**The Consequences of Long Term Unemployment:
Evidence from Matched Employer-Employee Data**

Katharine G. Abraham
University of Maryland
kabraham@umd.edu

John Haltiwanger
University of Maryland
haltiwan@econ.umd.edu

Kristin Sandusky
U.S. Census Bureau
Lee.K.Sandusky@census.gov

James R. Spletzer
U.S. Census Bureau
James.R.Spletzer@census.gov

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I. Introduction

Long-term unemployment soared during the 2007-2009 recession and has remained stubbornly high even as the economy has recovered. By December 2009, the number of people unemployed for 27 weeks or more had risen above 6 million and it did not fall below that mark until October of 2011. The long-term share of total unemployment exceeded 40 percent from December 2009 through November 2012 and, as of April 2015, had not yet dropped below the previous series high of 26.0 percent attained in July 1983. Our goal in this paper is to provide new evidence on how passing through a spell of long-term unemployment affects subsequent employment and earnings.

Concern that the long-term unemployed may have become permanently detached from the labor market has risen in the wake of the Great Recession and the dramatic increase in long-term unemployment that followed. A recent paper by Kruger, Cramer and Cho (2014) using Current Population Survey (CPS) data, for example, found that just 35.9 percent of those who were long-term unemployed in their first wave of CPS data collection during 2008-2012 were employed 15 months later and just 10.8 percent were in full-time jobs that had lasted at least four months. While the short-term unemployed also appear to have experienced significant challenges in returning to work—just 49.5 percent of those observed as short-term unemployed during 2008-2012 were employed 15 months later and only 14.4 percent were in full-time stable jobs—outcomes for the long-term unemployed have been notably poorer than those for the short-term unemployed.

Although the statistics reported by Krueger, Cramer and Cho are striking, their finding that the long-term unemployed have fared less well than the short-term unemployed echoes earlier findings in the literature on how the job-finding hazard evolves over a spell of unemployment. A common finding for the United States, first documented by Kaitz (1970), is that longer unemployment durations are associated with lower exit or job-finding rates.

What is less clear from the existing literature is *why* the long-term unemployed in the United States experience poorer job-finding prospects than those who are more recently unemployed. One set of explanations rests on long-term unemployment having a causal effect on the job finding rate, due perhaps to employer discrimination (Eriksson and Rooth 2011, Kroft et. al. 2013, and Ghayad 2013), decreases in search intensity over the spell of unemployment (Krueger and Mueller 2011), or depreciation of human capital among the long-term unemployed (Mincer and Ofek 1982, Stratton 1995, Albrecht et al 1999 and Gorlich and de Grip 2009). Alternatively, what appears as a decline in the job finding rate could instead be the result of heterogeneity among the unemployed such that, at longer durations, more of the unemployed are people who began their spell with poorer job-finding prospects, perhaps including a lower probability of recall to a former employer (Fujita and Moscarini 2013).

In data consisting of a single spell of unemployment for each individual in the sample, it is difficult if not impossible to fully distinguish between these competing explanations. After reviewing a number of studies that have attempted this task, Machin and Manning (1999) conclude that "it does not really seem possible in practice to identify separately the effect of heterogeneity from that of duration dependence without making some very strong assumptions about functional form which have no foundation in any economic theory" (p. 3111). One possible approach to distinguishing between state dependence versus heterogeneity as explanations for the declining job-finding hazard is to exploit the information contained in multiple spells of unemployment for the same individual, as in Alvarez, Borovickova and Shimer (2015). Alternatively, to the extent that individuals have fixed but unobservable employment propensities, it may be possible to use information on individuals' pre-unemployment employment histories to inform the interpretation of their post-unemployment employment rates.

In addition to differences in the rate of entry into employment associated with longer versus shorter unemployment durations, there is also considerable interest in the earnings on their post-unemployment jobs of those experiencing longer versus shorter spells of unemployment. Longer durations of unemployment could be associated with either higher or lower subsequent earnings conditional on finding a job. On the one hand, setting a higher reservation wage and searching longer for a better match could lead to higher earnings on the job that is eventually accepted. On the other hand, the empirical evidence suggests that unemployed individuals turn down relatively few job offers (Schmieder, von Wachter and Bender 2014) and, to the extent that job searchers target their best opportunities first, a negative association between unemployment duration and subsequent earnings could be observed. Further, as with the probability of re-employment, if longer unemployment durations are associated with lower eventual wages, heterogeneity among the unemployed such that those with the lowest labor market productivity also take the longest on average to find a job could be a part of the explanation.

Questions very similar to those about post-unemployment employment and earnings have been addressed in a separate but related literature on the consequences of being displaced from a job. Unemployed and displaced individuals are overlapping but distinct populations—many displaced workers pass through a spell of unemployment, but displaced workers represent only a fraction of all unemployed persons and there are also displaced workers who move directly to a new job or leave the labor force without ever being unemployed.

Evidence of how employment and earnings are affected by displacement from a job can be found in the many studies based on the Displaced Workers Survey (DWS) supplements to the Current Population Survey that have been conducted biennially since 1984 (Farber 2015 is one recent example). In the DWS, respondents are asked whether they were displaced from a job at any time over the previous several years and, if so, their tenure and earnings at the time of the displacement. The survey also collects information on the current labor force status and, if employed, the current earnings of these workers, so that re-employment probabilities and earnings losses associated with displacement can be estimated. Research using the DWS data typically has focused on workers with several years of tenure on their pre-displacement jobs, finding significant declines in both employment and earnings resulting from job displacement for this group.

While the DWS data have been an important source of information about the consequences of job displacement, they contain limited information on the employment and earnings histories of affected individuals and do not offer a comparison group against which the experiences of the displaced workers can be evaluated. These are limitations that research using job histories derived from unemployment insurance or social security records has addressed. In their seminal paper, Jacobson, LaLonde and Sullivan (1993) use administrative records from the state of Pennsylvania unemployment insurance system to examine the declines in employment and earnings experienced by high-tenure workers who lose their jobs in a mass layoff. A major advantage of these data is that they include extensive information on the pre-displacement employment and earnings of workers who are later displaced, as well as similar information for workers who do not experience any displacement. Jacobson, LaLonde and Sullivan find that the average high-tenure worker affected by a mass layoff experiences a sharp initial drop in quarterly earnings, even conditional on having secured at least some employment, and that their earnings never fully recover. Subsequent papers by Couch and Placzek (2010), von Wachter, Song and Manchester (2011) and Davis and von Wachter (2011), among others, have adopted a similar approach and reached qualitatively (though not necessarily quantitatively) similar conclusions.

In this paper, we use novel data and methods adapted from the displaced worker literature to address the question of how experiencing a longer versus a shorter spell of unemployment affects subsequent labor market outcomes. The data that we analyze consist of CPS observations on both employed and unemployed individuals linked to job histories for the same people derived from unemployment insurance (UI) wage records. This linked data set combines the relatively rich information about observable individual characteristics collected in the CPS together with the pre- and post-unemployment job histories that can be constructed using the UI wage records.

Similar to the existing literature on job finding rates among the unemployed, we use these linked data to track the job finding success of individuals with different unemployment durations. Because we have information about the corresponding probabilities of employment in the quarters prior to the date these individuals are observed in the CPS, however, we also are able to examine the *change* in the probability of being employed that is associated with passing through a spell of unemployment. To the extent that the long-term unemployed are people with fixed characteristics that make them less likely to be employed, we would expect them also to have been less likely to be employed prior to their spells of unemployment. In this case, controlling for fixed individual effects by looking at how the probability of employment has changed in the post-unemployment period compared to the pre-unemployment period should show less marked differences between the long-term and the short-term unemployed than a simple comparison of post-unemployment UI employment rates. This will not be the case if individuals with longer unemployment durations have fixed employment-determining characteristics that are similar to those with shorter unemployment durations.

In addition to studying the changes in employment probabilities associated with longer versus shorter spells of unemployment, we also use our linked data to study the pattern of earnings losses experienced by the unemployed. Our data include information on the amount earned by each of the individuals in our sample during each quarter of their job history. This allows us to compare individuals' earnings prior to and subsequent to the date they are observed as unemployed. We ask whether individuals who have experienced a longer spell of unemployment experience larger earnings losses and, if so, the extent to which this reflects their accepting jobs that pay less relative to their previous positions versus their simply being less likely to be employed.

The plan of the paper is as follows. Section II describes the linked data used in our analysis. In Section III, a visual analysis of the employment and earnings impact of longer versus shorter spells of unemployment is presented in the form of graphs that show how these variables evolve from the period twelve quarters before through eleven quarters after the month in which individuals are observed in our linked sample in the CPS data. Section IV presents a more formal regression analysis focused on the same labor market outcomes and Section V concludes.

II. Data

The data used in our analysis are a unique match between CPS and Longitudinal Employer-Household Dynamics (LEHD) micro-data. The CPS collects information on labor force activity and demographics from the members of approximately 50,000 households per month. The LEHD is a longitudinally linked employer-employee dataset created at the U.S. Census Bureau. The LEHD source data are administrative records from states' unemployment insurance (UI) systems that contain information on the earnings of all covered workers in that quarter, often referred to as wage records, along with Quarterly Census of Employment and Wages (QCEW) data containing information about the establishments at which these workers are employed. Every quarter, employers who are subject to state UI laws—approximately 98% of all private sector employers, plus state and local governments—are required to submit information on their workers (the wage records) and their workplaces (the QCEW) to the state UI agencies. The wage records and the QCEW data submitted to the Census Bureau by the state agencies are combined and enhanced with various census and survey micro-data to create the LEHD. Abowd et.al. (2009) provide a thorough description of the source data and the methodology underlying the LEHD data.

For recent years, the LEHD comes close to being a universe of all workers employed in the U.S. private sector, state government or local government. Because states have joined the LEHD at different points in time, however, data for fewer states are available in earlier years. Data for 30 states accounting for approximately 65 percent of the U.S. population are available beginning in 1998. A limitation of the available data is that the CPS identifier needed to link the CPS and LEHD records is available only for March of each year. Our sample consists of respondents to the 2001 through 2010 March CPS's for whom we have the linking identifier and who lived in the 30 states for which LEHD data are available from 1998 onwards (see Abraham et al 2013 for details regarding the linkage procedures).

The linked data set we have constructed allows us to follow unemployed individuals backwards in time for 12 quarters and forward in time for 11 quarters (provided they remain in the states for which we have LEHD data). This means we are able to attach prior and future employment trajectories to the records of CPS respondents. In addition, the LEHD includes information on earnings for each reported job, so that we are able to observe the prior and future earnings profiles of the CPS respondents. Our interest lies primarily with those who are classified as unemployed in the CPS as of the date of the CPS-LEHD match, but for comparison purposes, we also construct similar employment and earnings profiles for the CPS employed and for the CPS not in the labor force (NILF). Because the linking variable is missing for about 20 to 30 percent of CPS respondents, we use propensity score methods as described in Abraham et al (2013) to weight the observations for those for whom we have a link identifier so that they represent the entire population.[1]

Weighted tabulations of the CPS observations for which we have the identifiers necessary to link to the LEHD microdata match published tabulations almost identically. Appendix Figure A1 presents the 2001 to 2010 time series of the CPS employment-to-population ratio and the unemployment rate from our weighted data (labeled as AHSS in the figure) and from the BLS website (labeled as BLS in the figure). The BLS data are non-seasonally adjusted statistics for the month of March. The AHSS and the BLS lines are essentially identical, implying that our propensity score weights are working as intended. Appendix Figure A2 presents similar graphs for the percent of the unemployed in each of several unemployment duration categories (<5 weeks, 5-10 weeks, 11-14 weeks, 15-26 weeks, 27-51 weeks, and ≥52 weeks). Again, the time series from AHSS weighted sample is essentially identical to the published data.

Table 1 presents descriptive statistics of the dependent variables and many of the explanatory variables used in our subsequent analysis. The quarterly employment and earnings outcome measures come from the UI wage records that are part of the LEHD; the numbers reported in the table refer to the quarter eight quarters before and the quarter eight quarters after the CPS-LEHD link quarter. The demographic variables, including age, education, race, gender, marital status and nativity, are based on the CPS record and are measured as of the date of the CPS-LEHD link. Finally, the job history variables at the bottom of the table are constructed from information contained in the UI wage records and refer to the year that includes the quarters twelve through nine quarters before the CPS-LEHD link quarter. Because we are interested in how subsequent labor market outcomes differ for people who have been unemployed for longer versus shorter lengths of time as of the time of the CPS-LEHD link, the descriptive statistics are reported separately for people who had been unemployed up to 13 weeks, 14-26 weeks, 27-39 weeks, 40-52 weeks, 52-65 weeks, or more than 65 weeks as of the March CPS reference week. We refer to these groups as the one quarter, two quarter, three quarter, four quarter, five quarter and six plus quarter unemployment duration groups. For comparison, descriptive statistics for people who were employed at the time of the CPS-LEHD link also are reported.

Among the features of interest in Table 1 are the differences in the values of the employment and earnings variables eight quarters prior to and eight quarters following the CPS-LEHD merge quarter. Persons who are employed in the CPS at q=0 have a 72-73 percent UI employment rate two years before and two years after the link quarter. Conditioning on having UI employment, these individuals have average real quarterly earnings of $12,050 two years before and $12,741 two years after the link quarter. The employment rates and average earnings for persons who are unemployed at q=0 are much lower, especially in the post-unemployment period. Several of the demographic variables show differences across the unemployment duration groups. Most notable are the differences in age distribution for the short-duration versus the long-duration unemployed, with a higher proportion of persons age 15-24 at short

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[1] To be exact, we use step 2 of the two-step propensity score procedure described in appendix A of Abraham et al (2013). Individuals with a linking identifier are retained in our sample regardless of whether we are able to locate any employment records for them in the LEHD data.

durations and a higher proportion of persons age 45 plus at long durations. The numbers of underlying observations in each unemployment duration group, as well as the number for the group that is employed in a CPS job in March of the link quarter, are shown at the bottom of the table.

III. Employment and Earnings Profiles

One way to begin to learn about the labor market consequences of longer versus shorter spells of unemployment is to use the linked CPS-LEHD data to plot employment probabilities and measures of earnings for the time periods before and after those in our sample are observed in the CPS. Many of the conclusions to be drawn from the more formal analysis that follows can be previewed in simple graphs of employment and earnings profiles.

IIIa. Employment Profiles for the Full Matched Sample

Figure 1 displays employment profiles for the full sample of employed, unemployed, and NILF individuals for whom we have the identifier needed to link a March CPS record to the UI wage records contained in the LEHD. The horizontal axis in the figure is time period, normalized so that q=0 is the quarter of the CPS-LEHD match (i.e., the quarter including the March in which the individual's labor force status is recorded in the CPS). Data for all of the years from 2001 through 2010 have been pooled, so that q=0 represents different calendar years for different people; in our more formal regression analyses, we estimate models that include year dummy controls. The points to the left of q=0 along the horizontal axis are the 12 quarters preceding the quarter of the CPS-LEHD merge q={-12,…,-1} and those to the right are the 11 quarters following the quarter of the CPS-LEHD merge q={1,…,11}. The vertical axis represents the percentage of individuals with UI employment in the indicated quarter. These percentages are estimated using weights constructed so that the linked sample represents the relevant population.

The dashed line at the top of the figure shows the quarterly UI employment probabilities for people who reported in the CPS that they were employed during the q=0 March survey reference week. Of those reporting CPS employment in March, 80.1 percent had at least one UI job during the first quarter of that same year. The UI data do not capture federal government employment or self-employment and, on average over the 2001 through 2010 period, 9.6 percent of those employed in the CPS fell into one of these two categories. From our previous research (Abraham et al 2013), we also know that about 18 percent of CPS respondents who reported wage and salary jobs in sectors covered by the UI data in one or more months of the quarter do not have corresponding wage records. Because individuals with stable employment account for a higher share of those employed in any single month than of those employed at any point during the quarter, we would expect the share of those who reported CPS employment in March who do not have a UI job to be less—and potentially substantially less—than 18 percent. The 80.1 percent UI employment rate for those classified as employed in the CPS thus seems generally in line with what we would have expected based on prior information. Because some spells of employment are transitory, we also might expect the employment rates of a sample defined on the basis of employment as of a specific date to be somewhat lower before and after that date.

This is exactly what the figure shows—the UI employment probabilities for those categorized as employed in the CPS resemble an inverted "V" across time. Even in quarters other than q=0, however, the LEHD employment rates for the group classified as employed at q=0 consistently exceed 70 percent.

Similarly, the dotted line at the bottom of Figure 1 shows the UI employment probabilities for people who report being NILF in the March CPS. We find that 9.6 percent of persons NILF during the March CPS survey week have a UI-covered job at some point during the first quarter of the same year. This percentage rises as we look either backward or forward in time, most likely reflecting the fact that some of the NILF are older persons who have recently retired and others are young persons who subsequently leave school and find jobs. Because they are not obviously relevant for the questions in which we are interested, we have not incorporated the NILF in our subsequent analysis.

The more interesting information presented in Figure 1 is the pattern of UI employment probabilities for those who are classified as unemployed in the CPS. Separate employment probability profiles are shown for those who had been unemployed up to 13 weeks (which we refer to as the one quarter unemployed), 14-26 weeks (two quarter unemployed), 27-39 weeks (three quarter unemployed), 40-52 weeks (four quarter unemployed), 52-65 weeks (five quarter unemployed), or more than 65 weeks (six plus quarter unemployed) as of the March CPS reference week.

One feature of these plots that may require some comment is the 10 to 20 percent employment rate in the q=0 quarter among those who are classified in the March CPS as having been unemployed 14 or more weeks. Similar employment rates also are observed for prior quarters that, based on the duration of unemployment reported in the CPS, fell within the span of the individual's current unemployment spell. We initially found this puzzling, as a literal interpretation of what it means to be unemployed implies that none of these people should have done any work for pay during the quarters falling wholly within their unemployment spell.[2] On reflection, however, this finding seems less surprising. Previous research has found that reported unemployment durations often incorporate one or more months a person has spent out of the labor force (see, for example, Clark and Summers 1979). Similarly, individuals who move from employment to unemployment or from out of the labor force to unemployment in the CPS commonly report initial unemployment durations of more than the 4 or 5 weeks between survey reference periods (see, for example, Kroft et al 2014). The non-zero UI employment rates among those classified as unemployed may simply indicate that these individuals do not consider the employment in question to be a "real" job. Consistent with this interpretation, when we look at earnings, we find that the earnings on jobs held during the q=0 quarter by individuals classified as unemployed in the CPS are substantially lower than the earnings on jobs held prior to the start of the same individuals' unemployment spells.

Accepting that there will be some UI employment reported even during quarters that fall within a spell of unemployment, the employment probabilities to the left of q=0 seem very

[2] Employment during the q=0 quarter for those unemployed 13 weeks or less is not surprising, as all of these individuals would have started their unemployment spell in that quarter and many of them would have been employed immediately before the spell began.

consistent with the unemployment durations recorded in the CPS. For example, among those reporting two quarters of unemployment in the CPS (14-26 weeks duration), the UI employment rate is just 19 percent during the CPS-LEHD match quarter but 52 percent in the previous quarter, which precedes the start of their spell of unemployment. Of those reporting three quarters of unemployment in the CPS (27-39 weeks), the UI employment rate is 15 percent in the match quarter and 19 percent in the previous quarter, but 47 percent two quarters before the match quarter. The pattern is similar for those with four and five quarters of unemployment, so that the number of quarters with an UI employment rate under 20 percent aligns precisely with the duration of unemployment, measured in quarters, recorded in the CPS.

The economic questions motivating our paper relate to the labor market trajectories of those observed as unemployed in the CPS. Figure 1 tells us that 55 to 60 percent of individuals with one to five quarters of unemployment at the CPS-LEHD link quarter were employed eight quarters before the link quarter, before their spell of unemployment began. Further, for each of these unemployment duration groups, the probability of being employed was relatively flat over the one-to-two year period before the start of the unemployment spell. The data for those with six or more quarters of unemployment are harder to interpret, as some of these people already were unemployed even as far back as two years before the link quarter. In what follows, we focus mainly on the first five unemployment duration groups, those with unemployment durations of one to five quarters. Those who will be employed at q=0 are 13 to 19 percentage points more likely to be employed eight quarters before the link quarter than those who will be in one of the first five unemployment duration groups at q=0.

While pre-spell employment probabilities are very similar for the different unemployment duration groups, the post-spell outcomes for these groups vary more noticeably. Those with shorter unemployment spells are substantially more likely to be employed two to three years after their unemployment spell is recorded in the CPS than those who have longer unemployment spells recorded. Individuals with one quarter of unemployment (1 to 13 weeks) at q=0 have an average employment rate of 57 percent in the 8^{th} through 11^{th} quarters after the CPS-LEHD match. The corresponding average employment rate is 54 percent for those with two quarters of unemployment, 51 percent for those with three quarters of unemployment, and 42 percent for those with four or five quarters of unemployment.

The transition from unemployment to eventual employment also appears to occur more quickly for the short-term unemployed than for those who already have been unemployed for an extended period. The red line in the figure (for individuals with 2 quarters of unemployment) crosses the 40 percent threshold at q=1 and the 50 percent threshold at q=2; the green line (individuals with 3 quarters of unemployment) crosses 40 percent at q=2 and 50 percent at q=6; and the blue line (for individuals with 4 quarters of unemployment) crosses 40 percent at q=5.

The employment probabilities for the duration groups with 3 or more quarters of unemployment appear to flatten around 7 quarters following the link quarter (q=0). The employment probability of the 3 quarter duration group crosses 50 percent at q=6 and remains between 48 and 53 percent thereafter, the 4 quarter duration group crosses 40% at q=5 and remains between 41 and 45 percent thereafter, and the 5 quarter duration group crosses 40 percent at q=7 and remains between 42 and 43 percent thereafter. An implication is that analyses of employment outcomes based on CPS data, which restrict the window of observation to no more than 15 months or roughly five quarters from the date a person's labor force status is first observed, will capture much but not all of the eventual employment outcomes of the long-term unemployed.

Finally, Figure 1 shows that employment probabilities following an unemployment spell are lower for many of the unemployment duration groups than the employment probabilities for the same people preceding the start of the unemployment spell. The exception is the group with 1 to 13 weeks (1 quarter) of unemployment at the time of the CPS-LEHD link. The decline in the likelihood of being employed is notably larger for those with longer unemployment durations as of q=0.

IIIb. Earnings Profiles

In addition to learning about the pre-unemployment and post-unemployment employment profiles associated with short-term and long-term unemployment, we also are interested in the corresponding earnings profiles. Figure 2 plots a measure of the earnings of individuals who were employed or belonged to one of the six unemployment duration groups as of q=0. More specifically, the variable that we have plotted is the inverse hyperbolic sine (hereafter IHS) of real earnings, where the IHS of a variable is defined as:

$$IHS(x) = \ln\{x + \mathrm{sqrt}[1 + (x*x)]\}$$

For x>0, the value of this expression is approximately ln(x) plus ln(2); for x=0, it is just zero. The IHS transformation thus behaves very similarly to the more familiar logarithmic transformation but with any zero values treated consistently rather than in some unavoidably ad hoc fashion (e.g., replacing zeroes with a value of one so that the ln transformation can be applied). The top panel of Figure 2 includes everyone in our matched sample even if they had no earnings in a given quarter; the bottom panel of Figure 2 includes only those people who have positive earnings in a given quarter.

At a glance, the profiles plotted in the top panel of Figure 2 appear very similar to the employment probability profiles we have already discussed. Individuals employed at q=0 had higher IHS(real earnings) in earlier periods than any of the unemployment by duration groups, but the earnings of the first five unemployment by duration groups do not look very different from one another. In the quarters following the link quarter, individuals employed at q=0 continue to have higher IHS(real earnings) than any of the unemployment by duration groups, but now there are also obvious differences in IHS(real earnings) across the unemployment by duration groups, with longer durations associated with lower real earnings.

The profiles plotted in the bottom panel of Figure 2 looks quite different.[3] Restricting attention to individuals with positive earnings, it is still the case that those who were employed at

[3] The top and bottom panels of Figure 2 have different scales along the vertical axis. This is done to highlight the similar patterns in the quarters prior to q=0 as well as the different patterns in the quarters after q=0. Appendix Figure A3 presents the top and bottom panels with similar scales; these panels show how much of the earnings

q=0 have higher average IHS(real earnings) than any of the unemployment by duration groups. In this case, however, the unemployment by duration groups are much more similar to each other, especially in the period following the quarter in which they were observed as unemployed. Putting this somewhat differently, conditional on finding a job, the earnings of the short-duration and long-duration unemployed do not look very different. This suggests that most of the difference in earnings outcomes apparent in the top panel occurs along the extensive margin (whether or not people are employed) rather than along the intensive margin (how much they earn when they are working). We explore this issue more systematically in the next section of the paper.

IV. Regression Results

Although there is a great deal to be learned from Figure 1 and Figure 2, visual inspection of the data can only take us so far. The figures do not allow us to test for the statistical significance of observed differences across the employment and unemployment duration groups or to control for factors other than unemployment duration that might explain differences in labor market outcomes by unemployment duration group. We turn now to regression equations that permit us to do this.

IVa. Estimation Framework

Rather than including all available quarters of data, the regression models we have estimated focus on employment and earnings eight quarters prior to and eight quarters following the quarter of the CPS-LEHD match. The estimation framework borrows from that used by Jacobson, LaLonde, and Sullivan (1993) in their analysis of displaced workers' employment and earnings profiles. Specifically, we estimate equations of the form:

$$(1) \qquad Y_{dqi} = \sum_{d=0}^{6} \sum_{q=-8,+8} I_{dqi}\,\delta_{dq} + X_{dqi}\,\beta_q + \psi_{dqi}, \quad \psi_{dqi} = \mu_i + \varepsilon_{dqi}$$

where *d*={0,1, 2, … 5, 6+} indexes the employment and unemployment duration group to which a person belongs, with *d*=0 representing people who are CPS employed and d>0 representing people with different unemployment durations in the CPS as of the CPS-LEHD link quarter; *q*= -8 or +8 indexes the quarter eight quarters before or eight quarters after the link quarter; and *i* indexes the individual. In the employment equations, Y_{dqi} is a {0,1}indicator of whether the person has one or more UI jobs in the quarter, and in the earnings equation, Y_{dqi} is the person's IHS(real earnings) from any UI jobs held. The fourteen I_{dqi} variables are {0,1} indicators that take their values according to the various {d,q} combinations. Variables appearing in the X vector include the individual's demographic characteristics, year dummy variables, and the characteristics of jobs the individual held 9 to 12 quarters before the date of the CPS-LEHD merge, depending on the specific model. In some models, the coefficients of the variables included in the X vector are constrained to be the same in both q=-8 and in q=+8; in others they

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variation across duration groups is due to the extensive margin (employment versus non-employment) rather than the intensive margin (earnings variation conditional on employment).

are allowed to vary. The ψ_{dqi} are error terms, comprised of a fixed individual effect (μ_i) and a purely random error (ε_{dqi}).

Because μ_i and the individual's labor force status during the link quarter (whether employed or, if unemployed, how long unemployed) may be correlated, the estimates of the δ_{dq} may be biased. If we find, for example, that $\delta_{1,+8}$ is larger than $\delta_{2,+8}$, this could be either because having been unemployed just one quarter raises the chances of finding a job relative to having been unemployed two quarters or because the group of people unemployed just one quarter have values of μ_i that are higher on average than those for the group of people unemployed two quarters. Note, however, that for any *d*, assuming the regression specification to be correct, the bias in $\delta_{d,-8}$ is identical to the bias in $\delta_{d,+8}$, so that the difference $\delta_{d,-8} - \delta_{d,+8}$ is unbiased.

Using the regression coefficients from equation (1), we are able to test the significance of the employment losses for each of the link-quarter employment and unemployment duration groups and also the significance of the differences between any pair of losses. A first set of tests asks whether employment probabilities or earnings levels are the same eight quarters before the CPS-LEHD link as eight quarters after. We refer to this as the "loss" test and conduct it for each labor force status group:

[loss0] test $\delta_{d=0,q=-8} - \delta_{d=0,q=+8} = 0$
[loss1] test $\delta_{d=1,q=-8} - \delta_{d=1,q=+8} = 0$
. . .
[loss6] test $\delta_{d=6+,q=-8} - \delta_{d=6+,q=+8} = 0$.

The loss0 test looks at the change in UI employment probability or earnings level for individuals with CPS employment at the time of the CPS-LEHD link, the loss1 test looks at individuals with one quarter of unemployment duration at the time of the CPS-LEHD link, and so on.

The second set of tests asks whether the losses in the probability of employment or earnings level for those with longer term unemployment differ from the losses for those who only recently have become unemployed. We refer to this as the "diff" test and report comparisons of the losses for each unemployment duration group from two quarters through six or more quarters relative to the losses for the one quarter unemployment duration group:

[diff12] test $(\delta_{d=2,q=-8} - \delta_{d=2,q=+8}) - (\delta_{d=1,q=-8} - \delta_{d=1,q=+8}) = 0$
[diff13] test $(\delta_{d=3,q=-8} - \delta_{d=3,q=+8}) - (\delta_{d=1,q=-8} - \delta_{d=1,q=+8}) = 0$
. . .
[diff16+] test $(\delta_{d=6+,q=-8} - \delta_{d=6+,q=+8}) - (\delta_{d=1,q=-8} - \delta_{d=1,q=+8}) = 0$.

The diff12 test compares the losses for the two-quarter unemployed to the losses for the one-quarter unemployed, the diff13 test compares the losses for the three-quarter unemployed to those for the one-quarter unemployed, and so on.[4]

[4] We also have estimated but due to space constraints do not report corresponding diff01 through diff06 tests that compare the changes in employment probability and earnings level for individuals who are in each of the different

IVb. Employment Equation Estimates

Estimates of the δ parameters from a set of employment probability models are reported in the top two panels of Table 2. The q=-8 parameters for the employment and six unemployment duration groups are reported in the top panel of the table; the q=+8 parameters for the same groups are reported in the second panel of the table. The model in the first column includes no other controls. For the model in the second column, indicator variables from the CPS are added for gender, age (15-24, 25-34, 45-54, 55-64, 65+), education (<HS, some college, college, >college), race (black, other), marital status, foreign born and year, with the coefficients on all of the variables restricted to be the same in the two quarters. The model in the third column adds a set of nine job history variables based on LEHD employment and earnings during quarters q=-12 through q=-9, including the number of quarters and full quarters the person worked, the mean number of jobs and full quarter jobs held, the number of hires and separations experienced, the annual sum of real earnings, and the quarterly sum (across all jobs) and average (across all jobs) of real earnings. As in column (2), the coefficients in the column (3) model are restricted to be the same in q=-8 and q=+8. Finally, the models in the fourth and fifth columns replicate those in the second and third columns, but with the estimated control variable coefficients allowed to differ across the pre-link and post-link quarters.

The parameter estimates in the first column of Table 2 simply reproduce the employment probability values that can be read off the plot displayed in Figure 1 for the two quarters in question. In both q=-8 and q=+8, the UI employment probabilities for people who are employed in the link quarter are substantially higher than those for people who are unemployed (tests not presented in Table 1 show that these differences are statistically significant). Except for the group unemployed six quarters or more, the q=-8 employment probability differs little across the unemployment duration groups; in q=+8, however, the probability of having UI employment falls with link quarter unemployment duration. More formally, the "loss" tests in the third panel of the table show that the probability of having UI employment does not change between q=-8 and q=+8 either for those who are employed in the link quarter or for the one-quarter unemployed, but that there are statistically significant UI employment probability losses at longer unemployment durations.[5] The "diff" tests show that the losses for those with unemployment durations of 14 weeks or more (2 or more quarters) as of the link quarter are larger than for those who had been unemployed just 1-13 weeks (1 quarter), with the point estimate of the difference rising through 53-65 weeks of unemployment (5 quarters).[6]

The second model in Table 2 adds demographic variables and year dummies, all measured as of the link quarter, but constrains their coefficients to be the same in q=-8 and q=+8; the third model in the table includes additional variables reflecting the characteristics of jobs held

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unemployment duration groups in the link quarter to the change for individuals who are employed in the link quarter.

[5] As already noted, it is difficult to interpret the estimates for those unemployed six or more quarters. With respect to these specific estimates, some of those unemployed six or more quarters began their spell of unemployment more than eight quarters earlier, so that the estimated losses do not in fact represent a comparison of employment rates before and after the unemployment spell.

[6] All of the unemployment duration groups experiences losses in employment probability that are significantly larger than the losses for those employed in the link quarter.

during quarters q=-12 through q=-9, again constraining their effects to be the same in q=-8 and q=+8. The addition of the demographic and year dummies in column (2) raises the estimated q=-8 and q=+8 employment probabilities slightly for all of the unemployment duration groups. In other words, had the observable demographic characteristics and observation years for the unemployed been the same as those of the average person in the linked sample (which, because there are many more people who are employed than unemployed, are very close to the characteristics of the average employed person), their q=-8 and q=+8 employment rates would have been slightly higher. The job history variables have a more noticeable effect on the employment probability levels for the unemployed.

By construction, introducing time-unvarying variables and constraining their effects to be the same in both q=-8 and q=+8 can have no effect on the estimated employment losses across the two periods and thus cannot change the estimated differences in the losses across the labor force status groups. This can be seen in the third and fourth panels of Table 2, where the "loss" tests and the "diff" tests are reported. Note that the point estimates for the losses and the differences reported are identical across the first three columns of the table.

This is not the case, however, if the effects of the time-unvarying variables are permitted to differ between q=-8 and q=+8. Consider, for example, how age might affect the probability of employment in these two periods. Employment probabilities generally are rising for those in their teens and twenties, as people finish school and enter the labor market; we might therefore expect the effect of being, say, age 15-24 as of the link month on the probability of employment to be greater in q=+8 than four years earlier in q=-8. In contrast, employment probabilities generally are falling for those age 50 and older, as people begin to enter retirement and leave the labor market; we might therefore expect the effect of being, say, age 55-64 as of the link month on the probability of employment to be smaller in q=+8 than in q=-8. Age is a relevant variable because more of the short-term unemployed are young and more of the long-term unemployed are older. Accounting properly for the fact that we should expect employment rates to be rising for the young and falling for those age 50 plus, differences in age across unemployment duration groups should help to explain the larger employment losses associated with longer unemployment durations.

The models in column (4) and column (5) of Table 2 put this idea to the test. Like the model in column (2), the column (4) model adds gender, age, education, race, marital status, foreign born and year dummies to the basic no-controls model; like the model in column (3), the column (5) model in addition includes characteristics of the jobs held from q=-12 to q=-9. Now, however, the coefficients on the added variables are allowed to differ between q=-8 and q=+8. Estimating these models is equivalent to fitting first-differenced forms of equation (1) that include the listed variables, allowing them to affect the *change* in the employment probability between the two periods.

The variables added to the column (4) model raise both the estimated q=-8 employment probabilities and the q=+8 employment probabilities relative to those in the column (1) model, but the effects on the q=-8 probabilities are somewhat larger. As a result, the employment losses estimated for the first five unemployment duration groups are larger in column (4) than in column (1). Interestingly, however, this is more the case for the one-quarter unemployment duration group than for any of the longer duration groups. As a result, as can be seen in the "diff" tests in the bottom panel of the table, the addition of the column (4) controls makes the employment losses for the longer unemployment duration groups more similar to those for the shortest unemployment duration group than in the model with no controls. Based on the point estimates, roughly 20 to 30 percent of the difference in the employment losses experienced by those with 2, 3, 4, 5 or 6+ quarters of unemployment versus the loss experienced by those with just one quarter of unemployment can be explained by the addition of the model (4) controls. Age is the most important of these variables; we find that roughly 85 percent of the effect is captured if age is added to the model alone. Even with the demographic and year variables included in the model, however, the employment losses experienced by the long-term unemployed are larger than those experienced by the short-term unemployed.

The model in column (5) adds variables related to the individual's q=-12 to q=-9 job history. The job history variables have large effects on the estimated δ parameters, and increase the magnitude of the estimated losses for the unemployed. However, the employment losses increase for all unemployment duration groups, and as a result the relative losses of the long duration unemployed relative to the short duration unemployed do not change substantially relative to the estimates in column (4).

In summary, the employment probability regression results in Table 1 quantify the patterns that were evident in Figure 1. First, individuals who report CPS-LEHD link quarter CPS employment are substantially more likely to have UI employment eight quarters prior to the link quarter than any of the unemployed groups. Further, the corresponding pre-unemployment UI employment rates are similar for persons with unemployment durations of one to five quarters. Eight quarters after the CPS-LEHD match, those who report being unemployed in the CPS have lower employment probabilities than eight quarters before, and the losses for all but the shortest unemployment duration group are statistically significant.

An important finding in Table 1 is the increase in the magnitude of the estimated employment probability losses associated with longer reported CPS unemployment durations. The addition of control variables with time-varying coefficients weakens this relationship, but accounts for only a portion of the differential between the job finding success of the long-term versus the short-term unemployed. Our findings are consistent with a role for duration dependence that hinders the future employment prospects of the long-term unemployed.

IVc. Earnings Equation Estimates

Estimates of the δ parameters from two sets of earnings models are reported in the top two panels of Table 3 and Table 4. The model in Table 3 (which corresponds to Figure 2a) is fit using data for everyone in the sample whether they have earnings in a given quarter or not; in quarters with no UI earnings, a zero is assumed. The model in Table 4 (which corresponds to Figure 2b) uses only those observations for which positive UI earnings are reported in the quarter. In both cases, as already described, the dependent variable is IHS(real earnings). The structure of the tables reporting on the earnings models is the same as the structure of the table for the employment probability table just discussed.

The estimates that appear in Table 3 are in many respects very similar to those in Table 2. Looking at the full linked sample, at q=-8, the IHS(real earnings) of those who will be employed in the CPS at q=0 are significantly higher than those in any of the groups that will be unemployed in q=0. The point estimates of the differences in the q=-8 measure of earnings across the first five unemployment duration groups are generally similar and do not vary systematically with how long the person has been unemployed; only the point estimate for the group unemployed six plus quarters differs significantly from the others. At q=+8, it continues to be the case that those who were employed in the CPS at q=0 have higher IHS(real earnings) than those in any of the unemployment duration groups, but now there is a systematic decline in the measure of earnings with the duration of unemployment at q=0. Looking at the "loss" statistics, the quarterly earnings of employed individuals rise on average between q=-8 and q=+8, those for the group unemployed 1-13 weeks as of the link quarter do not change significantly, while those for all of the longer-term unemployment groups exhibit a significant decline. The losses in earnings are monotonically increasing in unemployment duration through the group with five quarters of unemployment at the link quarter; the losses of those unemployed six plus quarters are smaller because that group was doing poorly even at q=-8.

Controls for demographics and year are added in column (2) and for those variables plus job history in column (3). In these models, the coefficients on the added variables are constrained to be the same in q=-8 and q=+8. The same variables are added in column (4) and column (5) but with their coefficients permitted to differ across the two periods. As before, by construction, adding fixed controls with coefficients constrained to be equal across the two time periods may raise or lower the level of the estimated δ's but by the same amount for both periods and thus cannot affect the estimated losses in earnings between q=-8 and q=+8. This explains why the losses reported in column (2) and column (3) are identical to those reported in column (1). To affect the estimated losses, the coefficients on these variables must be allowed to differ across time periods. When this is done in column (4) and column (5), we observe larger estimated losses for several of the unemployment duration groups (those with one to four quarters of unemployment as of the date of the CPS-LEHD match). The implication is that, given the characteristics of the members of these groups, their earnings would have been expected to grow and the declines actually experienced between q=-8 and q=+8 look worse relative to this expected-growth benchmark than relative to the unadjusted benchmark implicit in column (1).

We also are interested in decomposing the earnings losses experienced by those who pass through a spell of unemployment into the pieces explained by the lower likelihood they are employed as opposed to the lower earnings they experience in post-unemployment jobs. Taken together, the results reported in Table 2, Table 3 and Table 4 allow us to do this.[7] To illustrate, consider the values δ(-8) and δ(+8) in column (1) of Table 3 for the group with four quarters of unemployment as of the link quarter—δ(-8) = 4.958 and δ(+8) = 3.633. The ratio of these two coefficients is 0.732, which means that IHS(real earnings) is approximately 26.8 percent lower in q=+8 than in q=-8. Note that, in each period, the value of IHS(real earnings) for the full sample (coefficients in Table 3) is just the product of the probability of employment (coefficients in Table 2) and the value of IHS(real earnings) for the portion of the sample that is employed

[7] Because the calculations involve an identity, any two of the three tables would provide the information necessary for our calculations, but reporting all three sets of coefficients helps to make the story clearer.

(coefficients in Table 4). Carrying out the relevant calculations, IHS(real earnings) would have fallen 23.3 percent as a result of the fall in the employment rate for the four-quarter unemployment group on its own and by 4.4 percent as a result of the fall in earnings for those in the group who held a post-unemployment job. Carrying out a logarithmic decomposition (that is, expressing the ln of the ratio of IHS(real earnings) as the sum of the ln of the employment ratio plus the ln of the ratio of IHS(real earnings) for those with positive earnings), 85.4 percent of the decline in the overall average level of IHS(real earnings) can be attributed to the fall in the employment rate and 14.6 percent to the fall in earnings among those who are employed.

We conduct this exercise for other duration groups, using the estimates from the five specifications for which results are reported in Tables 2, 3, and 4.[8] The following text table shows the percent of the change in IHS(real earnings) between quarter q=-8 and q=+8 for the indicated group that is accounted for by changes along the employment margin:

	(1)	(2)	(3)	(4)	(5)
Employed	29.1%	22.0%	16.2%	45.5%	56.7%
1 Qtr U Duration	-164.9%	75.0%	36.2%	87.2%	89.4%
2 Qtrs U Duration	88.2%	96.6%	104.7%	93.3%	93.3%
3 Qtrs U Duration	82.9%	89.7%	94.9%	88.9%	89.8%
4 Qtrs U Duration	85.4%	89.1%	92.1%	88.5%	89.6%
5 Qtrs U Duration	88.2%	90.4%	92.3%	89.5%	89.9%
6+ Qtrs U Duration	88.7%	89.8%	93.0%	88.7%	91.3%

In column (1) of this text table, which captures the patterns present in the raw data before the introduction of any controls, the decline in employment accounts for 83 to 89 percent of the overall loss in full sample earnings for unemployment duration groups 2 through 6+. Adding explanatory variables to the specification raises this estimate slightly. We conclude that the driving force behind the earnings losses shown in Figure 2a and Table 3 is the lower probability of employment in q=+8 rather than the reduction in what unemployed persons earn when they eventually do get a job.

IVd. Business Cycle Analysis

One of the questions raised by the unprecedented spike in long-term unemployment during and following the 2007-2009 recession is whether the employment and earnings outcomes experienced by the long-term unemployed are relatively worse in a weak labor market than when labor market conditions are stronger. Given that the variation in earnings outcomes is driven primarily by the variation in employment rather than by variation in earnings conditional on finding a job, we focus on employment outcomes as in Figure 1 and Table 2 in our examination of this question.

[8] The addition of control variables breaks the exact identity just described, but the resulting "error" is small. Defining error as the difference between the Table 3 δ estimates and the predicted Table 3 δ estimates calculated as the δ estimates from Table 2 times those from Table 4, this error never exceeds five percent of the actual δ estimates in Table 3.

To address the question of whether employment trajectories vary depending on business cycle conditions, we display plots similar to that shown in Figure 1 for groups of years representing different business cycle environments and fit models in which the δ parameters are interacted dummies representing those same groups of years. Good years are those in which neither the March two years before nor the March two years after are at the depth of any recession; we classify 2004, 2005, and 2006 as good years. Bad years are defined to be those in which the link quarter occurs during a period of high unemployment; we classify 2002, 2008, and 2009 as bad years. The remaining years in our sample (2001, 2003, 2007, and 2010) are grouped into a third "other" category.

Figure 3 displays employment probability profiles for the three groups of years—good years in the top panel, bad years in the middle panel and other years in the bottom panel. The pattern of UI employment probabilities for the pre-link quarters is generally similar to that in Figure 1 for all years pooled together. In the post-link quarters, however, there is a more noticeable difference between the pattern for the good years and that for the bad years. In the good years, employment rates for those in the first three unemployment duration groups return to a level very close to those of the pre-unemployment period; this is not the case in the bad years. Moreover, the differences between the longer-duration and shorter-duration unemployment groups are noticeably less pronounced in the good year graph than in the bad year graph.

Table 5 presents regression results with the d parameters interacted with the good years dummy and bad years dummy. In order to keep the table to a single page, we present only the column (1) and column (5) models from the earlier tables. Our main interest here lies with the loss statistics in the column (1) specification. In good years, the losses for the shortest duration unemployed (1 quarter) are actually negative: Employment probabilities rise from 50.57 percent in q=-8 to 57.46 percent in q=+8. Furthermore, in good years, the losses of even the long duration unemployed are small in magnitude (except for the five-quarter duration group) and never statistically significant. On the other hand, in bad years, there are losses for every duration group, including those employed at q=0.

These results change somewhat when explanatory variables with time-varying coefficients are added in column (5). In this specification, the losses for all unemployment duration groups are positive, and the losses are larger in magnitude the greater the duration of reported unemployment (with the exception of the 6+ group). Nevertheless, in the column (5) estimates, the losses in good years are smaller than the losses in bad years.

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Table 1: Descriptive Statistics

	Employed (in CPS) at q=0	U Duration 1 Quarter at q=0	U Duration 2 Qtrs at q=0	U Duration 3 Qtrs at q=0	U Duration 4 Qtrs at q=0	U Duration 5 Qtrs at q=0	U Duration 6+ Qtrs at q=0
Dep Var q=-8							
UI Employment	.7253	.5455	.5672	.5739	.5403	.5960	.4288
UI Real Earn (>0)	12,050	7,234	8,118	8,488	8,413	9,773	8,103
Dep Var q=+8							
UI Employment	.7277	.5499	.4916	.4801	.4142	.4174	.3155
UI Real Earn (>0)	12,741	6,098	6,240	6,212	5,765	6,532	5,498
CPS {0,1} Variables							
Age 15-24	.1336	.3337	.2471	.2743	.2063	.1698	.1391
Age 25-34	.2171	.2341	.2295	.2000	.2316	.1857	.1723
Age 35-44	.2482	.1888	.2163	.1950	.1994	.2278	.2290
Age 45-54	.2347	.1462	.1877	.2047	.2081	.2626	.2394
Age 55+	.1664	.0972	.1194	.126	.1546	.1541	.2202
Education <12	.1118	.2763	.2464	.2355	.2314	.1966	.2154
Education =12	.2896	.3426	.3837	.3561	.3729	.3654	.3499
Education 13-15	.2911	.2559	.2326	.2515	.2519	.2823	.2660
Education ≥16	.3075	.1252	.1373	.1569	.1438	.1557	.1687
White	.8292	.7611	.7353	.7172	.7021	.7174	.6526
Male	.5304	.5620	.6105	.5916	.5947	.6119	.5912
Married	.4150	.6270	.6199	.6458	.6177	.6194	.6014
Foreign Born	.1637	.1597	.1789	.1682	.1711	.1832	.2206
UI Job History							
# qtrs worked	2.8644	2.1956	2.3658	2.3711	2.2386	2.4460	1.9826
# qtrs worked FQ	1.7783	1.0471	1.1706	1.2301	1.0913	1.3122	.9370
# jobs per qtr	.9134	.8149	.8553	.8289	.8172	.8296	.7250
# FQ jobs per qtr	.4778	.2823	.3169	.3298	.2902	.3471	.2501
Sum hires 4 qtrs	.2673	.3610	.3747	.3168	.3074	.2879	.2188
Sum seps 4 qtrs	.2582	.3433	.3683	.3138	.3218	.2921	.2902
Sum earn 4 qtrs	28736	14290	17918	16719	15741	20558	14322
Sum earn per qtr	7551	4100	4888	4551	4376	5459	4135
Avg earn per qtr	7354	3967	4729	4428	4226	5305	4069
Sample Size	324,835	12,116	4,367	1,608	1,332	842	1,109

Figure 1: Employment Probabilities

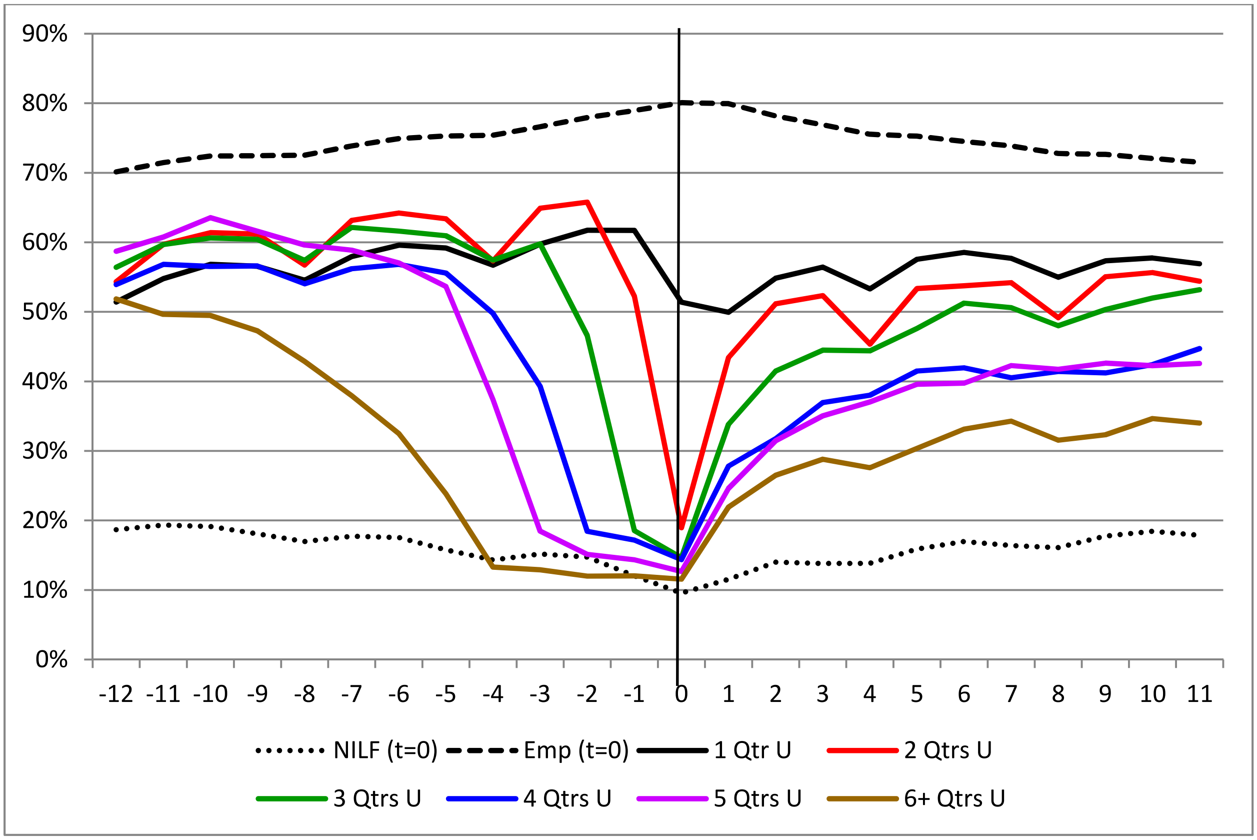


Figure 2a: Earnings (IHS, Earnings≥0)

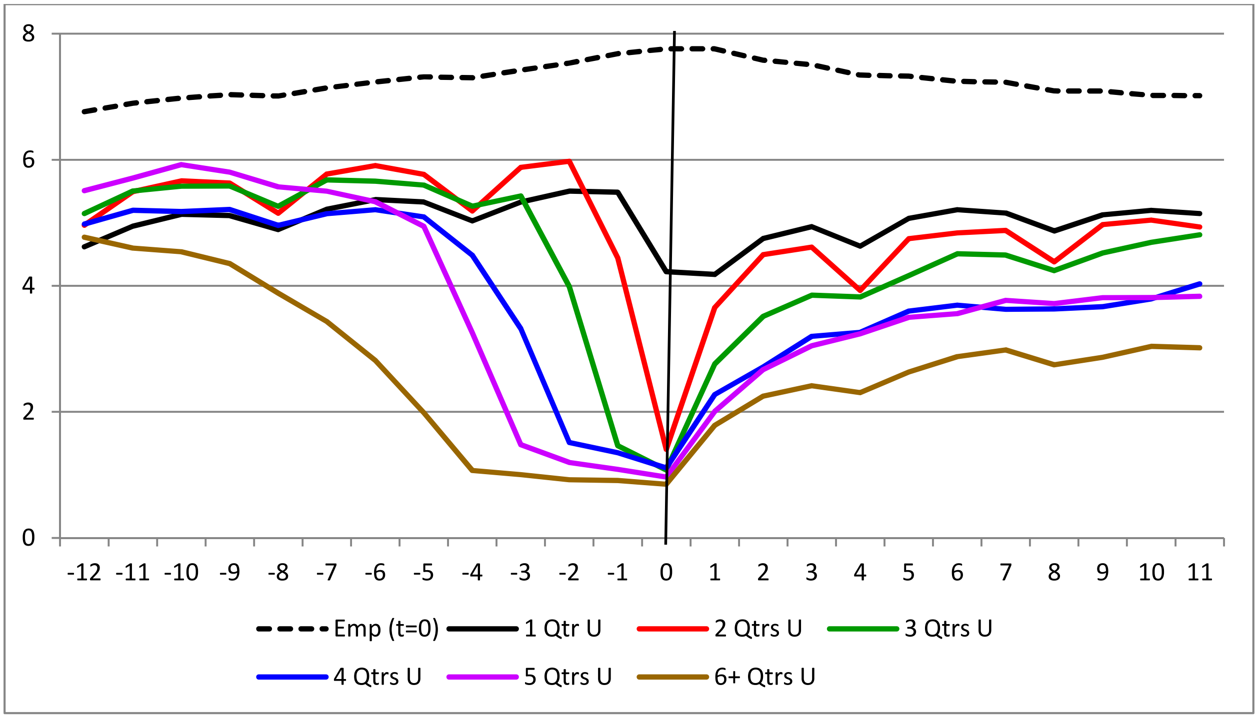


Figure 2b: Earnings (IHS, Earnings>0)

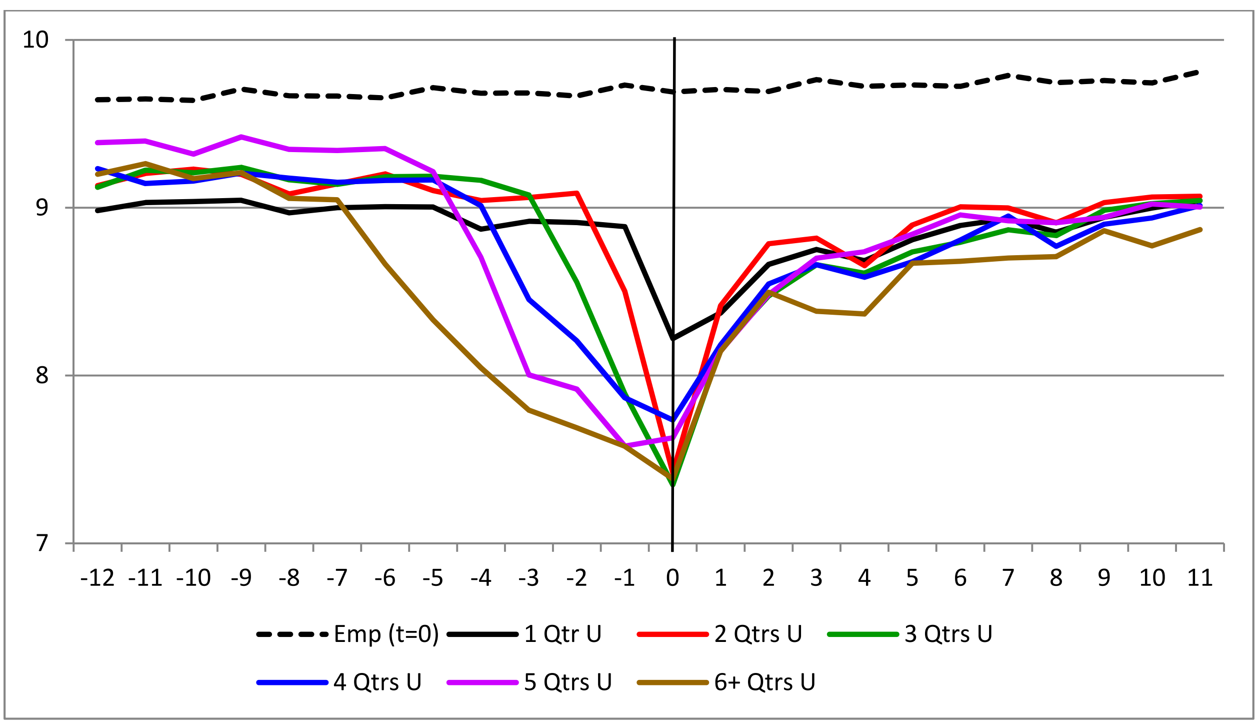


Table 2: Employment Probability Regressions

	(1)	(2)	(3)	(4)	(5)
JLS δ parameters (q=-8)					
$\delta_{d=0,q=-8}$	.7253	.7237	.7186	.7225	.7160
$\delta_{d=1,q=-8}$	.5455	.5724	.6466	.5965	.6924
$\delta_{d=2,q=-8}$	.5672	.5867	.6485	.5993	.6789
$\delta_{d=3,q=-8}$	.5739	.5950	.6529	.6096	.6849
$\delta_{d=4,q=-8}$	.5403	.5590	.6507	.5648	.6846
$\delta_{d=5,q=-8}$	.5960	.6086	.6719	.6088	.6914
$\delta_{d=6,q=-8}$	.4288	.4512	.6008	.4479	.6462
JLS δ parameters (q=8)					
$\delta_{d=0,q=8}$	.7277	.7261	.7211	.7273	.7238
$\delta_{d=1,q=8}$	.5499	.5769	.6511	.5527	.6053
$\delta_{d=2,q=8}$	.4916	.5111	.5729	.4984	.5424
$\delta_{d=3,q=8}$	.4801	.5013	.5591	.4867	.5270
$\delta_{d=4,q=8}$	.4142	.4329	.5246	.4271	.4906
$\delta_{d=5,q=8}$	.4174	.4299	.4933	.4297	.4738
$\delta_{d=6,q=8}$	.3155	.3379	.4875	.3412	.4421
Parameter Tests					
loss0: $\delta_{d=0,q=-8} - \delta_{d=0,q=8}$	-.0025	-.0024	-.0025	-.0048	-.0078
loss1: $\delta_{d=1,q=-8} - \delta_{d=1,q=8}$	-.0044	-.0044	-.0044	.0438	.0871
loss2: $\delta_{d=2,q=-8} - \delta_{d=2,q=8}$	.0756	.0756	.0756	.1009	.1365
loss3: $\delta_{d=3,q=-8} - \delta_{d=3,q=8}$	.0938	.0938	.0938	.1229	.1579
loss4: $\delta_{d=4,q=-8} - \delta_{d=4,q=8}$	.1261	.1261	.1261	.1377	.1940
loss5: $\delta_{d=5,q=-8} - \delta_{d=5,q=8}$	.1786	.1786	.1786	.1791	.2175
loss6: $\delta_{d=6,q=-8} - \delta_{d=6,q=8}$	.1133	.1133	.1133	.1066	.2042
Parameter Tests					
diff12: loss2 – loss1	.0800	.0800	.0800	.0571	.0494
diff13: loss3 – loss1	.0982	.0982	.0982	.0791	.0708
diff14: loss4 – loss1	.1305	.1305	.1305	.0939	.1069
diff15: loss5 – loss1	.1831	.1831	.1831	.1352	.1305
diff16: loss6 – loss1	.1178	.1178	.1178	.0628	.1171
R-squared	.0124	.0372	.4273	.0469	.4806
# right hand side variables	14	37	46	60	78
CPS Demographics controls		Yes	Yes	Yes	Yes
Year dummy controls		Yes	Yes	Yes	Yes
Job history controls			Yes		Yes
Coefficient vector β or β(q)	β	β	β	β(q)	β(q)

Sample is 346,209 persons who are employed or unemployed in CPS at q=0, with LEHD employment observations at q={-8,+8}. Number of observations in regression is 692,418.

The specification is $Y_{[i,t]dq} = \sum_{d=0}^{6+} \sum_{q=\{-8,+8\}} I_{\{i,t\}dq}\delta_{dq} + X_{\{i,t\}dq}\beta(q) + \varepsilon_{\{i,t\}dq}$. All estimated δ parameters are statistically different from zero. All control variables are deviations from means. Yellow shading indicates the p-value of the test is < .01. Dependent variable is {0,1} employment indicator; mean=.7139.

Table 3: Earnings Regressions (IHS, Earnings$\geq$0)

	(1)	(2)	(3)	(4)	(5)
JLS δ parameters (q=-8)					
$\delta_{d=0,q=-8}$	7.011	6.983	6.930	6.972	6.904
$\delta_{d=1,q=-8}$	4.893	5.377	6.148	5.617	6.603
$\delta_{d=2,q=-8}$	5.151	5.496	6.147	5.615	6.447
$\delta_{d=3,q=-8}$	5.260	5.626	6.234	5.765	6.548
$\delta_{d=4,q=-8}$	4.958	5.278	6.234	5.326	6.562
$\delta_{d=5,q=-8}$	5.571	5.779	6.439	5.770	6.621
$\delta_{d=6,q=-8}$	3.882	4.189	5.730	4.139	6.155
JLS δ parameters (q=8)					
$\delta_{d=0,q=8}$	7.091	7.063	7.011	7.075	7.037
$\delta_{d=1,q=8}$	4.869	5.354	6.125	5.115	5.671
$\delta_{d=2,q=8}$	4.380	4.725	5.376	4.606	5.076
$\delta_{d=3,q=8}$	4.241	4.607	5.215	4.469	4.901
$\delta_{d=4,q=8}$	3.633	3.952	4.909	3.904	4.581
$\delta_{d=5,q=8}$	3.719	3.927	4.587	3.936	4.404
$\delta_{d=6,q=8}$	2.747	3.054	4.594	3.103	4.169
Parameter Tests					
loss0: $\delta_{d=0,q=-8}$ - $\delta_{d=0,q=8}$	-.080	-.080	-.080	-.103	-.133
loss1: $\delta_{d=1,q=-8}$ - $\delta_{d=1,q=8}$	.024	.024	.024	.502	.932
loss2: $\delta_{d=2,q=-8}$ - $\delta_{d=2,q=8}$	.771	.771	.771	1.009	1.371
loss3: $\delta_{d=3,q=-8}$ - $\delta_{d=3,q=8}$	1.019	1.019	1.019	1.297	1.647
loss4: $\delta_{d=4,q=-8}$ - $\delta_{d=4,q=8}$	1.326	1.326	1.326	1.422	1.981
loss5: $\delta_{d=5,q=-8}$ - $\delta_{d=5,q=8}$	1.852	1.852	1.852	1.834	2.216
loss6: $\delta_{d=6,q=-8}$ - $\delta_{d=6,q=8}$	1.135	1.135	1.135	1.036	1.986
Parameter Tests					
diff12: loss2 – loss1	.747	.747	.747	.507	.439
diff13: loss3 – loss1	.995	.995	.995	.794	.715
diff14: loss4 – loss1	1.302	1.302	1.302	.919	1.049
diff15: loss5 – loss1	1.829	1.829	1.829	1.332	1.284
diff16: loss6 – loss1	1.112	1.112	1.112	.534	1.054
R-squared	.0170	.0574	.4631	.0683	.5129
# right hand side variables	14	37	46	60	78
CPS Demographics controls		Yes	Yes	Yes	Yes
Year dummy controls		Yes	Yes	Yes	Yes
Job history controls			Yes		Yes
Coefficient vector β or $\beta(q)$	β	β	β	$\beta(q)$	$\beta(q)$

See notes to Table 2.

Dependent variable is IHS(Real Quarterly Earnings); mean=6.904. Inverse Hyperbolic Sine is defined as IHS(x)=ln{x+sqrt[1+(x*x)]}.

Table 4: Earnings Regressions (IHS, Earnings>0)

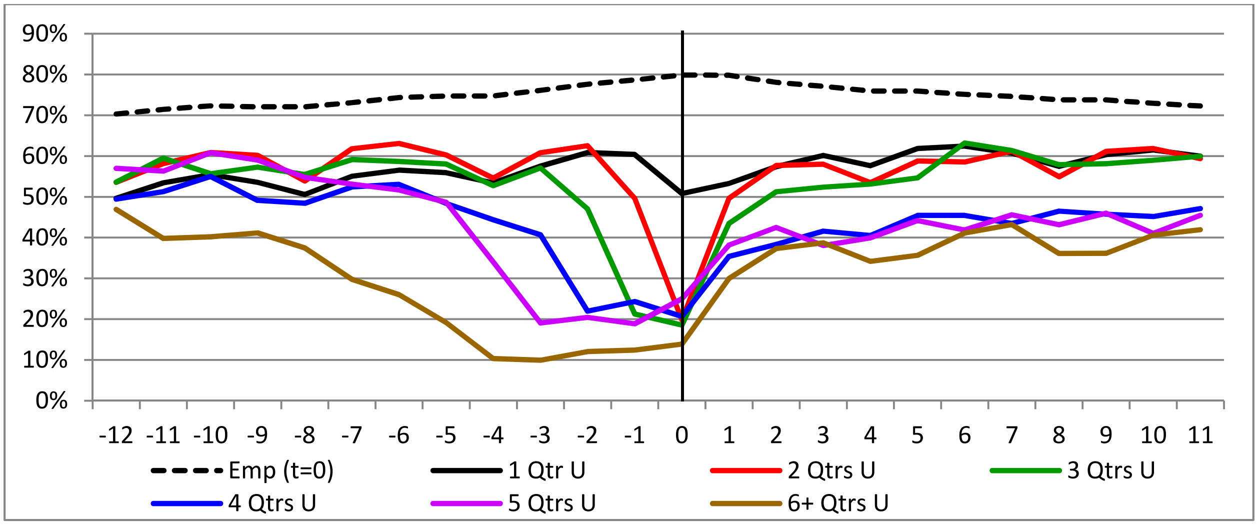
	(1)	(2)	(3)	(4)	(5)
JLS δ parameters (q=-8)					
$\delta_{d=0,q=-8}$	9.667	9.636	9.601	9.655	9.648
$\delta_{d=1,q=-8}$	8.969	9.205	9.272	9.263	9.399
$\delta_{d=2,q=-8}$	9.082	9.242	9.291	9.274	9.385
$\delta_{d=3,q=-8}$	9.166	9.298	9.346	9.326	9.433
$\delta_{d=4,q=-8}$	9.177	9.295	9.373	9.304	9.451
$\delta_{d=5,q=-8}$	9.347	9.418	9.458	9.426	9.525
$\delta_{d=6,q=-8}$	9.055	9.149	9.245	9.149	9.330
JLS δ parameters (q=8)					
$\delta_{d=0,q=8}$	9.745	9.750	9.775	9.732	9.728
$\delta_{d=1,q=8}$	8.854	9.229	9.386	9.160	9.250
$\delta_{d=2,q=8}$	8.910	9.197	9.343	9.152	9.235
$\delta_{d=3,q=8}$	8.834	9.116	9.268	9.067	9.156
$\delta_{d=4,q=8}$	8.770	9.009	9.201	8.973	9.091
$\delta_{d=5,q=8}$	8.910	9.078	9.216	9.050	9.129
$\delta_{d=6,q=8}$	8.708	8.852	9.100	8.836	8.997
Tests					
loss0: $\delta_{d=0,q=-8} - \delta_{d=0,q=8} = 0$	-.078	-.114	-.174	-.077	-.079
loss1: $\delta_{d=1,q=-8} - \delta_{d=1,q=8} = 0$	.115	-.023	-.114	.102	.148
loss2: $\delta_{d=2,q=-8} - \delta_{d=2,q=8} = 0$	.172	.045	-.053	.122	.151
loss3: $\delta_{d=3,q=-8} - \delta_{d=3,q=8} = 0$	.332	.182	.078	.259	.277
loss4: $\delta_{d=4,q=-8} - \delta_{d=4,q=8} = 0$	.407	.286	.172	.331	.360
loss5: $\delta_{d=5,q=-8} - \delta_{d=5,q=8} = 0$	.437	.340	.242	.376	.396
loss6: $\delta_{d=6,q=-8} - \delta_{d=6,q=8} = 0$	.347	.297	.146	.313	.332
Parameter Tests					
diff12: loss2 – loss1	-.057	-.068	-.062	-.020	-.002
diff13: loss3 – loss1	-.217	-.205	-.193	-.156	-.129
diff14: loss4 – loss1	-.292	-.309	-.287	-.228	-.211
diff15: loss5 – loss1	-.322	-.363	-.356	-.274	-.248
diff16: loss6 – loss1	-.231	-.320	-.260	-.210	-.184
R-squared	.0238	.2696	.3735	.2817	.3979
# right hand side variables	14	37	46	60	78
CPS Demographics controls		Yes	Yes	Yes	Yes
Year dummy controls		Yes	Yes	Yes	Yes
Job history controls			Yes		Yes
Coefficient vector β or β(q)	β	β	β	β(q)	β(q)

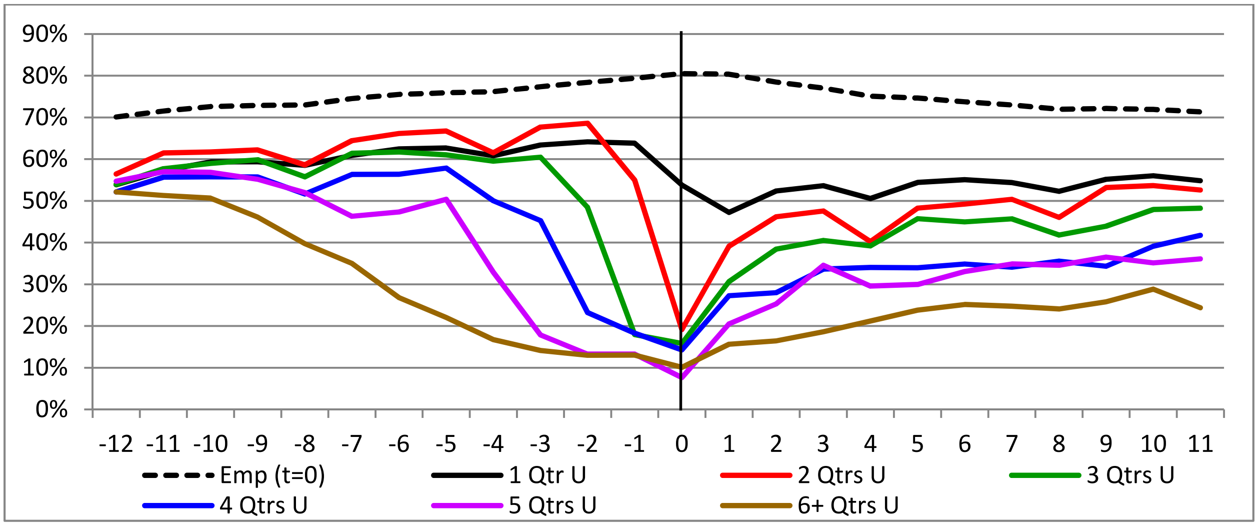
See notes to Table 1.

Sample is 346,209 persons who are employed or unemployed in CPS at q=0, and are employed at either q=-8 or q=+8. Number of observations in regression is 492,917.

Dependent variable is IHS(Real Quarterly Earnings); mean=9.671. Inverse Hyperbolic Sine is defined as IHS(x)=ln{x+sqrt[1+(x*x)]}.

Figure 3: Employment Probabilities, by Year {Good, Bad, Other}





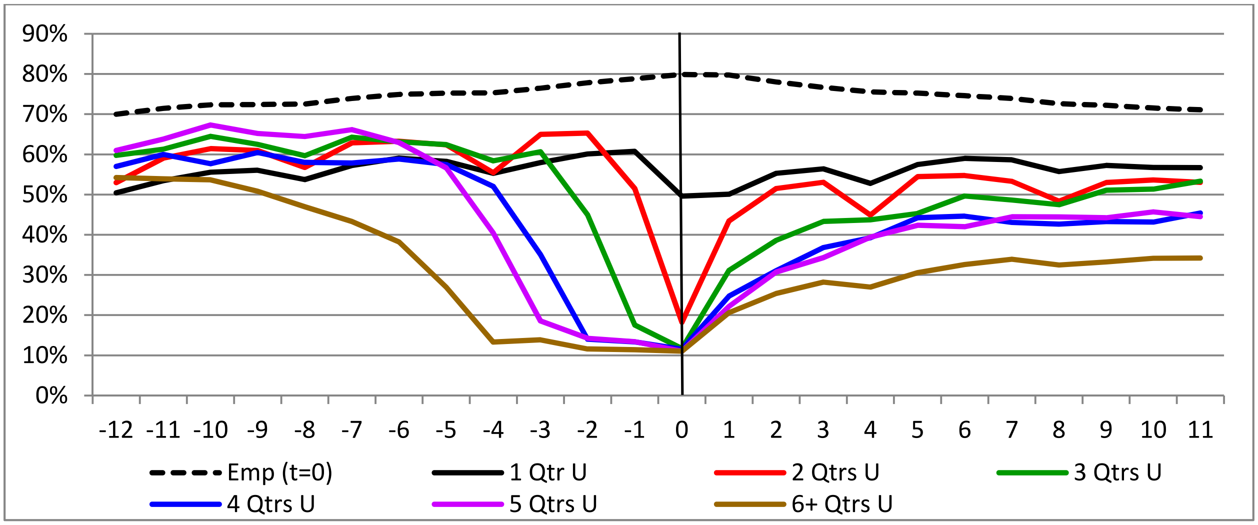


Table 5: Employment Probability Regressions, with δ * Year Interactions

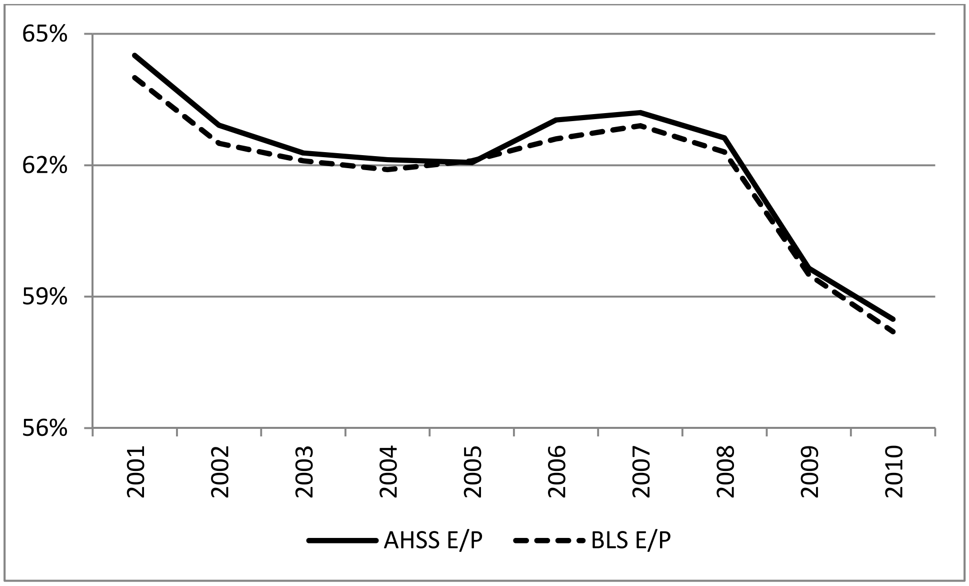
	(1) Good Years	(1) Bad Years	(1) Other Years	(5) Good Years	(5) Bad Years	(5) Other Years
JLS δ parameters (q=-8)						
$\delta_{d=0,q=-8}$	.7206	.7299	.7253	.7142	.7171	.7165
$\delta_{d=1,q=-8}$	.5057	.5852	.5372	.6763	.7088	.6888
$\delta_{d=2,q=-8}$	.5387	.5865	.5676	.6576	.6904	.6819
$\delta_{d=3,q=-8}$	.5546	.5576	.5965	.6942	.6810	.6824
$\delta_{d=4,q=-8}$	.4841	.5165	.5798	.6660	.6715	.7002
$\delta_{d=5,q=-8}$	.5478	.5198	.6443	.6709	.6639	.7087
$\delta_{d=6,q=-8}$	.3748	.3973	.4695	.6473	.6188	.6561
JLS δ parameters (q=8)						
$\delta_{d=0,q=8}$	.7381	.7194	.7262	.7347	.7146	.7228
$\delta_{d=1,q=8}$	.5746	.5231	.5571	.6331	.5687	.6162
$\delta_{d=2,q=8}$	.5494	.4605	.4837	.6002	.5065	.5335
$\delta_{d=3,q=8}$	.5786	.4181	.4750	.6326	.4707	.5067
$\delta_{d=4,q=8}$	.4650	.3554	.4264	.5516	.4348	.4895
$\delta_{d=5,q=8}$	.4315	.3456	.4443	.5060	.4275	.4755
$\delta_{d=6,q=8}$	.3611	.2408	.3248	.5082	.3635	.4372
Parameter Tests						
loss0: $\delta_{d=0,q=-8} - \delta_{d=0,q=8}$	-.0176	.0105	-.0009	-.0204	.0024	-.0063
loss1: $\delta_{d=1,q=-8} - \delta_{d=1,q=8}$	-.0689	.0620	-.0199	.0432	.1401	.0727
loss2: $\delta_{d=2,q=-8} - \delta_{d=2,q=8}$	-.0107	.1261	.0840	.0574	.1839	.1483
loss3: $\delta_{d=3,q=-8} - \delta_{d=3,q=8}$	-.0239	.1395	.1214	.0616	.2103	.1758
loss4: $\delta_{d=4,q=-8} - \delta_{d=4,q=8}$	.0191	.1611	.1534	.1144	.2367	.2107
loss5: $\delta_{d=5,q=-8} - \delta_{d=5,q=8}$	.1163	.1742	.2001	.1649	.2364	.2331
loss6: $\delta_{d=6,q=-8} - \delta_{d=6,q=8}$	.0138	.1565	.1447	.1391	.2553	.2189
Parameter Tests						
diff12: loss2 – loss1	.0582	.0641	.1039	.0142	.0438	.0757
diff13: loss3 – loss1	.0449	.0775	.1413	.0184	.0702	.1031
diff14: loss4 – loss1	.0880	.0991	.1733	.0712	.0966	.1381
diff15: loss5 – loss1	.1852	.1122	.2200	.1217	.0963	.1605
diff16: loss6 – loss1	.0826	.0945	.1646	.0959	.1153	.1463
R-squared		.0129			.4806	
# right hand side variables		42			88	
CPS Demographics controls					Yes	
Year dummy controls						
Job history controls					Yes	
Coefficient vector β or β(q)		β			β(q)	

See notes to Table 1.

The estimated specification is $Y_{[i,t\}dq} = \sum_{d=0}^{6+} \sum_{q=\{-8,+8\}} \sum_{Year} I_{\{i,t\}dqYear} \delta_{dqYear} + X_{\{i,t\}dq} \beta(q) + \varepsilon_{\{i,t\}dq}$.

Good years are {2004,2005,2006}, bad years are {2002,2008,2009}, and other years are {2001,2003,2007,2010}.

Figure A1: Employment-to-Population Rate and Unemployment Rate, 2001-2010
CPS-LEHD weighted microdata ("AHSS")
Tabulations from BLS website



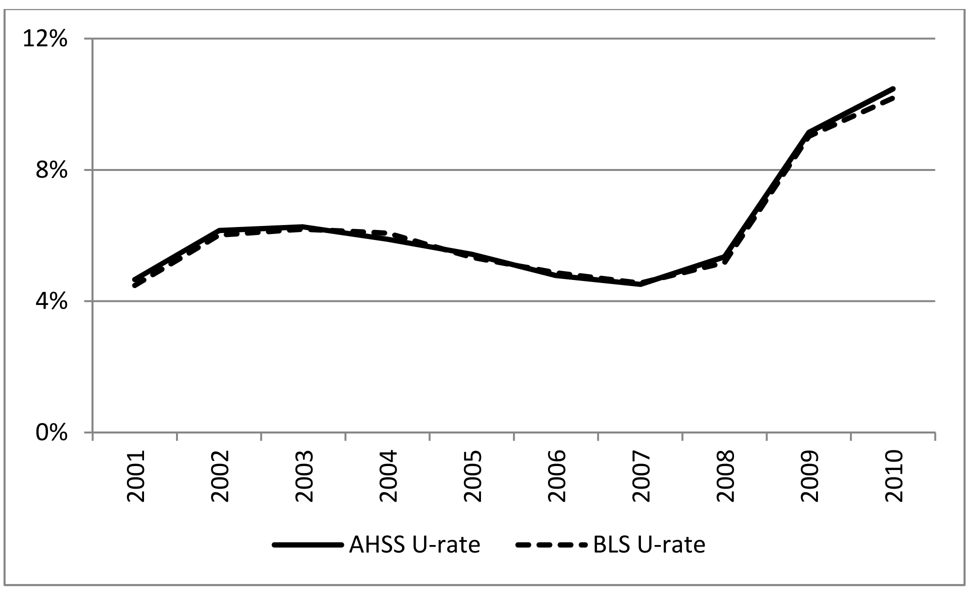


Figure A2: Duration of Unemployment, 2001-2010
CPS-LEHD weighted microdata ("AHSS")
Tabulations from BLS website

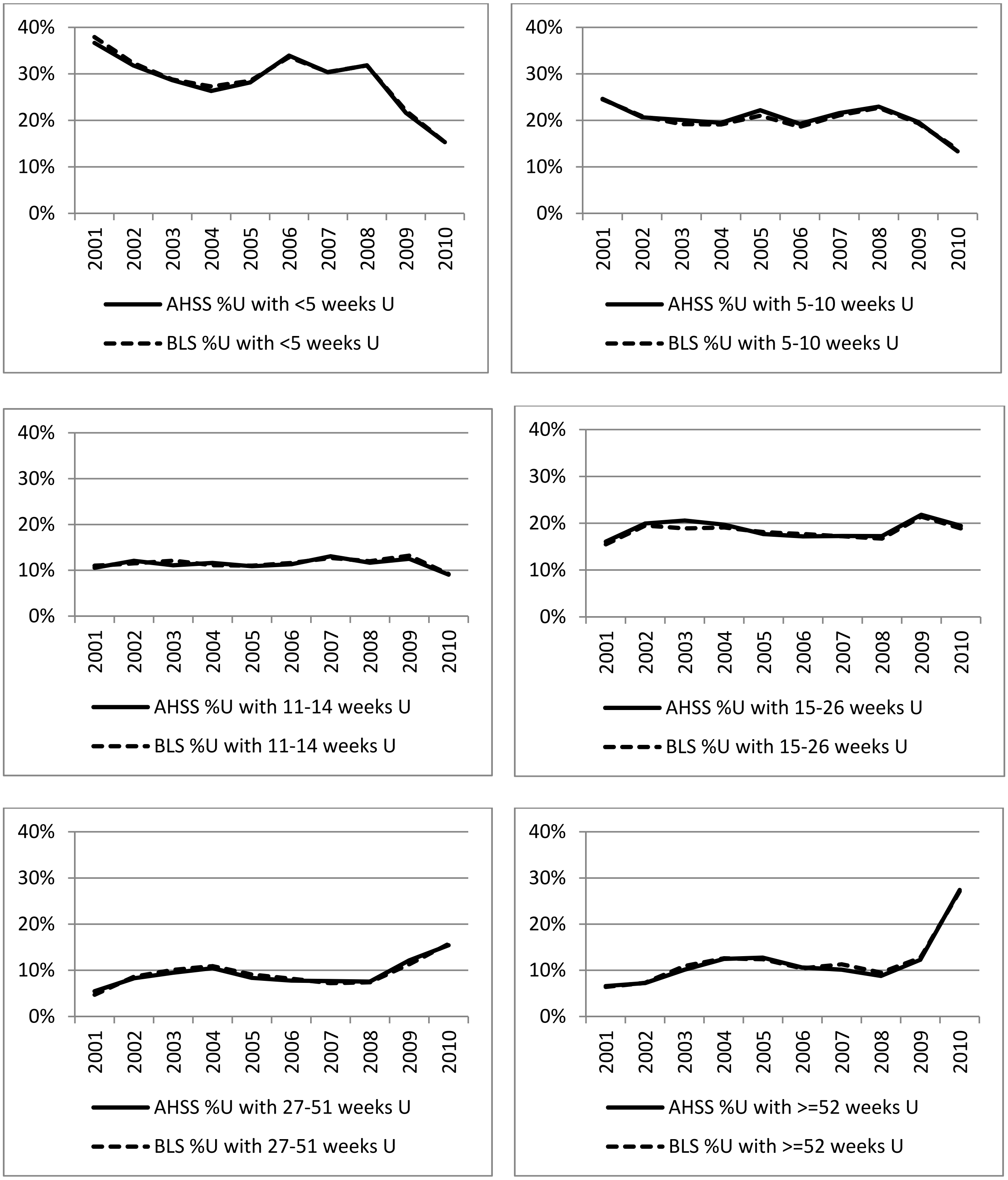


Figure A3a: Earnings (IHS, Earnings≥0)

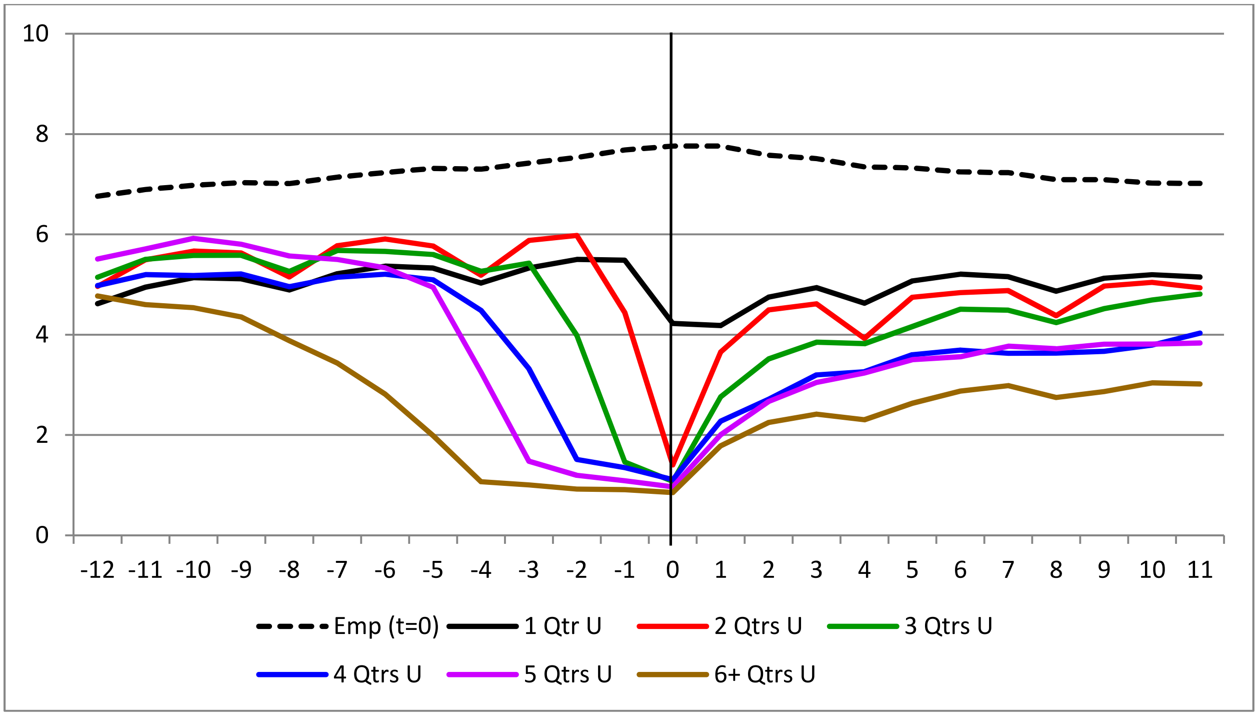


Figure A3b: Earnings (IHS, Earnings>0)

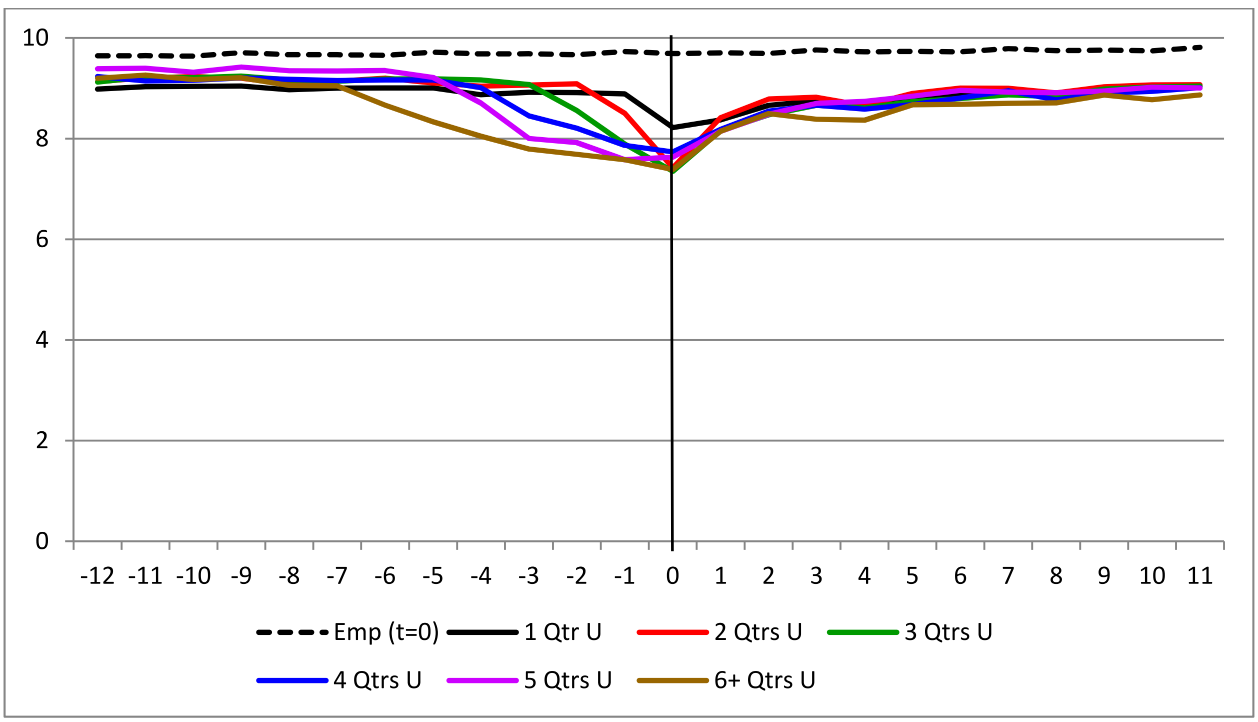


Figure A4: Employment Probabilities, by Age {<30, 30-50, ≥50}

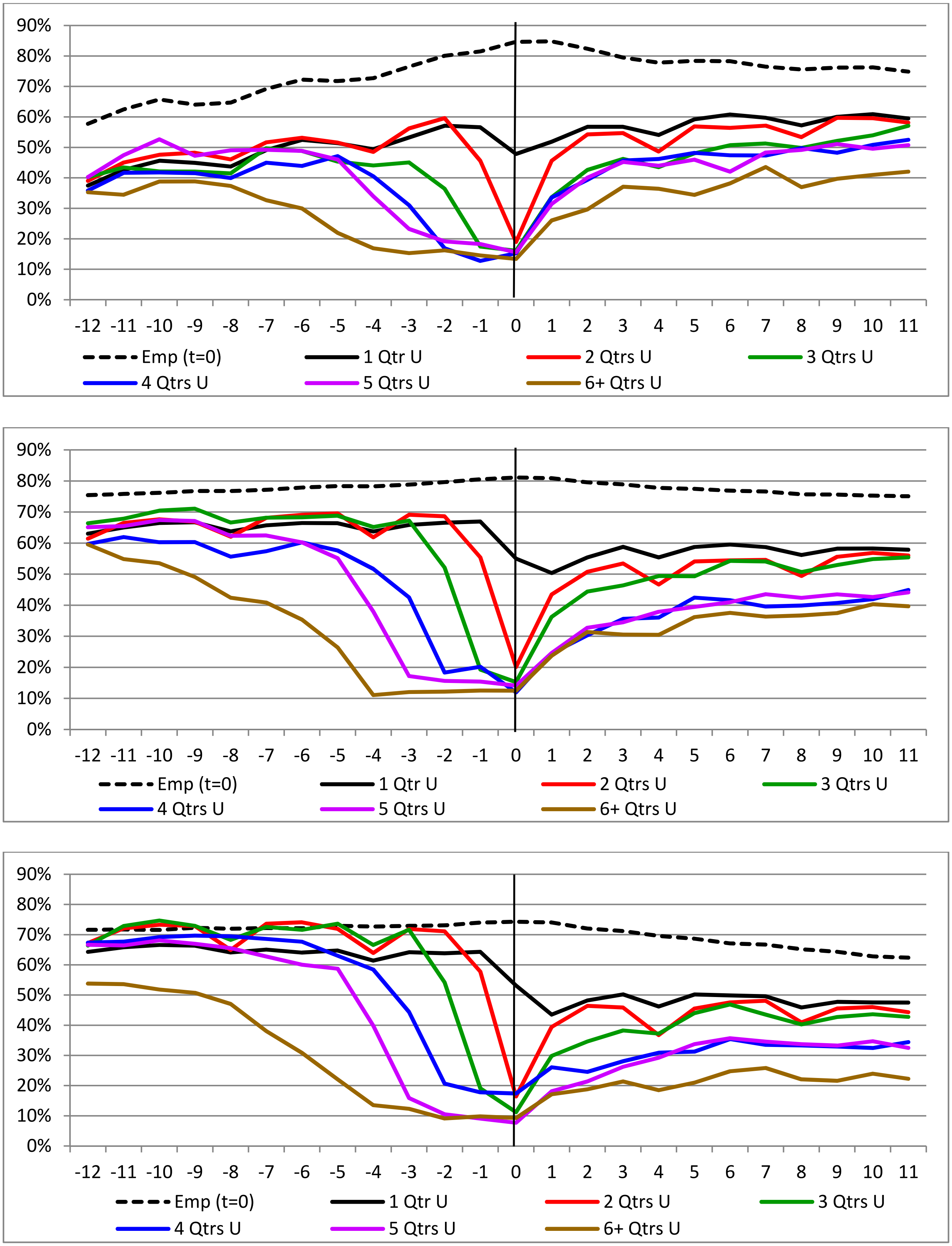


Figure A5: Employment Probabilities, by Reason for U {Job Loser, Other EU, NU}