New Data on Worker Flows During Business Cycles

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The most obvious economic cost of recessions is that workers become involuntarily unemployed. During the average business cycle contraction, total employment declines by about 1.5 percent, the unemployment rate rises by 2.7 percentage points, and it takes almost two years before employment recovers its pre-recession level. In the worst of the postwar recessions (July 1981 through November 1982), the unemployment rate rose to nearly 11 percent of the employable labor force, employment declined by 3 percent or almost 3 million jobs, and it was 27 months before the level of employment regained its mid 1981 level. If a recession is seen as a disruption in the economy from its *trend* rate of employment growth—about 2 percent per year over the past 25 years (including recession periods)—the time elapsed before the economy regains its trend is significantly longer, averaging four and one-half years.[1] Viewed through these aggregate statistics, recessions entail large and long-lived disruptions to the normal path of employment growth, characterized by significant increases in the ranks of the unemployed.

Both fiscal policy and monetary policy are concerned with these business cycle deviations of employment from its "full-employment" or "potential" or "equilibrium" level. If monetary policy, for example, is to stabilize employment around its full-employment level, it should have a good idea of what that full-employment level looks like. And yet economists have achieved little agreement on what constitutes a full-employment equilibrium. Many central banks use the NAIRU or an equivalent concept as a proxy for the equilibrium level of unemployment, but the equivalence of the NAIRU and equilibrium unemployment is not guaranteed by economic theory.[2] Moreover, to the extent that they *are* linked, researchers may want to uncover shifts in the NAIRU through methods other than the indirect evidence from Phillips curve regressions.

In addition, the aggregate statistics on employment and unemployment mask economically important information about the composition of the unemployed and their experience over time. This paper will examine the differential experience during a business cycle of those who are *voluntarily* unemployed (those who quit their jobs), those who are *temporarily* unemployed (those on layoff subject to future recall), and those who are *involuntarily* unemployed (those who suffer permanent job separations). In addition to the sensitivity of these three classes of unemployed to business cycle fluctuations, we will examine the differences in the duration of unemployment spells, by reasons for unemployment, for all those currently unemployed and (using a new data set) for those who leave unemployment to take jobs or to leave the labor force. The ability to obtain a new job may depend on the duration of

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one's unemployment spell (see, for example, Hall 1995), so the economic welfare implications of an unemployment spell can be linked to its duration. Intuition suggests, and we will document, that the durations of completed spells of unemployment suffered by these three different classes of unemployed persons differ significantly. Finally, we find that disaggregating unemployment duration by destination after unemployment provides the beginnings of an explanation of the relatively high duration of unemployment spells observed in the late 1990s.

Using a new data set that assembles the flows of workers into and out of unemployment (for all reasons), employment, and not-in-the-labor-force, we will examine the behavior over time of workers who enter and leave the ranks of the unemployed, grouped by the reasons for unemployment described above. By doing so, we hope to gain a better understanding of the economic losses suffered by the unemployed during recessions and to make some progress toward characterizing what a "normally functioning" or equilibrium labor market looks like from this worker flow perspective.

Many models of inflation suggest that the state of labor markets relative to their equilibrium has an important influence on the evolution of inflation. Underlying these models is the notion that "tight" labor markets—markets with few unemployed workers relative to the demand for labor—will produce upward pressures on wage inflation. The most common proxy for labor market tightness is the deviation of the unemployment rate from the NAIRU. But it is likely that not all changes in the unemployment rate arise from the same underlying labor market conditions. Thus, a closer look at the flows into and out of unemployment that lie beneath changes in total unemployment may improve our predictions of wage and price inflation.

In fact, we find that our more detailed information on labor market conditions does improve forecasts of inflation and unemployment, relative to standard models (an expectations-augmented Phillips curve and a demographically adjusted Okun's Law, respectively). The time series that we develop for flows into and out of unemployment by reason not only add significantly to the explanatory power of a benchmark Phillips curve, they supplant the unemployment rate as a labor market indicator. Disappointingly, despite this overall improvement in the simple inflation forecasting equation, the worker flows do not explain the over-forecasting of most inflation equations over the past several years. In addition, we find that incorporating data on the duration of completed unemployment spells improves forecasts of unemployment from Okun's Law, even after important demographic trends are taken into account. The recent under-forecasting of unemployment from many Okun's Law relationships is rectified by this addition.

I. Earlier Research on Labor Market Flows

For almost as long as there has been a monthly labor force survey, the U. S. Bureau of the Census and the U.S. Bureau of Labor Statistics (BLS) have constructed gross flows among the labor force states of employment, unemployment, and not in the labor force. (We will often use the abbreviations E, U, and N to represent these states.) Each flow represents the

[1] These computations include all the recessions from 1960 to the present. Trend employment growth is computed from a logarithmic time trend with a split in 1974. The time to reattain trend does not include the 1980 "credit crunch" recession, as employment never fell below trend in that brief episode.

[2] James Tobin's 1972 presidential address to the American Economic Association provides a number of reasons why the two concepts might differ.

number of workers who make a transition from state *i* to state *j*. Researchers have shied away from making extensive use of these flows because of concerns about the quality of the data. It has long been known that misclassifications of labor force status can cause the measured flows to dramatically overstate actual movement in the labor market, particularly between states that are similar. Misclassification can also affect, to a lesser degree, differences in labor market characteristics between different demographic groups. In addition, transitions (at monthly rates) are relatively rare and thus are vulnerable to the noise characteristic of any binomial process. Various researchers have looked at these problems over the past 20 years.

Research on labor-market flows considers two varieties: flows of workers and flows of jobs. Job flows in theory measure whether a new position has been created or destroyed by a firm, rather than changes in the labor market status of a worker. Two principal summary studies of time series properties of worker flows and job flows have been conducted by Blanchard and Diamond (1990) and Davis, Haltiwanger, and Schuh (DHS 1996), respectively. The worker flows

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measure month-to-month transitions in labor-force status of workers surveyed in the Current Population Survey (CPS). DHS use the net changes in employment at individual manufacturing plants in the Longitudinal Research Database (LRD) to measure gross changes in manufacturing employment: job creation and destruction. As such, these statistics do not measure precisely the same concept. Nevertheless, a central observation of each study is that separations from employment are more volatile than movements into employment. That is, the amplitude of time series fluctuations in the flow out of employment is greater than that for the flow into employment in the worker data, and job destruction fluctuates more than job creation in the establishment data.

Figure 1 presents gross worker flows into and out of employment for all industries over the past three decades, scaled by the working-age population. These data come in part from published tabulations by the BLS and in part from our own computations using the CPS micro data.[3] "Eyeballing" the figure, one can see this feature: The time series of flows out of employment (the red line) contain periodic spikes, particularly during recessions. The flows into employment (the black line) move around during the business cycle, but not nearly as much. Indeed, once the trend is removed, the flows out of employment have more than twice the variance of the flows into employment. This observation may be a bit too stylized: Foote (1998) looked at job flows using methodology similar to DHS, but was not restricted by his data set to the manufacturing sector alone.[4] He found that in some industries job creation was the more volatile of the two flows, and that this feature was strongly related to net employment growth in those sectors. For our purposes, this points to a heterogeneity that is present in the worker flows as well. Perhaps a better understanding of worker flows during the business cycle can be gained by looking at flows disaggregated by industry. We present some preliminary results in Section IV, below.

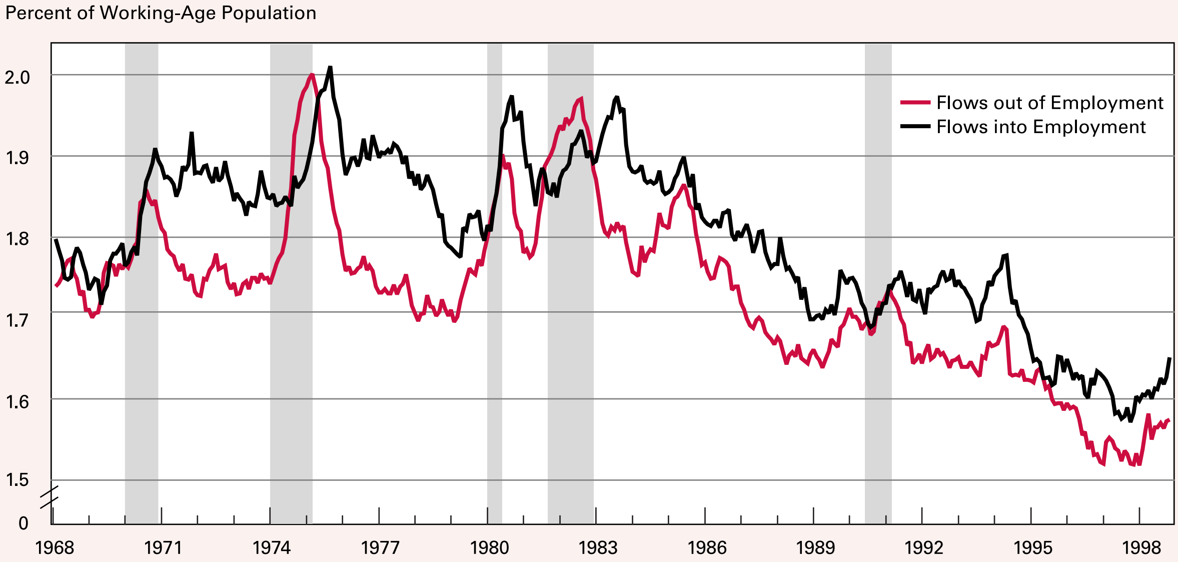
The figure also suggests another important feature of the flows data: Abstracting from business cycles, we see a plateau or perhaps a modest increase in the early 1980s and a substantial falloff since then. As noted by Bleakley and Fuhrer (1997), these changes in worker flows coincide with the entry of the baby boom generation into the labor force (initially passing through years of weaker attachment to employment) and its subsequent maturation (and greater labor force attachment). Thus, when discussing the cyclical properties of worker flows, one also needs to take some account of movements at other frequencies. At the lower frequencies, an important factor will be changes in demographics: the age structure of the labor force, the participation of women, and retirement patterns. At higher frequencies, seasonal factors play a large role in the observed worker flows (for example, the large movements in and out of the labor force related to the academic calendar). We briefly discuss these

[3] We are grateful to Olivier Blanchard for providing the earlier data with the Abowd-Zellner adjustments, and we also thank Joe Ritter for providing more up-to-date time series. Our component of the displayed time series begins in February of 1976. For the time period in which these series overlap, there remain some differences among these series. None of these differences influence the broad patterns highlighted in the text. We describe how we constructed our series in the next section. (Our methodology is substantially similar to that of the BLS.)

[4] He was, however, restricted to data from firms in Michigan only, since he used records from that state's unemployment insurance system.

Figure 1

Gross Worker Flows into and out of Employment



Note: Nine-month centered moving average, seasonally adjusted and Abowd-Zellner mean adjusted. Shadings indicate recessions.
Source: U.S. Bureau of Labor Statistics, Current Population Survey micro data.

other features while discussing the cyclical properties below.

In addition, this secular decline in the flows does not seem consistent with stories of restructuring or reallocation that abounded in the early stages of the recovery from the 1990–91 recession. As we will see below from a number of perspectives, the flow data generally paint a fairly consistent picture of a very strong and healthy labor market with a level of reallocation or "churning" that is consistent with the rapid growth in GDP and employment and low levels of aggregate unemployment.[5]

Another feature of the worker flows data noted by Blanchard and Diamond (1990) is that flows between E and U are markedly different from those between E and N. The E↔U flows are sharply countercyclical (that is, they go up during recessions) and the E↔N flows are cyclical. Blanchard and Diamond tell a story of "primary" and "secondary" workers, who pass through U and N, respectively, when not employed. Primary workers have a strong attachment to employment (for whatever reason) and thus only separate from jobs involuntarily. Firms prefer to hire primary workers when available, and they are mostly available during recessions when masses of them have suffered involuntary terminations. Secondary workers are hired (N→E) only in booms, when primary workers are not available for hiring.

Whether or not this story is valid, it is clear that the U/N distinction is important to our understanding of the cyclicality of flows. It is this heterogeneous response to the business cycle that motivates us to look at the data at a more disaggregated level. In our work, we extend the disaggregation to include flows into and out of unemployment by various reasons for separation (quit versus termination versus temporary layoff). Several authors have approximated the flows *into* unemployment using the CPS tabulations of unemployment by reason, for duration of five weeks or less. None of these previous studies has been able to examine flows *out of* unemployment by reason, or to determine *from where* detailed inflows to unemployment come (for example, employment versus not in

[5] A more accurate measure of restructuring may be gained from an examination of the fraction of workers who make labor market transitions that entail a switch in occupation and/or industry. The CPS data set allows such a comparison, and we plan to examine this question in more detail in later work.

the labor force, from which sector). Nor have previous studies examined the duration of unemployment spells, breaking them down by reason for unemployment or by how that spell was eventually completed (for example, by finding a job or by getting discouraged and discontinuing the job search). We present some evidence below that these decompositions matter for our understanding of the labor market.

II. Data Used in This Study

Our data are constructed from the monthly Current Population Surveys (CPS). These surveys are conducted by household but also provide information on individuals in the household. We have compiled all of the monthly surveys from January 1976 through March 1999 and computed worker flows for each month in that period. A host of difficult data construction issues surround the use of the survey; many are summarized in the Data Appendix, and we touch on a few key issues here. We do this first by describing the time series we wish to construct, and then by sketching the recipe for constructing them.

The two primary constructs that this paper examines are worker flows and unemployment duration statistics. Worker flows are changes in the employment status of individuals from one month to the next. For example, a worker who makes a transition from employment (E) to unemployment (U) is counted as one E to U flow for the month in which the transition to U occurs. The aggregate flows presented here are the population-weighted sums of all workers who make such transitions.

Several problems complicate the construction of these flows. The procedure begins with CPS micro data from two consecutive months. To compute worker transitions, we have to observe a given worker in both months. This involves matching workers across the two months using CPS identification codes and observable characteristics. Not all workers can be matched, so we reweight the matched workers to represent the U.S. population. At this point, we choose a categorization scheme for labor force status. Cross-tabulating the labor force status in each month gives us a matrix describing the gross flows for that month. (Alternately we tabulate median duration for the relevant transitions, giving more detailed statistics on completed spells of unemployment.) Repeating this process for each pair of adjacent months in the sample generates time series of gross worker flows. We then adjust the time series for seasonal factors, misclassification errors, and methodological breaks in the survey design. The remainder of this section describes this procedure in greater detail.

The CPS is a monthly survey of 60,000 households. Participants are in the survey for a 16-month period, with a "4–8–4" pattern: four months in the survey, eight months out, four months in again. The CPS uses a rotating panel, meaning that part of the sample is changed each month. As a result it is not possible to match one-quarter of the individuals between any two consecutive months, as they have "rotated out" of the sample.

The survey is organized by household, with a unique household identifier. The survey also includes unique line numbers for each individual in the household, but this feature is not always perfectly implemented, so we use other information to track the same individual from one month to the next. We use several combinations, including age, sex, and educational attainment. In some cases, individuals join or leave the household, making matches impossible. In addition, households may move, making it impossible to match any of the individuals in the household the next month.

In order to generate flows that are representative of the U.S. population, we use the Census/BLS sampling weights. However, since we can only match a fraction of the sample, we have to modify these weights for the matchable subsample. If match failure were a perfectly random event, then it would suffice to simply reassign the weight from the unmatched observations proportionately to the matched ones. We used logit regressions to analyze patterns in matching. These regressions suggest that almost every observable characteristic can be significantly linked to an increased or decreased probability of matching. We therefore divide the sample up into cells based on observable characteristics and redistribute weights *within* cells. This controls for the disproportionate representation of various subgroups in the unmatched group. In practice, we find that the flows are substantially similar whether we divide the sample simply using gender or using everything observable.

After we reweight the matchable sample, we choose the level of detail for which we categorize labor force status. The literature on gross worker flows has heretofore used employment, unemployment, and not in the labor force (E, U, and N, respectively). To this we add breakdowns of unemployment by reason. These "reasons" for spells of unemployment as measured by the CPS consist of a permanent termination, a quit, a temporary layoff, a new entrance, and a reentrance to the labor force (UT, UQ, UL, UNE, and URE, respectively). In addition to U by reason, we disaggregate by single-digit industry of employment.

The duration statistics are compiled from workers who are completing an unemployment spell, that is, workers who make a transition out of unemployment. These data provide a new and potentially important source for studies of unemployment duration. Previously, duration has been estimated from the sample of all unemployed workers, some of whom just started a spell, some of whom were midway through, and some of whom were finishing a spell. Data on the duration of completed unemployment spells, with particular attention to *how* these spells are completed, can add to our picture of how the labor market is functioning.

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The matched sample is then cross-tabulated according to the chosen breakdown, and gross flows (or duration statistics) are computed for that particular set of consecutive months. For certain months, the household indentifiers were scrambled by the Census Bureau for privacy considerations. We are unable to compute flows across these few months. (See the Data Appendix for a complete listing.) The quarterly flows presented in the empirical section below use averages of the months available in the quarter.

After the time series of the flows are generated, they require several adjustments. We discuss seasonal adjustment below. Next, the series require adjustment for misclassification error in labor force status. Perhaps because of ambiguities in the survey questions, or recording errors or simple mistakes on the part of the respondents, some individuals answer incorrectly as to their employment status (as unemployed when they are really not in the labor force, to take a leading example). An error would show up as a transition even when none actually occurred. It is for this reason that many of the flows are thought to be substantially biased. The effect of misclassification error has been studied by Abowd and Zellner (1985) and by Poterba and Summers (1986) using the CPS reinterview survey. This survey is conducted by a more experienced interviewer for a sample of households the week after the original survey to check results and to reconcile any apparent inconsistencies in responses. Misclassification errors have been computed by Abowd and Zellner from the reinterview surveys only up until 1986, and only for the aggregated employment status codes E, U, N. Without considerable additional effort to tabulate the reinterview surveys for more years and without more categories, we cannot improve on their adjustments. In the data presented below, we use average misclassification probabilities from Abowd and Zellner to adjust the levels of flow series in figures (of course, the average levels of the flows do not matter for regression analysis). In subsequent work, we plan to obtain additional reinterview surveys and compute adjustment factors for the complete sample.

Changes in the CPS survey methodology can also render certain measures not comparable from one month to the next. The most pronounced of these is the January 1994 CPS redesign, implemented to improve the collection of labor force information. For example, in order to be classified as unemployed, on temporary layoff, respondents must now provide a date when they expect to be recalled to work. We apply corrections estimated by Polivka and Miller (1998) from a survey that overlaps the pre-1994 and post-1993 surveys. While they found monthly measures of E, U, and N to be largely unaffected by the redesign, measures of the stock of unemployed by reason were affected, as were duration measures. The redesign also changed the "topcoding" of duration from 99 weeks to 999 weeks. Estimates of the mean duration will be influenced by the topcoding, so we focus primarily on *median* unemployment duration estimates.

It should be clear from this section that the process for generating these data is far from perfect. Nevertheless, we believe that our efforts reflect a good compromise given the available data. Moreover, we present evidence of substantial benefits to using gross worker flows at these added levels of disaggregation.

III. Business Cycle Characteristics of Worker Flow Data

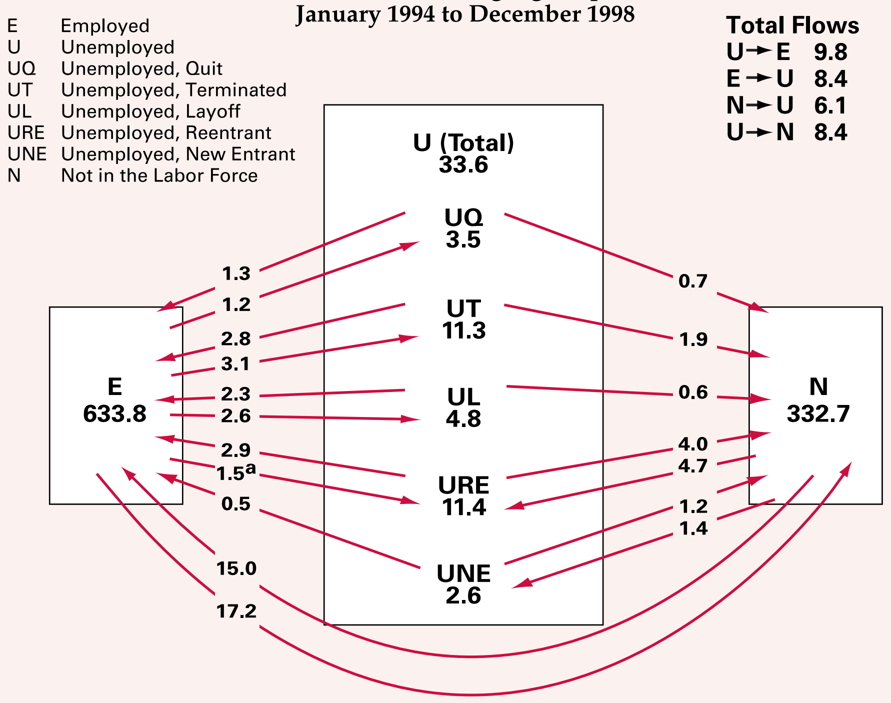
In this section we present time series on worker flows among E, U, and N, and also in and out of U disaggregated by reason for unemployment. As has been discussed above, we are interested in flows into and out of U because we suspect that the reasons for unemployment spells and the unemployment experience for workers who are on layoff[6] or who quit may differ substantially from those for workers who have been permanently separated from their jobs. Below, we show that both the cyclical sensitivities of these subcategories and the durations of their unemployment spells differ significantly.

In what follows, we adopt the following notation to refer to disaggregated unemployment states. The three categories of unemployment that include those who came from E are quits, UQ, terminations (or permanent separations), UT, and layoffs, UL. Entrants from N into the labor force who are currently unemployed are either reentrants, URE, or new entrants, UNE. Directions of flows among these categories are indicated by an arrow (→); for example, the flows from employment into layoffs are abbreviated as E→UL.

Figure 2

Average Monthly Values of Gross Stocks and Flows for Employment, Unemployment, and Not in the Labor Force

Per Thousand Working-Age Population
January 1994 to December 1998



[a] We present worker flows that generally make logical sense. One exception is flows from employment to the unemployed, reentrant category. This category serves as a "catch-all" for the unemployed who do not choose another reason for unemployment and have been employed at some point previously.
Source: U.S. Bureau of Labor Statistics, Current Population Survey micro data, and authors' calculations.

Before analyzing these data at business cycle frequencies, we first discuss aspects of the data at lower and higher frequencies. Figure 2 displays the average monthly gross flows during the period between January 1994 and December 1998, and the stocks of workers, computed using the matchable sample for consistency. The stocks that dominate the picture are employment and not in the labor force. The flows between these two states are also large. Flows between U and E are somewhat smaller, largely because the period is a time of economic expansion. Nevertheless, in spite of the strong economy, flows between E and "involuntary" unemployment (terminations and layoffs) are still larger than quits.

Table 1 highlights the seasonal variation in these worker flows, using a regression of the logarithm of the flows on monthly dummies.[7] Columns 1 and 2 display the extremes of each flow, along with the months in which they occur. Column 3 indicates how

[6] From here forward references to "layoff" will connote a temporary layoff. Longer-term layoffs, without promise of future recall, are indicated by "termination," or permanent separation.

[7] Note that this method implicitly assumes a fixed seasonal factor for each month of the year. This need not be the case. We have compared the results of the regression method with an X-11 seasonal adjustment procedure, and found the results to differ relatively little.

Table 1

Regression Results: Seasonal Properties of Gross Worker Flows by Reason for Unemployment

February 1976 to March 1999

	(1) Max. Seasonal Coefficient (Month)	(2) Min. Seasonal Coefficient (Month)	(3) R-squared
Flows out of Employment			
E →			
N	.44 (Sep.)	−.23 (Mar.)	.82
U (layoffs)	.56 (Jan.)	−.24 (Sep.)	.46
U (quits)	.20 (Sep.)	−.31 (Dec.)	.31
U (reentrants)	.28 (Sep.)	−.20 (Dec.)	.48
U (terminations)	.27 (Jan.)	−.11 (May)	.17
Flows out of Not in the Labor Force			
N →			
E	.32 (Jun.)	−.22 (Dec.)	.73
U (new entrants)	.71 (Jun.)	−.32 (Dec.)	.71
U (reentrants)	.26 (Jun.)	−.25 (Dec.)	.54
Flows from Unemployment to Employment			
→ E			
U (layoffs)	.37 (Apr.)	−.30 (Nov.)	.50
U (new entrants)	.79 (Jul.)	−.51 (Jan.)	.72
U (quits)	.23 (Sep.)	−.32 (Jan.)	.39
U (reentrants)	.33 (Jul.)	−.41 (Jan.)	.74
U (terminations)	.12 (Apr.)	−.19 (Dec.)	.17
Flows from Unemployment to Not in the Labor Force			
→ N			
U (layoffs)	.24 (Feb.)	−.21 (Oct.)	.25
U (new entrants)	.33 (Aug.)	−.16 (Jun.)	.39
U (quits)	.06 (Aug.)	−.09 (Jun.)	.05
U (reentrants)	.10 (Apr.)	−.13 (Jun.)	.15
U (terminations)	.12 (Jan.)	−.09 (Oct.)	.03

much of the (log) variance is explained using this rather simple seasonal adjustment procedure. A seasonal factor that apparently plays an important role is the school calendar: Flows with the greatest seasonal component ($R^2>.5$) all have peaks that are likely due to students and summer employment.

While we suggest that it is important to note that these cycles are going on in the background, in what follows we remove the seasonal component of each flow series using the regression method described above. Turning to the business cycle frequencies, we begin by focusing on the cyclical sensitivity of flows between E and U. Figure 3 displays flows from E to U (scaled by employment) by reason for unemployment. Most of the flows behave as one might expect. The flow into voluntary quits declines fairly sharply during recessions, consistent with the notion that quits are largely motivated by prospects for finding another job.

"Involuntary" separations—both layoffs and terminations—rise sharply during recessions and gradually taper off during the expansions that follow. Interestingly, temporary layoffs appear to have been relatively more important in the earlier recessions than in the 1990–91 recession. Controlling for the magnitude of the recession, terminations rose to a higher level and remained relatively high well after the 1990–91 recession ended. Unlike the period following the 1980s recessions, quits remained low after the 1990–91 recession and still have not regained their late 1980s peak, a fact that is particularly striking given the very low levels of aggregate unemployment in the late 1990s. Clearly, the outflows from E to U vary across the business cycle, and these data provide some evidence that the sensitivity and composition of flows from E to U by reason have changed over the past 20 years.

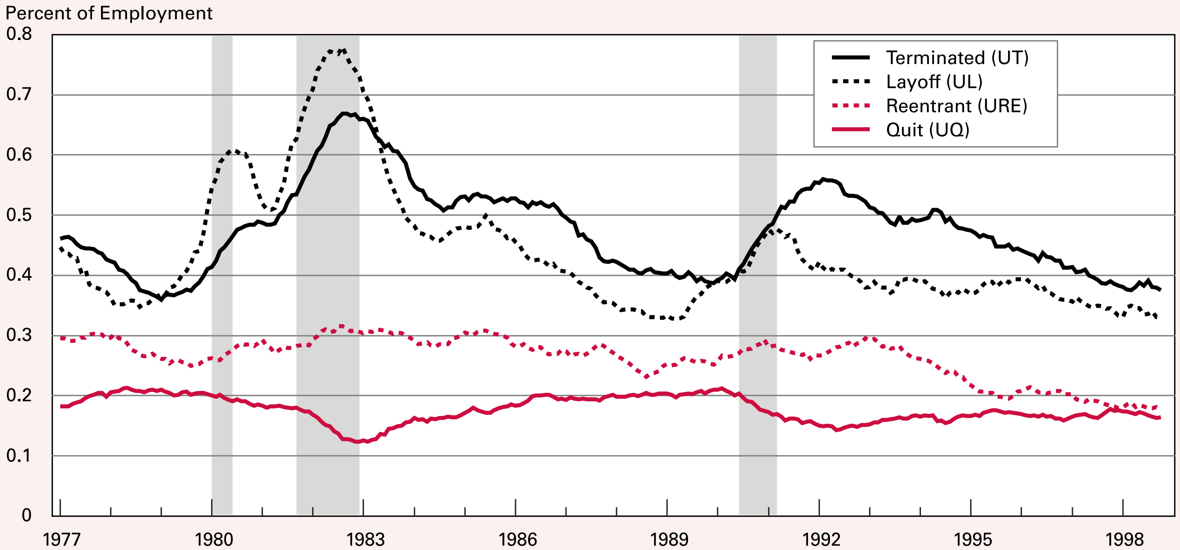
Of course, loss of employment is less costly if one is more likely to quickly find a job while unemployed. The probability of leaving unemployment—the "escape rate" from U—is therefore critical in assessing the welfare cost to individuals who are unemployed. Figure 4 displays these escape rates from unemployment, by reason, where the escape rate is defined as the ratio of the U→E flow by reason to the stock of those unemployed for that reason.[8]

As the figure suggests, recessions are (not surprisingly) not good times to become unemployed. The probability of finding employment while unemployed

[8] In computing escape rates, we use the stocks of unemployed from the sample that is used to compute the flows, rather than the published stocks of unemployed from the overall CPS sample.

Figure 3

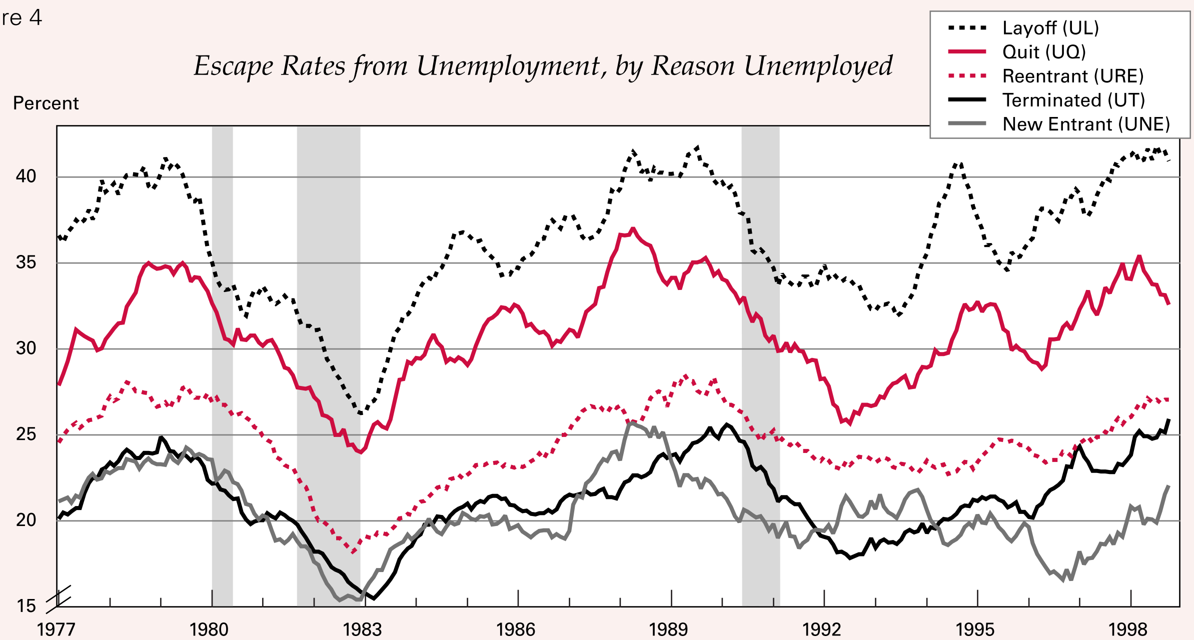
Flows out of Employment, by Reason for Unemployment



Note: 11-month centered moving average, seasonally adjusted, Abowd-Zellner mean adjusted, and Polivka-Miller adjusted. Shadings indicate recessions.
Source: U.S. Bureau of Labor Statistics, Current Population Survey micro data, and authors' calculations.

Figure 4

Escape Rates from Unemployment, by Reason Unemployed



Note: Escape rate is percent of unemployed in category who become employed. Data expressed as 11-month centered moving average, seasonally adjusted, Abowd-Zellner mean adjusted, and Polivka-Miller adjusted. Escape rates are adjusted for the 1994 redesign, using coefficients from a regression that includes one lag of the escape rate and a redesign dummy. Shadings indicate recessions.
Source: U.S. Bureau of Labor Statistics, Current Population Survey micro data, and authors' calculations.

drops precipitously during recessions, for all those unemployed. The ordering from top to bottom of the lines in Figure 4 conforms to our understanding of the reasons for unemployment. Workers on temporary layoff have a job waiting for them, and thus their escape rate is uniformly highest, although it still displays declines of 10 percentage points or more during recessions. Voluntary quits are next highest, which suggests that on average, workers quit when prospects for reemployment are significant. The lowest escape rates are registered for terminations and new entrants. By the first quarter of 1999, the last quarter for which we have complete data as of the time of writing, all of the escape rates except for those new entrants were at or very near historic peaks. It would appear that, confirming evidence from the aggregate data, the late 1990s have been a good time to escape unemployment.

Table 2
Regression Results: Seasonal Properties of Gross Worker Flows by Industrial Sector
February 1976 to March 1999

	(1) Max. Seasonal Coefficient (Month)	(2) Min. Seasonal Coefficient (Month)	(3) R-squared
Flows out of E into U or N			
Agriculture	.41 (Sep.)	−.41 (Mar.)	.71
Construction	.36 (Jan.)	−.20 (May)	.59
FIRE	.36 (Sep.)	−.17 (Dec.)	.32
Manufacturing Durables	.23 (Sep.)	−.13 (Mar.)	.27
Manufacturing Nondurables	.25 (Sep.)	−.11 (Dec.)	.34
Mining	.46 (Jan.)	−.39 (Jul.)	.01
Public Administration	.62 (Sep.)	−.33 (Mar.)	.48
Retail Trade	.38 (Sep.)	−.20 (Dec.)	.70
Services	.30 (Sep.)	−.20 (Dec.)	.73
Transportation	.27 (Sep.)	−.16 (Dec.)	.40
Wholesale Trade	.31 (Sep.)	−.15 (Mar.)	.26
Flows out of U or N into E			
Agriculture	.44 (Jun.)	−.42 (Dec.)	.63
Construction	.28 (Jun.)	−.33 (Dec.)	.65
FIRE	.22 (Jun.)	−.25 (Dec.)	.30
Manufacturing Durables	.18 (Jun.)	−.32 (Dec.)	.32
Manufacturing Nondurables	.24 (Jun.)	−.26 (Dec.)	.36
Mining	.42 (Jun.)	−.43 (Dec.)	.09
Public Administration	.44 (Jul.)	−.44 (Dec.)	.40
Retail Trade	.21 (Jun.)	−.21 (Jan.)	.43
Services	.29 (Sep.)	−.23 (Dec.)	.67
Transportation	.24 (Jun.)	−.16 (Nov.)	.29
Wholesale Trade	.24 (Jun.)	−.22 (Dec.)	.24

IV. Industry Differences

The CPS data also allow us to examine transitions disaggregated by industrial sector. Such comparisons can shed light on debates over the extent to which patterns observed in manufacturing flows are typical of the rest of the economy. For example, Foote (1998) has questioned the comparability of job flows for nonmanufacturing sectors with flows calculated from the LRD for the downward-trending manufacturing sector. This section examines several of the summary statistics presented above for the all-industry aggregates for some key industry breakdowns, most notably manufacturing versus nonmanufacturing.

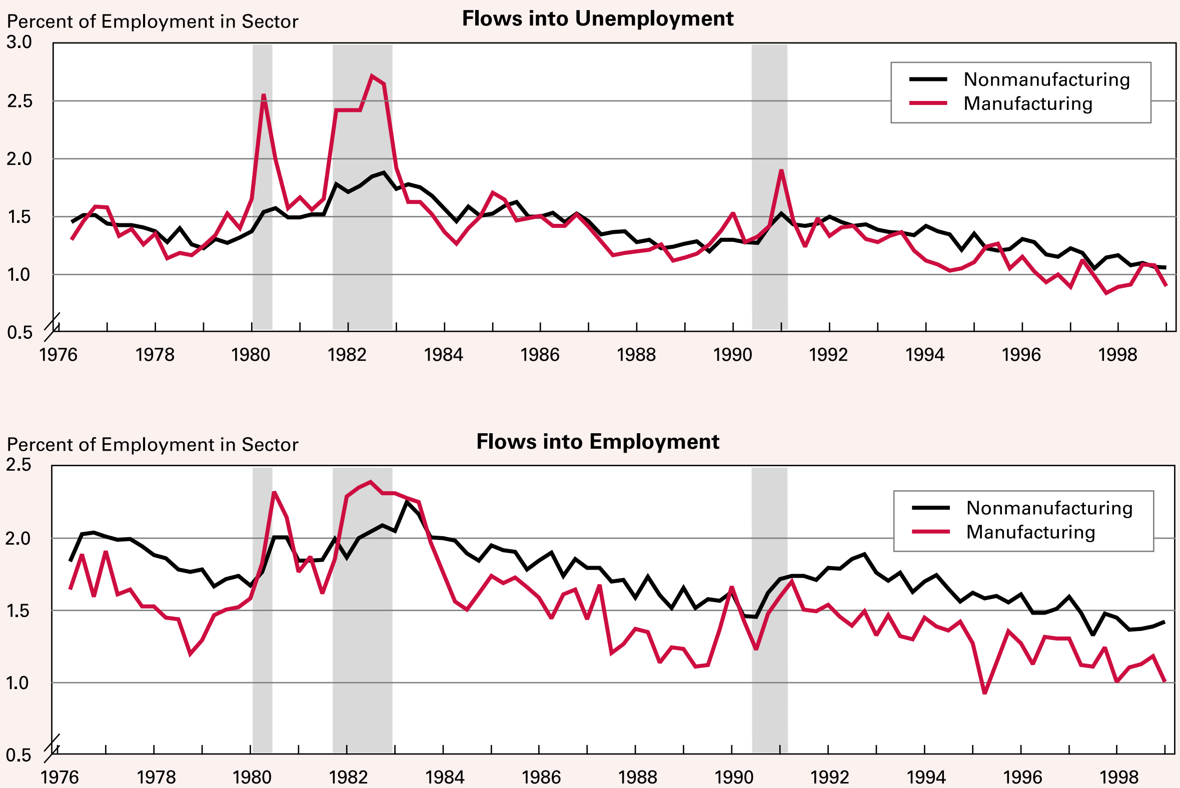
As in the previous section, we begin by examining the seasonal patterns in the industry data. As Table 2 shows, seasonal variation in flows accounts for from 1 to 73 percent of the flows' overall variation, with flows out of mining employment the least seasonal series, and construction, agriculture, and retail trade, not surprisingly, the most subject to seasonal fluctuations.[9] We remove the seasonal component of all of these series in the analysis that follows.

The top panel of Figure 5 displays the flows from E to U for the nonmanufacturing and manufacturing sectors, as a percentage of the workers employed in that sector. As the figure indicates, the manufacturing flows are considerably more volatile, and much more responsive to the business cycle. The surge in inflows into U during the 1980s recessions is roughly four times as large (relative to employment) in manufacturing as in nonmanufacturing (Table 3). Interestingly, the bulk of manufacturing's "excess volatility" for

[9] Somewhat more surprising is the seasonality into and out of services employment. For both inflows and outflows, the maximum seasonal factor occurs in September, suggesting that normal transitions into and out of school account for the seasonality.

Figure 5

Worker Flows in Manufacturing and Nonmanufacturing Sectors



Note: Quarterly averages of monthly data, seasonally adjusted, Abowd-Zellner mean adjusted, and Polivka-Miller adjusted. Shadings indicate recessions.
Source: U.S. Bureau of Labor Statistics, Current Population Survey micro data, and authors' calculations.

E→U flows is manifested in the upswings associated with recessions.

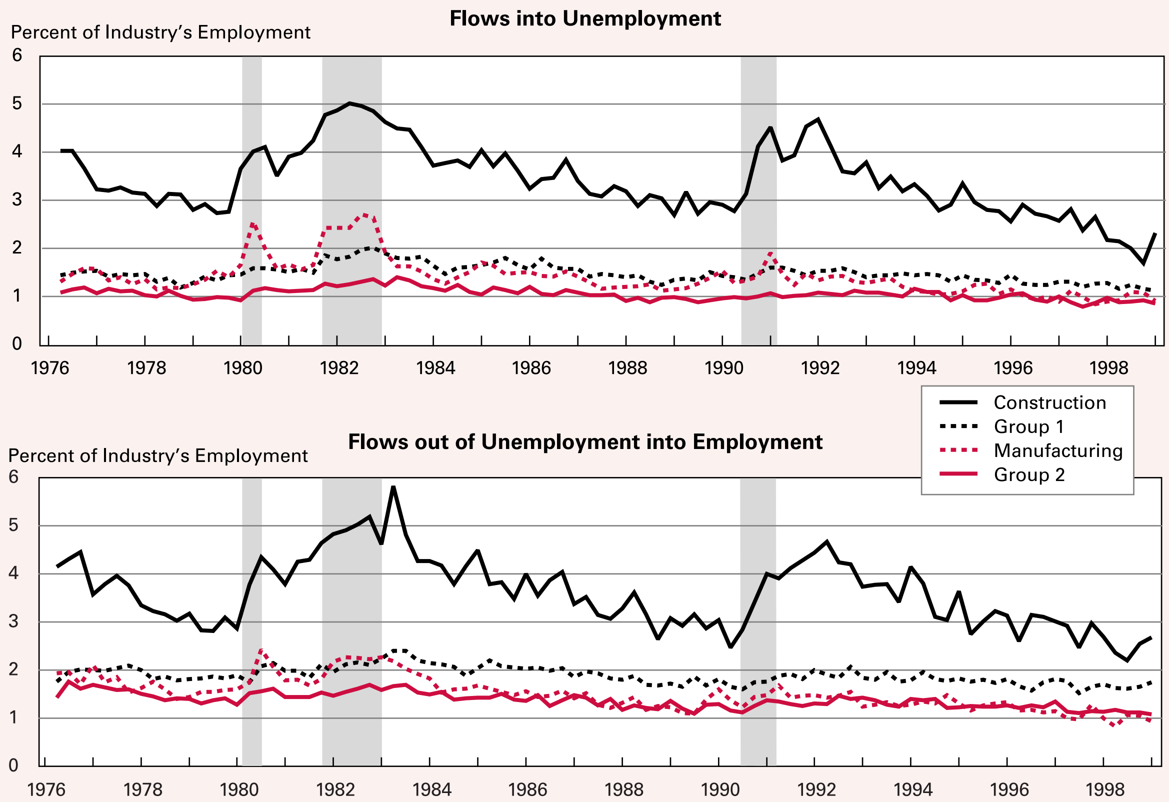
The bottom panel of Figure 5 shows that U→E flows for manufacturing again are both more sensitive to the business cycle and more volatile generally than flows for nonmanufacturing. As indicated in Table 3, the variance of flows in manufacturing between E and U is about four times that of flows in nonmanufacturing. While the difference in the peaks during recessions is not as great, the overall variance of manufacturing U→E flows is significantly larger than in nonmanufacturing (about three times the size). Many time-honored stories explain the heightened cyclical sensitivity of manufacturing, especially durables manufacturing, to business cycles. Still, the figure suggests caution in extrapolating from observations on the manufacturing sector to the behavior of the nonmanufacturing sectors of the economy.

Table 3
Variance of E and U Flows by Sector
February 1976 to March 1999

	Variance of E to U Flows (as a Percentage of Emp. Stock)	Variance of U to E Flows (as a Percentage of Emp. Stock)
Manufacturing	.16	.14
Nonmanufacturing	.04	.05
Construction	.64	.69
Retail Trade, Wholesale Trade, Transportation, Agriculture and Mining	.05	.05
Services, FIRE, and Public Administration	.02	.04

Figure 6

Worker Flows by Industry



Note: Group 1 is Trade, Transportation, Agriculture and Mining. Group 2 is Services, FIRE, and Public Administration. Quarterly averages of monthly data, seasonally adjusted, Abowd-Zellner mean adjusted, and Polivka-Miller adjusted. Shadings indicate recessions.
Source: U.S. Bureau of Labor Statistics, Current Population Survey micro data, and authors' calculations.

Figure 6 displays a more detailed breakdown of the flows between E and U by sector. Beyond the manufacturing/nonmanufacturing split discussed above, the flows fall into three categories. First, construction—even after adjusting for the tremendous seasonal fluctuations noted above—is the most turbulent sector in the economy, by a wide margin. As Table 3 shows, the variance of its flows between E and U is four to five times larger than the next most volatile sector, manufacturing.[10] From 2 to 6 percent of those employed in construction make an E→U or U→E transition in any quarter; the fraction is obviously highest during recessions. Second, the relatively placid services, FIRE (finance, insurance, and real estate), and public administration sectors (indicated by "Group 2" in the figure) experience the fewest worker transitions, generally around 1 percent of the employed. In the remaining sectors, which include trade, transportation, agriculture, and mining, (indicated by "Group 1" in the figure), 1 to 2 percent of the employed, on average, experience a transition. Manufacturing is considerably more volatile than Group 1, but the "normal" fraction of the employed involved in churning is about the same as that for trade and transportation, for example.

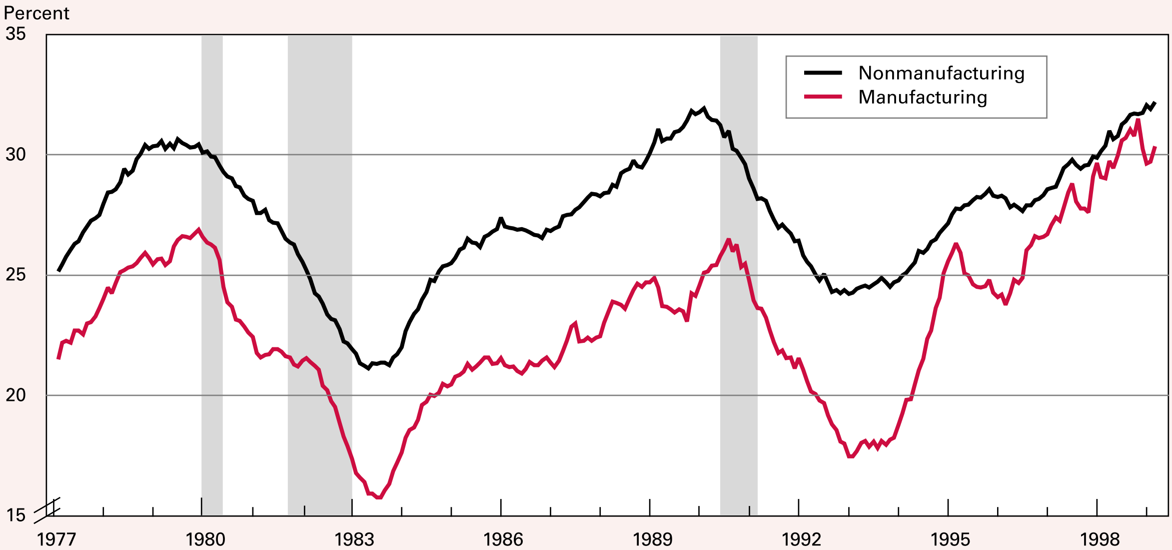
Figure 7 displays escape rates (ratio of U→E flow to stock) from unemployment to employment for workers who had been engaged in manufacturing and nonmanufacturing work.[11] As the figure indicates, the

[10] Construction represents a small share of nonmanufacturing employment, so the variability of the all non-manufacturing flows still falls short of the variability of the manufacturing flows.

[11] Note that we can classify a worker's industry from the industry code reported in the month in which she was unemployed, or the month in which she becomes employed. The two need not be the same, even absent misclassification, because workers can shift

Figure 7

Escape Rates from Unemployment into Employment, by Sector of Previous Employment



Note: Escape rate is percent of unemployed in sector who become employed. Data expressed as 12-month moving average, seasonally adjusted, Abowd-Zellner mean adjusted, and Polivka-Miller adjusted.
Shadings indicate recessions.
Source: U.S. Bureau of Labor Statistics, Current Population Survey micro data, and authors' calculations.

general business cycle contours of escape rates are quite similar for the two broad sectors. Both escape rates peak just before the onset of recessions, both drop significantly during recessions, and both tend to reattain their previous peaks after several years of expansion. The average *level* of the manufacturing escape rate is about 5 percentage points below that of the nonmanufacturing rate. However, recently the manufacturing escape rate has exceeded its previous peaks, and is now at a level (above 30 percent) that roughly matches that of the nonmanufacturing sector. The increase in the escape rate for former manufacturing workers may be another signal of the tremendous strength in current and recent U.S. labor markets. Even in the long-declining manufacturing sector, the probability of leaving unemployment is about as good as in any other sector in the economy.[12]

sectors upon becoming employed. In this figure, we employ industry codes from the month in which the worker is unemployed. The reason is that this figure focuses on the probability of an unemployed manufacturing (or non-manufacturing) worker becoming reemployed, in whatever industry. However, the differences in exit rates computed using the alternative methods are generally quite small.

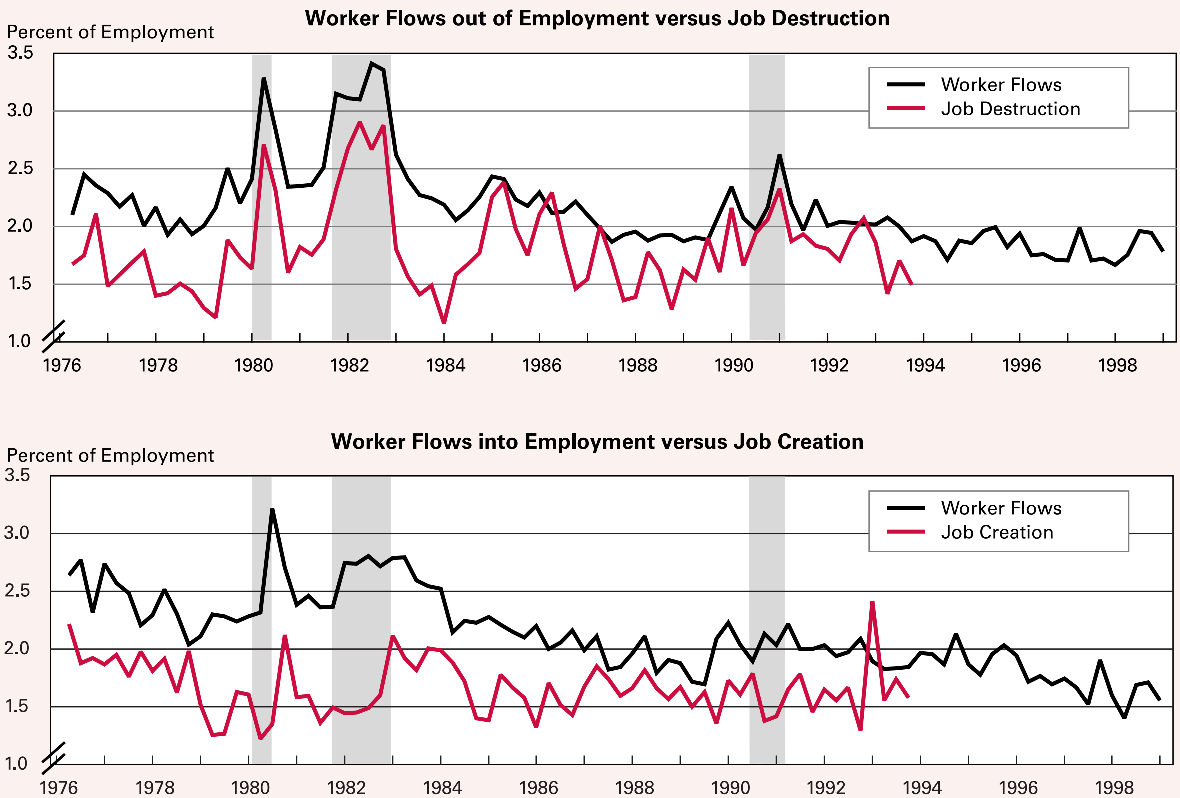
Comparison with Job Flow Data

Davis, Haltiwanger, and Schuh (DHS 1996) construct series of *job* flows for manufacturing establishments. The worker flows that we construct for the manufacturing sector should reflect, at least in part, the *worker* sides of the same phenomena. That is, when a job is "destroyed," often a worker becomes unemployed. Similarly, when a job is "created," often a worker makes a transition into employment. Of course, not every worker transition corresponds to the creation or destruction of a job. For example, workers make transitions into unemployment because they are fired or because they quit, with no associated job destruction if the vacant post is promptly filled. In addition, a worker whose job is destroyed can switch to another job, an E→E transition, without an observed spell of unemployment. Still, the correspondence between the series should be reasonably strong,

[12] Part of the rise in the escape rate for manufacturing occurs after the 1994 methodological break. While we have adjusted the series for the break, it is still possible that some of the increase in the escape rate arises from the change in methodology.

Figure 8

Worker and Job Flows in Manufacturing



Note: Worker flows are quarterly averages of monthly data; job flows are quarterly and are scaled for comparison. All data are seasonally adjusted; worker flows are Abowd-Zellner mean adjusted and Polivka-Miller adjusted. Shadings indicate recessions.
Source: Worker flows: U.S. Bureau of Labor Statistics, Current Population Survey micro data, and authors' calculations; job flows: Davis, Haltiwanger, and Schuh (1996).

especially for the large fluctuations that we believe are associated with business cycles.

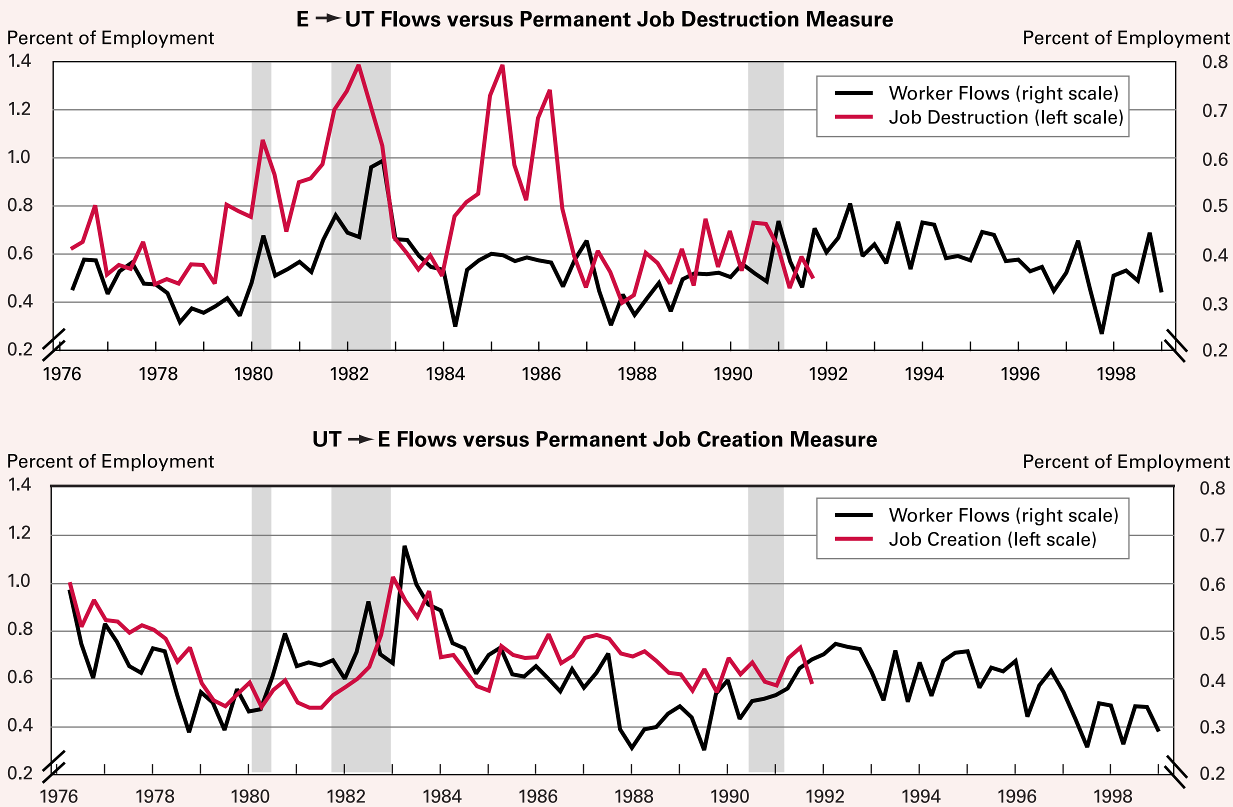
The top panel of Figure 8 displays the worker flows from E to U or N for the manufacturing sector (the black line) along with the DHS series for job destruction.[13] As the figure indicates, the correspondence for the 1980 and 1982 recessions is good, as is the spike in destruction and flows out of E in the 1990–91 recession. The bottom panel of the figure displays a similar comparison between flows from all sources into E for manufacturing and job creation. Here, the match-up is not as close. A substantial decline in job creation in the 1982 recession is not matched by a similar falloff in flows into E; the same is true during the 1980 credit control period and the year preceding it. The correspondence during the 1990–91 recession is not as obvious, either.

One possible explanation for the divergence is that both the worker and the job flows contain short-run transitions. The worker flows include temporary layoffs that should result in quick round-trip transitions from E to U and back to E. The job flows include the short-lived destruction of jobs that are quickly recreated. Figure 9 excludes the effects of these short-run phenomena by comparing worker flows from manufacturing employment to unemployment terminations (permanent job separations) with job flows that last more than two years and are thus approxi-

[13] The somewhat higher level of flows as a share of employment as compared to destruction or creation as a share of employment arises from two differences in data creation. First, we measure all transitions at the worker level, whereas the job flows measure the net creation or destruction at the establishment level. Second, our quarterly data are sums of flows for all the months within the quarter, capturing within-month flows, whereas the job flows measure only net flows within the quarter.

Figure 9

Comparison of "Permanent" Worker Flows and Job Flows in Manufacturing



For note and source: See Figure 8.

mately "permanent" (see DHS, pp. 21–26). As the figure indicates, the match between worker flows from permanent separations into manufacturing employment and "permanent" job creation is much closer than the corresponding overall measures in the preceding figures, although the match between destruction and E→U flows is more questionable.[14]

V. New Duration Statistics

Each month, the Bureau of Labor Statistics publishes statistics summarizing the central tendency of the lengths of current unemployment spells. These duration statistics, reported as the median and mean, tell us how much time currently unemployed workers have spent searching for work. What is missing from the picture is a sense of how long *completed* spells of unemployment last, and of where the unemployed go after unemployment.[15] An unemployment spell that ends with a discouraged worker leaving the labor force may have different economic significance from one that ends with a job. Moreover, unemployment caused by a permanent separation may imply a dif-

[14] However, note the difference in the scales of the flows in the figure. The average share of manufacturing workers who become unemployed on permanent separation is only two-thirds that of the share of jobs permanently destroyed. We remain puzzled about this mismatch.

[15] Of course, many authors have attempted to estimate duration from micro data on partial unemployment spells for single points in time, notably Lancaster (1979) and Nickell (1979).

ferent expected duration pattern and employment outcome than a quit does.[16]

The coexistence of duration data and labor force status in the CPS survey allows us to calculate duration statistics for completed spells of unemployment. We do so by tabulating the duration of unemployment for all those individuals in the survey who change labor force status from unemployed (for whatever reason) to employed or not in the labor force.[17] Our data on unemployment duration differ from those traditionally used in the duration literature, which uses the standard published data that take a "snapshot" of the current distribution of unemployment durations for all those who are unemployed, whether they are beginning, in the middle of, or ending an unemployment spell. Bowers (1980) discusses the biases that may arise in estimating unemployment duration from incomplete unemployment spells. Such data are, of course, still useful for assessing the central tendency and distributional characteristics of unemployment spells in progress.

Figure 10 displays the median duration of unemployment by reason for unemployment, splitting out those who become employed (the top panel) from those who leave the labor force (the bottom panel) at the end of their unemployment spell. Several characteristics of the data stand out immediately.

First, unemployed workers who eventually leave the labor force will have spent a longer time unemployed than workers who find jobs. Second, the workers who unequivocally suffer the longest spells of unemployment are those who end up leaving the labor force after being permanently separated from their jobs (UT). Their median duration of unemployment peaks at more than 16 weeks following both the 1982 and the 1990 recessions. Third, the median duration of unemployment for workers on layoff (UL) is a reassuring three to six weeks, regardless of destination, and it varies less across business cycles than most other categories. Fourth, outflows from U to E for different reasons all behave similarly; outflows from U to N can differ dramatically, depending on the reason for the job loss. Finally, the unemployment durations for workers who leave the labor force (with the exception of layoffs) have not fallen quite as low during this expansion as they did in the 1980 recession.

Unemployed workers who eventually leave the labor force will have spent a longer time unemployed than workers who find jobs. Workers who end up leaving the labor force after being permanently separated from their jobs will have suffered the longest spells of unemployment.

An Explanation of the High Relative Duration in the 1990s

This last observation may help explain one conundrum of the current expansion: Why has the median duration of unemployment in the mid to late 1990s been so high relative to the unemployment rate? Our disaggregated data allow us to shed some light on this. The top panel of Figure 11 displays the ratio of the published median duration of (partial spells of) unemployment to the civilian unemployment rate. This ratio, which roughly normalizes median duration by stage of the business cycle, was quite stable through the early 1990s and has since risen to historically high levels.[18] Rising relative duration seems to contradict the notion of a booming economy and a tight labor market, as well as the possibility of in-

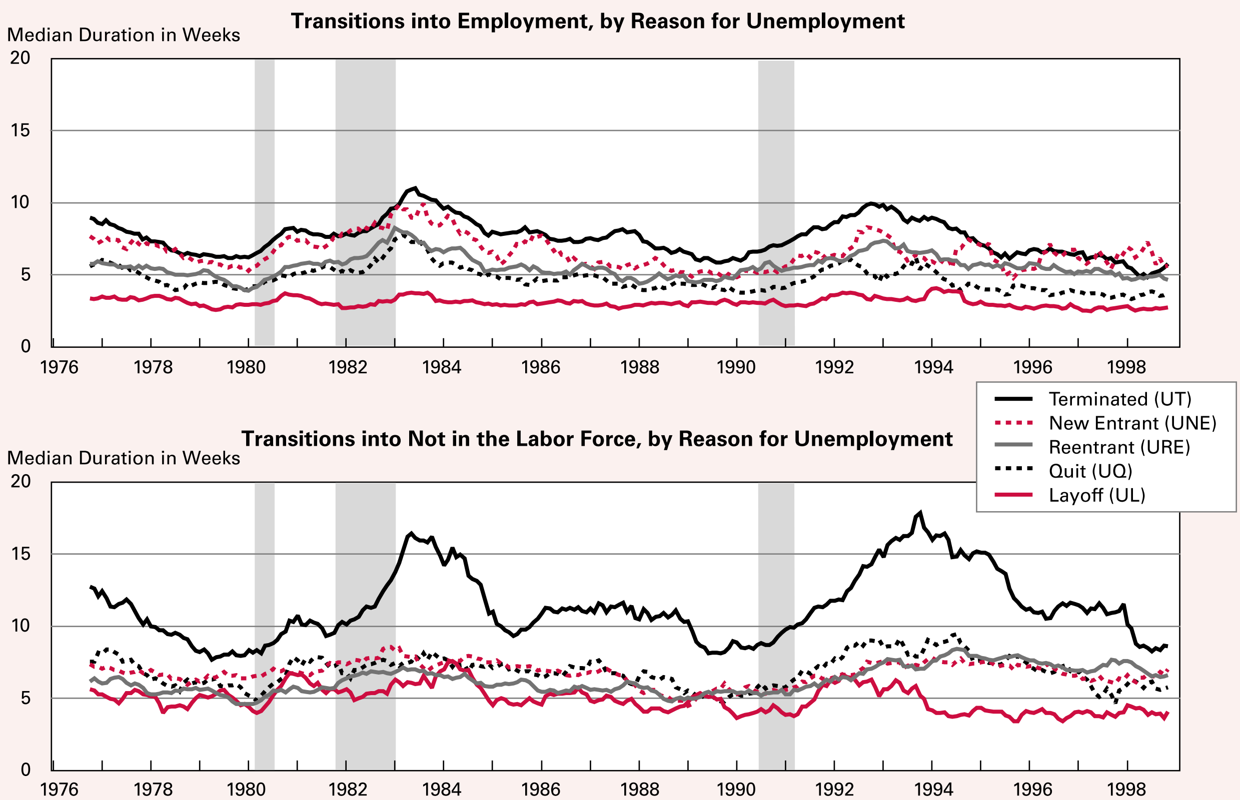
[16] Baker (1992) examines unemployment duration by reason for unemployment, for incomplete spells of unemployment. Fallick (1996) uses the Survey of Income and Program Participation to compute unemployment duration for quits. A number of other authors have examined short samples of completed spells of unemployment, often using the Continuous Wage and Benefit History sample. Spells in this sample are often truncated when benefits expire, so longer duration spells are underrepresented. See, for example, Meyer (1990), and the papers referred to in Chapter 5 of Devine and Kiefer (1991).

[17] We discuss problems associated with constructing duration data in Section II above, as well as the corrections and adjustments that we have implemented to address these problems. A complete description of these adjustments appears in the Data Appendix. In particular, we have implemented the adjustments to duration estimated by Polivka (1996). Bowers (1980) and Sider (1985) also discuss some of these problems in more detail, especially the biases that arise from measuring duration of incomplete unemployment spells.

[18] A regression of median duration on the unemployment rate reveals the same pattern: The relationship is fairly stable until the early 1990s, at which point the residuals begin to increase markedly.

Figure 10

Duration of Completed Unemployment Spells



Note: 9-month moving average, seasonally adjusted, Abowd-Zellner mean adjusted, and Polivka-Miller adjusted.
Shadings indicate recessions.
Source: U.S. Bureau of Labor Statistics, Current Population Survey micro data, and authors' calculations.

creased "job matching efficiency" (the rate at which unemployed workers find a match with an employment opportunity) suggested by Bleakley and Fuhrer (1997).

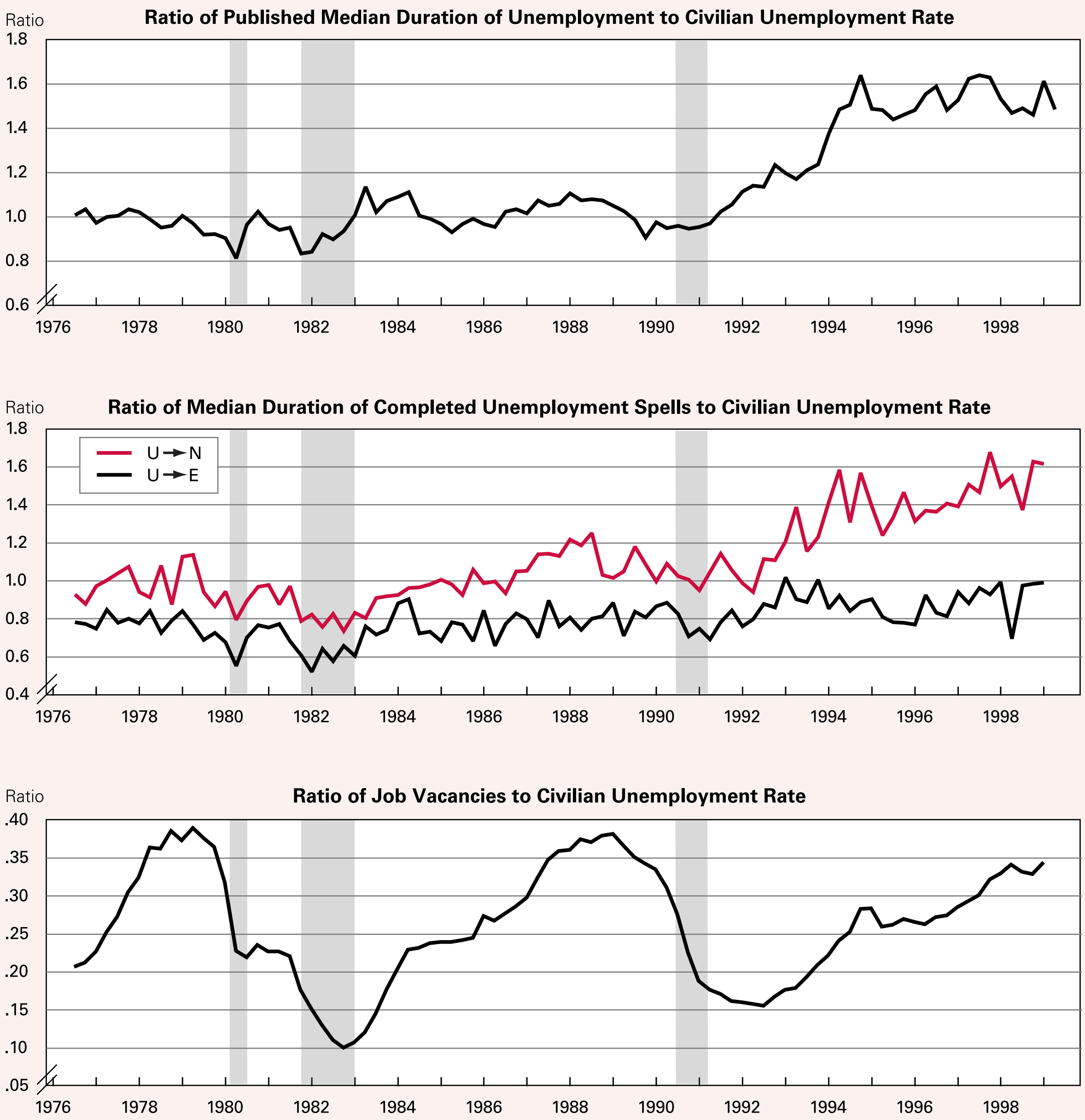
However, the published duration statistics do not distinguish between the duration of unemployment spells for workers who become reemployed and the duration for those who eventually leave the labor force. The former are those who fill vacant jobs and thus determine the estimates of job-matching efficiency; the latter, however, are not part of a job match. Instead, they stop searching for employment, perhaps because they are discouraged, opt for early retirement, or return to school. As the middle panel of the figure shows, the ratio of unemployment duration to the unemployment rate for workers who become reemployed has shown little upward trend over the past 25 years. But duration relative to unemployment for workers who leave the labor force has shown a distinct uptrend since 1991. The bottom panel shows that, if anything, the stock of jobs available for the pool of unemployed workers is relatively high (although not unusually high for this phase in the business cycle), so that increased duration overall cannot be explained by a dearth of available jobs.[19]

This suggests that the explanation for relatively high unemployment duration lies with the experience of those who leave the labor force. Matching efficiency for those who leave U for E may well have increased, but offsetting that has been an increase in the median

[19] Note that the link between the help-wanted index, derived from newspaper employment ads, and job vacancies has likely shifted over the decades. This figure makes use of empirical work by Abraham (1987) to estimate the vacancy rate from the help-wanted index, adjusting for the estimated shift in the relationship between the help-wanted index and the vacancy rate.

Figure 11

Explaining High Unemployment Duration in the 1990s

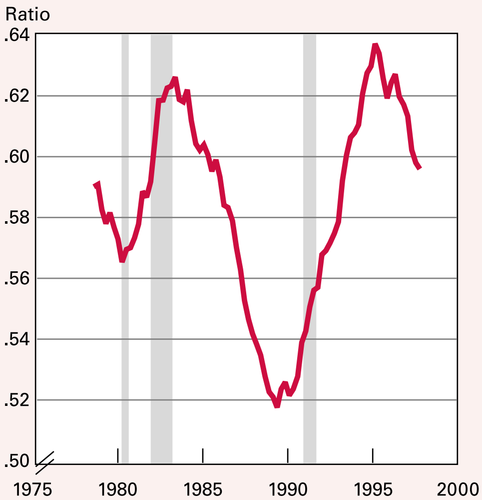


Note: Completed unemployment spells are quarterly averages of monthly data, seasonally adjusted, and Polivka-Miller adjusted. Shadings indicate recessions.
Sources: Unemployment rate and median duration: U.S. Bureau of Labor Statistics; vacancies: Abraham (1987); completed unemployment spells: authors' calculations.

duration (relative to the unemployment rate) of completed unemployment spells for those who eventually leave the labor force. In addition, given the higher median duration for unemployed workers who leave the labor force, an increase in the proportion of those workers would also raise the median duration of the total. Figure 12 shows that the ratio of U→N to U→E flows has been high recently, so that part of the

Figure 12

Ratio of U→N Flows to U→E Flows



Note: Nine-quarter centered moving average, seasonally adjusted and Abowd-Zellner mean adjusted.
Shadings indicate recessions.
Source: U.S. Bureau of Labor Statistics, Current Population Survey micro data, and authors' calculations.

rise in overall duration may be attributed to a greater share of U→N flows in the total flows out of unemployment.

A simple regression formalizes the insights gleaned from the graphical evidence. Regressing the published median duration/unemployment ratio on lags of the median duration/unemployment ratios for U→E and U→N flows, as well as the ratio of U→N to U→E flows, we find that the most significant contributors to the rise in median duration over the past decade, both economically and statistically, are the relatively high duration of U→N flows and the elevated ratio of U→N flows to U→E flows. Changes in the duration of U→E flows are insignificant.

Thus, the rise in median duration of unemployment over the past decade is not inconsistent with increased job matching efficiency. It is a symptom, however, of a rise in both the median duration for unemployed workers who subsequently leave the labor force and their share of the unemployed. Both trends require further investigation. One interpretation of these data is that, perhaps because of the enduring strength of the economy and the resultant strength of labor demand, workers are now willing to spend a longer time searching for work, even when their searches are ultimately unsuccessful. Another interpretation is that more unemployed workers in the 1990s have outmoded skills, are older, or hold higher reservation wages. Our data set contains information on these demographic characteristics that will allow us to disentangle these competing hypotheses in future work.

Why Has Unemployment Been So High in the 1990s?

Given the historically low unemployment rates in the late 1990s, this question may seem surprising. But in fact, unemployment has been high, compared to what one might have predicted using Okun's Law, the well-known and widely used relationship between the unemployment rate and real GDP growth. Okun's Law predicts that, when real GDP growth exceeds potential, unemployment will fall, as the economy requires more workers than can be provided by growth in the labor force plus growth in productivity. The result is that workers are drawn from the pool of unemployed, reducing their numbers.

Using an estimated Okun's Law relationship that includes the effect of changes in the demographic composition of the labor force, one would have predicted an unemployment rate today below 4 percent, as the black line in Figure 13 illustrates.[20] Of course, an under-prediction of unemployment from Okun's Law could also imply too low an estimate of potential growth. If potential growth were higher by half a percentage point or more, then the predicted unemployment rate would be closer to the actual.

However, before concluding that recent productivity growth and hence potential growth have improved, we suggest an alternative explanation for the unexpectedly high rate of unemployment compared to Okun's Law projections, one that is based on understanding the composition of unemployment experiences. Figure 11 shows, and the discussion above

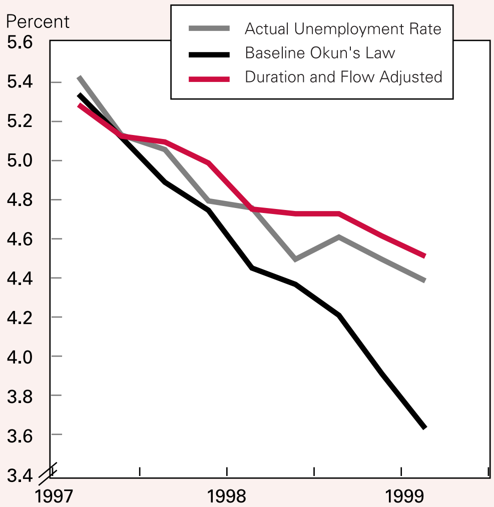
[20] This paper employs an Okun's Law that makes the change in the unemployment rate, U_t-U_{t-1}, a function of deviations of current and lagged real GDP growth from potential, (ΔGDP_t-ΔGDP^*), as well as the share of teenage workers in the working-age population, D_t:

$$U_t - U_{t-1} = \sum_{i=0}^{2} \alpha_i(\Delta GDP_{t-i} - \Delta GDP^*) + bD_t + c.$$

The equation is estimated from 1980 to 1999:Q1, and uses the Congressional Budget Office's estimate of potential GDP growth, which averages 2.5 percent over the period. This average coincides with the unconstrained estimate of potential growth.

Figure 13

Recent Unemployment Forecasts
Using Disaggregated Duration and Flow Data



Note: Unemployment rate is a quarterly average of monthly data.
Source: U.S. Bureau of Labor Statistics, Current Population Survey micro data and authors' calculations.

suggests, that both the median duration of unemployment (particularly among those who subsequently leave the labor force), and the share of unemployed who leave the labor force, have increased recently. Could these compositional changes in the work force account for the doggedly high unemployment rate?

Augmenting Okun's Law to include measures of lagged unemployment duration for all U→ N transitions, as well as the share of outflows from U that go to N versus E, we find the following:

- The addition of duration and outflow destination measures significantly improves the explanatory power of the standard Okun's Law equation, estimated from 1980 to the present and allowing for other demographic shifts;[21]
- Using the augmented Okun's Law equation to forecast unemployment over the past three years eliminates the under-forecasting of the conventional specification, as shown in the red line in Figure 13.[22]

Interestingly, the key increment to explanatory power comes from the duration of UT→N flows. A rise in the duration of terminated workers who ultimately leave the labor force is associated with a *decline* in unemployment. This correlation arises because these duration measures are the last indicators of labor market weakness following a recession, and thus peak shortly before real GDP growth surges during expansions. Thus, a rise in the duration of UT→N flows is a leading indicator of expansionary GDP growth that would normally lower the unemployment rate, and hence enters Okun's Law with a negative coefficient.

We cannot rule out the possibility that potential growth is higher now than it has been. However, these results suggest that taking into account the relatively high duration of the unemployment spells also provides an alternative, empirically verified explanation for the unexpectedly high recent unemployment.

VI. Some Preliminary Results on Wage and Price Dynamics

A simple way to gauge the usefulness of disaggregated flows data in understanding wage and price dynamics is to add them to conventional wage and price Phillips curves. Flows might well contain important information about the labor market beyond that contained in the aggregate unemployment rate. The simple Phillips curve suggests that, other things equal, inflation will fall when the unemployment rate rises above its equilibrium point. However, if the unemployment rate rises because of a large inflow of reentrants to the labor market who are optimistic about job prospects, this might signal very different wage and price pressures from the case in which the unemployment rate rises because jobs are destroyed, workers are terminated, and the escape rate from unemployment to employment falls dramatically. The flow data can help us to distinguish among these and other underlying labor market conditions, which might entail the same movement in the aggregate unemployment rate but imply very different forecasts of inflation.

Table 4 displays the results from estimating re-

[21] The forecasting equation is estimated on the unadjusted flows data from 1980 through 1997. The hypothesis that the duration and flow shares can be costlessly omitted from the Okun's Law regression can be rejected with 99 percent confidence.

[22] The forecast displayed is a dynamic out-of-sample forecast. That is, forecasted values of the lagged unemployment rate are used to explain current unemployment. The equation is estimated from 1980 to 1996:Q4, and includes a term that captures the effect of changes in the teenage share of the labor force. Other demographic influences were not significant in this equation.

Table 4

Empirical Significance of Worker Flows in Phillips Curve Regressions

Explanatory Variables	Dependent variable: Price inflation — Sum of coefficients (1) Baseline Standard Phillips Curve	(2) Flows instead of Unemployment Level	(3) Add explanatory variables to flows regression (2); *p*-value for test that these coefficients are zero					Dependent variable: Wage inflation — Sum of coefficients (4) Baseline Standard Phillips Curve	(5) Flows instead of Unemployment Level	(6) Add explanatory variables to flows regression (5); *p*-value for test that these coefficients are zero				
Unemployment	−.34***							−.58***						
Relative price of oil	.61							.59						
E → UT		−8.34***							−8.48***					
UT → E		4.71***							2.67*					
Δ(E → U)		−3.98***							−2.22***					
Add to equation (2) or (5):														
Unemployment			.13							.36				
Capacity Utilization				.46							.22			
Help-Wanted Index					.03							.73		
Productivity Growth						.71							.26	
Disaggregated U Stocks							.54							.70
Standard Error of Regression	1.33	1.24	1.22	1.25	1.21	1.26	1.24	1.30	1.13	1.13	1.12	1.13	1.12	1.13

Estimation equation: $\Delta x_t = \sum_{i=1}^{m} \alpha_i \pi_{t-i} + \sum_{j=1}^{2} \beta_j U_{t-j} + \sum_{k=1}^{2} \gamma_k p^o_{t-k} + \sum_{l=1}^{n} \delta_l Z_{t-l}$

Note: * denotes significance at the 10 percent level or better; ** denotes significance at the 5 percent level or better; and *** denotes significance at the 1 percent level or better.

All estimates in this table employ data described in Table 2, over estimation sample 1976:Q3–1998:Q4.

All specifications include 12 quarterly lags of price inflation, with the coefficients constrained to sum to one.

Columns (3) and (6) add two quarterly lags of indicated variables.

gressions that explain either wage or price inflation with lags of price inflation, the relative price of oil, and measures of labor market activity. The leading candidate for labor market activity has been the unemployment rate, but we allow in these regressions for the influence of the flows into and out of unemployment. In addition, we examine the importance of other measures of resource utilization, including capacity utilization and disaggregated *stocks* of unemployed, as well as the help-wanted index, which proxies for the demand for labor, and productivity growth, which should affect the wedge between wage and price inflation. Thus, the Phillips curves that we estimate may be represented as

$$\Delta x_t = \sum_{i=1}^{m} \alpha_i \pi_{t-i} + \sum_{j=1}^{2} \beta_j U_{t-j} + \sum_{k=1}^{2} \gamma_k p^o_{t-k} + \sum_{l=1}^{n} \delta_l Z_{t-1} \qquad (1)$$

where Δx_t is the rate of inflation of wages or prices, π_t is the rate of inflation in prices (whose coefficients are constrained to sum to one in these estimates), U_t is the civilian unemployment rate, p^o is the relative price of oil, and Z_t is a vector that includes the worker flows (as a share of the labor force), alternative measures of resource utilization, labor demand, and productivity growth.

As the table indicates, the baseline Phillips curve for price inflation (column 1) yields parameter estimates much like those in previous studies. However, the inclusion of the flow variables (column 2), particularly for flows in and out of unemployment for permanent separations, significantly decreases the average error made by the equation over the sample.[23]

[23] In our specification search, we also included flows into and out of unemployment for quits and layoffs, but these did not enter significantly. In addition, we conducted a similar exercise using escape rates, and none were significant.

The signs of the coefficients conform to intuition: Flows *into* unemployment indicate more slack in labor markets, and thus decreased pressure on prices. Flows out of unemployment connote the reverse. As the next group of columns (3) shows, once flows are included in the Phillips curve, unemployment is insignificant.[24] Perhaps as interesting is that the estimated *sign* of the unemployment coefficient is reversed from negative to positive. Additional variables that reflect resource utilization and productivity are also insignificant in the presence of the unemployment flow variables. The single exception is the help-wanted index, an indicator of the demand for labor, which displays a moderate level of significance for the price inflation Phillips curve (see Abraham (1987) for further evidence of the empirical relevance of the help-wanted index). None of these variables provides a significant reduction in average error beyond that afforded by the inclusion of the flow variables.

The results are qualitatively similar for the wage compensation inflation Phillips curve, shown in the next set of columns in Table 4. Again, the use of flows as the primary labor market variable significantly lowers the average error made by the equation (column 5). The decrease in the equation error is larger for the compensation equation than for the price equation. Perhaps this is not surprising given the link between labor market conditions and *wages* in the original Phillips curve. Once flows are taken into account, neither unemployment nor capacity utilization, productivity growth nor help-wanted add significantly to the explanatory power of the equation (columns 6). Once again, none of these variables significantly reduces the average error made by the "flows Phillips curve."[25]

Why do the flows capture labor market pressure better than the level of the unemployment rate? The flows reflect inflows to and outflows from unemployment, which presumably behave more like the change in the unemployment rate. However, the traditional specification shows that the sum of the coefficients on the *level* of unemployment is highly significant. Additional regressions show that explicitly including the change in the unemployment rate does not eliminate the significance of the flows. One possibility is that the disaggregated *flows* could simply reflect the importance of distinguishing disaggregated *stocks* of unemployment—the fraction of the labor force who are unemployed due to layoff or quits, as compared to those unemployed due to a permanent separation. The last column in the "add regressors" columns (3 and 6) shows the result of a test for this possibility. The test regression allows the disaggregated stocks (by reason for unemployment) to enter the Phillips curve along with flow variables. As the table indicates, the inclusion of these stocks provides only insignificant improvement in explaining price or compensation inflation.

Figure 14 displays an index of the labor market conditions implied by the Phillips curve regression with worker flows. The index represents the influence of the flow variables on price inflation in the Phillips curve, and it is computed as the sum of the products of the regression coefficients for the flow variables with their values over the estimation sample. As the top panel of the figure shows, the index behaves differently than the unemployment rate (the unemployment rate has been inverted for comparison with the index). It does not, for example, indicate as marked an increase in labor market pressures over the past 20 years as does the unemployment rate. As shown in the bottom panel, the two labor market measures show significantly different correlations with the smoothed changes in inflation. The flows-based index is more tightly correlated with changes in inflation than the unemployment rate over the past two decades. The correlation between the change in inflation and the flows index over the past 20 years is 0.43, versus 0.15 for the unemployment rate. It is important to note, however, that the improvement provided by the flows in forecasting inflation does not extend to any significant extent to the past two years of inflation overforecasting.[26]

Note that the flows Phillips curve in the simple form of equation (1) (with the coefficients on unemployment set to zero and the Zs representing the flows) implies a "balancing point" at which inflation

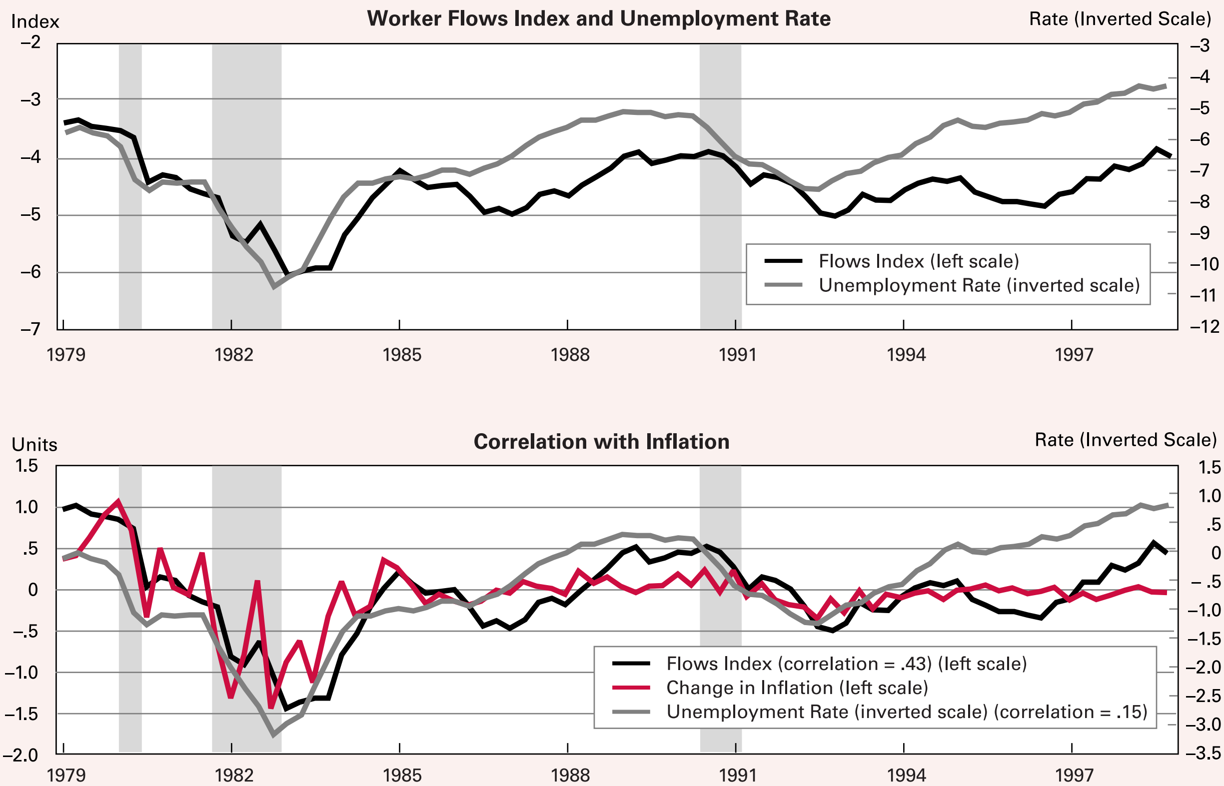
[24] The relative price of oil, which is only marginally significant in the baseline specification for price inflation, remains insignificant for all of the specifications considered in Table 4.

[25] The reported regressions use flow data that incorporate the Abowd-Zellner adjustments for misclassification error. The same regressions using data without this adjustment produce the same qualitative results: Once the flows are included, the sum of the coefficients on the level of the unemployment rate is no longer significant, the flows enter significantly and with the expected signs, and the addition of other variables (other than the help-wanted index in the price inflation regression) adds insignificantly to the explanatory power of the regression.

[26] These results are not an artifact of the estimation sample chosen. Tests that break the sample at five-year intervals within the full sample show that the significance of the flows and the flip in sign and reduced significance of the unemployment rate hold up across subsamples as well.

Figure 14

Alternative Labor Market Indicators of Inflation



Source: Unemployment rate (multiplied by negative one) and change in inflation (annual percent change in core CPI, 8-quarter moving average): U.S. Bureau of Labor Statistics; flows index (8-quarter moving average): Current Population Survey micro data and authors' calculations. Flows index and unemployment rate are standardized to mean zero and standard deviation of one for the bottom figure.

neither rises nor falls.[27] When the relative price of oil is constant, a constant inflation rate implies that the weighted sum of flow variables (weighted by their regression coefficients) must settle at a constant value. But unlike the Phillips curve with a single aggregate unemployment rate, there is no unique balancing point for any one of the flows. Many configurations of the disaggregated flows could correspond to the constant balancing point. This reinforces the idea that it may be difficult to characterize equilibrium in labor markets with a single number.

These empirical results are striking. First, information on disaggregated worker flows between UT and E provides economically and statistically significant predictive power for both price and wage inflation. Second, the information in the flows is important enough that the level of the unemployment rate is no longer required to predict price or wage inflation. We plan to explore the reasons behind these results in future work.

VII. Conclusion

This paper documents the construction, business cycle characteristics, and predictive content of a new data set of disaggregated labor market data. The data include gross worker flows among a variety of states of employment, unemployment, and not in the labor force; disaggregated worker flows by sector of em-

[27] Darby, Haltiwanger, and Plant (1985) pursue a similar idea, using job flows to estimate a NAIRU that varies over time.

ployment; and estimates of unemployment duration for completed spells of unemployment, by reason for unemployment. In addition, the data can be used to construct a host of measures of interest to labor and macroeconomists, including estimates of earnings for newly employed workers and measures of "reallocation" gleaned from sectoral and occupational transitions. With these data, we hope to gain a better understanding of the behavior of labor markets, with an eye toward a more complete understanding of the macroeconomic and monetary policy implications of labor market behavior for unemployment and inflation.

The preliminary results presented in this paper suggest that the data set holds great promise for addressing these issues. First, the availability of more detailed data on flows and unemployment duration affords a clearer picture of the relatively subdued level of overall reallocation in the 1990s, and helps explain the reasons behind the relatively high duration of unemployment in the 1990s. Second, the comparison of these economywide worker flows with manufacturing job flows indicates that there may be qualitative differences in the labor market behavior of the manufacturing and nonmanufacturing sectors. This result suggests a need for care in applying insights gained from the valuable work on manufacturing flows to the nonmanufacturing sector.

Finally, our estimates of forecasting equations for inflation and unemployment provide preliminary evidence that these disaggregated labor market statistics may become useful inputs to monetary policy decisions. Our results show that disaggregated data provide a better summary of the labor market conditions relevant for forecasting inflation than the aggregate unemployment rate; they also help to explain the recent behavior of the aggregate unemployment rate, without assuming an increase in the growth rate of potential. The worker flows do not, however, explain the widespread over-forecasts of inflation of the past few years.

We hope that further exploration of the vast array of data available in this data set will help us to better understand the workings of the labor market. The preliminary empirical results in this paper suggest that these data will ultimately provide monetary policymakers with a more accurate assessment of labor market conditions, allowing them to gauge better the appropriate policy response to labor market conditions.

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Bleakley gratefully acknowledges the financial support of the National Science Foundation. Fuhrer thanks the Reserve Bank of Australia for support during the early development of this paper. The authors thank Robert McIntire of the BLS for answering our ample supply of questions about the CPS data. We are grateful to Olivier Blanchard for providing adjusted gross flow data and Anne Polivka of the BLS for answering more questions. We received helpful comments from our colleagues at the Federal Reserve Bank of Boston.

Data Appendix

Constructing Worker Flows

[28]The data used in this study are from the Current Population Survey (CPS). Each month, about 60 thousand households are surveyed, resulting in responses from approximately 120 thousand to 150 thousand individuals. The CPS is a primary source of labor market information and published statistics such as the unemployment rate. We use the basic monthly surveys from January 1976 to March 1999 to compile gross worker flows. The Federal Reserve Bank of Boston purchased the public-use, basic monthly survey data on CD-ROM from the U. S. Bureau of Labor Statistics (BLS) for the years 1976 to 1997. The data for 1998 and 1999 were obtained from a joint website of the U.S. Bureau of the Census and the BLS, created for data extraction. CPS public-use micro data are available to the public on this website for each month beginning in January 1994.

This appendix discusses a number of issues regarding the construction of these flows. We present our methods used to match individuals in consecutive months, reweight the matched subsample, disaggregate and adjust the flows, calculate median unemployment duration, and adjust for changes in survey methodology.

Matching Methodology

In constructing worker flows, we track individuals' labor market status in two consecutive months. We match individual responses about employment status in these two months. The CPS is broken into two rotation groups. Households spend four months in the survey, are rotated out for eight months, then return again for four months. Given the structure of the survey, the most we can hope to match is three-quarters of the survey respondents. In practice, the

[28] http://ferret.bls.census.gov.

fraction is lower because of survey dropouts and non-responses. We use a method that matches observations in consecutive months based on a core group of variables. Should the matching algorithm fail on this core group, we use ancillary variables to check for further matches. Specifically, if two individuals have identical core characteristics in both months, we use additional variables to break this "tie" and match the individuals.

In principle, there are two bases for computing transitions, either a change in status today relative to last month ("backward matching") or a change next month relative to today ("forward matching"). In the first case, months 2, 3, and 4 are matched in the sample with their obvious counterparts looking backward; in the second, months 1, 2, and 3 are matched with their counterparts forward. This is not merely a time-indexing convention; the gross flows will be slightly different because the sampling weights are drawn from different months and reweighted using the unmatched individuals from that month. We use the backward-matching approach in this study, but the generated flows look very similar in either case.

We tested two methods to match individuals: a "BLS" method[29] (Jaeger 1997) and our own method, "FRB," which slightly modifies the BLS methodology.[30] We first used the BLS method to design a function that matches households based on household ID and individuals based on household ID, individual's line number, gender, race, and age, allowing for age to increase in the second month. This method retains an average of 91.8 percent (over our sample of February 1976 to March 1999) of those individuals who could possibly be matched.

Our way of improving this matching function is to first try to match households in two consecutive months based on household ID. Then, of the households that can be matched, we match individuals based on a core group of variables: household ID, gender, race, and age (again allowing for age to increase in the second month). We find that the individual's line number is not always a unique identifier, so we do not include it as a matching criterion. Individuals who are not matched are next compared by adding marital status to the previous characteristics. At each iteration we continue to allow for age to increase by one year. Those who are still not matched are put back into the matching function, with grade attainment replacing marital status as the ancillary variable to our core matching group. Finally, we attempt to match the remaining individuals with veteran status replacing grade attainment. Our method retains an average of 92.2 percent of those who could possibly be matched, with less variation than the BLS method. Correlations between BLS-matched and FRB-matched series are all 0.999 or above. Therefore the data presented in this paper are matched using our method (FRB).

The probability of matching an individual may be biased if there are systematic reasons why individuals drop out of the survey. In order to determine the factors that may affect the probability of matching an individual across months, we used logit regressions on a variety of demographic and time dummies (as done by Peracchi and Welch 1995). We find that most demographic characteristics (such as age, sex, race, and marital status) are significantly related to match success, with the exception of education. Individuals who remain in the sample in the third and fourth months of the rotation have a higher probability of being matched than those in the second month. We also find that the probability of a successful match did increase from our average of 92.2 percent to 94.3 percent with the CPS redesign starting in 1994.

Reweighting of Individuals

CPS weights are used to make the sample observations representative of the U.S. population. When using only the subsample of individuals who can be matched across both months, the CPS final weights are no longer representative and need to be "blown up" to correctly represent their population weights. We follow the BLS methods and redistribute the weights by gender for our subsample. Based on our results from the logit regressions of matching probabilities, which find other characteristics besides gender to be significant factors in matching success, we tested a weighting scheme based on further disaggregation besides gender. This causes little difference in comparison to published statistics (correlations between gender-weighted series and "kitchen sink" weighted series are all above 0.999), and so we chose to reweight by gender alone.

We divide the CPS final weight for an individual by ¾ (for the optimal percentage that could have been matched for two consecutive months) and multiply by a ratio of the summed weights of successfully matched individuals (for each cell, the ratio is the sum of overall weights minus the sum of weights of failed matches, divided by the sum of weights overall). These revised weights were used to calculate the gross worker flows. When looking at unemployment duration, we use results from Polivka and Miller (1998) to adjust the reweighted individual CPS weights to reflect changes in the survey design in 1994, in order to construct historically comparable series. This will be explained in greater detail below.

Disaggregation of Flows

After constructing our matched sample, we classify individuals according to their labor force status (using the employment status recode in the CPS and additional variables). Basically, individuals can be employed (E), unemployed (U), or not in the labor force (N). These are determined by the CPS variable PEMLR (1994+) "Monthly Labor Force Recode," known as "Employment Status Recode" in prior years. It is a variable created by the CPS and derived from a series of questions regarding labor force status.

By Unemployment Reason

In order to be classified as unemployed, an individual must have been looking for work in the last four weeks unless he or she is on temporary layoff. To classify the

[29] "BLS" is our moniker and is so named because David Jaeger was an economist at the Bureau of Labor Statistics (BLS) at the time of his study. In addition, we benefited from conversations with Robert McIntire of the BLS.

[30] With credit to Welch (1993), who first matched the remaining unmatched records and wrote a Stata program to match March files. It allows the user to choose key matching variables.

unemployed by reason for unemployment, we use the CPS variable PRUNTYPE (1994+) and code obtained from the BLS for the prior years (1976–1993), therefore following the BLS methods of classifying the unemployed by reason.[31] Individuals can be classified as unemployed if they were permanently separated from their jobs (UT), laid off (UL), quit (UQ), or are reentrants (URE) or new entrants (UNE) to the labor force.

The categories of new entrants and reentrants are somewhat problematic, especially the reentrants, as we find that they are a "catch-all" category for the unemployed. If only the CPS question coded for new and reentrants (Item 22F) is used to determine the unemployed for these reasons, the results would be incorrect. The universe for that question does not restrict the possibility that individuals may answer other unemployment reason questions, and therefore also be classified as on layoff, having quit, or lost their jobs. A series of questions is required to correctly determine unemployment reason. The code obtained from the BLS presents a clear hierarchy of unemployment classification by reason, with new and reentrants at the bottom. We follow this example and code individuals as new or reentrants only if they did not elsewhere classify themselves. Even then, we find a significant number of individuals claiming to make a transition between employment in the first month and then becoming unemployed as a reentrant in the second month (see Figure 2). Obviously these individuals have held jobs before, in fact quite recently, so if they do not answer that they were laid off, quit, or otherwise lost that job, the only category remaining is "reentrant." We present these E→URE flows because they are not insignificant and presumably representative of some "other," undefined, or "refused to answer" reason for unemployment.

The number of purportedly temporarily laid-off workers (UL) who report being unemployed, terminated (UT), in the second month is quite high. This deficiency is rectified in the 1994 survey, which classifies workers on temporary layoff (hereafter refered to as simply "layoff") only if they have a specific recall date. In order to make the layoff data more compatible with the 1994 methodology, we exclude from layoffs those workers who have searched for work during the past four weeks.[32] Workers who classify themselves as on layoff and have not been searching for work are arguably more confident of the temporary nature of their unemployment. We classify those on layoff who reported that they searched for work as permanent separations (UT), consistent with the large number of UL to UT transitions noted above. Another plausible option is to make a separate category for these workers purportedly on layoff, although we could not construct such a category after 1994. In any case, the impact on our results is undetectable, as this cohort of workers accounts for at most a few tenths of a percentage point of either layoffs or terminations, whether measured as a percentage of the flows or of the stocks.

By Industry

The CPS data for industry are not historically continuous owing to changes in the industry codes. The CPS uses the Census classification systems to define industry categories, and these change with each decennial census. The 1980 to 1990 changes were relatively minor, but the 1970 to 1980 changes (implemented in 1983) were more involved.

The industry definition data are coded into 3-digit categories, from 1 to 999. The CPS aggregates them by major and detailed categories; we use the major definitions and aggregate them further. Our industry classification is broken down as follows: Agriculture; Mining; Construction; Manufacturing Nondurable Goods; Manufacturing Durable Goods; Transportation, Communications and Other Public Utilities; Wholesale Trade; Retail Trade; Finance, Insurance, and Real Estate; Services; and Public Administration. The only change between these categories was the movement of the United States Postal Service from Public Administration in the 1970 coding scheme to Transportation in the 1980 methodology; we placed the USPS in Transportation for our entire sample.

We disaggregate worker flows based on the industry of the employed. In this paper, flows in and out of employment by industry are categorized by the industry code for the month of employment. Flows into employment can occur from both unemployment and not in the labor force, and some unemployed individuals do change industries when they find employment. Here we measure those unemployed who find jobs in each industry, regardless of where they had previous experience. The one exception is escape rates from unemployment, which are categorized by the industry reported while unemployed.

Survey Methodology Changes

There are two main obstacles to constructing a continuous set of gross worker flows from 1976 to the present: (1) Households cannot be matched across certain months because of CPS sample changes; and (2) the 1994 CPS redesign implemented a significant change in methodology, making some series based on demographic or labor market characteristics discontinuous. In January 1978, the CPS expanded their sample with 9,000 additional households, and they added another 9,000 households in January 1980. We are unable to match the majority of households in January 1978 because of changes in household ID related to the first expansion of the sample. The CPS has imposed an additional measure to protect confidentiality of the data by scrambling the household ID codes at regular intervals. We are unable to match July and October of 1985, and June through September of 1995 because of these mid-decade breakpoints for household ID. The November 1987 micro-data file was not available from the BLS.

The 1994 redesign of the CPS involved updating the questionnaire and changing categories for certain questions, such as layoffs and reentrants, and implementing the use of dependent (computerized) interviewing. The redesign has been found to have had no significant effect on major statistics, such as the unemployment rate, but it greatly affected some disaggregated statistics, such as certain worker flows and duration measures. For both constructs that we study (worker flows and unemployment duration statistics), we have used results from previous research (Polivka and Miller 1998) to adjust our measures for the 1994 redesign. This is explained in greater detail in the next section.

[31] We are grateful to Robert McIntire of the BLS for providing code that determines unemployment by reason.

[32] The code obtained from Robert McIntire defines, prior to 1994, workers on layoff as those not searching for work.

Adjustments to Flows

The CPS published gross flow data from 1949 until 1953, when publication was suspended until 1982, and the data are now available only upon request. The flow data are noisy and have two major problems. First, a substantial number of individuals cannot be matched (even after taking account of the three-quarters who are available to be matched) because some observations are missing. They consist mostly of households that move out of the sample and individuals who move out of households remaining in the sample. The remaining sample may be biased if there is any systematic reason (or reasons) why individuals and households drop out of the sample.

Second, misclassification is particularly problematic when looking at worker flows. CPS interviewers or respondents can 'check off the wrong boxes' and misclassify an individual's labor force status. If this misclassification is corrected in the second month by correctly coding the labor force status (or if the reverse is true), then a spurious transition is recorded. Several researchers (Abowd and Zellner 1985; Poterba and Summers 1986) have found that classification problems lead to a significant number of spurious transitions in the gross worker flows.

By using information from the CPS reinterview surveys, these researchers estimated the amount of misclassification occurring with flows between E, N, and U. Abowd and Zellner (1985) used the CPS reinterview surveys from 1976 to 1982 to estimate the spurious transitions due to both types of error. Poterba and Summers (1986) chose only to look at misclassification, not missing observations. We chose to apply Abowd and Zellner's adjustments based on comprehensiveness and their use by other researchers who have studied gross worker flows (Blanchard and Diamond 1990).

In order to apply Abowd and Zellner's adjustments to the gross flows, we obtained adjusted gross flow data for January 1968 to May 1986 from Olivier Blanchard (Blanchard and Diamond 1990). The data have been Abowd-Zellner adjusted, using the reinterview surveys, and are not seasonally adjusted.

By dividing these adjusted data by the raw gross flows, we obtained the multiplicative adjustment factors for each month from January 1976 to May 1986. Appendix Table 1 presents these factors. The Abowd-Zellner adjustments reduce the transitions between labor market states (the off-diagonal elements); N↔E flows are the largest reduction, almost 50 percent. Flows between the same labor market state, the diagonal elements, are all slightly increased, with the greatest increase of 32 percent for U↔U flows. Adjusting the data after May 1986 proves to be a difficult issue because Abowd and Zellner have not updated their series and we do not have the reinterview survey information to extend their findings. Based on the adjustment information we do have, the adjustment factors do change over time. We have estimates of misclassification for 1994 and 1995 from the BLS, which indicate that the 1994 misclassification rates differ dramatically from those for the 1976–86 period. Most error rates dropped substantially, with the exception of those between N and U. Therefore, to accurately adjust the gross flows using reinterview data, we plan on obtaining reinterview survey data from 1986 to the present.

Appendix Table 1
Mean Adjustment Factors for Gross Worker Flows
January 1976 to May 1986

	Month 2		
Month 1	E	N	U
E	1.02	.51	.89
N	.51	1.01	.77
U	.95	.69	1.32

Source: Abowd-Zellner adjusted gross flow data from Olivier Blanchard (Blanchard and Diamond 1990), CPS micro data, and authors' calculations.

For this paper, we have chosen to use the mean adjustment for the period February 1976 to May 1986 for each seasonally adjusted transition (flow). Graphs of the flows are adjusted to reflect this average estimate of misclassification and nonresponse error. Regression analysis is not affected by this factor adjustment. We apply these factors to our gross flows data for E, N, and U (and U by reason) for our entire sample (1976 to 1999). For U by reason, we apply the Abowd-Zellner factor for U to each reason.

In an effort to study the effects of the CPS redesign, the BLS implemented a parallel survey at the time of the redesign implementation to compare the old and new questionnaires and methods. Using the parallel and basic monthly survey data, Polivka (1996) and Polivka and Miller (1998) estimated adjustment factors for various demographic groups to make the pre-1994 data comparable. These papers present regression results using both sets of CPS data (basic and parallel survey) over the time period October 1992 to May 1994, to calculate adjustment factors for historical series. These are all based on monthly stock numbers, not flows.

For the flows data we use Polivka and Miller's multiplicative adjustment factors, either by reason for unemployment or by the industry of the employed or unemployed. The factors are applied after the seasonal adjustments and Abowd-Zellner adjustments to the gross flows, for the period 1976 to 1993. We adjust the industry flows for the 1994 redesign using Polivka-Miller adjustments for a few major categories of industries.

The duration measures are adjusted by reweighting individual observations. We use a version of the suggested micro-data method (see Polivka and Miller 1998, Appendix A), where each observation's CPS weight is multiplied by the adjustment factor. We use the multiplicative adjustment factors (Polivka 1996) that group individuals by unemployment duration and reason. To generate the flows we use a weighted tabulation of the observations by labor force status category and unemployment reason. This shifting of the sample results in removal of the break in the series in January 1994, and it alters the pre-1993 series to resemble those in post-1994. Prior to adjustment, the median duration for most series remains around 4 weeks, regardless of unemployment reason. No adjustment was made for misclassification error.

Duration of Unemployment

The BLS publishes the mean and median duration of unemployment each month using CPS data. This gives an overall snapshot of the average time spent unemployed, but the composition of the unemployment pool is heterogeneous with respect to both the reasons for unemployment and the length (duration) of unemployment spells. We are interested in those individuals who complete their spell of unemployment by either moving to employment (E) or leaving the labor force (N). We then calculate the median value of these completed unemployment durations, by reason for unemployment.

The survey redesign allows respondents to choose how to report unemployment duration. Prior to 1994, individuals were asked to report only in weeks. Now individuals are able to report duration in weeks or months. Additionally, if a respondent is unemployed in the second consecutive month, the reported duration from the prior month is automatically updated, removing this possibility for error. Using our matched samples, we find that adjustments to unemployment duration are necessary for the 1994 CPS redesign.

We reweight the sample by gender and Polivka and Miller's adjustments by duration and unemployment reason. We take weighted medians of unemployment duration. Because of the topcoding of unemployment duration, the median is a less biased measure than the mean.

Topcoding of Unemployment Duration

Prior to the 1994 redesign, unemployment duration was topcoded at 99 weeks. After 1993, the duration question was topcoded at 999 weeks, and none of our matched observations were topcoded. The number of topcoded matched observations for 1976 to 1993 exhibits a marked increase after recessions and tapers as expansions progress. Less than 1 percent of unemployed workers who leave either for employment or drop out of the labor force have topcoded duration values. The largest group of the unemployed, with respect to topcoded duration, are terminations. They make up, on average, 0.25 percent of the unemployment pool. New entrants leaving unemployment have the least number of topcodes, at 0.09 percent of the unemployed. We used medians to avoid this topcoding issue. The median is also a desirable measure of central tendency because the distribution is skewed toward the longer durations (for example, the mean is, on average, 4 weeks higher than the median).

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