitions between two subsequent months when no actual transition took place.[12] All studies that correct for this problem use data prior to the mid-1980s (the best known are those by Abowd and Zellner (1985) and by Poterba and Summers (1986)).

An open question is how the extent of this source of error changed when the CPS was redesigned. This can be assessed by looking at reinterview data. About one percent of CPS households are assigned for reinterview each month in order to assess response error. The reinterview is a second interview about a week after the original one; all the labor-force questions are repeated using the same reference period as in the original interview.[13] To assess the extent of classification error following the CPS redesign, I use pooled interview-reinterview data from 1998 through 2006, reproduced in Table 1.[14] The discrepancies between the original and the reinterview responses are large. For example, 3.54% of the reinterviewed population reports being employed in the original interview but out of the labor force in the reinterview.

Since 1994, the Bureau of Census has not attempted to reconcile the discrepancies between the interview and the reinterview responses, as in earlier periods, so only unreconciled

[11]Further details about matching the CPS across months, and how I correct for non-random attrition, are described in the Appendix.

[12]For an example of how the presence of classification error leads to spurious worker transitions, see Blanchard and Diamond (1990).

[13]There is also a quality control reinterview program that uses a much shorter survey instrument than the original one and aims to verify that the interviewer conducted the CPS interview correctly.

[14]I am grateful to Christopher Damich at the Bureau of Census for providing me with the interview-reinterview data.

interview-reinterview tables are available. Comparing the responses for the period between 1998 and 2006 with those reported in Poterba and Summers (1986) for 1981 implies that the discrepancies between the interview and the reinterview responses became larger over the past decades (i.e., the share of off-diagonal observations increased).[15] Given the lack of reconciled interview-reinterview data after the 1994 redesign, I cannot use the methods proposed by Abowd and Zellner (1985) or Poterba and Summers (1986) to extract estimates of classification error from interview-reinterview data. Rather, I use the method proposed by Chua and Fuller (1987), which relies only on unreconciled data.[16]

Transitions between employment and out-of-labor-force are particularly susceptible to the classification problem, given the large discrepancy reported in Table 1. This means that transitions between employment and out-of-labor-force cannot be measured reliably in the CPS because they are sensitive to the particular adjustment procedure used to correct for this classification error. (This is in accordance with Abowd and Zellner's for an earlier period.) Therefore, I focus on separations from employers that do not lead to withdrawal from the labor force. In the CPS, neither EE nor EU transitions are adjusted for time aggregation; i.e., they measure transitions between two points in time a month apart without accounting for any intervening short spells of employment or non-employment.

Figures 1 and 2 plot the seasonally-adjusted EE and EU transition probabilities, both unadjusted and adjusted for classification error.[17] As is apparent, the classification-error adjustment significantly affects the level of the EU transition probability, reducing it by

[15]Bleakley, Ferris, and Fuhrer (1999) reach a different conclusion based on interview-reinterview data from 1994-1995. Unfortunately, the Bureau of Census does not publish public-use interview-reinterview data, so it is not possible to assess this question more in depth.

[16]All adjustment procedures need to be treated with great caution (as noted earlier by Blanchard and Diamond (1989)), because they all rely on strong assumptions about the correlation between the responses in the interview and the reinterview and on the validity of the reconciliation, in case reconciled data are used. For example, Abowd and Zellner (1985) assume that the reconciled reinterview data reveal the true labor-market state. The Chua and Fuller (1987) method assumes independent classification errors across the interview and the reinterview and a particular parametric form for the classification error probabilities in order to achieve identification. What all adjustment procedures have in common is that they significantly reduce the level of predicted transitions, especially those between employment and out of labor force.

[17]To arrive at the adjusted EE transition probability, I simply take the employment-to-employment transition probability adjusted for classification error and multiply it by the estimated EE transition probability conditional on being employed both months. Given that to measure EE transitions I study workers who report being employed in two consecutive months and have an employer reported in both months, it is not clear to what extent classification error in labor force status biases these estimates.

30% on average. EE transitions represent 68.5% of all separations into the labor force in the unadjusted data and 76.4% in the adjusted data. This implies that they play a key role in worker turnover. These transitions declined considerably during and following the recession of 2001 (indicated by gray shading), suggesting that the EE transition probability is procyclical. At the same time, the EU transition probability increased considerably during the 2001 recession, suggesting that this probability is countercyclical. The classification adjustment does not alter the cyclicality of the EE transition probability, but it does reduce the cyclicality of the EU transition probability somewhat, although this result is presumably sensitive to the adjustment procedure used. Nonetheless, the effect of classification adjustment on cyclicality should be kept in mind when considering the results from the microdata in Section 3. There, because of the lack of an appropriate classification-error adjustment procedure in the microdata, I use unadjusted transitions to formally establish the cyclical properties of the different transition probabilities.

Of course, the classification-error adjustment only allows us to adjust transition probabilities between labor-market states, not the probability of making a transition conditional on staying employed. How accurately the dependent interviewing question measures EE transitions is an open question. Therefore, I attempt to validate my findings in two ways. In the next section, I compare my results from the CPS to those from the SIPP. Here, I compare the EE measure derived from dependent interviewing with a second measure that can derived from the CPS for selected months. The source of this measure is the Employee Tenure Supplement administered once every two years, which reports each employed worker's tenure with his or her current employer. In this supplement, an EE transition conceptually equivalent to one based on dependent interviewing can be defined as one where a worker reports being employed in two consecutive months and reports tenure of less than one month in the second month. Table 2 reports estimated EE transition probabilities in the pooled sample over all months when a supplement is available, using the two different measures.

The estimated EE transition probability is 19% lower with the tenure-based measure than with the dependent-interviewing-based measure. When restricting the sample to observations in the last month in sample, the measure of EE transition probability drops by 12% under the dependent-interviewing-based measure and by 2% with the tenure-based measure, thus reducing the discrepancy between the two. This decrease in the measured EE transition probability is most likely attributable to two sources: the fact that more mobile individuals are more likely to drop out of the sample between the first and the third month of interviewing; and the fact that by the third month of interviewing, it is more likely that an employer name is established for workers in continuing employment relationships (this is supported by the fact that the share of observations with a missing answer to the dependent interviewing question declines from 2.13% to 1.79%). Overall, these results imply that the dependent-interviewing-based measure might somewhat overestimate the true extent of employer-to-employer transitions.

An even more cautionary note is raised when the two measures of EE transitions are cross-tabulated in the months when the relevant supplement is available. Table 3 reports the fraction of all individuals who are employed in two consecutive months, by their reported change in employer and their reported tenure in the second month. Only about 1% of workers employed in both months are reported to be working for a different employer based on both measures. An additional 2.67% (2.35% in the last month in sample) are reported to have changed employers based on one of the two measures, but not both. Of course, there is no reason to believe that the tenure-based measure gives a more accurate view of EE transitions, because measurement error can affect both estimates. (The tenure-based measure also has more missing values, 11.5% as opposed to 2.13% for the dependent-interviewing-based measure).

Based on these results, a conservative estimate of how much the dependent interviewing measure overstates true employer-to-employer transitions is 20-30%. Given this uncertainty about the level of EE transitions, it is useful to validate the CPS findings with a second source of data. That is one reason I use the Survey of Income and Program Participation in the next section.

Figure 3 shows the seasonally-adjusted transition probability from unemployment into employment (UE), both unadjusted and adjusted for classification error. Adjustment for classification error reduces this transition probability by 26%.[18] The UE transition probability declined considerably during and after the recession of 2001, implying that it is procyclical. It is also worth noting that the classification adjustment increases the cyclicality of the UE transition probability somewhat, although again this is presumably sensitive to the adjustment procedure used.

Finally, Tables 4 and 5 report the cross-sectional characteristics of labor-market transitions conditional on staying in the labor force. I correct for classification error by multiplying the raw numbers by the average classification error correction factor for each transition. Overall, almost 4% of workers separate from their employer and stay in the labor force in any given month. The vast majority, 77% of them, go to jobs at new employers. These aggregate numbers mask a large variation in transition probabilities by observable characteristics of workers, although the share of transitions explained by EE transitions is surprisingly constant across different demographic groups (the only characteristic with which is varies noticeably is education). As expected, teenage workers have the highest separation probability into the labor force at 8.05% per month. For workers in their early 20s, the probability of separation into the labor force is also fairly high at 6.77% per month. The probability of separations into the labor force declines substantially with age, although the distribution of separations between EE and EU transitions stays roughly the same.

In the remainder of Table 4 and in Table 5, I focus on prime-age workers between the ages of 25 and 60. Prime-age women have lower probabilities of separation into the labor force than men. There are also clear patterns in the comparison of education groups among

[18]Using the interview-reinterview tables used by Bleakley, Ferris, and Fuhrer (1999) for 1994-1995 reduces the difference between the adjusted and unadjusted EU transition probability by 18%, and between the adjusted and unadjusted UE transition probability by 26%. Moreover, it lowers the difference between the adjusted and unadjusted EO transition probability by 46%, again emphasizing the sensitivity of these transitions to the classification error problem. I am grateful to Jeffrey Fuhrer for providing me with the reinterview data discussed by Bleakley, Ferris, and Fuhrer (1999).

prime-age workers. The probability of separations into the labor force clearly declines with educational attainment: EE transitions become a larger and larger share of the separations into the labor force. For workers with less than a high school education, 67% of separations into the labor force result in an EE transition; for workers with an advanced degree, this share is almost 88%.

Table 5 reports the same statistics by different job characteristics for prime-age workers. Separations into the labor force are much more prevalent among part-time workers, who are almost twice as likely to separate from their employer into the labor force in any given month. This is most likely because that part-time work arrangements have a tendency to be more temporary in nature. Table 5 also reports the level and composition of separation probabilities into the labor force for full-time workers by industry. The industry-level differences are less substantial than differences by worker characteristics in general, although some differences do arise. The separation probability into the labor force is higher than average in agriculture and in construction, indicating that jobs in these sectors tend to be more temporary in nature. Not surprisingly, separation probabilities into the labor force are below average in public administration. In terms of the composition of separations, EE transitions are most prevalent in the public administration and FIRE sectors, and least prevalent in agriculture and in construction.

2.2. **Survey of Income and Program Participation.** Although the Current Population Survey is the largest source of information on monthly worker flows in the U.S., the Survey of Income and Program Participation has several advantages over it.[19] First, the SIPP is a panel data set, and is explicitly collected as such, with one aim being to measure worker turnover. Therefore, the problem of classification error is presumably much less serious in the SIPP data. Second, the SIPP data contain weekly labor-force status information, thereby allowing us to distinguish between employer-to-employer transitions with an intervening period of non-employment versus those where employment was continuous. This means that monthly worker turnover measures can be adjusted for time aggregation bias, which matters

[19]Gottschalk and Moffitt (1999) were the first to use the SIPP data to measure worker turnover.

substantially for the level and cycliclity of worker flows according to Shimer (2007). Third, the SIPP contains information on the reason for ending a job, so we can explicitly study the correspondence between quits and EE transitions that often has been assumed in the literature using indirect measures of EE transitions.[20]

The SIPP is a longitudinal survey of about 30,000 households that are interviewed every four months. At each interview, a complete weekly employment history for each member of the household for the last four months is collected, together with information about as many as two jobs that the individual has held and two businesses that the individual has owned during those four months (referred to as the "wave"). In the case of separation from any of these jobs or businesses, data on the reported reason for separation is collected.

I use the 1996 and 2001 panels to analyze the most recent recession.[21] I construct monthly transition probabilities by combining labor force and job history information. I then construct time-aggregation adjusted transition probabilities using the weekly labor force status data and asking whether a transition between employers involved an intervening nonemployment spell. The Appendix provides further details on the data construction procedure.

The greatest measurement challenge in the SIPP is seam bias: that is that a disproportionate number of labor-market transitions are reported as taking place between waves, not during waves. This indicates that transitions are underreported during the wave and are reported instead between the waves. To the extent that eventually all transitions are reported, averaging across rotation groups allows us to adjust for seam bias. This is possible for all calendar months covered by the SIPP (except the first three and last four months) because of the rotating nature of the SIPP. To the extent that some labor-market transitions are never reported, though, the SIPP estimates provide a lower bound for the magnitude of labor-market transition probabilities.

[20]Besides its smaller sample size, the SIPP's panels are not fully comparable over time; there are months that are not covered by any of the panels; and it is released with a much greater time lag than the CPS.

[21]There was a significant redesign of the SIPP with the 1996 panel. Due to differences in the way labor-force status and job history information is elicited in the panels prior to 1996, one cannot construct a longitudinally consistent measure of EE transitions in the SIPP. Mazumder (2007) constructs annual EE transition probabilities prior to 1996 by disregarding self-employment spells and using monthly as opposed to weekly labor-force status data.

Figures 4 and 5 display the seasonally-adjusted EE and EU transition probabilities, both unadjusted and adjusted for time aggregation.[22] The time-aggregation adjustment decreases the probability of EE transitions by 7.2% and increases the probability of EU transitions by 8.4%. This adjustment is much smaller than what is advocated by Shimer (2007). (He suggests 30%-50%).[23] Figures 6 and 7, in turn, compare the time-aggregation unadjusted probabilities (for the sake of comparability) to their counterparts in the CPS (adjusted for classification error). In the months where the two surveys overlap, the EE transition probability in the SIPP is about 25% lower than in the CPS. This confirms once again that the CPS measure slightly overestimates the extent of EE transitions. The two series display similar cyclical characteristics, though, including a significant decline between early 2001 and mid-2003. As for the EU transition probability, the SIPP and CPS series correspond closely, both in terms of levels and in terms of cyclicality. This indicates that the classification-error correction in the CPS yields accurate results for this series.

Figure 8 depicts the seasonally-adjusted UE transition probability in the SIPP data, adjusted and unadjusted for time aggregation. Time aggregation results in a 5.6% increase in the UE transition probability. Finally, Figure 9 compares UE transition probability series from the CPS and SIPP data. The two series correspond well in their level, but less in their cyclical behavior. While both series decline between 2001 and 2003, the decline in the CPS series is somewhat larger.

Table 6 reports the cross-sectional characteristics of labor-market transitions from an employer. The total monthly separation probability is 4.53% in the SIPP data,[24] with 49% of separations accounted for by EE transitions, 20% by EU transitions, and 31% by EO transitions.[25] The trends are similar to those found in the CPS, although the EE transition

[22]Neither the 1996 nor the 2001 panels cover the period between November 1999 and December 2000. Data for these months are extrapolated by the seasonal-adjustment procedure and are marked by asterisks.
[23]One reason for this is that Shimer (2007) uses a much higher job-finding probability than what is found in the SIPP data. It is straightforward to show that the use of a higher job-finding probability results in a higher and less cyclical adjusted EU probability.
[24]The total separation rate is 3.3% in the Job Openings and Turnover Survey (JOLTS) data, although that survey underreports separations (Nagypál (2007b).
[25]These are my preferred estimates of the share of EE transitions in all separations from an employer, because of the problem of measuring EO transitions in the CPS data caused by classification error.

probability is uniformly lower in the SIPP data. This implies that they only account for 71% of all separations into the labor force, as opposed to 77% in the CPS. EO transitions account for 31% of all transitions out of employment in the SIPP.[26] They have the expected patterns by demographic group: they are largest for young workers, they increase as workers approach retirement, they are larger for women, and they decrease with education.

Next, to study the reasons for separation, I sort the reported reasons for separation into four categories:

(1) Personal quits (P): retirement, child care, other family reason, illness, injury, schooling;

(2) Job-related quits (Q): quit to take another job, unsatisfactory work arrangements, other quits;

(3) Layoffs or employer-initiated separations (L): on layoff, discharged or fired, employer bankrupt, business sold, slack work or business conditions; and

(4) End of temporary jobs (T).

In Table 7, I report the reason for separation by education group. In the case of prime-age workers, education is by far the most important determinant of the reason for separation. As Table 7 shows, the two major reasons for separation are layoffs and job-related quits, comprising 75% to 80% of all separations. End of temporary jobs and personal quits make up the remaining 20% to 25%. The fraction of layoffs decreases substantially with the level of education of the worker. The fraction of job-related quits increases, reaching 58% of all separations for workers with an advanced degree compared to 49% for high-school dropouts. Overall, job-related quits make up over half of all separations.[27]

In Table 8, I report EE transition probabilities, conditioning on staying in the labor force after separation, by education level overall and by reason for separation. The overall EE transition probability conditional on staying in the labor force is 70.88%, somewhat

[26]This is notably smaller than their share in the CPS data unadjusted for classification error, 41%.

[27]All together, personal and job-related quits make up 71% of separations. This can be compared to the share of quits and other separations in total separations in the employer-reported JOLTS data, which is 63%. The higher level of quits in the SIPP may not be surprising, given that there it is employees who report the cause of separation.

lower than in the CPS. This probability increases with education, from 59% for high-school dropouts to 82% for workers with an advanced degree. EE transitions follow both layoffs and quits, although their share among quits is higher.[28] Despite this fact even among layoffs, 55% of exits are followed by an EE transition. These results explain why previous estimates of EE transitions were too low. First, they only considered EE transitions following quits, which misses 23% of all EE transitions. Second, they underestimated the fraction of quits resulting in an EE transition. For example, Blanchard and Diamond (1989) estimated that the fraction of quits followed by an EE transition was 40%, while this number is 73% in the SIPP data.

Tables 7 and 8 imply that the reason for the higher EE transition probability for more educated workers is that: 1) they are more likely to experience a job-related quit versus a layoff; and 2) both types of separation are more likely to be followed by an EE transition for them. Taken at face value, these statistics show that the correspondence between quits and EE transitions assumed in the earlier literature is far from perfect. It is important to keep in mind, though, that the categorization of quit versus layoff is based on the subjective ex-post self-report of the worker.

3. Cyclical properties of employer-to-employer transitions

To study the cyclical properties of the transition probabilities just discussed, I estimate their semi-elasticity with respect to the cyclical component of the aggregate unemployment rate, u_t^c, using individual-level data. I extract u_t^c by removing a sixth-order polynomial time trend from the seasonally-adjusted unemployment rate series for the period 1948 to 2007. Specifically, let the labor-market state of worker i in period t be $s_{it} \in \{U, E, O\}$. For the transition probability from state k to state l between time t and $t+1$, estimate the model

$$P_{it}^{kl} = P\left(s_{it+1} = l | s_{it} = k\right) = f^{kl}(\mathbf{X_{it}}, u_t^c), \tag{1}$$

[28]The finding that the EE transition probability is much higher among job quitters is in accordance with Parsons (1991) that job quitters are more likely than job losers to have a new job lined up.

where $\mathbf{X}_{it}$ is a vector of individual demographic and job characteristics at time t that includes dummies for age (9 groups), education (5 groups), gender, marital status (3 groups), race (3 groups), and part-time work, and survey characteristics, including calendar month and month-in sample. This model takes into account possible changes in the demographic composition of worker flows over the business cycle, because they could contribute to any observed cyclical changes.

To study the factors that contribute to the change in the EU transition probability, I statistically decompose of this probability into three components and analyze the cyclical properties of each separately. That is, the probability that worker i working in month t becomes unemployed in month $t+1$ can be decomposed as follows:

$$\begin{aligned} P_{it}^{EU} &= P\left(s_{it+1}=U|s_{it}=E\right) = P\left(\text{separate from period } t \text{ employer}|s_{it}=E\right) \times \\ & \times P\left(s_{it+1}\in\{E,U\}\,|s_{it}=E, \text{separate from period } t \text{ employer}\right) \times \\ & \times \left(1-P\left(s_{it+1}=E|s_{it}=E, \text{separate from period } t \text{ employer}, s_{it+1}\in\{E,U\}\right)\right) \\ &= P_{it}^{S}P_{it}^{LF|S}\left(1-P_{it}^{EE|S\&LF}\right). \qquad (2) \end{aligned}$$

In other words, the probability of going from employment to unemployment can be broken down into three parts: the probability of a worker separating from his or her employer; the probability of staying in the labor force upon separation; and the probability of entering unemployment upon separation and staying in the labor force, which is just one minus the probability of making an EE transition upon separation and staying in the labor force. Figure 10 shows this decomposition graphically. As discussed earlier, one needs to take into account possible cyclical changes in the demographic composition of the worker flows. In order to do that, I assume that, for a given worker i, the probabilities described above can be represented as:

$$P_{it}^{j} = f^{j}\left(\mathbf{X_{it}}, u_t^c\right), \qquad (3)$$

where $j \in \{S, LF|S, EE|LF\&S\}$. Holding the demographic characteristics of transitioning workers constant across the cycle, Equation (2) then implies that

$$(4) \qquad f^{EU}\left(\overline{\mathbf{X}}, u_t^c\right) = f^{S}\left(\overline{\mathbf{X}}, u_t^c\right) f^{LF|S}\left(\overline{\mathbf{X}}, u_t^c\right)\left(1 - f^{EE|S\&LF}\left(\overline{\mathbf{X}}, u_t^c\right)\right),$$

or

$$(5) \qquad \overline{P}_t^{EU} = \overline{P}_t^{S}\overline{P}_t^{LF|S}\left(1 - \overline{P}_t^{EE|S\&LF}\right),$$

where $\overline{P}_t^{j}$ is the probability of transition j for a worker with average characteristics over the pooled sample, $\overline{\mathbf{X}}$. Equation (5) implies that the semi-elasticity of the EU transition probability with respect to cyclical unemployment can be decomposed as

$$(6) \qquad \frac{d\log \overline{P}_t^{EU}}{du_t^c} = \frac{d\log \overline{P}_t^{S}}{du_t^c} + \frac{d\log \overline{P}_t^{LF|S}}{du_t^c} + \frac{d\log\left(1 - \overline{P}_t^{EE|S\&LF}\right)}{du_t^c}.$$

In addition, given the rapid adjustment of the unemployment rate to its state-contingent value in a two-state model, the steady-state relationship

$$(7) \qquad u_t \approx \frac{s_t}{f_t + s_t}$$

holds as a good approximation[29], where f_t is the job-finding rate and s_t is the separation rate into unemployment. Approximating f_t by $\overline{P}_t^{UE}$ and s_t by $\overline{P}_t^{EU}$, Equations (6) and (7) imply that, in the aggregate,

$$(8) \qquad \frac{d\log u_t}{du_t^c} \approx \frac{\overline{P}_t^{UE}}{\overline{P}_t^{UE} + \overline{P}_t^{EU}}\left(\frac{d\log \overline{P}_t^{EU}}{du_t^c} - \frac{d\log \overline{P}_t^{UE}}{du_t^c}\right) =$$

$$= \frac{\overline{P}_t^{UE}}{\overline{P}_t^{UE} + \overline{P}_t^{EU}}\left(\frac{d\log \overline{P}_t^{S}}{du_t^c} + \frac{d\log \overline{P}_t^{LF|S}}{du_t^c} + \frac{d\log\left(1 - \overline{P}_t^{EE|S\&LF}\right)}{du_t^c} - \frac{d\log \overline{P}_t^{UE}}{du_t^c}\right).$$

[29] See Mortensen and Nagypál (2007).

3.1. **Findings from the CPS.** I estimate the model in Equation (1) using a linear probability model

$$f^{kl}(\mathbf{X_{it}}, u_t^c) = \mathbf{X_{it}}\beta + u_t^c\alpha + \varepsilon_{it} \tag{9}$$

for the population as a whole and by education group for prime-age workers (ages 25-60). I estimate a similar model for the EE transition probability. In Table 9, I report the semi-elasticities with respect to u_t^c of the EE, EU, and UE transition probabilities (estimated as $\alpha/\overline{P}_t^{kl}$) without and with controlling for demographic characteristics.[30]

Table 9 contains several important results. First, the UE transition probability varies about twice as much with u_t^c over the period covered than the EU transition probability does. This implies that the variation in the EU transition probability accounted for about one third of the variation in the unemployment rate. This is in contrast to Shimer's (2007) finding that changes in the unemployment inflow probability did not contribute to the increase in unemployment in the last two recessions. One reason for this is that Shimer (2007) adjusts for time aggregation using a job-finding probability that is much larger than found in the data I study; that leads him to overadjust the EU transition probability. Second, I find that controlling for demographic composition does not have a large impact on the estimated semi-elasticities. This does agree with Shimer (2007). Third, the EE transition probability is procyclical, but it varies less than the probability of unemployed workers transitioning into employment. This is an important feature that I address in the context of my theoretical model in Section 4. Fourth, these findings hold qualitatively for all education groups except college graduates; for them, the variation in the EU transition accounts for about a half of the variation in their unemployment rate, although the estimates by education groups are less precise.

[30]Given that EO transition probabilities are acyclical, not having a good measure for them does not alter the cyclical decomposition.

Next, I decompose the semi-elasticity of the EU transition probability into its three components: the semi-elasticity of the probability of workers leaving their employer; the semi-elasticity of the probability of staying in the labor force upon separation; and the semi-elasticity of the probability of entering unemployment upon separation and staying in the labor force. I base this decomposition on Equation (6). In the first row of Table 10 I report these results, together with the semi-elasticity of the UE transition probability, for all education groups, controlling for demographic characteristics. As can be seen, both the probability of separation and the probability of staying in the labor force upon separation contributed somewhat negatively to the probability of transiting from employment to unemployment. This means that as the unemployment rate rises in a recession, workers are less likely to separate from their employers and are more likely to exit the labor force upon separation.[31] Both of these results imply that, ceteris paribus, the EU transition probability declines. So why does the EU transition probability increase as the unemployment rate rises? It is exclusively because during times of high unemployment individuals who separate and stay in the labor force, individuals are much more likely to experience unemployment than an employer-to-employer transition. In other words, all of the increase in the EU transition probability during the period covered was due to a decline in the EE transition probability.

The second row of Table 10 shows the contribution of each component to the volatility of unemployment, based on Equation (8).[32] Clearly, variation in the UE transition probability is the greatest contributor to the volatility of unemployment, explaining 64.2% of unemployment volatility. Variation in the EE transition probability is the second largest contributor, explaining almost half of unemployment volatility. Variation in the total separation probability, and in the probability of staying in the labor force, contribute negatively to unemployment volatility.

The rest of Table 10 reports the semi-elasticity decomposition for different age groups and for prime-age workers by education group. The same picture arises for all groups of workers

[31]The mild procyclicality of the total separation probability is also confirmed by the JOLTS data, see Hall (2005).

[32]The numbers in the second row of Table 10 add up to 102.11% implying that the approximation based on Equation (8) is very good.

with a few notable exceptions. For teenage workers, the probability of exiting the labor force upon separation increases more during times of high unemployment than in the aggregate. For older workers, the probability of exiting the labor force upon separation declines during times of high unemployment; this might be explained by the shift in the composition of older workers who experience separation in a recession towards workers who are less likely to retire. Finally, the change in the conditional EE transition probability explains more than half of the total variation in unemployment for college educated workers.

The view of labor markets over the business cycle that comes from the job-flows literature pioneered by Davis, Haltiwanger, and Schuh (1996) posits a large burst of job destruction at the beginning of recessions. My findings seemingly contradict this view — at least if one assumes that the cyclical properties of job and worker flows are the same — instead implying that the separation probability does not increase in a recession. One possible reason for this could be that the job-flows data correspond to the findings on the EU transition rate as opposed to the total separation rate from employers. As I show in Section 4, the quick runup in the EU transition probability cannot be solely explained by the change in the composition of separations, giving support for this interpretation. Another possible reason could be that — given the availability of data — most job-flows research focuses on manufacturing (with the notable exception of Foote (1998)), while I focus here on all sectors of the economy. In order to examine this possibility, I repeat the above exercise using data only for workers employed in manufacturing jobs. The last line of Table 10 shows the semi-elasticity decomposition for manufacturing. The results for manufacturing are not substantially different from those for the rest of the economy, implying that the divergence of the results on the cyclicality of job and worker flows cannot be explained simply by the difference in sectoral coverage.

3.2. **Findings from the SIPP.** I now examine the cyclical properties of the same transition probabilities using the SIPP data. With the same procedure, I estimate the semi-elasticities with respect to the cyclical component of the unemployment rate of the EE, EU, and UE transition probabilities. I report these in Table 11, which also contains the semi-elasticities for the time-aggregation corrected transition probabilities.

The results in Table 11 are mostly consistent with those in Table 9. The estimated semi-elasticity of the EU transition probability is somewhat larger than in the CPS (although their equality cannot be rejected at the 95% confidence level). One significant difference is that the EE transition probability is about 80% more procyclical in the SIPP than in the CPS. This could be because of the different time-series coverage of the two datasets.

As for the time-aggregation adjustment, it results in a less countercyclical EU transition probability and a more procyclical UE transition probability, as argued by Shimer (2007). The time-aggregation effect is not large, though. The time aggregation adjustment also results in a somewhat less procyclical EE transition probability, as would be predicted by a time-aggregation model with EE transitions. But again, this effect is small. Finally, controlling for demographic composition does not have a large effect on the estimated semi-elasticities.

Table 12 presents results similar to those in Table 10. Again, the probability of separation and the probability of staying in the labor force upon separation both contribute negatively to the probability of transiting from employment to unemployment, and the semi-elasticity of the separation probability is more negative than in the CPS.[33] The contribution of the UE transition probability to unemployment volatility is the same as in the CPS. In line with the findings shown in Table 11, the EE transition probability is more procyclical in the SIPP than in the CPS, thereby contributing more to the volatility of the unemployment rate.[34] Time aggregation has the largest impact on the contribution of the EE transition probability to unemployment volatility, reducing its estimate by 11 percentage points.

Next, I ask why the probability of EE transitions falls in a recession. Is it because the share of quits (which are most likely to be followed by an EE transition) falls, or is it because the probability of EE transition conditional on the reason for separation falls, or a combination of the two? I refer to the first explanation as the *composition effect* and the second explanation

[33]Gottschalk and Moffitt (1999) report annual total separation rates for male workers from the SIPP, which does not have a cyclical pattern.

[34]The numbers for the contribution to unemployment volatility add up to 115.08% and 108.13% without and with time aggregation, implying that the approximation based on Equation (8) is less precise in the SIPP than in the CPS.

as the *change-in-rate effect*. To do so, notice that the probability of an EE transition upon separation into the labor force can be expressed as

$$\begin{aligned} P\left(EE|\text{separation into LF}\right) &= \sum_r P\left(EE \text{ and } r|\text{separation into LF}\right) = \\ &= \sum_r P\left(EE|r, \text{separation into LF}\right) P\left(r|\text{separation into LF}\right). \end{aligned} \tag{10}$$

I assume that, for a given worker i in period t, the probability of experiencing a type r separation conditional on separation, where $r \in R = \{P, Q, L, T\}$, can be represented as

$$P_{it}^{r} = P\left(r|\text{ separation into LF }\right) = g^{r}\left(\mathbf{X_{it}}, u_t^c\right) \tag{11}$$

while the probability of an employer-to-employer transition conditional on the reason for separation can be expressed as

$$P_{it}^{EE|r} = P\left(EE|r, \text{ separation into LF }\right) = h^{r}\left(\mathbf{X_{it}}, u_t^c\right). \tag{12}$$

Then, based on Equation(10), evaluated at the the average characteristics over the pooled sample, $\overline{\mathbf{X}}$, we get

$$\frac{d\log \overline{P}_t\left(EE|\text{separation into LF}\right)}{du_t^c} = \sum_r \frac{\overline{P}_t^{r}\overline{P}_t^{EE|r}}{\overline{P}_t^{EE}} \left(\frac{d\log \overline{P}_t^{EE|r}}{du_t^c} + \frac{d\log \overline{P}_t^{r}}{du_t^c}\right). \tag{13}$$

Based on this decomposition, the composition effect can be approximated as

$$\sum_r \frac{\overline{P}_t^{r}\overline{P}_t^{EE,r}}{\overline{P}_t^{EE}} \frac{d\log \overline{P}_t^{r}}{du_t^c}, \tag{14}$$

while the change-in-rate effect can be approximated as

$$\sum_r \frac{\overline{P}_t^{r}\overline{P}_t^{EE|r}}{\overline{P}_t^{EE}} \frac{d\log \overline{P}_t^{EE|r}}{du_t^c}. \tag{15}$$

Once again, I estimate g^r and h^r under the assumption of linearity. Table 13 reports the two components of the change in the EE transition probability, overall and by education groups.[35]

As can be seen from the table, the composition effect does not contribute much to the cyclical change in the EE transition probability. So, the view of the cycle that posits that the EE transition probability falls (and thus the EU transition probability rises) because of a burst of layoffs that are followed much less often by an EE transition is not supported by the data.[36] In fact, the composition of separations changes little. Rather, it is the fall in the EE transition probability for each type of separation (the change-in-rate effect) that explains the drop in the overall EE transition probability. The results also imply that the correspondence between quits and EE transitions in terms of cyclicality is tenuous at best.

4. A simple model of worker turnover with employer-to-employer transitions

In this section, I present a parsimonious model of worker turnover that can help us understand the change in the composition of separations over the business cycle. I also show that despite its simplicity, the model can account for the observed pattern of EE transitions and some, but not all of the time-series properties of EU transitions in response to the observed variation in the job-finding rate of workers via a pure shift in the composition of separations.

Time is continuous. There are two types of jobs: stable and unstable. Stable jobs are not subject to exogenous destruction, while unstable jobs are destroyed at rate δ. At time t, unemployed workers find a stable job at rate λ_t. At rate η, a stable job becomes unstable. Workers in unstable jobs undertake on-the-job search and find new (stable) jobs at rate λ_t. This pattern of turnover can be rationalized with several wage-setting mechanisms (for example, Nash bargaining) as long as perverse wage incentives do not make unstable jobs

[35] The rows do not add up to 100% because the semi-elasticities are estimates.

[36] There is significant change in the share of layoffs, but they make up a small share of all separations, and the probability that a layoff is followed by an EE transition is 74% of the same probability following a quit, so this does not have a large impact on the overall EE transition probability.

more attractive. I do not endogenize λ_t; rather, I take it to be equal to the classification-error-adjusted UE transition probability from the data[37]. I then ask the following question: can the observed pattern of EE transitions and EU transitions be explained in this simple model as a result of the observed variation in the job-finding rate? (There is an extensive recent literature discussing the ability of matching models to explain the observed variation in the job-finding rate.[38]

At time t, g_{ti} workers are employed in jobs of type $i \in \{s, u\}$. Given initial conditions g_{0i}, the evolution of g_{ti} is characterized by the differential equations

$$\frac{dg_{ts}}{dt} = \lambda_t (1 - g_{ts}) - \eta g_{ts} \tag{16}$$

$$\frac{dg_{tu}}{dt} = \eta g_{ts} - (\delta + \lambda_t) g_{tu}. \tag{17}$$

The rate at which workers make EE and EU transitions at time t is

$$EE_t = \frac{\lambda_t g_{tu}}{g_{ts} + g_{tu}} \tag{18}$$

$$EU_t = \frac{\delta g_{tu}}{g_{ts} + g_{tu}}. \tag{19}$$

This model is extremely parsimonious because it only has two parameters, δ and η, the rate at which unstable jobs are destroyed and the rate at which stable jobs become unstable. I estimate these two parameters by minimizing the sum of squared residuals between the observed (MA(4) smoothed) EE and EU transition rate series and the corresponding simulated series.[39] I discretize the model and assume that the initial distribution g_0 is the stationary distribution corresponding to the initial value of λ. The estimated value of δ is 0.063, implying that unstable jobs are destroyed in about five quarters. The estimated value of η is 0.0483, implying that stable jobs turn unstable in about seven quarters. The model implied and the observed (MA(4) smoothed) EE and EU series are shown in Figures 11 and 12.

[37]A similar approach is used by Shimer (2005b)

[38]see, for example, Shimer (2005a), Mortensen and Nagypál (2007), or Nagypál (2007a)) in the presence of EE transitions.

[39]For simplicity, I do not account for time aggregation here, but I adjust for classification error.

In Figure 11, I also plot the job-finding rate series that I feed into the model. The model captures several characteristics of the data. First, it exactly matches the magnitude of the EE transition rate which, as argued by Nagypál (2005), in itself is not trivial and requires shocks to the job-destruction rate that jobs experience. Second, it matches its time-series evolution and the fact that the EE transition rate is less volatile over the period of study than the UE transition rate (the standard deviation of the log job-finding rate is 0.1622 in the data, while the standard deviation of the log EE transition rate is 0.0873, and is 0.0725 in the simulated model.) The reason for this lower cyclicality is the endogenous evolution of the distribution g: in times of a high job-finding rate, more workers end up in stable jobs, thus reducing the EE transition rate for a given job-finding rate. Not surprisingly, the model cannot account for the fact that during 2005-2006, the EE transition rate shows a downward trend while the job-finding rate was increasing.

The model also matches the average level of the EU transition rate fairly well, although it underpredicts the level before 2002 and overpredicts the level subsequently. Further, the actual EU transition rate exhibits a 47.6% increase between February of 2000 and November of 2001. The simulated transition rate, in turn, exhibits a 46.8% rise following February 2000 *without resorting to any changes in the underlying job-destruction rate*. This is because when the job-finding rate is lower, workers have less of a chance of escaping the large unemployment risk they face in unstable jobs; thus the fraction of workers in such unstable jobs increases, driving up the EU transition rate. This mechanism also explains the drop in the EU transition rate that took place in the second half of the 1990s quite well. However, the simulated series takes twice as long to reach its peak after 2000 as the observed series. This implies that the model can explain the size of the increase in the EU transition rate, but not the speed at which this increase takes place.[40] Thus a burst of job destruction could play a role in explaining the sharp rise in the EU transition rate. The magnitude of this burst, however, need not be nearly as large in the presence of EE transitions as without them.

[40] This feature is preserved by more parameter-rich model specifications.

5. Conclusions

This paper argues not only that employer-to-employer transitions constitute a large fraction of worker flows in the labor market, but also that these transitions must be an integral part of any model that attempts to explain business-cycle variation in worker reallocation. I document that all of the variation in the employment-to-unemployment transition probability is due to the fact that, while roughly the same number of workers separate from employers in a boom as in a recession, the fraction of workers that immediately take up a new job is significantly lower in a recession.

I also present a parsimonious model of worker transitions that goes a long way towards matching the evolution of the employer-to-employer and employment-to-unemployment transition probability since 1994. The model is a much simplified version of the one in Nagypál (2005). A critical feature of the model is that workers undertake on-the-job search when they face higher-than-average unemployment risk. Employer-to-employer transitions therefore are a way to "escape" unemployment. When the job-finding probability declines in a recession, such an escape is less likely, and the share of employment-to-unemployment transitions among exits from employers increases.

This study highlights the importance of incorporating employer-to-employer transitions into models of worker turnover. Many of the cyclical regularities presented here cannot be explained by models that abstract from EE transitions because, as I show, these transitions are very much intertwined with transitions between employment and non-employment. Theoretical research into cyclical labor-market fluctuations with employer-to-employer transitions is scarce. One recent exception is Nagypál (2007a)), in which I embed EE transitions into a matching model of the labor market. I show that, in the presence of moderate hiring costs, EE transitions provide a strong propagation mechanism by which even small productivity shocks have a large effect on the volatility of the unemployment and vacancy rates. In fact, my model reproduces all of the variability in the unemployment and vacancy rates in response to productivity shocks of the observed magnitude, without resorting to an excessively high value of leisure (as in Hagedorn and Manovskii (2007)), or to wage rigidity (for which there seems to be scant evidence among newly hired workers (see Haefke, Sonntag, and van Rens (2007)).

My results also imply that there are important differences between the cyclical behavior of worker versus job flows (with the latter documented by Davis, Haltiwanger, and Schuh (1996)). Thus, models of the labor market must distinguish between the two. Introducing partially irreversible organizational capital formation into a matching model (as in Faberman and Nagypál (2007)) is one fruitful avenue for pursuing this.

Finally, this paper shows that, if one takes self-reported reasons for separation at face value, there are important differences between quits and layoffs in terms of the prevalence of subsequent EE transitions. Most current models of the employment relationship rely on the bilaterally efficient separations framework, in which there is no meaningful distinction between quits and layoffs, because all separations are agreed upon mutually. Developing models that allow for a distinction between quits and layoffs, for example by considering environments with multiple heterogeneous workers in a single firm where it is possible to have multilaterally efficient separations that are bilaterally inefficient, is another fruitful avenue for research.

Appendix

Current Population Survey. I match data from two consecutive months using household and person identifiers in the CPS and checking for consistency of basic demographic characteristics (sex, age, and race). Table 14 contains the matching rate for individuals present in the sample in the first month and the fraction of observations that are not matched, broken down by reason for all observations age 15 and over, and for observations by employment status in the first month.

The largest difference by employment status in the first month is that unemployed individuals are more likely to move than individuals who are employed or are out of the labor force. This likely contributes to the inconsistency between worker flows and stocks in the

CPS where flows consistently underpredict the level of employment by missing some of the flow into employment (the so-called margin error, see Abowd and Zellner (1985)).

To allocate the the missing observations, I estimate for each quarter the probability of making a labor-force transition, separately for each labor-force status in the first month, based on a multinomial logit with 9 age dummies, 5 education dummies, a gender dummy, month-in-sample dummies, 3 marital status dummies, 3 race dummies, and a dummy for part-time status. I then predict the probability of making a particular transition for each non-matched observation. Based on the predicted probabilities, I randomly assign a transition to the non-matched observations.

An additional issue is the relatively large number of observations (2.13%) where an individual is reported to be working in two consecutive months but where there is a missing response to the question of whether he or she is working for the same employer. Here I follow the same procedure for the allocation of transitions but, following the suggestion of Moscarini and Thomsson (2008), I also add occupation change because it is a strong predictor of making an EE transition.

Survey of Income and Program Participation. I use the reported labor-force status of individuals during the last week of each month to categorize them as employed, unemployed, or out of the labor force. To make the definition of labor-force status as comparable as possible across the CPS and the SIPP, I classify workers as follows:

- a worker is *employed* if she has a job and is working or has a job, is not on layoff nor absent without pay.
- a worker is *unemployed* if she has a job, is on layoff, and is absent without pay, or has no job and is looking for work or on layoff.
- a worker is *out of labor force* is she has no job and is not looking for work, nor is she on layoff.

For 1997, a representative year, this categorization yields a labor-force participation rate of 66.68% in the SIPP versus 67.10% in the CPS and an unemployment rate of 4.41% in the

SIPP versus 4.94% in the CPS.[41] One reason for this discrepancy is that the definition of unemployment considers a longer time period in the CPS (that is, whether an individual was looking for a job during the preceding four weeks) than in the SIPP weekly labor-force status (where looking for a job only during the week is considered). Using a monthly categorization, Mazumder (2007) finds that the unemployment rates from the CPS and the SIPP line up well.

In each wave, the SIPP records information on up to two non-contingent jobs for each person (the two longest held) and on up to two spells of self-employment, thus providing information (starting and possible ending date) on up to four jobs per worker during the four-month reference period. Based on this information, I determine for each of the four jobs whether it was held at the end of each month. For workers who report working on a contingent job during the reference period, I record them as working on that job if no other job is recorded to be held at the end of the month. Among all employed workers in the 1996 panel, 8.83% had more than one job, 0.61% worked only on contingent jobs (including odd jobs, on-call work, day labor, one-time jobs, and informal arrangements like babysitting), 0.98% held jobs other than those reported for the reference period, while 0.02% are not clearly categorizable. For workers who held more than one job at the end of the month, I define the worker's main job to be the one where he or she has worked the most hours; or, if the hours worked were the same across jobs, then the job that the worker has held the longest. Where the main job is identified, I record the occupation and the class of the worker on that main job, the reported reason that the job ended if it did, and the identifier for the worker's employer, which is constant across waves (this allows me to identify EE transitions at the seam).

Next, I construct transition data for two consecutive months based on the reported labor-force status and on the employer's identifier for workers who were employed in both months. For contingent workers during the entire wave, an EE transition (change in employer identifier) is only possible at the seam, which means that my measure of EE transitions provides

[41] Fujita and Ramey (2007b) categorize workers with a job, on layoff, absent without pay as employed, which further reduces the SIPP unemployment rate to 3.81% in 1997.

a lower bound (as expected, contingent workers account for 3.94% of turnover in the 1996 panel, more than their share among employed workers). For workers who held none of the reported jobs at the end of the first month, an EE transition can be identified if the worker then switches into a reported job, or vice versa.

Based on the worker's main job[42], it is possible to construct EE transition indicators for all but 0.10% of workers who are employed in both months in the 1996 panel. Based on a person's labor-force status, it is possible to construct changes in labor force status for all but 1.69% of all persons. (The latter are persons for whom labor-force status is missing in the second month, which is a particularly large problem at the seams, where 5.71% of persons are missing labor-force status information in the next wave). I impute these missing transition data based on a multinomial logit, conditional on a person's demographic characteristics (sex, age, education, marital status, race) and on indicators for part-time status (if employed) and calendar month.

Next, for each separation, I assign a reason based on what the worker reported for ending his or her main job. These reports do not exist for 22.04% of the observations with a separation in non-seam months and for 87.92% of the separations in seam months (this latter is the case because the likelihood of separating between the last week of the last month and the end of the wave is very small) in the 1996 panel. I impute the reason for these missing data based on a multinomial logit, conditional on a person's demographic characteristics (sex, age, education, marital status, race) and indicators for part-time status (if employed) and calendar month.

Finally I construct an indicator for whether a worker who was employed in two consecutive months was employed continually during the month. I use it to examine the extent to which EE transitions between two dates, one month apart, represent a short spell of non-employment rather than an EU or an EO transition. Using this information, I construct time-aggregation adjusted EE, EU, and EO transition rates.

[42]Similarly to the CPS, if a worker holds multiple jobs and his main job is reported to be different in subsequent months, this is counted as an EE transition.

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Tables

	Original interview		
Reinterview	Employed	Unemployed	Out of labor force
Employed	58.34%	0.40%	1.63%
Unemployed	0.36%	1.72%	0.77%
Out of labor force	3.54%	0.91%	32.32%

Table 1. Interview-reinterview labor-force classification cross-tabulation as fraction of the reinterviewed population, pooled data from the Current Population Survey 1998-2006.

	EE transition probability	
	All months in sample	Last month in sample
Dependent interviewing	2.61%	2.29%
Reported tenure	2.11%	2.06%

Table 2. Two different measures of the EE transition probability in the Current Population Survey, the first based on dependent interviewing and the second based on reported tenure, age 16 and over.

	Reported tenure All months in sample		Reported tenure Last month in sample	
Dependent interviewing	30 days+	30 days −	30 days+	30 days −
Same employer	96.31%	1.07%	96.66%	1.04%
Different employer	1.60%	1.02%	1.31%	0.99%

Table 3. Cross-tabulation of the dependent-interviewing-based and the tenure-based measures of EE transitions in the Current Population Survey, age 16 and over.

	As share of employment		
	EE transitions	EU transition	EE share
All observations	2.88%	0.89%	76.52%
By age			
Age 16-19	5.76%	2.29%	71.53%
Age 20-24	5.11%	1.66%	75.49%
Age 25-29	3.53%	1.02%	77.59%
Age 30-34	2.80%	0.86%	76.61%
Age 35-44	2.38%	0.73%	76.58%
Age 45-54	2.09%	0.59%	78.01%
Age 55-59	2.12%	0.56%	79.20%
Age 60-64	2.12%	0.54%	79.82%
Age 65 and up	2.02%	0.52%	79.55%
By gender, age 25-60			
Male	2.57%	0.79%	76.37%
Female	2.42%	0.66%	78.57%
By education, age 25-60			
Less than HS	3.10%	1.56%	66.59%
High school	2.47%	0.86%	74.09%
Some college	2.49%	0.68%	78.67%
College	2.42%	0.45%	84.34%
Advanced degree	2.23%	0.32%	87.50%
By race, age 25-60			
White	2.46%	0.68%	78.44%
Black	2.74%	1.14%	70.61%
Other non-white	2.56%	0.74%	77.55%
By marital status, age 25-60			
Married	2.30%	0.58%	79.85%
Was married	2.60%	0.98%	72.62%
Never married	3.15%	1.08%	74.51%

TABLE 4. Monthly separations into the labor force in the Current Population Survey as a fraction of employment by different characteristics of workers.

	As share of employment		
	EE flows	EU flows	EE share
All observations, age 25-60			
	2.50%	0.73%	77.34%
By hours, age 25-60			
Full time	2.37%	0.62%	79.22%
Part time	3.44%	1.55%	69.00%
By industry, age 25-60, full-time			
Agriculture	3.04%	1.27%	70.55%
Mining	2.21%	0.74%	74.80%
Construction	3.20%	1.51%	67.94%
Manufacturing	2.01%	0.64%	75.88%
TCU	2.11%	0.49%	81.29%
Wholesale trade	2.57%	0.66%	79.70%
Retail trade	2.43%	0.50%	82.98%
FIRE	2.55%	0.50%	83.73%
Private hholds	2.50%	0.67%	79.39%
Other services	2.45%	0.49%	83.41%
Public Admin	1.63%	0.21%	88.57%

TABLE 5. Monthly separations into the labor force in the Current Population Survey as a fraction of employment by different job characteristics.

	As share of employment		
	EE transitions	EU transitions	EO transitions
All observations	2.20%	0.91%	1.42%
By age			
Age 16-19	5.30%	2.18%	6.47%
Age 20-24	4.26%	1.65%	2.83%
Age 25-29	2.88%	1.04%	1.28%
Age 30-34	2.15%	0.86%	0.97%
Age 35-44	1.77%	0.77%	0.78%
Age 45-54	1.49%	0.62%	0.70%
Age 55-59	1.27%	0.60%	0.99%
Age 60-64	1.18%	0.59%	1.78%
Age 65 and up	1.18%	0.76%	2.60%
By gender, age 25-60			
Male	1.88%	0.78%	0.64%
Female	1.83%	0.75%	1.15%
By education, age 25-60			
Less than HS	2.10%	1.47%	1.36%
High school	1.78%	0.89%	0.91%
Some college	1.96%	0.72%	0.87%
College	1.82%	0.52%	0.77%
Advanced degree	1.62%	0.36%	0.64%
By race, age 25-60			
White	1.84%	0.73%	0.85%
Black	1.99%	1.03%	1.02%
Other non-white	1.86%	0.78%	1.03%
By marital status, age 25-60			
Married	1.69%	0.61%	0.83%
Was married	2.03%	1.00%	0.93%
Never married	2.34%	1.11%	1.02%

Table 6. Monthly separations in the Survey of Income and Program Participation as a fraction of employment by different worker characteristics.

	Fraction of reason for end of job			
	Personal quit	Job-related quit	Layoff	End of temp
All education groups	16.06%	55.14%	23.27%	5.52%
Less than HS	14.04%	49.24%	30.37%	6.35%
High school	13.73%	55.60%	26.04%	4.63%
Some college	17.73%	54.92%	22.02%	5.33%
College	17.54%	57.83%	18.66%	5.97%
Advanced degree	18.34%	58.17%	16.13%	7.36%

Table 7. Composition of reason for separations from an employer by education group, Survey of Income and Program Dynamics, 1996-2003, age 25-60.

	Fraction experiencing employer-to-employer transition				
	All	Personal quit	Job-related quit	Layoff	End of temp
All education groups	70.88%	91.69%	73.25%	55.45%	68.32%
Less than HS	58.85%	83.52%	61.84%	46.95%	53.88%
High school	66.69%	87.72%	68.87%	55.50%	64.59%
Some college	73.10%	92.55%	75.10%	56.52%	71.97%
College	77.85%	95.76%	79.90%	59.26%	76.98%
Advanced degree	81.67%	97.24%	83.46%	64.57%	72.34%

Table 8. Incidence of employer-to-employer transition following separation into the labor force by different reason and by education group, Survey of Income and Program Dynamics, 1996-2003, age 25-60.

	Semi-elasticity with respect to cyclical unemployment		
	$\frac{d\log \overline{P}_t^{EE}}{du_t^c}$	$\frac{d\log \overline{P}_t^{EU}}{du_t^c}$	$\frac{d\log \overline{P}_t^{UE}}{du_t^c}$
No demographic controls			
All education groups	-6.053 (0.365)	6.181 (0.551)	-11.745 (0.428)
With demographic controls			
All education groups	-5.433 (-0.363)	7.226 (0.548)	-12.029 (0.426)
High school dropouts age 25-60	-3.014 (1.339)	5.910 (1.563)	-9.304 (1.289)
High school graduates age 25-60	-5.067 (0.800)	9.608 (1.120)	-11.481 (0.906)
Some college age 25-60	-5.549 (0.827)	9.339 (1.335)	-13.860 (1.030)
College grads age 25-60	-6.617 (0.958)	13.500 (1.848)	-13.683 (1.427)
Advanced degree age 25-60	-3.528 (1.408)	9.296 (3.152)	-12.716 (2.372)

Table 9. Semi-elasticity of the EE, EU, and UE transition probabilities with respect to the cyclical component of the unemployment rate in the Current Population Survey data, age 16 and over.

	$\frac{d\log \overline{P}_t^{S}}{du_t^c}$	$\frac{d\log \overline{P}_t^{LF\mid S}}{du_t^c}$	$\frac{d\log\left(1-\overline{P}_t^{EE\mid S\&LF}\right)}{du_t^c}$	$\frac{d\log \overline{P}_t^{UE}}{du_t^c}$
All education groups	-0.955 (0.230)	-0.768 (0.185)	8.820 (0.448)	-12.029 (0.426)
Contrib to unemp volatility	-5.10%	-4.10%	47.09%	64.22%
Age 16-19	-1.748 (0.570)	-3.804 (0.684)	8.835 (1.213)	-12.766 (1.062)
Age 20-24	-3.068 (0.569)	-0.471 (0.453)	6.279 (1.078)	-11.485 (0.965)
Age 25-29	-1.040 (0.716)	-1.428 (0.470)	10.171 (1.320)	-11.877 (1.211)
Age 30-34	0.247 (0.746)	-1.931 (0.494)	12.534 (1.330)	-11.983 (1.289)
Age 35-44	-0.285 (0.543)	-0.676 (0.359)	10.283 (0.949)	-12.028 (0.944)
Age 45-54	0.317 (0.602)	-0.106 (0.429)	7.780 (1.129)	-12.744 (1.140)
Age 55-59	0.369 (0.977)	0.964 (0.848)	8.778 (2.037)	-11.829 (2.086)
Age 60-64	-0.836 (1.093)	3.160 (1.317)	12.416 (2.750)	-6.853 (2.964)
Age 65+	-1.790 (0.884)	4.738 (1.743)	-5.559 (3.089)	-11.518 (3.322)
High school dropouts age 25-60	1.088 (0.794)	-0.507 (0.603)	5.329 (1.184)	-9.304 (1.289)
High school graduate age 25-60	0.065 (0.532)	-0.361 (0.370)	9.657 (0.894)	-11.481 (0.906)
Some college age 25-60	-0.513 (0.578)	-0.825 (0.392)	10.927 (1.116)	-13.860 (1.030)
College graduates age 25-60	-0.594 (0.708)	-1.689 (0.468)	15.449 (1.640)	-13.683 (1.427)
Advanced degree age 25-60	-1.026 (1.079)	-0.583 (0.679)	10.901 (2.781)	-12.716 (2.372)
Manufacturing age 25-60	-0.732 (0.722)	-0.820 (0.467)	8.242 (1.222)	-15.014 (1.222)

Table 10. Decomposition of the semi-elasticity of the unemployment rate with respect to its cyclical part into its four components in the Current Population Survey data, age 16 and over.

	Semi-elasticity with respect to cyclical unemployment		
	$\frac{d \log \overline{P}_t^{EE}}{du_t^c}$	$\frac{d \log \overline{P}_t^{EU}}{du_t^c}$	$\frac{d \log \overline{P}_t^{UE}}{du_t^c}$
No time-aggregation correction			
No demographic controls	-10.897 (0.685)	7.646 (1.074)	-13.038 (0.848)
With demographic controls groups	-9.520 (-0.667)	8.889 (1.068)	-12.034 (0.745)
With time-aggregation correction			
No demographic controls	-10.356 (0.707)	5.951 (1.042)	-13.780 (0.836)
With demographic controls	-8.997 (-0.692)	7.321 (1.033)	-12.572 (0.733)

TABLE 11. Semi-elasticity of the EE, EU, and UE transition probabilities and their time-aggregation adjusted counterparts with respect to the cyclical part of the unemployment rate in the SIPP data, age 16 and over.

	$\frac{d \log \overline{P}_t^{S}}{du_t^c}$	$\frac{d \log \overline{P}_t^{LF\|S}}{du_t^c}$	$\frac{d \log \left(1-\overline{P}_t^{EE\|S\&LF}\right)}{du_t^c}$	$\frac{d \log \overline{P}_t^{UE}}{du_t^c}$
No time-aggregation correction				
Semi-elasticity	-3.231 (0.489)	-1.065 (0.304)	13.532 (0.841)	-12.034 (0.745)
Contrib to unemp volatility	-17.33%	-5.71%	72.58%	64.54%
With time-aggregation correction				
Semi-elasticity	-3.231 (0.489)	-0.653 (0.318)	11.492 (0.783)	-12.572 (0.733)
Contrib to unemp volatility	-17.33%	-3.50%	61.59%	67.37%

TABLE 12. Decomposition of the semi-elasticity of the unemployment rate with respect to its cyclical component into its four components in the SIPP data, age 16 and over.

	Composition effect	Change in rate effect
All workers	19.3%	74.2%
High school dropouts	27.5%	69.9%
High school grads	14.1%	81.4%
Some college	20.6%	70.7%
College grads	20.4%	73.1%
Advanced degree	14.1%	81.6%

Table 13. Share of the composition effect and the change in rate effect in explaining the cyclical change in the employer-to-employer transition probability, age 16 and over.

	All observations	Employed	Unemployed	Out of labor force
Matched	94.82%	94.87%	92.12%	95.00%
Inconsistent demographics	0.78%	0.73%	0.65%	0.90%
Household or individual moved	2.62%	2.51%	5.08%	2.56%
Noone home	1.03%	1.10%	1.23%	0.88%
Refused answer	0.66%	0.69%	0.73%	0.58%
Unexplained non-match	0.09%	0.09%	0.19%	0.09%

Table 14. Matching rate in the Current Population Survey overall and by labor-force status in the first month, pooled data 1994-2007.

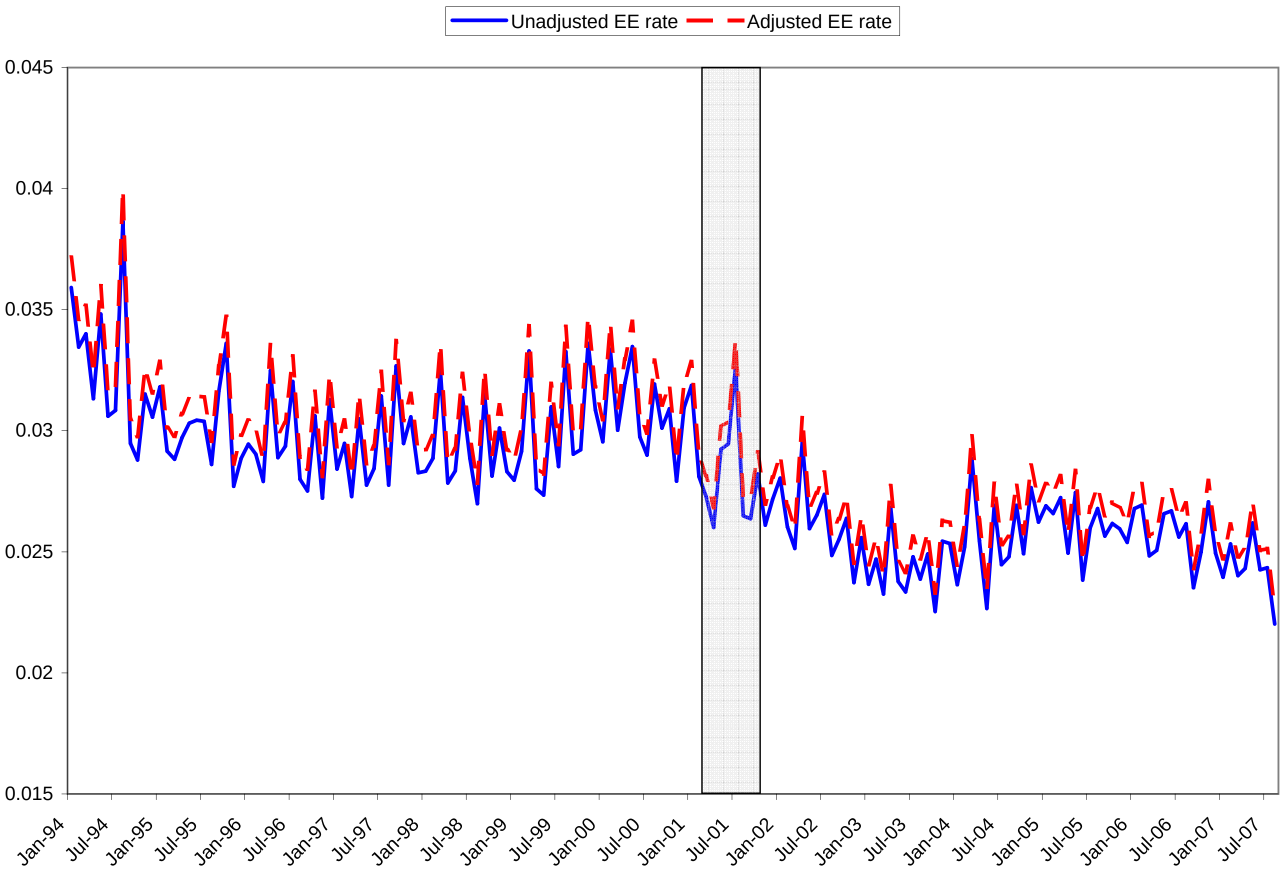

FIGURE 1. Seasonally adjusted employer-to-employer transition probability in the Current Population Survey, 1994-2007, unadjusted and adjusted for classification error.

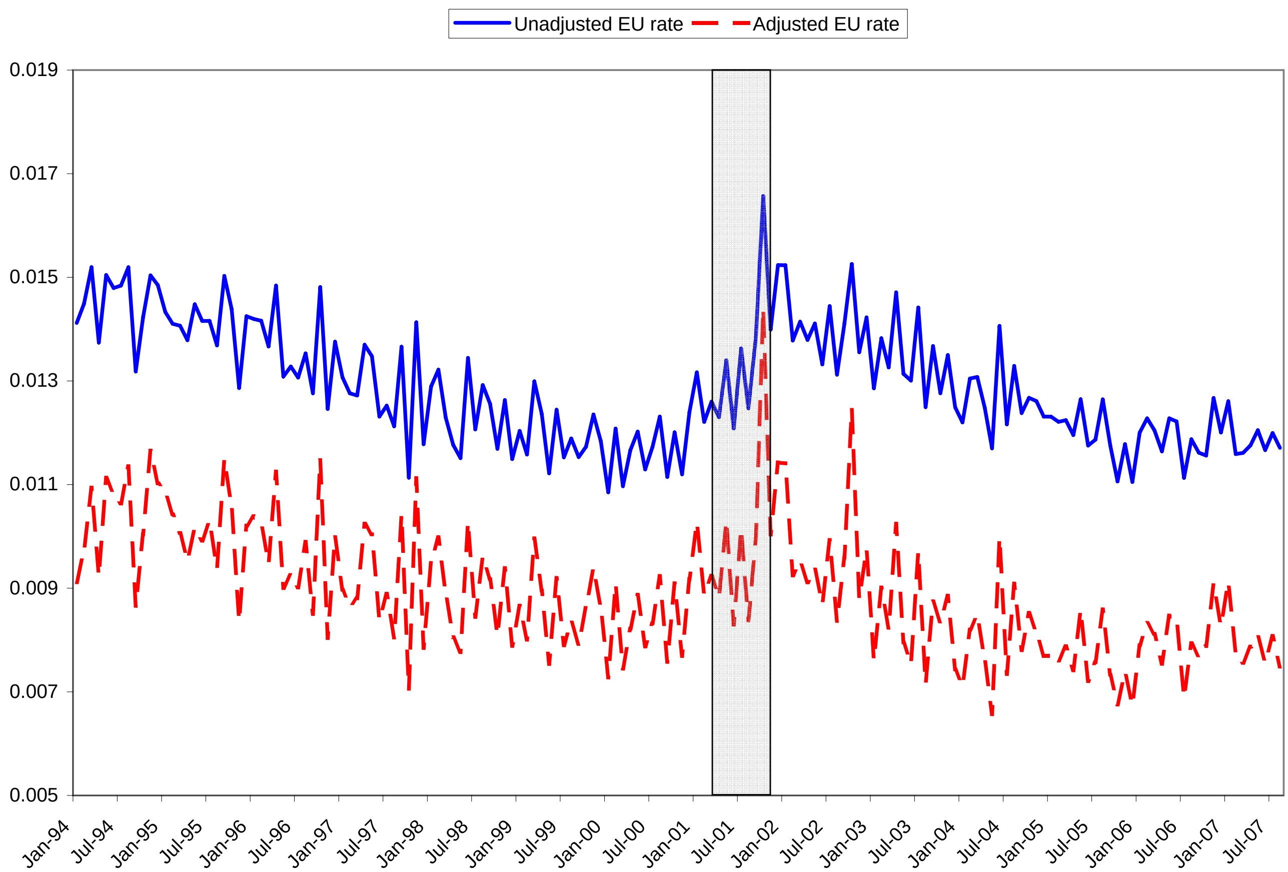

FIGURE 2. Seasonally adjusted employment-to-unemployment transition probability in the Current Population Survey, 1994-2007, unadjusted and adjusted for classification error.

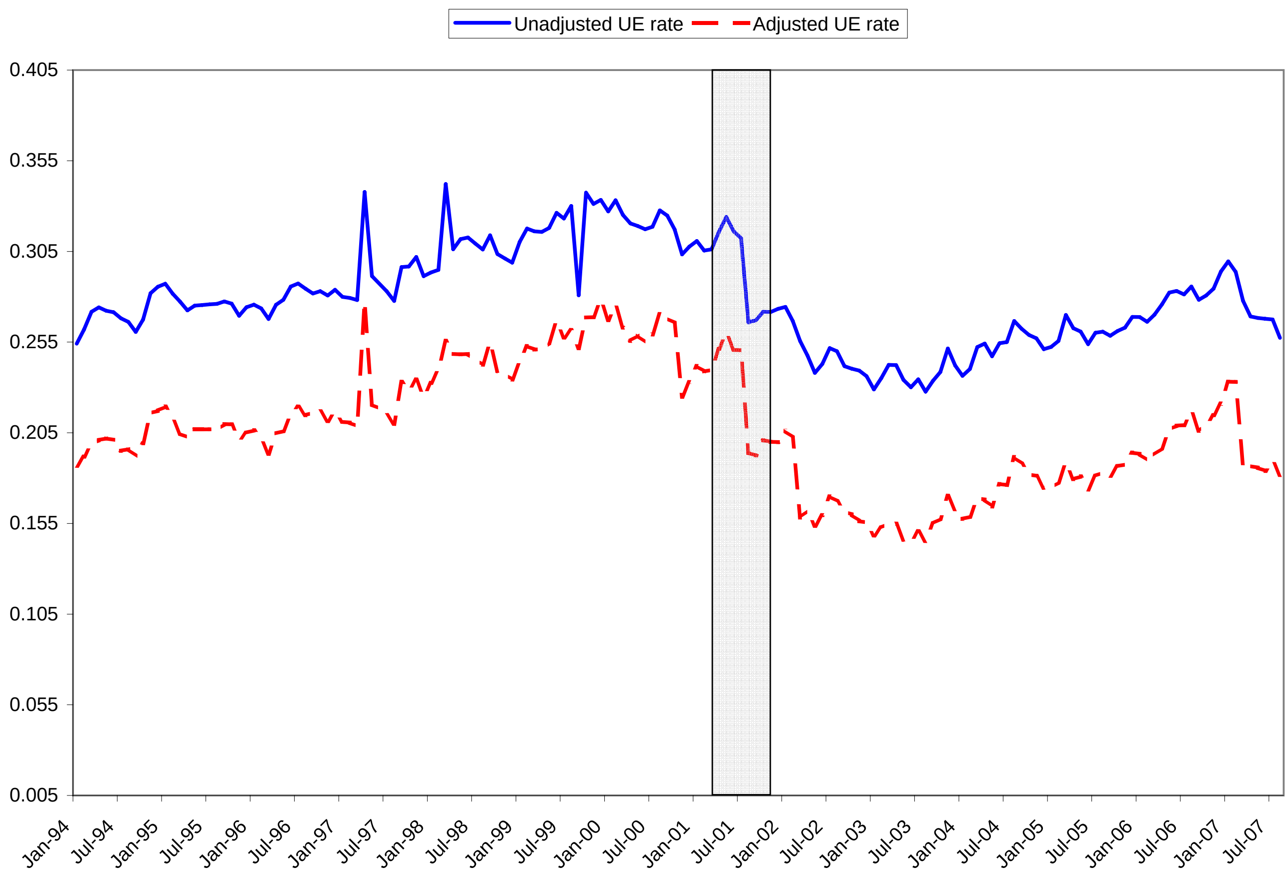

FIGURE 3. Seasonally adjusted employment-to-unemployment transition probability in the Current Population Survey, 1994-2007, unadjusted and adjusted for classification error.

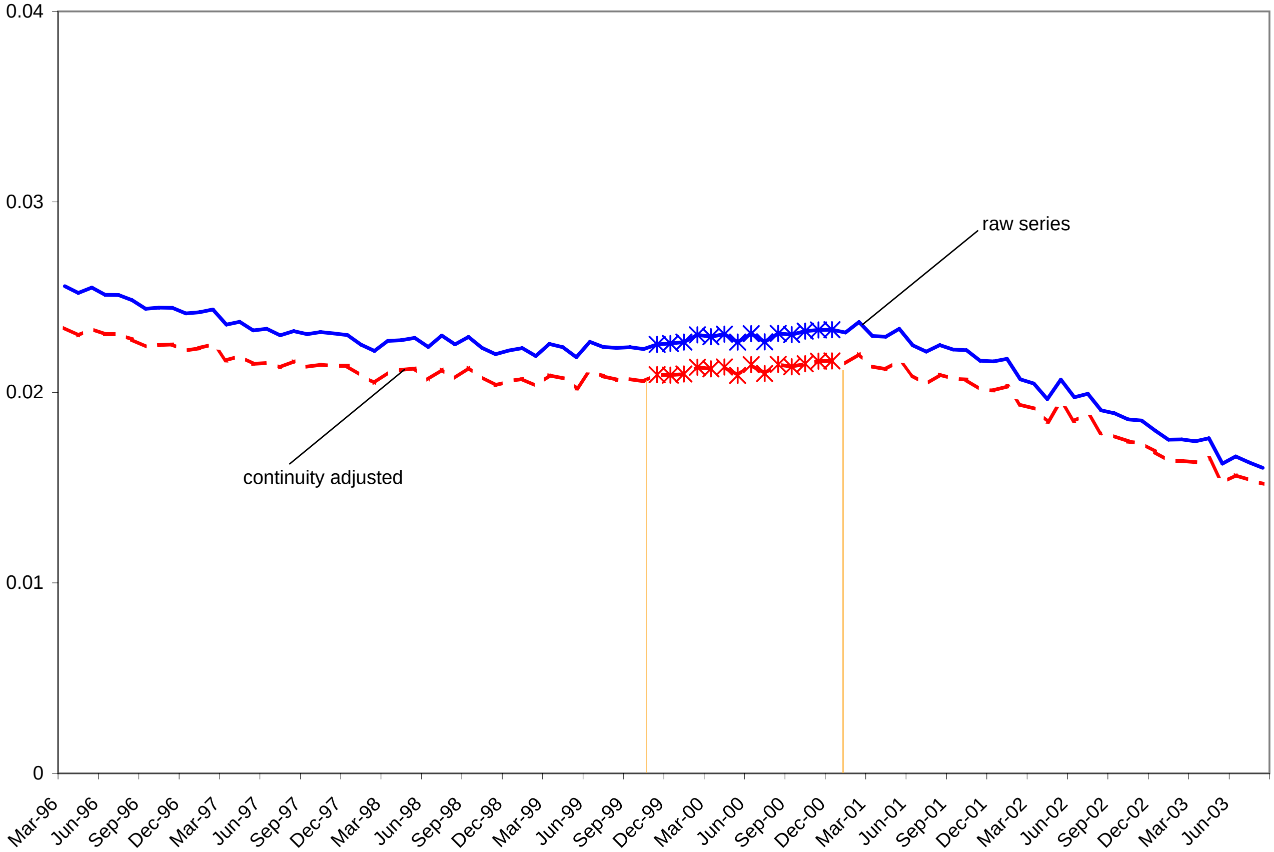

FIGURE 4. Seasonally adjusted employer-to-employer transition probability in the Survey of Income and Program Participation, 1996-2003, unadjusted and adjusted for time aggregation. Asterisks mark extrapolated observations.

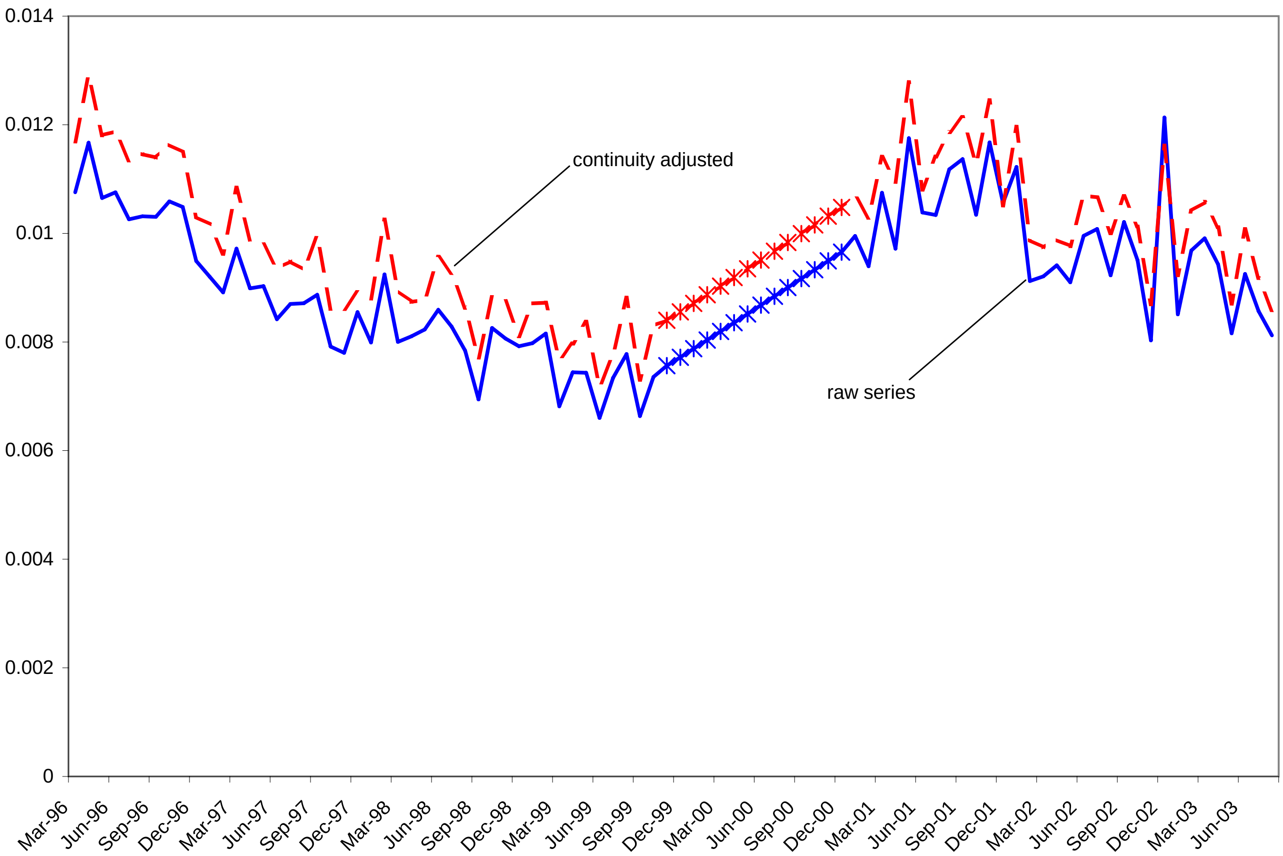

FIGURE 5. Seasonally adjusted employment-to-unemployment transition probability in the Survey of Income and Program Participation, 1996-2003, unadjusted and adjusted for time aggregation. Asterisks mark extrapolated observations.

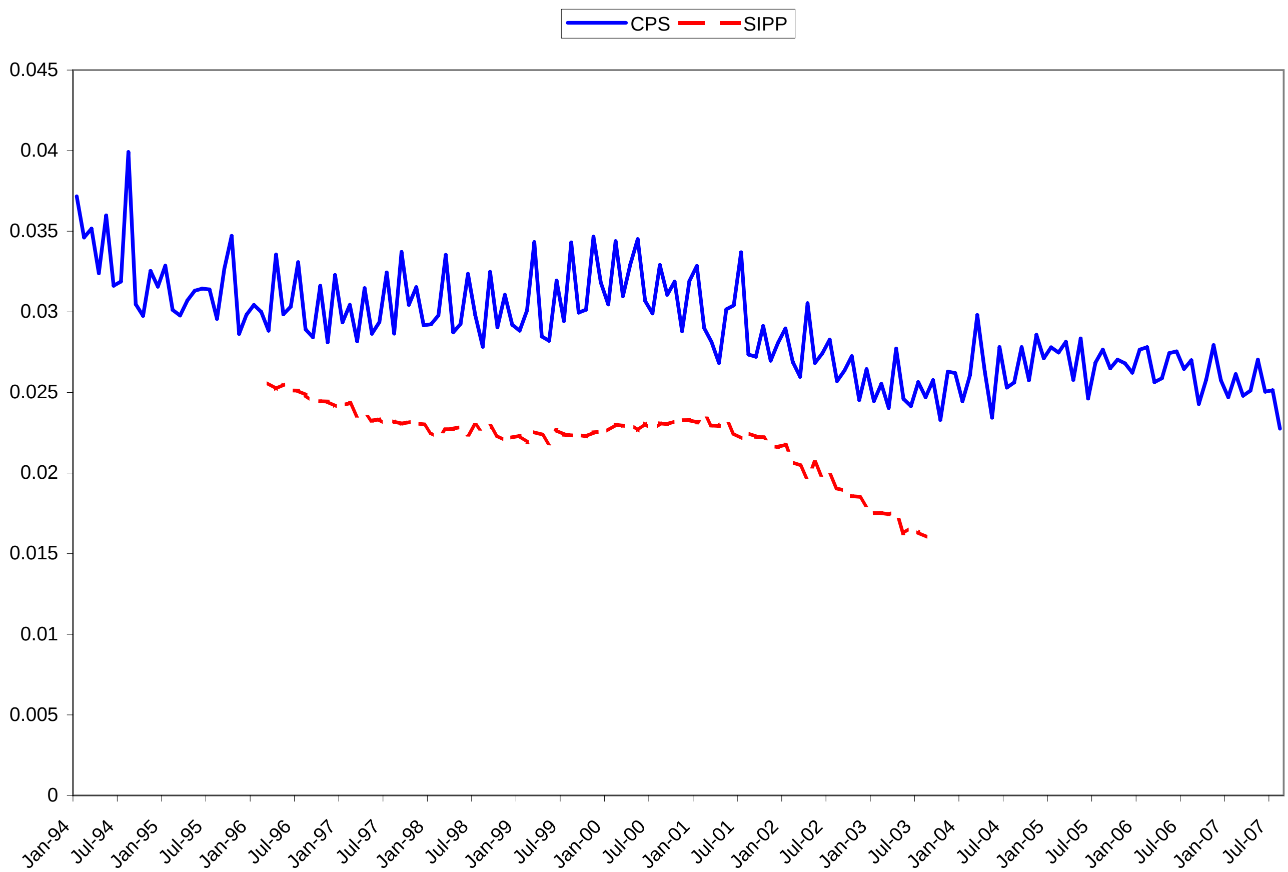

FIGURE 6. Comparison of the seasonally-adjusted employer-to-employer transition probabilities in the Current Population Survey, 1994-2007, and the Survey of Income and Program Participation, 1996-2003.

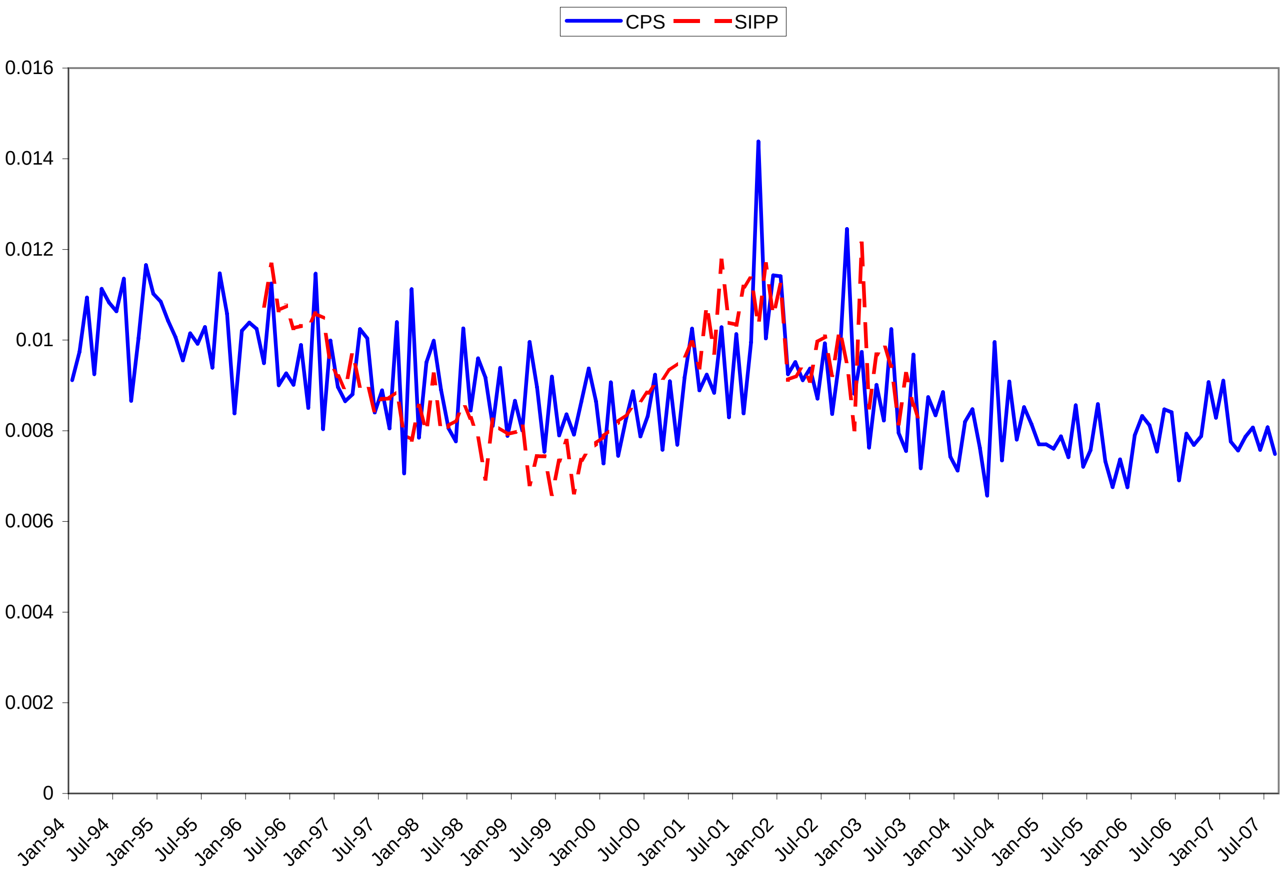

Figure 7. Comparison of the seasonally-adjusted employment-to-unemployment transition probabilities in the Current Population Survey, 1994-2007, and the Survey of Income and Program Participation, 1996-2003.

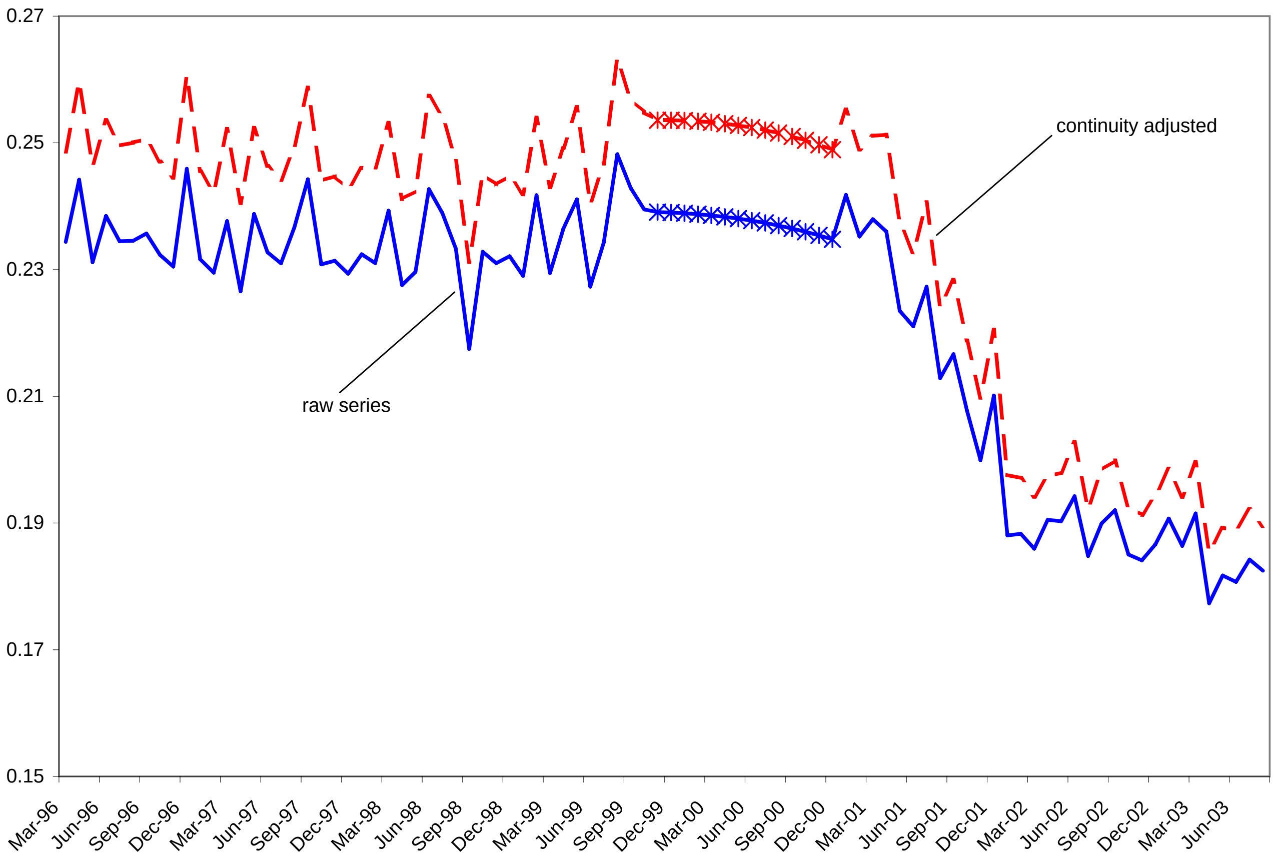

FIGURE 8. Seasonally adjusted unemployment-to-employment transition probability in the Survey of Income and Program Participation, 1996-2003, unadjusted and adjusted for time aggregation. Asterisks mark extrapolated observations.

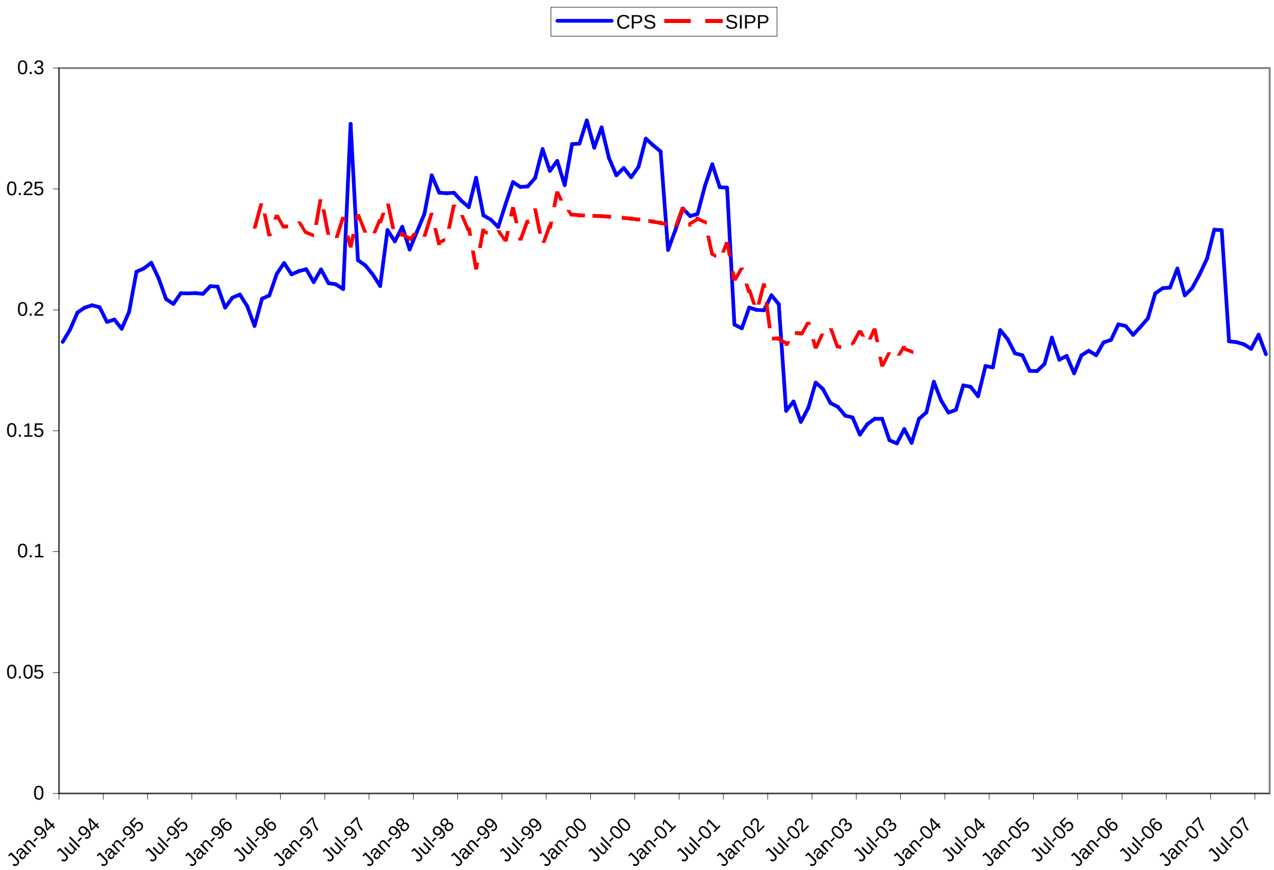

FIGURE 9. Comparison of the seasonally-adjusted unemployment-to-employment transition probabilities in the Current Population Survey, 1994-2007, and the Survey of Income and Program Participation, 1996-2003.

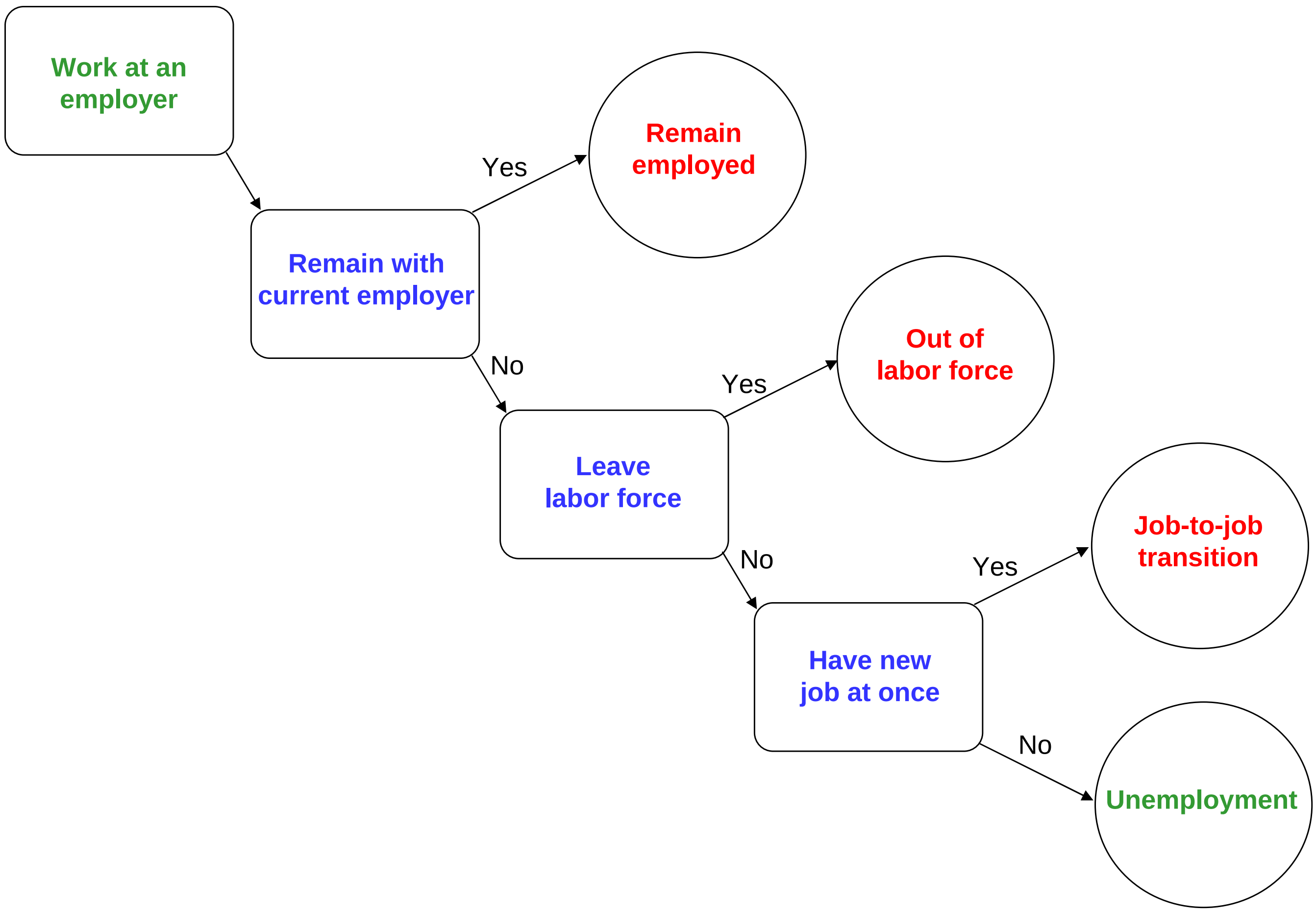

FIGURE 10. The decomposition of the employment-to-unemployment probability into its three components.

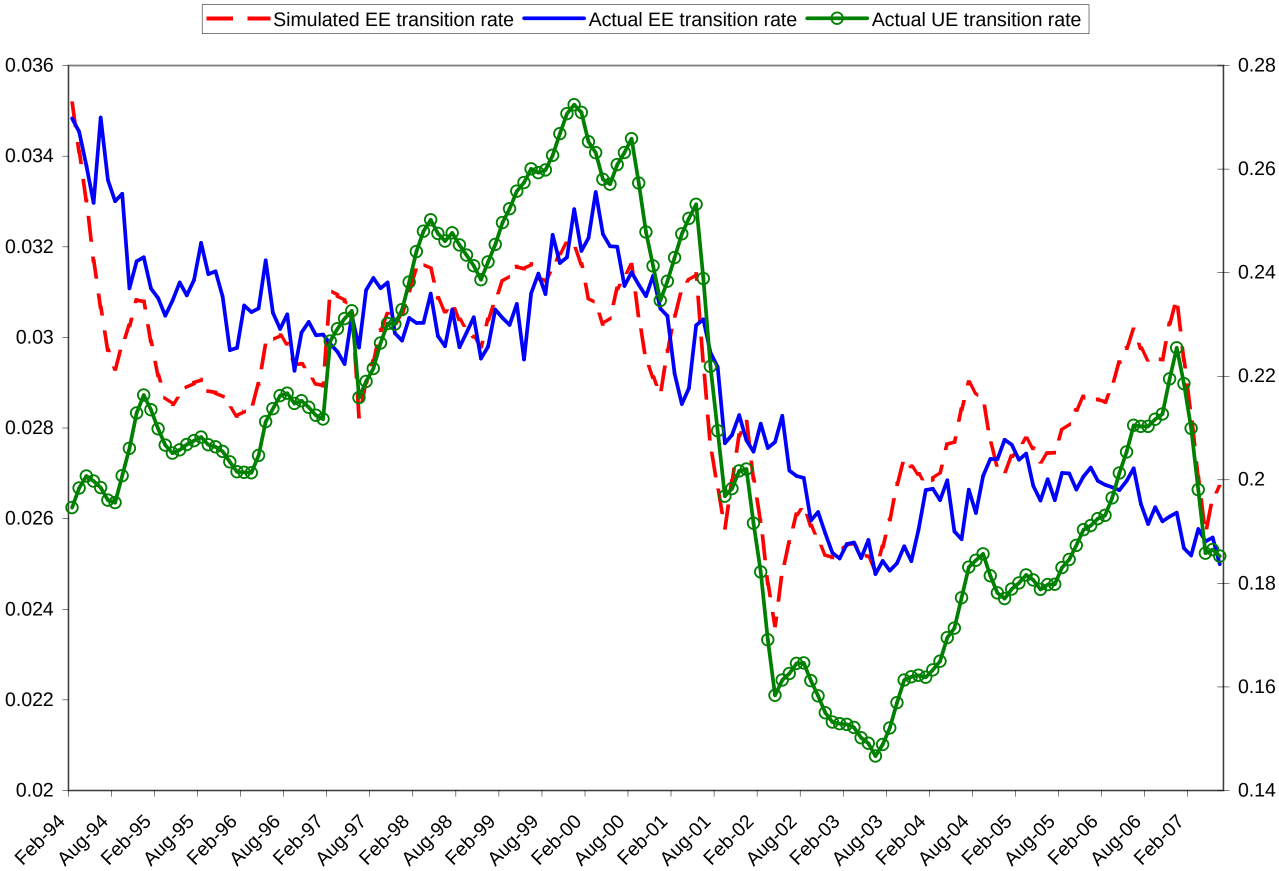

FIGURE 11. Actual employer-to-employer transition rate (left axis) and unemployment-to-employment transition rate (right axis) in the Current Population Survey, 1994-2007, and employer-to-employer transition rate simulated using the theoretical model (left axis).

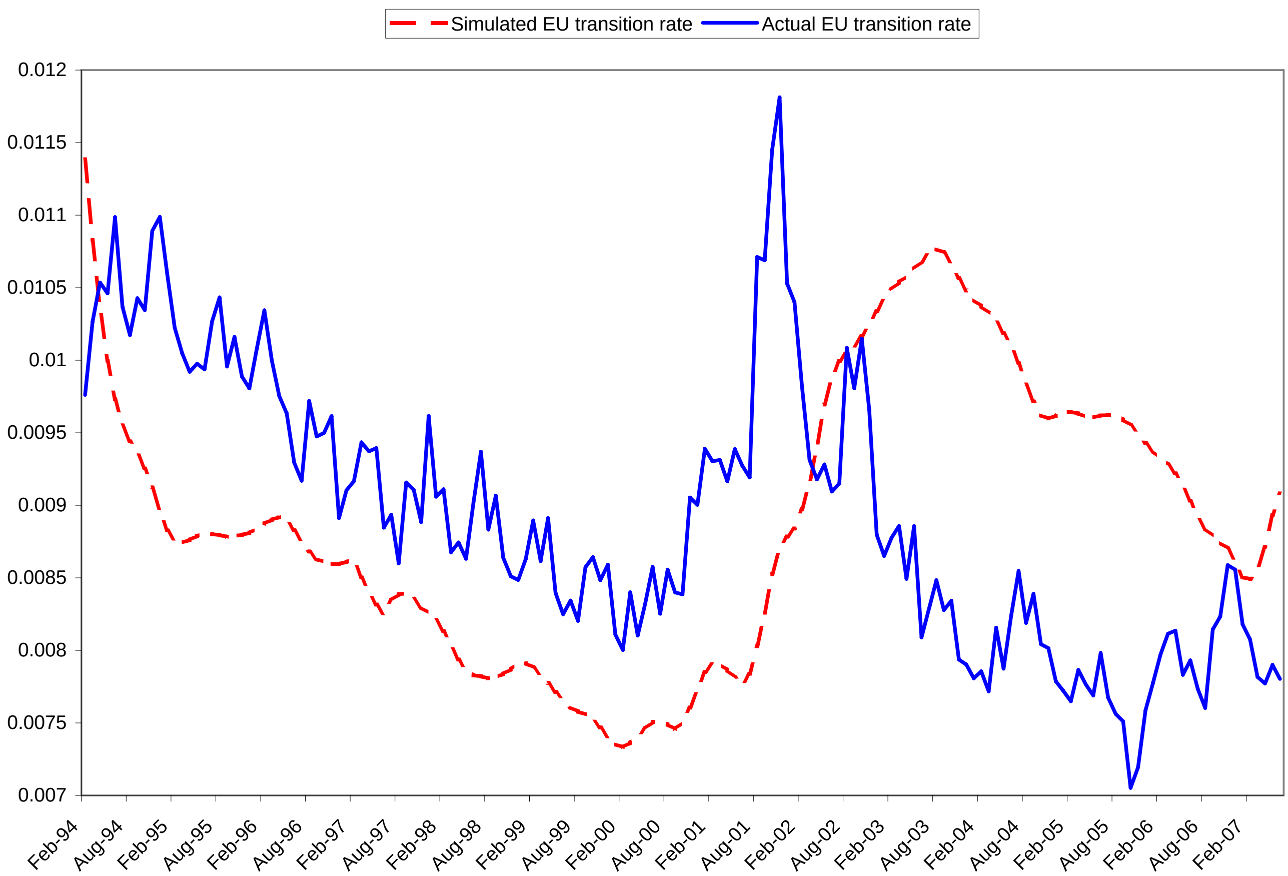

FIGURE 12. Actual employment-to-unemployment transition rate in the Current Population Survey, 1994-2007, and employment-to-unemployment transition rate simulated using the theoretical model.