Conference Draft

Recessions and the Costs of Job Loss

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1. Introduction

Economic downturns involve high numbers of lost jobs and laid-off workers. Severe recessions, in particular, bring large increases in permanent layoffs among workers with high prior tenure on the job. We refer to this type of job loss event as a job displacement. Previous research shows that job displacements lead to large and highly persistent earnings losses for the affected workers.[1] The available evidence also indicates that job displacement leads to lasting declines in earnings and job stability, worse health outcomes, higher mortality, lower achievements by children, and other unwelcome consequences.

We estimate the present value earnings losses associated with job displacement, and we present new evidence on how the near-term and long-term earnings losses vary with labor market conditions at the time of displacement. We also document cyclical fluctuations in the incidence of job loss and job displacement, and we investigate how worker anxieties about job loss, wage cuts and other labor market prospects respond to contemporaneous conditions in the labor market. Finally, we confront leading models of unemployment fluctuations in the tradition of work by Peter Diamond, Dale Mortensen and Christopher Pissarides with our evidence on the magnitude and cyclicality of the present value earnings losses associated with job displacement.

Our study builds on and draws from three major areas of research: empirical work on cyclical fluctuations in job destruction, job loss and unemployment; empirical work on earnings losses and other outcomes associated with job displacement; and theoretical work on search and matching models of unemployment fluctuations along the lines of Mortensen and Pissarides (1994). In terms of a broad effort to bring together these three areas of research, the closest antecedent to our study is Hall (1995). In terms of its effort to confront equilibrium search and matching models with evidence on the earnings losses

[1] See, for example, Jacobson, Lalonde, and Sullivan (1993), Couch and Placzek (2010) and von Wachter, Song, and Manchester (2011).

[2] The BED contains longitudinally linked records for all businesses covered by state unemployment insurance agencies – virtually a census of nonfarm private business establishments.

[3] To deal with weaknesses in the JOLTS sample design, Davis et al. (2011) rely on BED data to track the cross-sectional distribution of establishment-level growth rates over time. They combine micro data from the BED and JOLTS to obtain the layoff series in Figure 1. To extend the layoff series back in time before the advent of JOLTS, they use the BED to construct synthetic JOLTS-like layoff rates. Davis et al. (2010) discuss sample design issues

associated with job displacement, the closest prior work is Den Haan, Ramey and Watson (2000).

Our empirical investigation of the earnings losses associated with job displacement draws heavily on recent research by von Wachter, Song, and Manchester (2011). They develop new evidence on the short- and long-term earnings effects of job loss using longitudinal Social Security records covering U.S. workers for a period of more than 30 years. Drawing on their estimated empirical models, our first main contribution is to characterize how present value earnings losses due to job displacement vary with business cycle conditions at the time of displacement. For men with 3 or more years of prior tenure who lose jobs in mass-layoff events at larger firms, job displacement reduces the present value of earnings by 11 percent in an average year. The present value losses are high in all years, but they rise sharply with the unemployment rate in the year of displacement and are roughly twice as high in recessions as in expansions. The entire future path of earnings losses is much higher for displacements that occur in recessions. In short, the present value earnings losses associated with job displacement are very large, and they are highly sensitive to labor market conditions at the time of displacement.

Drawing on data from the General Social Survey and Gallup polling, we examine the relationship of anxieties about job loss, wage cuts, ease of job finding and other labor market prospects to actual labor market conditions. The available evidence indicates that cyclical fluctuations in worker perceptions and anxieties track actual labor market conditions rather closely, and that they respond quickly to deteriorations in the economic outlook. Gallup data, in particular, show a tremendous increase in worker anxieties about labor market prospects after the peak of the financial crisis in 2008 and 2009. They also show a recent return to the same high levels of anxiety. These data suggest that fears about job loss and other negative labor market outcomes are themselves a significant and costly aspect of economic downturns for a broad segment of the population.

Our second main contribution is to analyze whether leading theoretical models of unemployment fluctuations can account for our evidence on the magnitude and cyclicality of present value earnings losses associated with job displacement. Following Hall and Milgrom (2008), we consider three variants of the basic Mortensen-Pissarides model analyzed by Shimer (2005) and many others. We also consider a richer model of Burgess and Turon (2010) that introduces search on the job and replacement hiring into the model of Mortensen and Pissarides (1994). The richer model generates worker flows apart from job flows, some heterogeneity in productivity and match surplus values, and recessionary spikes in job destruction, job loss and unemployment inflows of the sort we see in the data.

The search and matching models we consider cannot account for the empirical evidence on present value earnings losses associated with job displacement. The empirical losses are at least an order of magnitude larger than those implied by basic versions of the Mortensen-Pissarides model. The model is also unable to generate the sensitivity to contemporaneous conditions at displacement that we see in the data. Wage rigidity of the form considered by Hall and Milgrom (2008) greatly improves the model's ability to explain aggregate unemployment fluctuations, but it does not bring the model closer to the evidence on the magnitude and cyclicality of earnings losses associated with job displacement. The richer model of Burgess and Turon (2010) generates somewhat larger income losses than the basic model, but the losses remain quite small. Indeed, a fundamental weakness of these models is their implication that job loss is a rather inconsequential event. In this sense, and despite their many virtues and attractions, this class of models fail to address a central reason that job loss, unemployment and recessions attract so much attention and concern from economists, policymakers and others.

The paper proceeds as follows. Section 2 presents evidence on the incidence of job destruction, layoffs, unemployment inflows and job displacement over the business cycle. Section 3 first summarizes previous research on the short- and long-term consequences of job displacements for earnings. It then draws on work by von Wachter, Song, and Manchester (2011) to estimate near-term and present value earnings losses associated with job displacement, and to investigate how these losses vary with conditions at the time of displacement. Section 4 reviews previous work on non-monetary costs of displacement and presents evidence on cyclical fluctuations in perceptions and anxieties related to labor market prospects. Section 5 considers selected equilibrium search and matching models of unemployment fluctuations and evaluates their implications for the magnitude and cyclicality of earnings and income losses associated with job loss. Section 6 offers concluding remarks.

2. The Incidence of Job Loss and Job Displacement over Time

Figure 1 displays four time series that draw on distinct sources of data and pertain to different concepts of job loss. The job destruction measure captures gross employment losses summed over shrinking and closing establishments in the Business Employment Dynamics (BED) database.[2] The layoff measure reflects data on employer-initiated separations, as reported by employers in the Job Openings and Labor Turnover Survey and as aggregated and extended back to 1990 by Davis et al. (2011).[3] We calculate unemployment inflow rates using monthly Current Population Survey (CPS) data on the number of employed persons and the number unemployed less than 5 weeks. Summing over months yields the quarterly rates. The measure of initial unemployment insurance (UI) claims is the quarterly sum of weekly new claims for unemployment insurance benefits, expressed as a percent of nonfarm employment.

Figure 1 highlights two key points. First, the sheer volume of job loss and unemployment incidence is enormous – in good economic times and bad. For example, the JOLTS-based layoff rate in Figure 1 averages 7 percent per quarter from 1990 to 2011. Multiplying this figure by nonfarm employment in 2011 yields nearly 10 million layoffs per quarter. The quarterly averages for job destruction and unemployment inflows are of similar magnitude. Initial UI claims average about 5 million per quarter. In short, the U.S. economy routinely accommodates huge numbers of lost jobs and unemployment spells.

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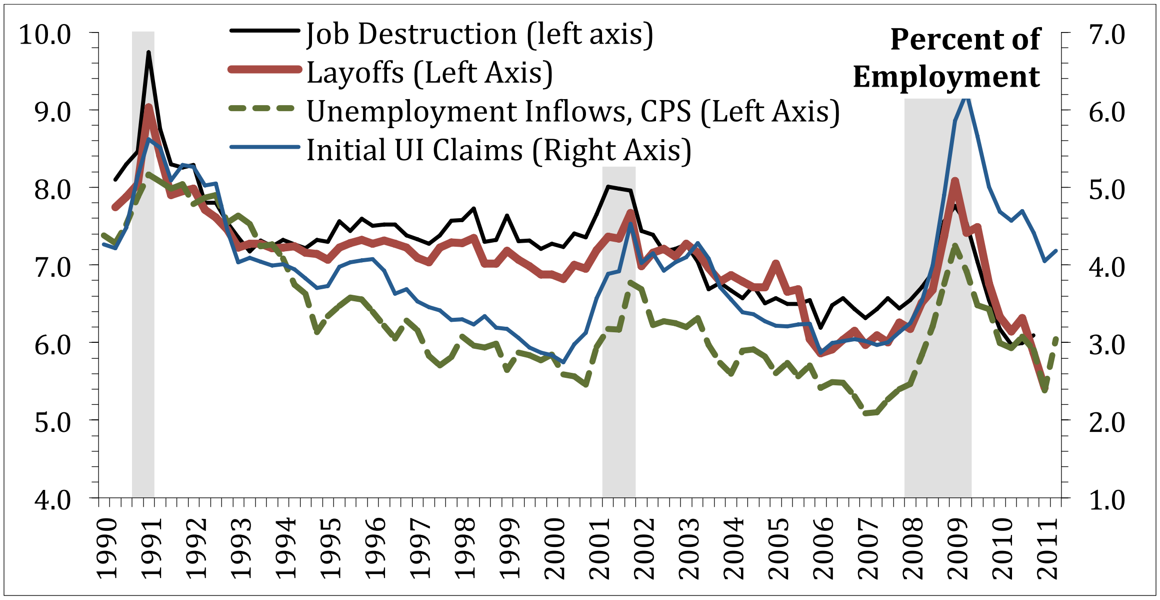
[3] To deal with weaknesses in the JOLTS sample design, Davis et al. (2011) rely on BED data to track the cross-sectional distribution of establishment-level growth rates over time. They combine micro data from the BED and JOLTS to obtain the layoff series in Figure 1. To extend the layoff series back in time before the advent of JOLTS, they use the BED to construct synthetic JOLTS-like layoff rates. Davis et al. (2010) discuss sample design issues in the JOLTS and develop the adjustment methodology implemented by Davis et al. (2011).

Figure 1. Layoffs, Unemployment Inflows, Job Destruction, and Initial Claims for Unemployment Insurance Benefits, Quarterly Rates, 1990 to 2011Q2



Notes to Figure 1:

1. All series are seasonally adjusted and expressed as a percent of employment. Shaded regions indicate NBER-dated recessions.
2. Job destruction rates in the private sector from the Business Employment Dynamics (BED) program, as tabulated directly from establishment-level data by Davis, Faberman and Haltiwanger (2011) for 1990Q2 to 2010Q2 and spliced to published BED data for 2010Q3 and 2010Q4. The splice is based on overlapping data from 2006Q1 to 2010Q2.
3. Quarterly layoff rates based on the layoff concept in the Job Openings and Labor Turnover Survey (JOLTS), as constructed from establishment-level data from 2001Q3 to 2010Q2 and extended back to 1990Q2 by Davis, Faberman and Haltiwanger (2011). From 2010Q3 to 2011Q2, we sum the monthly layoff rate published by the JOLTS program and splice to the quarterly layoff rates in earlier years. The splice is based on overlapping data from 2006Q1 to 2010Q2.
4. Unemployment inflow rates calculated from Current Population Survey (CPS) data as number of short-term unemployed (less than 5 weeks) divided by civilian employment. We calculate monthly inflow rates in the CPS data and sum over months to obtain quarterly inflow rates. To adjust for the 1994 CPS redesign, we divide the number of short-term unemployed by 1.1 prior to 1994. See Polivka and Miller (1998) and Shimer (2007) on the CPS redesign.
5. Initial UI claims are quarterly sums of weekly new claims for unemployment insurance benefits as a percent of nonfarm employment in the Current Employment Statistics. To compute the series, we sum weekly claims in the month, rescale the sum to represent 4 and 1/3 weeks worth of claims, and divide by employment in the month. We sum over months to obtain a quarterly series.

Many, perhaps most, of these job loss events involve little financial loss or other hardship for individuals and families. Indeed, the high rates shown in Figure 1 reflect an impressive capacity for constant renewal and productivity-enhancing reallocation of jobs, workers and capital in the U.S. economy.[4] It is important to keep this point in mind when interpreting the evidence on the costs associated with job displacement. That evidence focuses, quite deliberately, on the types of job loss events that often involve serious consequences for workers and their families.

Second, all four series in Figure 1 exhibit strongly countercyclical movements, with clear spikes in the three recessions covered by our sample period.[5] For example, the quarterly layoff rate rises by 129 basis points from 1990Q2 to 1991Q1, 85 basis points from 2000Q2 to 2001Q4, and 208 basis points from 2007Q3 to 2009Q1. Interestingly, each measure in Figure 1 starts to rise before the onset of a recession (as dated by the NBER) and turns down before the resumption of an expansion. This pattern confirms the well-known usefulness of initial UI claims as a leading indicator for business cycles, and it suggests that other job loss indicators behave similarly in this respect.

Much of our study examines the earnings losses of high-tenure workers who lose jobs in large-scale layoff events. To quantify those losses, we follow individual workers over time using annual earnings records maintained by the Social Security Administration (SSA). Figure 2 plots a measure of job displacement constructed from the SSA data and compares it to annual measures of job destruction and initial claims for unemployment insurance benefits.[6] We measure displacement as the number of workers who lose jobs in mass-layoff events and who had at least 3 years of tenure with the firm before job loss. A

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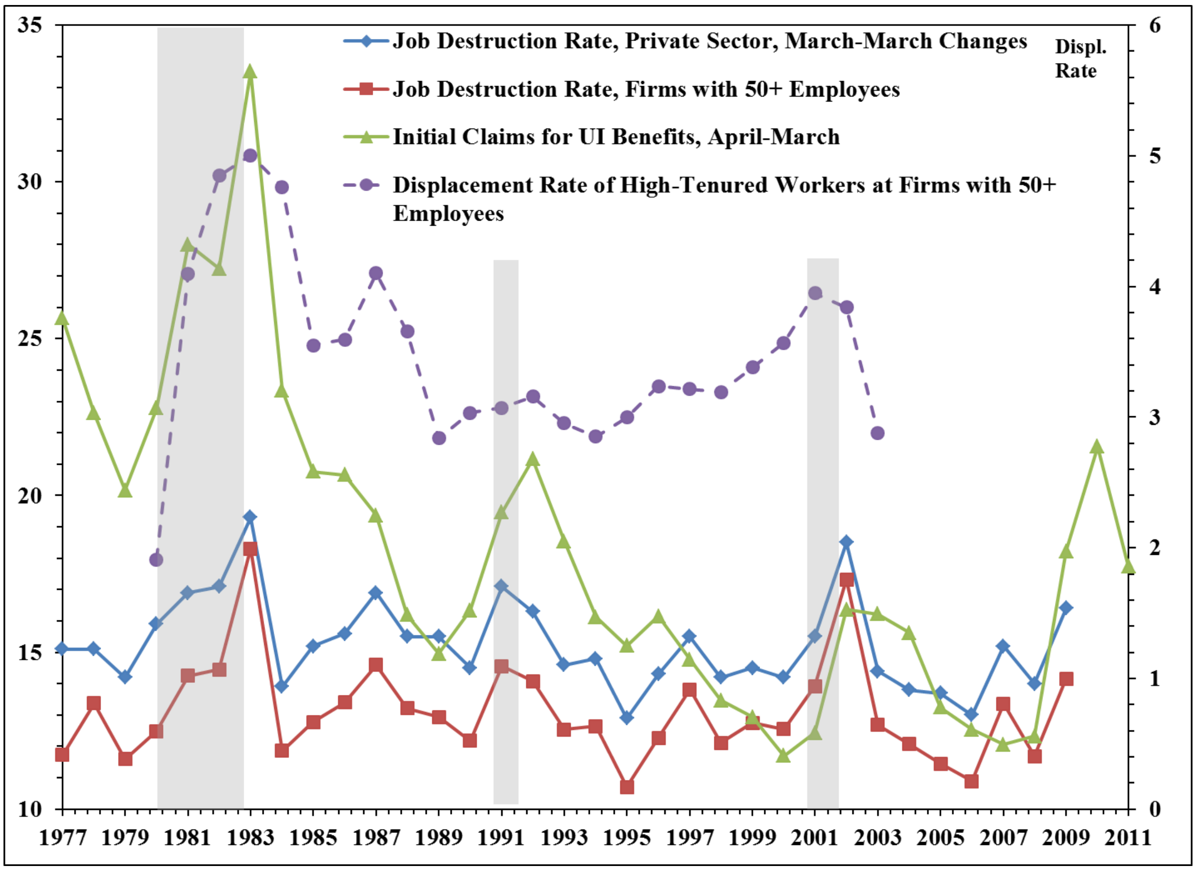
[4] See Bartlesman and Doms (2000) and Foster, Haltiwanger and Krizan (2000) for reviews of the evidence on reallocation and productivity growth.

[5] This pattern holds in earlier postwar U.S. recessions as well. See, for example, Blanchard and Diamond (1989), Davis and Haltiwanger (1990), Davis, Faberman and Haltiwanger (2006) and Elsby, Michaels and Solon (2009).

[6] We cumulate weekly UI claims over twelve months in Figure 2 but the calculations otherwise follow the same approach as in Figure 1. The job destruction series in Figure 2 rely on data from Business Dynamics Statistics (BDS) program at the Bureau of the Census. They are available at an annual frequency and extend farther back in time than the BED-based job destruction series in Figure 1, but they are not as timely. Because the BDS-based destruction series reflects 12-month changes in establishment-level employment, it is not directly comparable to the BED-based job destruction series based on 3-month changes.

mass-layoff event is one in which a firm with 50 or more employees prior to the event experiences a lasting employment decline of at least 30% over two years. To express job displacements as a rate, we divide by the number of workers with at least 3 years of job tenure at firms with 50 or more employees. These workers comprise 31 to 36 percent of all workers covered by the SSA from 1980 to 2003, depending on year.[7]

Figure 2. Job Displacement, Job Destruction, and Initial Claims for Unemployment Insurance Benefits, Annual Rates, 1977 to 2010



Notes:

1. Job destruction rates for the nonfarm private sector are from the Business Dynamics Statistics program at the U.S. Census Bureau. They are tabulated from March-to-March employment changes summed over all contracting establishments in the

[7] 40 to 48 percent of workers have 3 or more years of job tenure, depending on year. 70 to 74 percent work at firms with 50 or more employees. Those with 6 or more years of job tenure at firms with 50 or more employees account for 16-20 percent. These statistics are based on the worker's main job during the year, defined as the one with the highest earnings.

Longitudinal Business Database. Available at www.ces.census.gov/index.php/bds/bds_database_list.

2. Job destruction rates for larger firms reflect establishment-level employment changes for firms with at least 50 employees, computed as an average of current and previous-year employment.
3. Initial UI Claims are annual sums of weekly new claims for unemployment insurance benefits, expressed as a percent of employment. Its construction parallels that of the quarterly Initial UI Claims series in Figure 1, except that the monthly rates are summed from April of the previous year through March of the indicated year.
4. [Right Axis] Job displacement of high-tenure workers is the incidence of job loss in mass-layoff events among workers with at least 3 years of tenure before the year of job loss for workers up to age 50, expressed as a percent of all employees with at least 3 years of tenure at firms with at least 50 employees in the same age range.
5. A mass-layoff event is one in which a firm with at least 50 employees (prior to the event) experiences a lasting employment decline of at least 30% over two years. Mass layoffs include employment contractions up to 99%, but exclude instances in which the Employer Identification Number (EIN) disappears. See the text for further discussion. By a "lasting" decline from, say, t-2 to t, we mean one in which EIN employment at t+1 is no more than 90 percent of employment of its employment at t-2. Similarly, we require that EIN employment grow by no more than 30% from t-3 to t-2.
6. The displacement rate is calculated using administrative data from W2 earnings records as in von Wachter, Song, and Manchester (2011) and described in the text.

To clarify the timing of job displacements in our data, consider a worker at a firm with 50 or more employees who permanently loses his job in April 1982. This worker has earnings at the firm in 1982 but not 1983. Suppose the job loss occurs as part of an employer contraction that qualifies as a mass-layoff event by our definition. Then, if the worker also has 3 or more years of job tenure with the firm as of 1982, we record a displacement event in 1983, the first year in which the affected worker no longer receives wages from the firm.

The annual frequency of the measures in Figure 2 somewhat obscures the timing of cyclical movements, but the broad patterns echo those in Figure 1: job loss rates move in a countercyclical manner, and recessions involve notable jumps in job loss. The deep recession in the early 1980s involves dramatic increases in rates of job destruction and job displacement. For example, the annual job destruction rate at firms with 50 or more employees rose from 11.6% in 1979 to 18.3% in 1983. To be clear, the latter figure reflects establishment-level employment contractions that occur from March 1982 to March 1983.

Our measure of the job displacement rate rose from 1.9% in 1980 to 5.0% in 1983.[8] More generally, the job displacement rate is roughly 20 to 25 percent as large as annual job destruction rates, although it is worth stressing that the two measures pertain to different at-risk populations.

Although the number of workers who experience job displacement by our definition might seem modest in any given year, it can cumulate to a large number in severe recessions. For example, 16% of all workers with 3 or more years of job tenure at firms with 50 or more employees lost jobs in mass-layoff events during the early 1980s. In raw numbers, about 1.7 million workers suffered a job displacement in this period. Given our fairly stringent criteria for mass-layoff events, this figure is a conservative one. According to the Displaced Worker Supplement to the CPS, 6.9 million persons with at least 3 years of prior tenure lost jobs due to layoffs from 2007 to 2009 (BLS, 2011).

Figure 3 shows job displacement rates for men with 3-5 years of prior job tenure and 6 or more years. Displacement rates are considerably higher for those with 3-5 years of tenure and more cyclically sensitive in the relatively shallow recessions of the early 1990s and early 2002. These patterns conform to the view that workers with lower job tenure face greater exposure to negative firm-specific and aggregate shocks. Figure 4 shows job displacement rates for men in three broad age groups. The basic pattern is clear: younger men tend to be more exposed to negative firm-specific and aggregate shocks that lead to job destruction.

Putting Figures 3 and 4 together, higher job tenure and greater labor market experience afford some insulation from the vicissitudes of firm-level employment fluctuations. However, it is well worth noting that greater job tenure and experience provide less insulation in the deep aggregate downturn in the early 1980s. This aspect of Figures 4 and 5 suggests that severe recessions bite especially deeply into the distribution of valuable employment relationships. Evidence below on the cyclical behavior of the earnings losses associated with job loss support this view as well.

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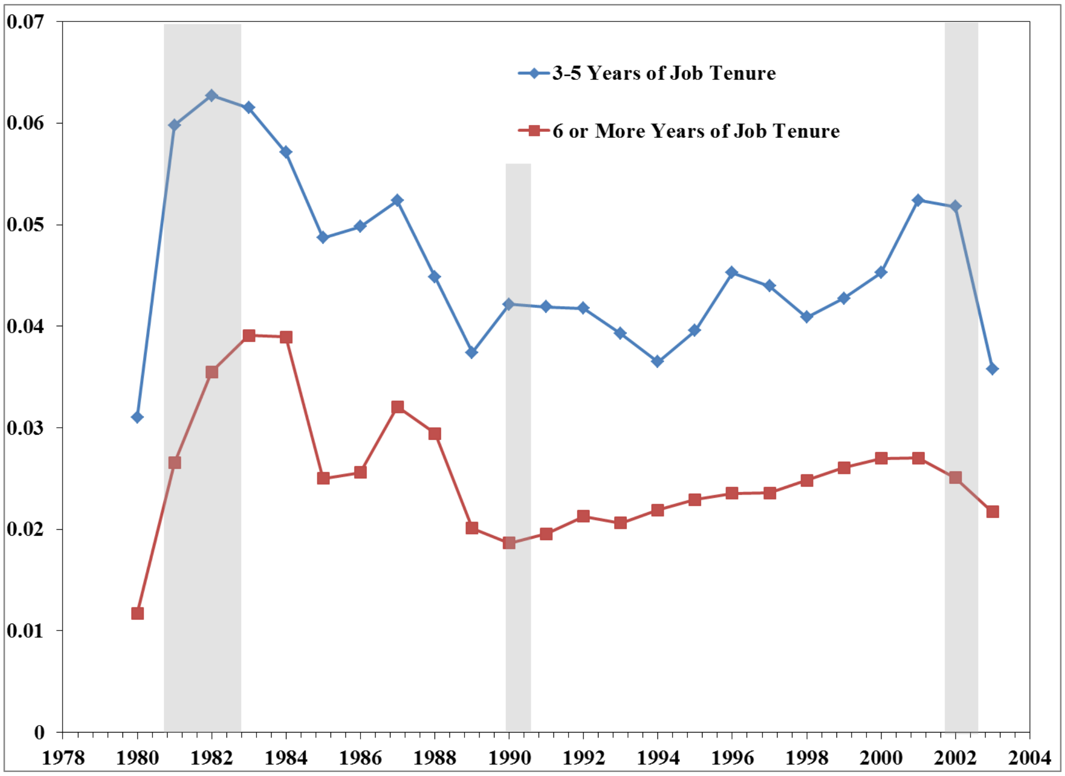
[8] The very high rates of Initial UI Claims in the early 1980s should be interpreted with some caution. Temporary layoffs were a major phenomenon in the early 1980s, unlike in later recessions, and many temporarily laid off workers qualified for unemployment insurance benefits. Temporary layoffs are not captured by our job displacement measure and, for the most part, neither are they reflected in the annual job destruction measures.

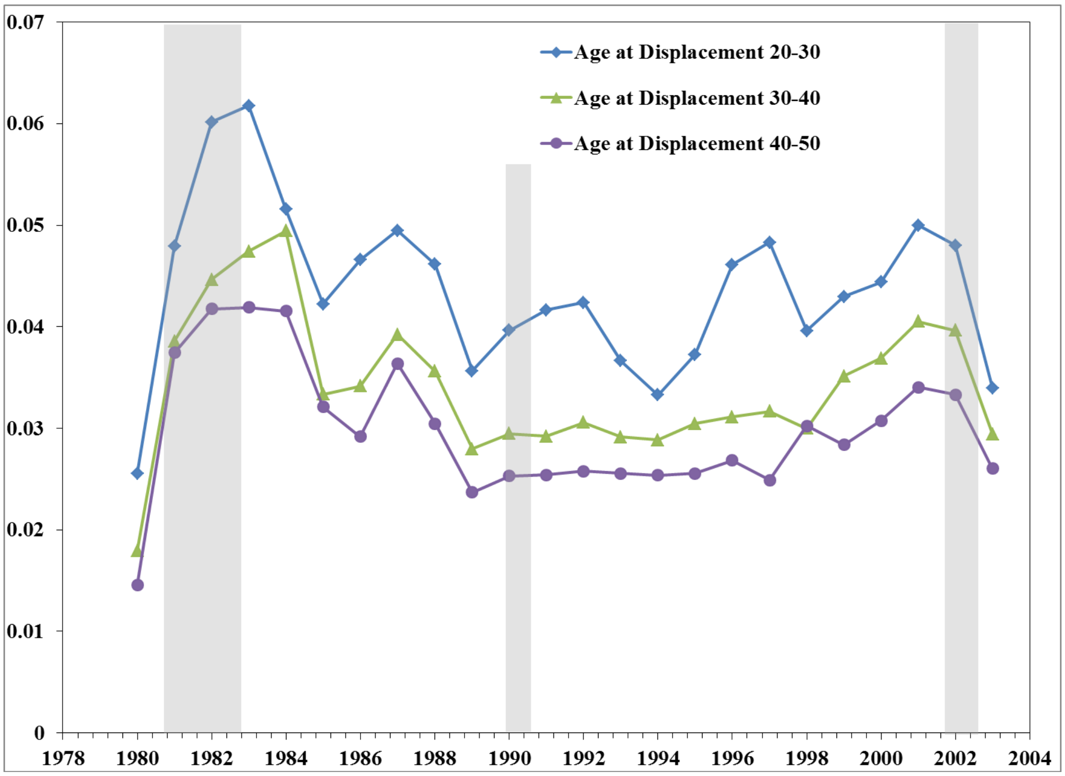
Figure 3: Job Displacement by Years of Job Tenure for 1980-2003, Men with at 3 to 5 or 6 or more Years of Job Tenure at Firms with at Least 50 Employees Displaced During Mass-Layoff Events



Notes to Figure 3:

1. Job displacement is the incidence of job loss in mass-layoff events for two groups of men who are 20-50 years of age prior to the event: men with 3 to 5 years of tenure before the year of job loss, and men with 6 or more years. Incidence is expressed as the percent of all employees in the same age range with at least 3-5 years or 6 years tenure at firms with at least 50 employees, respectively.
2. See notes 4, 5 and 6 to Figure 2.

Figure 4: Annual Displacement Rate by Age at Displacement for 1980-2003 Men with At Least 3 Years of Job Tenure Displaced at Firms Size 50+ Displaced as Firm has Lasting 30% Employment Drop Over 2 Years



Notes:

1. The figure shows the displacement rate in percent for workers in three age groups.
2. See notes 4, 5 and 6 in Figure 2.

3. The Long-Term Earnings Effects of Job Displacement

a. Previous Research

A growing body of research finds that job displacements lead to substantial and long lasting negative effects on earnings. For example, von Wachter, Song, and Manchester (2011) [henceforth VSM] analyze the long-term earnings effects of job displacement in longitudinal data from the Social Security Administration over more than 30 years. Following earlier research, VSM define job displacement as the separation of a "stable" worker from his main employer during a period when the employer experiences a lasting employment decline of at least 30%. A stable worker is one with at least three years of consecutive earnings at the firm prior to the displacement event. They also require the employer to have at least 50 employees in the baseline period before the mass layoff. VSM compare the evolution of annual earnings for displaced workers with that of a control group of similar workers that did not separate from their employers. They find that job displacements during the early 1980s recession led to large declines in average earnings of more than 30% relative to pre-displacement earnings. Despite some earnings recovery in the years following displacement, earnings are 15-20% lower than pre-displacement earnings even after 20 years.

The short- to medium-run effects of job displacement are larger in depressed areas and sectors. For example, using information on earnings and employers from unemployment insurance records and a comparable definition of job displacement, Jacobson, Lalonde, and Sullivan (1993) [henceforth JLS] find that job displacement in Pennsylvania in the early 1980s led on average led to earnings losses of more than 50%. Even five years after displacement, JLS find losses of 30% relative to the pre-displacement mean. These losses do not substantially fade even 10 years after job displacement (von Wachter and Sullivan, 2009). Schoeni and Dardia (2003) and Kodrzcki (2007) find similar results for job displacement in manufacturing industries in the mild recession of the early 1990s in California and Massachusetts, respectively.

Earnings losses are substantial and long lasting even in regions and periods that do not experience difficulties in the labor market. For example, Couch and Placzek (2010) examine job displacement using quarterly earnings data from unemployment insurance records in Connecticut in the 1990s. They find that high attachment workers suffer persistent losses in quarterly earnings up to five years after a job displacement. Similarly, JLS show that workers displaced in Pennsylvania counties with below-average unemployment rates and above-average employment growth fare significantly better than the average worker, but still suffer earnings losses. VSM find substantial earnings losses for job displacements during the late-1980s expansion that fade only after 15 years. Studies using longitudinal survey data to compare the earnings of job losers to a control group also find substantial earnings and wage losses that persist up to five to ten years (e.g., Ruhm, 1991, and Stevens, 1997).

The findings from administrative data pertain to annual or quarterly earnings. Hence, the earnings losses potentially arise from reductions in both employment and wages. However, the earnings loss for the median worker in the sample is about as large, and more persistent, than the mean loss (VSM, Schoeni and Dardia, 2003). This result and survey-based evidence that employment reductions after a job loss tend to be temporary (e.g., Farber 1999) suggest that the majority of earnings losses after job displacement reflects a reduction in wage rates or hours worked per employed. Although retrospective survey data suffer from errors in the recall of job-loss events and earnings outcomes (e.g., Topel 1990, and von Wachter, Handwerker, and Hildreth, 2008), studies based on such data also typicaly find large losses associated with job displacement.

One natural question about studies based on administrative data is how the earnings loss results depend on the definition of job displacement, the choice of control groups and the specification of mass-layoff events. VSM find that their results survive the use of alternative firm size thresholds, different definitions of a mass-layoff event, alternative employment stability requirements for control groups, and other robustness checks. von Wachter, Handwerker, and Hildreth (2008) obtain similar results using control groups constructed from workers in similar firms and industries. Studies based on annual panel survey data that do not impose restrictions on firm size or firm events yield results for earnings that are similar to those in results based on administrative data.

Overall, a key finding in previous research is that job displacement leads to substantial and long-lasting earnings losses, especially under weak labor market conditions. This observation suggests that workers who have experienced job displacements events since 2008 are likely to experience unusually severe and persistent earnings losses. Direct evidence on the losses of recently displaced workers is limited, in part because of lags in processing and analyzing administrative data sources. The latest Displaced Worker Supplement (DWS) to the Current Population Survey, conducted in January 2010, contains recall data for workers displaced from 2007 to 2009. Given the absence of a control group, the inability to incorporate earnings losses due to employment reductions, and the presence of measurement error in wages and job loss events, DWS data tend to show lower earnings losses than studies based on administrative data (von Wachter, Handwerker, and Hildreth 2008). However, even the DWS implies substantial earnings losses for persons who lost jobs from 2007 to 2009. Based on DWS data, the Bureau of Labor Statistics (2011) reports that only 49% of workers displaced in 2007-2009 who had 3 or more years of prior job tenure are currently employed, and that among the reemployed, 36% report current earnings at least 20% lower than on the previous job.

The earnings losses associated with job displacement are large and persistent for both women and men and for workers in all major industries. Older workers tend to have larger immediate earnings losses than younger workers. Relative to a control group of similar age, however, the earnings losses of younger displaced workers are non-negligible and persist over twenty years (VSM). Earnings losses tend to rise with tenure on the job, industry or occupation (e.g., Kletzer 1989, Neal 1995, Poletaev and Robinson, 2008). Yet, losses for workers with 3 to 5 years of job tenure are substantial and long lasting, and even workers with less than three years of job tenure experience non-negligible declines in annual earnings following a job displacement event (VSM).

b. Present Value Earnings Losses Associated with Job Displacement

Figures 5A to 5C show the average annual earnings losses before and after job displacement that underlie our present discounted value (PDV) calculations. The underlying estimates by year are from VSM and constructed as follows. As before, displaced workers are those who separate from a firm with at least 50 employees during a mass-layoff event and who had at least three consecutive years of positive earnings at the firm before separation. A mass-layoff event is a lasting drop in employment of 30% or more over two years. By "lasting", we mean an employment decline not immediately reversed in the following year and not preceded by a large employment increase. Moreover, we concentrate on workers who are no more than 50 years old at displacement.

We estimate earnings losses due to displacement using the distributed-lag model,

$$e_{it} = \alpha_i^y + \gamma_t^y + \bar{e}_i^y \lambda_t^y + \beta^y X_{it} + \sum_{k \geq -m,} \delta_k^y D_{it}^k + u_{it} \qquad (1)$$

where the outcome variable e_{it} represents annual earnings of individual i in year t, y indexes the year of displacement, γ_t^y are year dummies, X_{it} is the age of worker i at t, and the error u_{it} represents truly random components affecting the outcome. The model also allows for differential year effects λ_t^y depending on the worker's average earnings in the five years prior to displacement ($\bar{e}_i^y$). We estimate the model separately for workers displaced in each calendar year from 1980 to 2007.[9] The coefficients δ_k^y on the dummies D_{it}^k measure the time path of earnings changes for job separators before and after a displacement relative to the baseline and the control group. To interpret the estimated effects δ_k^y as the causal effect of job separation on earnings requires that, conditional on worker fixed effects and the other control variables displaced workers are identical to workers in the control group.

For workers displaced in year *t*, the control group consists of workers not separating from their employers in t, t+1, and t+2 ('non separators'). Hence, as typical in the literature on job displacement based on administrative data, we exclude so-called 'non-mass layoff separators' from t to t+2 from the control group. Non-mass layoff separators comprise workers who quit, retire, or leave the labor force for disability or other reasons. They also include workers laid off by firms with an employment drop of less than 30%. We discuss the impact of alternative definitions of the control group and concerns related to potential selection bias in earnings loss estimates in Section 3.C below.

Panel A of Figure 5 shows the average change in earnings before and after a job displacement relative to earnings four years before the displacement year, relative to the regular evolution of earnings of the control group. To obtain average earnings losses for job displacements in expansions and recessions, we average over estimated values of δ_k^y in recession and expansion years. If the peak or a through falls inside a given calendar year, we weight the year according to the number of its months in expansion or recession when computing the averages.

[9] In practice, to raise the number of observations, we also include displacements in years *y-1* and year *y+1* in the estimates for a given displacement year *y*. Thus, our estimates can be interpreted as a 3-year moving average with equal weights. Note that this approach works against finding differences in the effect of displacements in expansions and recessions.

Figure 5A: Average Annual Earnings Losses Before and After Job Displacement in NBER Recessions and Expansions, Men with At Least 3 Years of Job Tenure

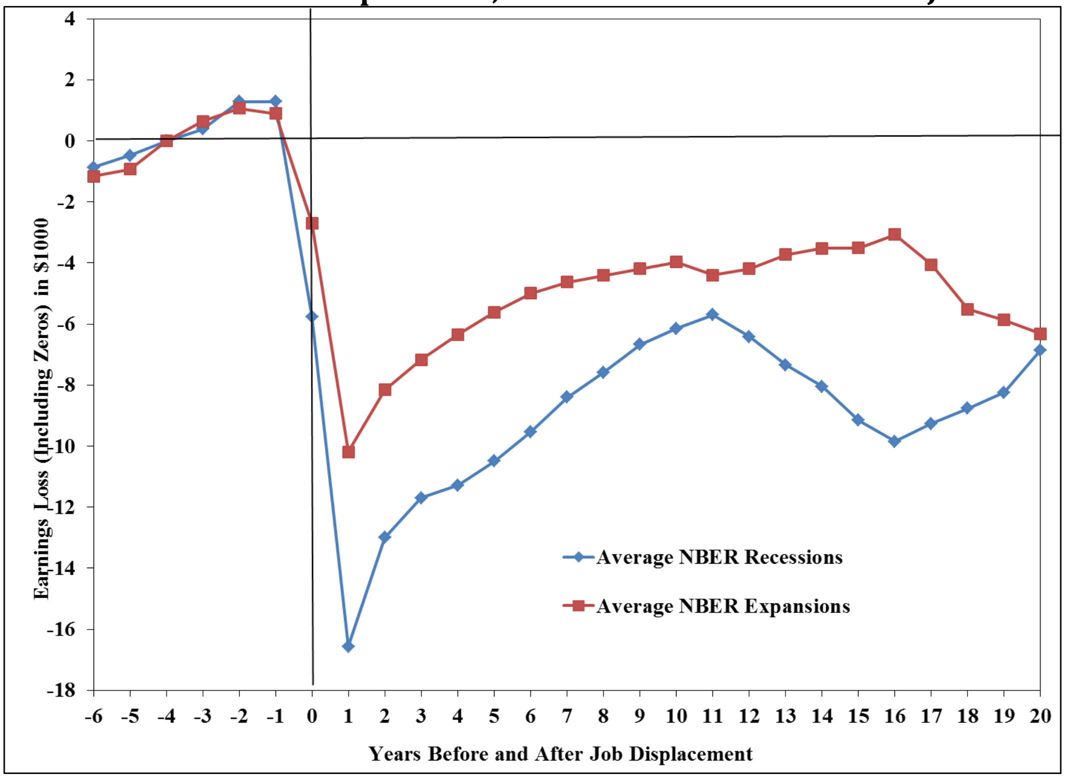


Figure 5B: Average Annual Earnings Before and After Job Displacement in NBER Recessions and Expansions Men with At Least 3 Years of Job Tenure

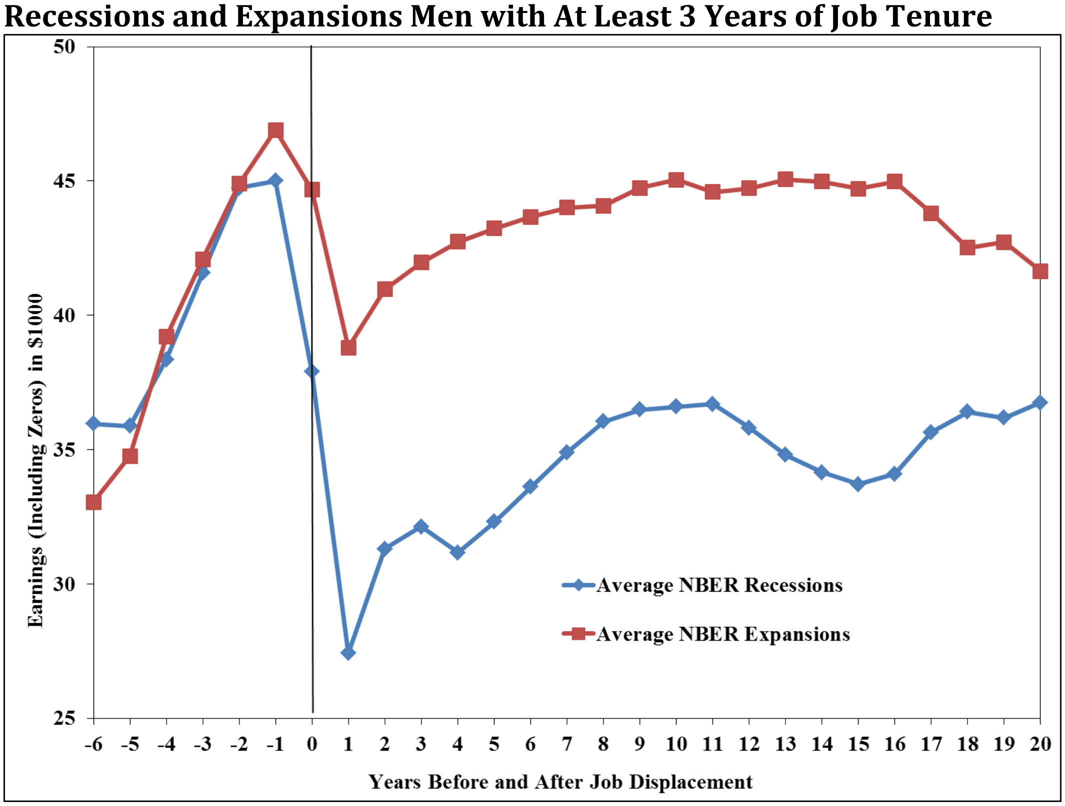
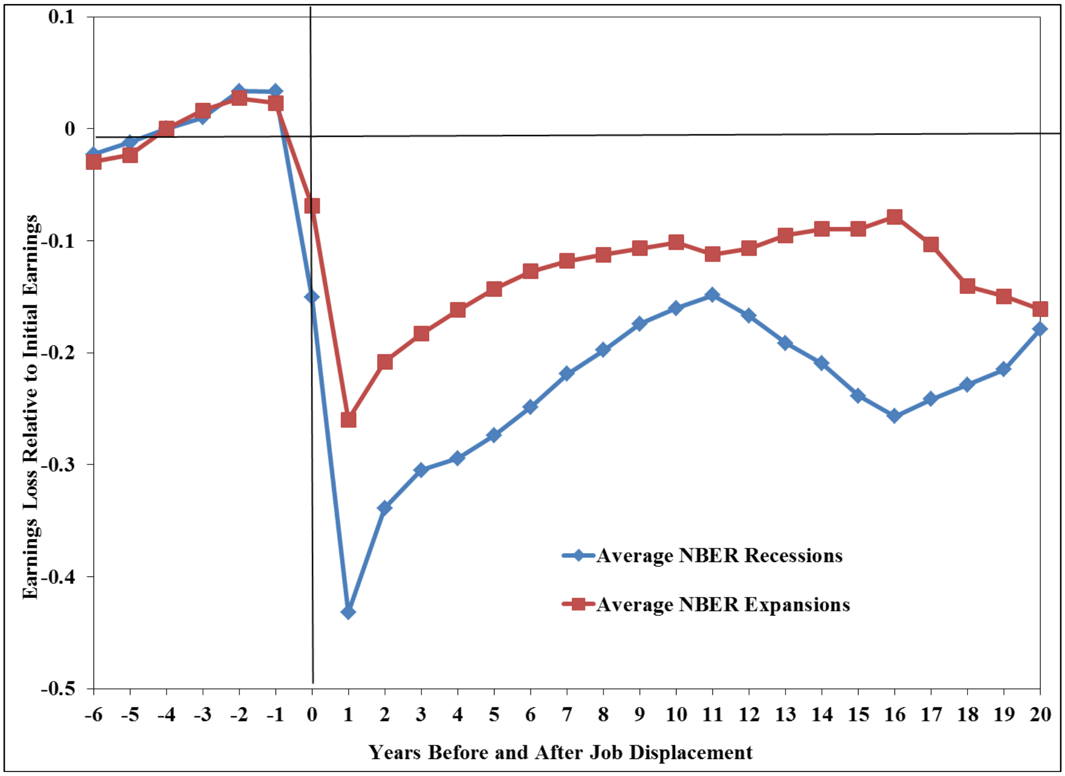


Figure 5C: Average Annual Earnings Losses Before and After Job Displacement in NBER Expansions and Recessions Relative to Pre-Displacement Earnings, Men with At Least 3 Years of Job Tenure



Notes to Figures 5A, 5B and 5C:

1. Panels A and C show average annual earnings losses relative to pre-displacement earnings for workers with 3 or more years of tenure prior to job loss. Similarly, Panel B shows average annual earnings rather annual earnings losses. One curve in each panel shows average outcomes for workers displaced in recession years from 1980 to 2003, and the other shows average outcomes for those displaced in expansion years.
2. The earnings losses in Panels A and C for each year before and after displacement is the difference in average annual earnings (including zeros) for workers with 3 or more years of job tenure who separate from their main employers in mass-layoffs events, expressed relative to a baseline period of 4 years before layoff and relative to workers with 3 or more years of tenure who did not separate from employers. The underlying regression includes controls for worker effects, year effects, current age, and interacts year fixed-effects with average earnings in the five years preceding displacement. The earnings levels in Panel B are constructed in a similar manner.
3. The earnings losses and levels are calculated using administrative earnings data from W2 earnings records used in von Wachter, Song, and Manchester (2011) and described in the text.

Figure 5A has three key messages. First, earnings relative to the control group change little before displacement, drop steeply at displacement, experience somewhat of a recovery, but clearly remain below zero over an extended period afterwards.[10] The earnings losses do not completely fade even after 20 years. Second, the earnings losses are substantial and persistent even if the displacement happens in an expansion. Third, the earnings losses due to job displacements that occur in recessions (lower curve) are significantly larger than displacements that occur in expansions (upper curve). For a somewhat different perspective on the earnings losses associated with job displacement, Panel B shows the evolution of average earnings before and after job displacement (i.e., without comparison to a control group).

Panel C in Figure 5 shows the Panel A losses as a percentage of earnings in the year before job displacement. Earnings losses at displacement relative to the control group are very large initially, about 35% and 20% in the years after job displacements in recessions and expansions, respectively. They are also long lasting, averaging about 20% 15-20 years after job displacements in recessions and more than 10% for displacements in expansions. These estimates are robust to many specification checks [see VSM]. For example, the earnings losses are similar if one were to define a mass-layoff event as an 80% decline in employment. They would be slightly larger if we were to consider workers with 6 years or more of job tenure (the main comparison group of JLS and others), and slightly smaller if we were to analyze workers with 3 to 5 years of job tenure.

Figure 6 plots estimated short-term earnings losses against the national unemployment rate in the year of displacement. The definition of short-term loss in this figure is the earnings loss in the third year after job displacement divided by average earnings prior to job displacement. The figure displays a clear inverse relationship that is strikingly close to linear. If we regress the percentage loss on the unemployment rate at displacement, we obtain a good fit (R^2 of 0.65) and a highly significant slope coefficient of -0.046 (standard error of 0.007). That is, a 4 point rise in the unemployment rate from 5% to 9% implies a doubling of the earnings loss three years after displacement from -0.15 to -0.34. Since the earnings recovery pattern in Figure 5C is approximately parallel in

[10] Note that the earnings loss at displacement occurs over two years because we use annual earnings to date the occurrence of job displacement.

expansions and recessions, Figure 6 suggests that the state of the labor market at displacement sets the initial level of losses, from which a gradual recovery occurs. We will use this result when calculating PDV earnings losses below.

Figures 5 and 6 point to large PDV earnings losses associated with job displacement and large differences between the PDV losses of displacements that occur in expansions versus those that occur in recessions. To derive estimates of PDV earnings losses from the annual earnings losses before and after job displacement shown in Figure 5, we proceed as follows. Using a real interest rate of 5%, we sum the discounted losses over a 20-year period starting with the year of displacement. Since we do not observe the full 20 years of earnings after a job displacement for workers displaced in later years, we impose a common rate of decay past the tenth year. Hence, the estimated PDV of earnings losses in, say, a recession can be written as

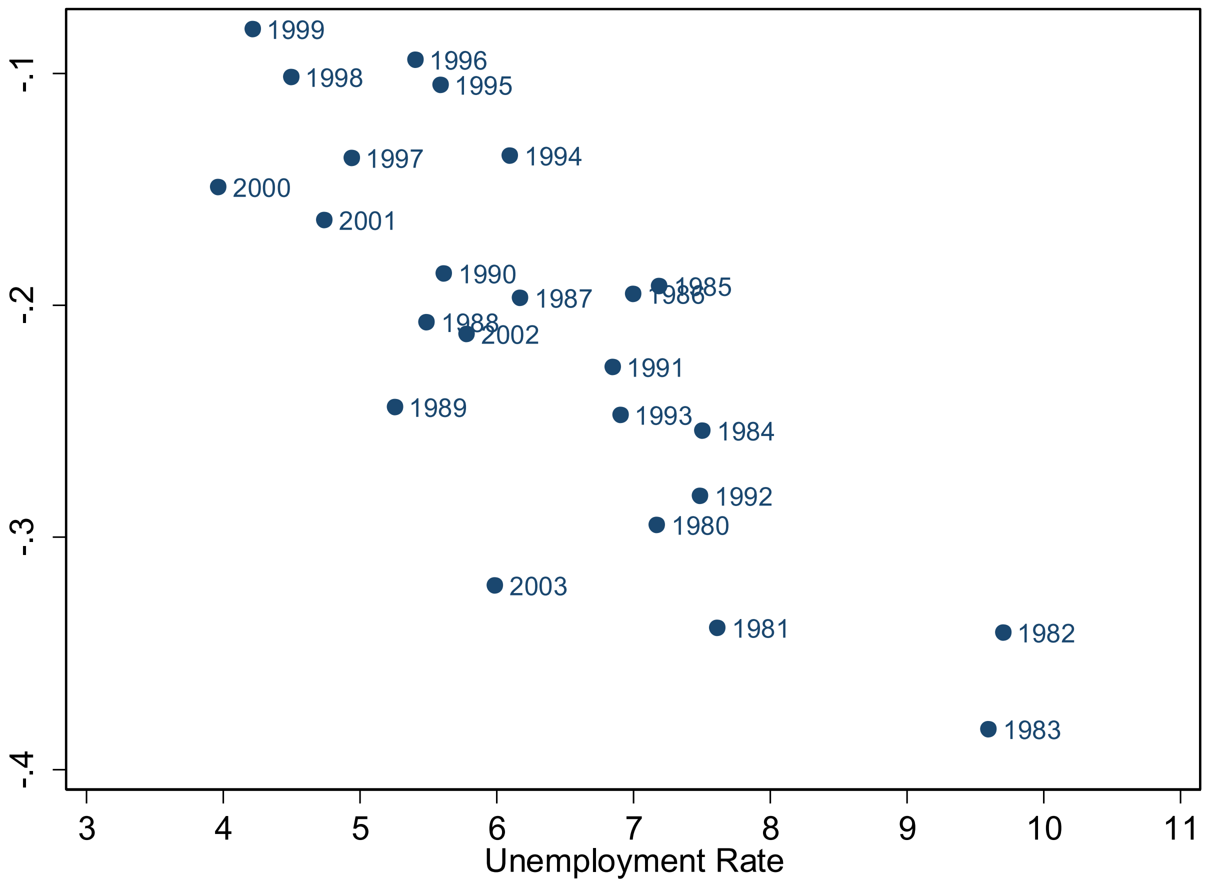
$$PDV^R_{\text{Loss}} = \sum_{s=1}^{10} \bar{\delta}^R_s \frac{1}{(1+r)^{s-1}} + \sum_{s=11}^{20} \bar{\delta}^R_{10} \frac{(1+\bar{\lambda})^{s-10}}{(1+r)^{s-1}} \qquad (2)$$

where $\bar{\delta}^R_s$ is the average estimated earnings losses of displacements occurring in recessions in year s after job displacement (derived by averaging the results for equation (1) over different years), and $\bar{\delta}^R_{10}(1+\bar{\lambda})^{s-10}$ is the extrapolated earnings loss using the rate of decay $\bar{\lambda}$. Since the evolution of earnings losses is roughly parallel for displacements in expansions and recessions, we use the average decay rate of earnings losses over all periods. To smooth out sampling variability in the recovery pattern and to maximize the number of available cohorts, we calculate the decay rate as the average of annualized log differences in earnings losses from years 6 to 10 and to years 11 to 15 after displacement.

Since earnings levels change over time and may differ in expansions and recessions, we also consider various ways of normalizing the absolute earnings losses. First, we scale the PDV earnings loss by annual earnings prior to displacement. This approach expresses the PDV earnings loss in terms of the number of earnings years lost at the previous level of earnings. As an alternative, instead of summing up the *level* of earnings losses in each year after displacement, we calculated the PDV of the *percentage* earnings losses in each year after displacement. To do so, we first construct a counterfactual earnings path in the absence of job displacement by adding the absolute value of the estimated earnings loss

(Panel A of Figure 5) back to the actual level of average earnings Panel B of Figure 5). In the notation of equation (1), for workers displaced in each year *y* we thereby effectively

Figure 6: Annual Earnings Losses in the Third Year After Job Displacement vs. National Unemployment Rate in the Year of Job Displacement, Men with at Least 3 Years of Job Tenure Prior to Displacement



Notes:

1. The figure shows the loss in annual earnings (including zeros) for high-tenure workers displaced in mass-layoff events three years *after* the job loss, expressed as a percent of annual earnings before displacement. The figure plots this percentage earnings loss three years after displacement against the unemployment rate in the year of displacement. High-tenure workers are those with 3 or more years of job tenure in the year before the mass-layoff event.
2. Data point labels in the figure refer to the year of displacement and the year of the unemployment rate.
3. The earnings loss is calculated using administrative earnings data from W2 earnings records used in von Wachter, Song, and Manchester (2011) and described in the text.

obtain $\bar{e}_t^{cf,y} = \bar{\alpha}^y + \gamma_t^y + \beta^y \bar{X}_t^y$. We then take the average of the counterfactual in years belonging to NBER recessions and expansions, respectively.[11]

Using these averages, we calculated the percentage earnings loss in two ways: first, by taking the log difference between the counterfactual earnings level and the actually realized average earnings; and second, by dividing the earnings loss by the counterfactual value. If we denote the percent loss in annual earnings as $\hat{\delta}_s^R$ the two measures are

$$\hat{\delta}_s^R = \log(\bar{e}_s^{act.,R}) - \log(\bar{e}_s^{cf,R}) \text{ and } \hat{\delta}_s^R = \bar{\delta}_s^R / \bar{e}_t^{cf,R}$$

In either case, and following the same procedure as for PDV_{Loss}^R, we obtain

$$PDV_{\%\text{Loss}}^R = \sum_{s=1}^{10} \hat{\delta}_s^R \frac{1}{(1+r)^{s-1}} + \sum_{s=11}^{20} \hat{\delta}_{10}^R \frac{(1+\bar{\lambda})^{s-10}}{(1+r)^{s-1}} \tag{3}$$

where we again use the average rate of decay $\bar{\lambda}$. Finally, we also express the PDV of absolute annual earnings losses as a percent of the PDV of the counterfactual earnings path.

Table 1 reports these alternative measures of the PDV loss in earnings after a job displacement. Again, the table is for workers with at least three years of positive earnings at an employer with at least 50 workers, and the definition of displacement is the same zx in Figure 5. The first row of the table shows estimates for the average PDV earnings loss over all displacement years. The average PDV earnings loss shown column 1 is about $70,000. This loss amounts to 1.8 times average pre-displacement annual earnings (column 2) and 11.3% of the PDV of counterfactual earnings absent job displacement. The PDV of the annual percentage earnings losses, shown in columns 3 and 4, are only somewhat larger than the multiple of pre-displacement wages in column 2. This is because for the workers in our sample, who on average are in middle age, earnings losses are not predicted to grow substantially in the absence of job displacement.

[11] Similarly, we calculate the corresponding mean of actual annual earnings before and after displacement by first obtaining the average for each displacement year, $\bar{e}_t^{act.,y}$, and then averaging over the years belonging to expansions and recessions.

Table 1. Magnitude and Cyclicality of Present Value Earnings Losses Associated with Displacement in Mass-Layoff Events from 1980 to 2003, Men with at Least Three Years of Job Tenure Before Displacement

		(1)	(2)	(3)	(4)	(5)
		Present Discounted Value (PDV) of Average Loss at Job Displacement Per Person		PDV of Average Loss as Percent of Counterfactual Annual Earnings Stream		
	Fraction of Years Covered by Row Category	Dollar Value	Relative to Annual Earnings in Year Before Displacement	PDV of Log Difference Between Loss & Counterf. Earnings	PDV of Percent Loss Relative to Counterf. Earnings	Ratio of PDV of Loss and PDV of Earnings
Average All Years	--	-72,685	-1.82	-1.8	-1.52	-11.3
Avg. in NBER Expansion Years	*0.85*	-65,424	-1.62	-1.5	-1.34	-10.0
Avg. in NBER Recession Years	*0.15*	-112,095	-2.92	-3.2	-2.58	-19.2
Average in Years with:						
UR< 5%	*0.18*	-30,222	-0.66	-0.6	-0.58	-8.6
5%<=UR<6%	*0.32*	-54,843	-1.32	-1.1	-1.09	-9.3
6%<=UR<7%	*0.14*	-58,063	-1.49	-1.7	-1.20	-9.1
7%<=UR<8%	*0.26*	-90,337	-2.44	-2.2	-1.93	-14.3
UR>=8%	*0.09*	-125,304	-3.87	-3.2	-2.73	-20.2

Notes:

1. Estimates for displaced workers with at least 3 years of job tenure before the year of displacement at firms with at least 50 employees prior to the mass layoff. Displaced workers are those who leave their main employer in the year before during or after a mass-layoff event. See note 5 to Figure 2 for the definition of mass-layoff events.
2. To compute the entries in this table, we estimated earnings losses and performed present value calculations by calendar year, and we then took averages over years. When a given calendar year straddled recession and expansion periods or multiple unemployment intervals, we apportioned that year's values based on its number of months in each category. For example, if 3 months of the year are in recession, then we allocated its values to recession and expansion categories with weights 0.25 and 0.75, respectively.
3. We calculated the estimated PV earnings losses over 25 years after job displacement, using a 5 percent annual discount rate. Since we do not observe earnings outcomes in the full 25-year interval following displacement for much of our sample, we impute missing earnings loss values as follows: First, through year

10 after displacement, we impute using the average earnings loss value for that year-since-displacement in our sample. For years from 11 to 25 after displacement, we estimate the average decay rate for the magnitude of earnings losses using the data for available years, and we extrapolate the earnings loss path using that decay rate. See text for additional explanation.

4. The earnings loss is calculated using administrative earnings data from W2 earnings records used in von Wachter, Song, and Manchester (2011) and described in the text.

The next two rows of the table show our measures of PDV earnings losses separately for expansions and recessions. As anticipated from Figure 5, the PDV of earnings losses is much larger in recessions than expansions. A worker displaced in a recession experiences PDV earnings losses of $112,095, which amounts to three years of pre-displacement earnings, and to a 20% decline relative to counterfactual earnings absent displacement. In contrast, the PDV of earnings losses experienced by workers displaced in an expansion amounts to $65,424, only 60% of the average loss for workers displaced in a recession. The remaining columns underscore the large difference in earnings losses between expansions and recessions. The average percent loss in columns 2 to 4 is about two times larger in recessions than in expansions. The percent gap with respect to counterfactual earnings is also about twice as high in recessions.

The results in Table 1 imply that job displacements lead to very large declines in PDV earnings, and that this reduction is much larger in recessions. Because there is more job destruction and job loss in recessions than expansions, and given that displacement has more severe consequences in recessions, the un-weighted averages over years in row 1 understates the true average PDV earnings losses across displaced workers.[12] Similarly, because we weigh all recession years equally in row 3, but recessions with higher job destruction also lead to higher earnings losses, the already large estimates in Table 1 understate the average PDV earnings losses in recessions taken over displaced workers.

The lower panel of Table 1 shows how estimated PDV earnings loss vary by the level of the unemployment rate in the year of displacement. As before, to calculate the numbers in the table, the first step is to obtain estimates estimate PDV earnings losses by year of

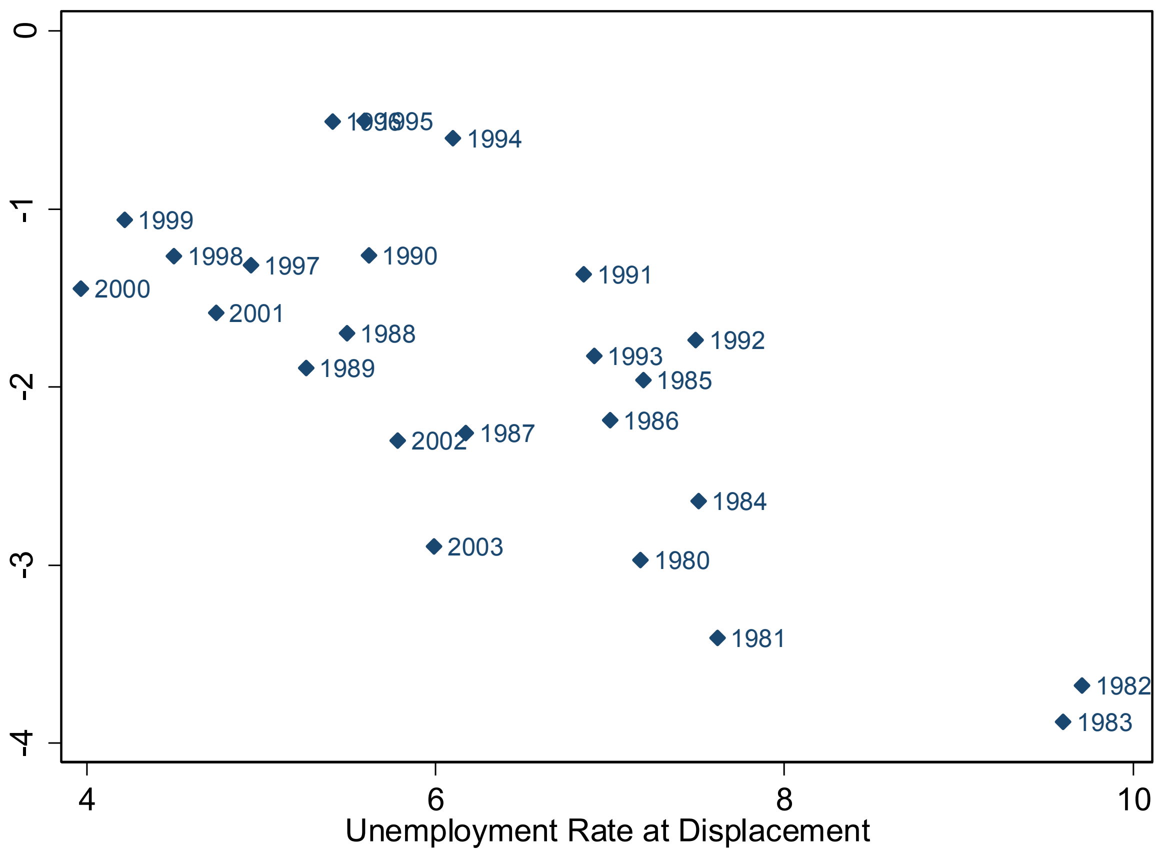
[12] Row 1 in the Table 1 effectively gives less weight to persons displaced in recessions as compared to those displaced in expansions. The next draft will include a row that shows averages taken over displacements. A similar point applies to Table 2 below.

displacement. In a second step, we average over all years falling into an indicated unemployment range, assigning fractional weights to years that fall partly into a given range. The results show that PDV earnings losses rise sharply and monotonically with the unemployment rate in the year of job displacement. This is an important finding that strongly reinforces and extends the evidence in Figure 6.

To take this result one step further, we repeat our procedure for calculating estimated PDV earnings losses by year of displacement. When we have more than ten years of post-displacement information, we use the first ten years and extrapolate from year 11 to 20 using the average rate of decay as before. When we have less than ten years of post-displacement information (i.e., starting in 1999), we also use the available information for other years to construct decay rates in the earlier post-displacement years, say 6 to 10 years after displacement. For years closer to the end of our sample period, we necessarily rely more heavily on extrapolation.

Figure 7 plots the resulting PDV earnings losses (expressed as multiples of pre-displacement annual earnings) against the unemployment rate in the year of displacement. The figure again shows an approximately linear relationship, wchi is not surprising given the linear relationship in Figure 6 and our use of a common decay rate beyond the tenth year after displacement. Unlike Figure 6, however, Figure 7 reflects estimated average earnings losses in the first ten years after displacements that occur before 1999 (and fewer post-displacement years after 1999) plus the average decay rate thereafter. Hence, the figure suggests that even allowing for different post-displacement recovery patterns, PDV earnings losses increase approximately linearly with the unemployment in the year of displacement. A linear regression of the PDV earnings loss measure on the unemployment rate in the year of displacement yields an R^2 of 0.55 with a slope coefficient of -0.47 (0.09). Thus, an increase from 5% to 9% in the unemployment rate at displacement implies that PDV earnings losses rise from 1.3 to 3.2 years of pre-displacement earnings. In sum, Table 1 and Figure 7 show that PDV earnings losses are highly sensitive to the unemployment rate at the time of displacement.

Figure 7: Present Discounted Value of Earnings Losses By Year of Displacement vs. Unemployment Rate in Year of Displacement, Men with At Least 3 of Job Tenure Prior to Displacement



Notes:

1. The present discounted value of earnings losses are defined as in Table 1. For each year of displacement, we compute the discounted sum of earnings losses in the first 25 years after a job displacement using a discount rate of 5%. To extrapolate for years beyond our sample window, we use the average rate of decay in the respective ranges of years after job displacement observed in the remainder of the sample.
2. The earnings losses are calculated using administrative earnings data from W2 earnings records used in von Wachter, Song, and Manchester (2011) and described in the text.

Table 2. Magnitude and Cyclicality of Present Value Earnings Losses Associated with Displacement in Mass-Layoff Events from 1980 to 2003: Various Subgroups

Sub-Group		(1) Present Discounted Value (PDV) of Average Loss at Job Displacement Per Person	(2) PDV of Log Difference Between Annual Earnings Loss & Counterf. Earnings	(3) 100*Ratio of PDV of Loss and PDV of Counterfactual Earnings Path in Absence of Displacement
Men with 6 or More Years of Job Tenure at Displacement	Average All Years	-97,024	-2.1	-13.6
	Avg. in NBER Expansion Years	-88,448	-1.9	-12.2
	Avg. in NBER Recession Years	-142,847	-3.5	-22.1
Women with 3 or More Years of Job Tenure at Displacement	Average All Years	0	0.0	0.0
	Avg. in NBER Expansion Years	0	0.0	0.0
	Avg. in NBER Recession Years	0	0.0	0.0
Men with 3 or More Years of Job Tenure and age 20-30 at Displacement	Average All Years	-50,893	-1.7	-9.9
	Avg. in NBER Expansion Years	-35,123	-1.2	-6.9
	Avg. in NBER Recession Years	-133,376	-4.2	-24.9
Men with 3 or More Years of Job Tenure and age 30-40 at Displacement	Average All Years	-52,086	-1.4	-8.3
	Avg. in NBER Expansion Years	-43,126	-1.1	-6.7
	Avg. in NBER Recession Years	-99,462	-2.7	-17.1
Men with 3 or More Years of Job Tenure and age 40-50 at Displacement	Average All Years	-99,588	-1.9	-16.5
	Avg. in NBER Expansion Years	-95,489	-1.8	-15.4
	Avg. in NBER Recession Years	-123,912	-2.9	-23.6
Men with 3 or More Years of Job Tenure and age 50-60 at Displacement	Average All Years	-102,940	-2.6	-25.6
	Avg. in NBER Expansion Years	-102,703	-2.5	-24.9
	Avg. in NBER Recession Years	-105,062	-3.2	-31.1

Notes to Table 2:

1. See notes to Table 1. This table differs from Table 1 only attention to job displacements for different groups of workers, and by focusing on a subset of measures of the present discounted value of earnings losses.
2. For workers displaced up to age 40, we calculate the present discounted value over the following 20 years. For workers displaced age 40-50 (50-60), we calculate it over 15 (10) years.

Table 2 shows PDV earnings losses for men with at least 6 years of tenure, for women, and for four age groups.[13] To economize on space, the table restricts attention to three measures of PDV earnings losses – absolute, relative to initial wages, and relative to counterfactual earnings, corresponding to columns 1, 2, and 5 in Table 1. The PDV earnings losses due to job displacement are large for all groups. Comparing Tables 1 and 2 shows that they are larger for men higher job tenure prior to displacement. Except for workers displaced near the end of their working lives, PDV earnings losses are strongly counter cyclical for all groups.

c. On Selection Bias and Sensitivity to Control Group Choice

We now discuss two potential concerns about the earnings loss estimates that underlie our results in Figures 5 to 7 and Tables 1 and 2: selection bias and the sensitivity of our results to the choice of control group. Relative to non-separators (our control group), non-mass layoff separators experience earnings losses that are smaller and less persistent than the losses experienced by mass-layoff separators. Thus, if we include non-mass layoff separators in the control group, the estimated earnings losses due to job displacement become smaller. VSM estimate a version of the displacement regression (1) with non-mass layoff separators as part of the control group. This change in the composition of the control group reduces the estimated earnings losses by about one quarter. VSM also consider instrumental variables estimates that are not affected by the presence of voluntary separators, obtaining results very similar to the ones we report based on our control group of non-separators. After considering various estimators, VSM conclude that the 'true' loss at displacement is closer to the estimates that exclude non-mass layoff separators from the control group.

[13] The appendix contains additional results by age group. Results for women are under development.

Estimates based on equation (1) may overstate earnings losses at displacement because displaced workers are negatively selected on observable and unobservable characteristics with respect to the control group. VSM conduct an in-depth investigation of this question, and conclude that earnings losses based on equation (1) are robust to a range of important sensitivity checks. The presence of worker fixed-effects in equation (1) implies that selection based on fixed worker attributes with a time-invariant effect on earnings poses no problem. However, different trends in counterfactual earnings between displaced workers and the control group may introduce a bias. For example, it is well known that there have been differential growth rates of earnings in different parts of the earnings distribution. Since displaced workers have lower average earnings prior to displacement than non-displaced workers, our regression models include interactions between average earnings in the five years prior to displacement and fixed effects for calendar years. VSM also present estimates that include differential trends by two-digit sector and by other observable characteristics of workers and firms prior to displacement. The estimates are reasonably robust to these modifications, and only decline somewhat when including sector-specific trends.

However, ex-ante differences in unobservable characteristics between treatment and control groups can still lead to differential counterfactual earnings trends. In this respect, VSM address two types of selection – within and between employers. To address the concern that displaced workers are negatively selected on potential earnings trends *within* firms, VSM replicate equation (1) using the mass-layoff event at the firm level as an indicator for the 'event'. That is, the main variable of interest becomes a dummy for the year of the mass-layoff at the firm, $D^k_{f(i)t}$, where *f(i)* is the worker's employer, instead of the individual layoff (D^k_{it}). Hence, the comparison is now between all workers present at firms experiencing mass layoffs and the evolution of earnings among all workers at non-mass layoff firms. Using this type of firm-level indicator, and controlling for differential trends by pre-mass layoff characteristics at the firm level, VSM obtain results very similar to those based on equation (1).

To address the potential concern that workers with lower potential earnings trends sort into firms likely to experience mass layoffs, VSM follow previous work and consider a version of equation (1) that includes firm fixed effects. This specification yields somewhat smaller estimated earnings losses, because the losses experienced by workers remaining at firms with mass layoffs are now subtracted from the losses experienced by displaced workers. It is not clear whether the decline in earnings for those remaining at mass-layoff firms should be subtracted or treated as part of the outcome. In any event, the estimated earnings losses remain substantial and very persistent. VSM conclude that estimates based on equation (1), on which we rely, are robust to a range of important sensitivity checks. Hence, despite some variation in the final magnitude of the loss depending on the exact specification, we believe that our calculations based on estimated versions of equation (1) from VSM accurately capture the magnitude and persistence of earnings losses caused by job displacement.

4. Other Costs of Job Displacement and Unemployment

Section 3 focuses on earnings losses associated with job displacement events. We turn now to the effects of job displacement on other outcomes such as consumption, health, mortality and children's achievement. We also present new evidence on cyclical movements in worker anxieties and perceptions about the risk of job loss and the ease or difficulty of job finding.

a. Effects on Income, Consumption and Employment Stability

It is not easy to estimate the effects of job displacement on consumption and income. Few, if any, data sets that track large numbers of workers over time contain high-quality information about consumption outcomes. Likewise, very few data sets that track large numbers of workers include the requisite data on earnings, asset incomes, and public and private transfer payments needed to identify income responses to job displacement events. Moreover, transfer payments are understated greatly in many household surveys that include such information (Meyer, Mok and Sullivan, 2010).

The few studies that estimate the effects of job loss or unemployment on consumption typically find sizable near-term declines in consumption expenditures (and lack evidence on long-term consumption responses). See Gruber (1997) and Stephens (2004), for example. The consumption responses tend to be concentrated at the lower end of the income distribution (Browning and Crossley, 2001, and CBO, 2004). While transfer programs often mitigate the earnings loss due to job displacement, the replacement amounts are quite modest compared to our estimates of present value earnings losses. Even the generous, long-lasting benefits available under the German unemployment insurance system replace only a modest share of the earnings loss associated with job displacement (Schmieder, von Wachter, and Bender, 2009).

Previous research also finds that job displacement leads to other adverse consequences. Lasting post-displacement earnings shortfalls occur alongside lower job stability, greater earnings instability, recurring spells of joblessness, and multiple switches of industry or occupation (Stevens 1997, VSM). Much of the increased mobility between jobs, industries and occupations probably reflects privately and socially beneficial adjustments. On average, however, displaced workers who immediately find a stable job in their pre-displacement industry obtain significantly higher earnings. Lower job stability and higher earnings volatility persist up to ten years after displacement. Thus, there is no indication that laid-off workers trade a lower earnings level for a more stable path of employment and earnings.

b. Effects on Health, Mortality, Emotional Well-Being and Family

There is also evidence that displaced workers suffer short- and long-term declines in health. Survey-based research in epidemiology finds that layoffs and unemployment spells involve a higher incidence of stress-related health problems such as strokes and heart attacks (e.g., Burgard, Brand, and House 2007).

While studies of self-reported health and job loss outcomes face significant challenges related to measurement error and recall and selection bias, the analysis of mortality outcomes lends itself to the use of large administrative data sources. Sullivan and von Wachter (2010) study the effects of job displacement on mortality outcomes for twenty years following displacement. They use administrative data on earnings and employers from the Pennsylvania unemployment insurance system and mortality data from the Social Security Administration. Their results show that mature men who lost stable jobs in Pennsylvania during the early 1980s experienced near-term increases in mortality rates of up to 100%. The initial impact on mortality falls over time, but it remains significantly higher for job losers than for comparable workers throughout the 20-year post-displacement period covered by their study. If sustained until the end of life, the higher mortality rates for displaced workers imply a reduction in life expectancy of 1 to 1.5 years.

Because the 1980s recession was especially deep in Pennsylvania involved unusually large earnings losses for displaced workers, the mortality effects estimated by Sullivan and von Wachter (2010) reflect a very bad-case scenario. It is reasonable to expect smaller mortality effects of job displacements in most other years and places. Unfortunately, U.S. labor market conditions in the past three years have also been dismal, with persistently high unemployment rates. In that respect, the mortality estimates in Sullivan and von Wachter may well provide a suitable guide to mortality effects for recently displaced American workers. The available evidence indicates that job displacement also raises mortality rates in countries with public health insurance systems and generous social welfare systems, for example in Sweden (Eliason and Storrie 2009) and Norway (Rege, Telle, and Votruba 2009), where higher mortality rates in the years following job displacement is observed, but with little information about long-term effects.

Several studies point to short- and long-term effects of layoffs on the children and families of job losers and unemployed workers. In the short run, parental job loss reduces schooling achievement of children (Stevens and Schaller, 2009). In the long run, it appears that a lasting reduction in the earnings of fathers reduces the earnings prospects of their sons (Oreopoulos, Page, and Stevens 2008). Wrightman (2009) also finds that parental job loss is harmful for the educational attainment and cognitive development of children.

Other studies find that layoffs raise the incidence of divorce, reduce fertility, reduce home ownership, and increase the rate of application to and entry into disability insurance programs.[14] Last but not least, and perhaps not surprisingly given the magnitude and range of adverse consequences discussed above, job loss and unemployment also lead to a reduction in happiness and life satisfaction. See, for example, Frey and Stutzer (2002).

Clearly, care should be taken in drawing welfare conclusions and policy prescriptions from the range of adverse consequences associated with job displacement. However, this brief review makes clear that job displacement entails a variety of significant short- and long-run costs for affected workers and their families. Neither the large present

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[14] Charles and Stephens (2004); von Wachter and Handwerker (2009); Rupp and Stapleton (1995).

value earnings losses we estimate nor measured consumption responses capture the full measure of costs associated with job displacement.

c. **Cyclical Movements in Worker Anxieties and Perceptions**

Given the severity of job displacement effects on earnings and other outcome measures, it is natural to ask how worker anxieties and perceptions about labor market conditions track actual conditions. Evidence on this issue is potentially informative in at least four respects. First, to the extent that recessions or high unemployment rates, for example, cause employed workers to become more fearful about layoffs and wage cuts, they involve psychological costs beyond the direct effects on job-losing workers and their families. Second, perceptions about labor market conditions are likely to influence search behavior by employed and unemployed workers, including those who experience a displacement event. Third, high levels of worker anxiety about labor market conditions are likely to undermine consumer confidence and depress consumption expenditures.[15] Fourth, perceptions about labor market conditions have important influences on policymaking, politics and electoral outcomes. Because they potentially influence so many voters, anxieties about labor market conditions may have more important political consequences than actual conditions.

For a long-running source of data on perceptions about labor market conditions, we turn to the General Source Survey (GSS). The GSS is a repeated cross-sectional household survey conducted since 1972. It includes two categorical response questions that are useful for gauging cyclical movements in perceptions about labor market conditions. One question asks the respondent about the perceived likelihood that he or she will lose a job or be laid off in the next 12 months. Another question asks about perceived difficulty of finding a job with the same income and fringe benefits as the respondent's current job. We examine data for these two questions by employed persons 18-64 and 25-54 years of age.

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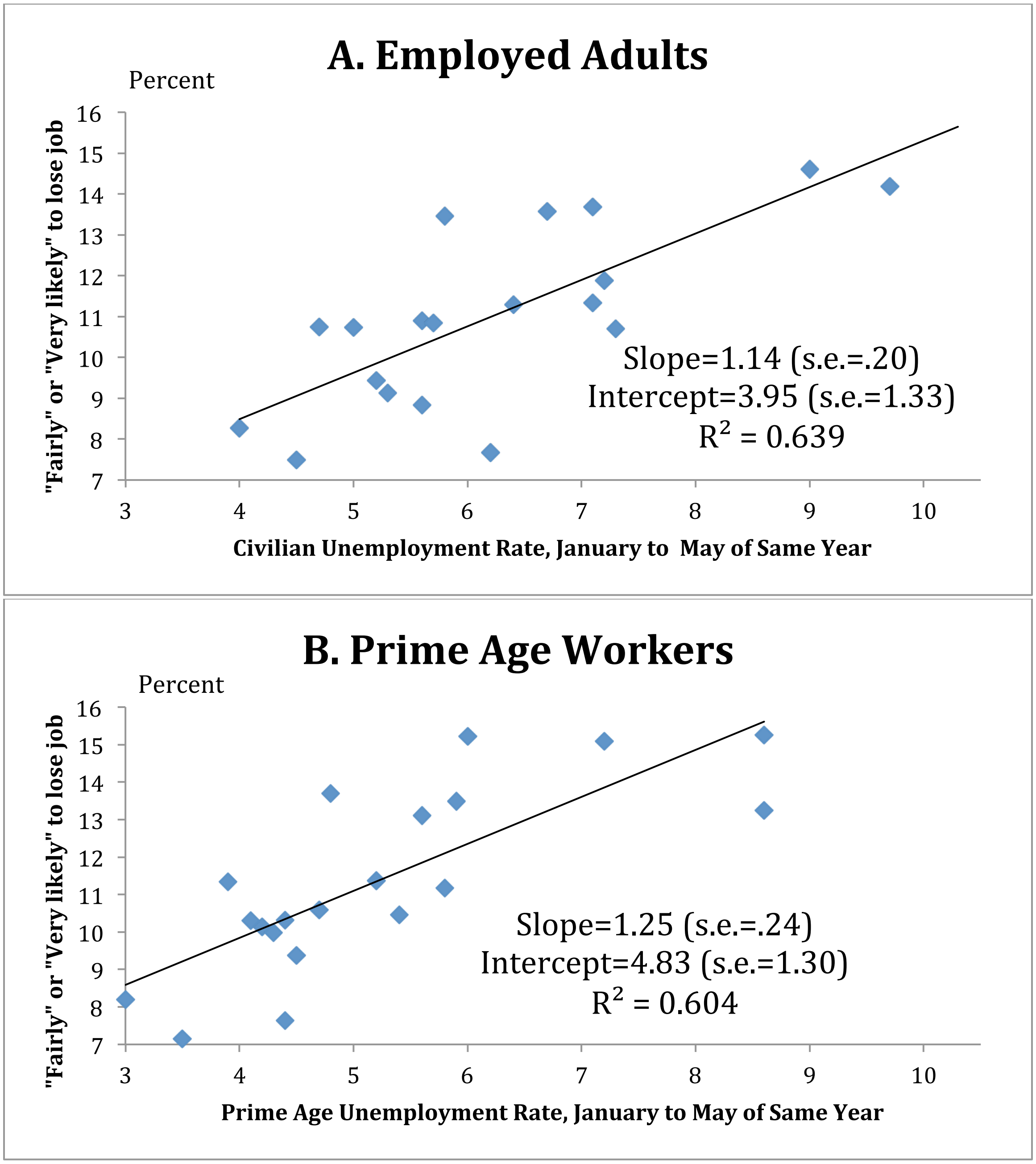
[15] Stevens (2004) provides survey-based evidence that subjective assessments of job loss probabilities have considerable predictive power for future layoffs at the individual level, even when conditioning on standard demographic variables that are correlated with layoff risks. Nevertheless, his main empirical specification yields no evidence of a relationship between job loss expectations and household consumption conditional upon losing a job.

Figure 8. Perceived Likelihood of Job Loss or Layoff in the Next 12 Months, All Available Years in the General Social Survey from 1977 to 2010



Notes:

1. Tabulations of micro data in the General Social Survey and published data on seasonally adjusted unemployment rates in the Current Population Survey. We report the weighted percent of GSS respondents that considers it "very likely" or "fairly likely" to lose a job or be laid off in the next 12 months.
2. Employed adults are persons between 18 and 16 years of age with a job, excluding active-duty armed forces, persons who report self employment as the main job, and

institutionalized persons. We exclude the black oversamples in the GSS in certain years, and weight JOBLOSE responses using the WTTSALL variable. Prime age workers are 25-54 years of age.

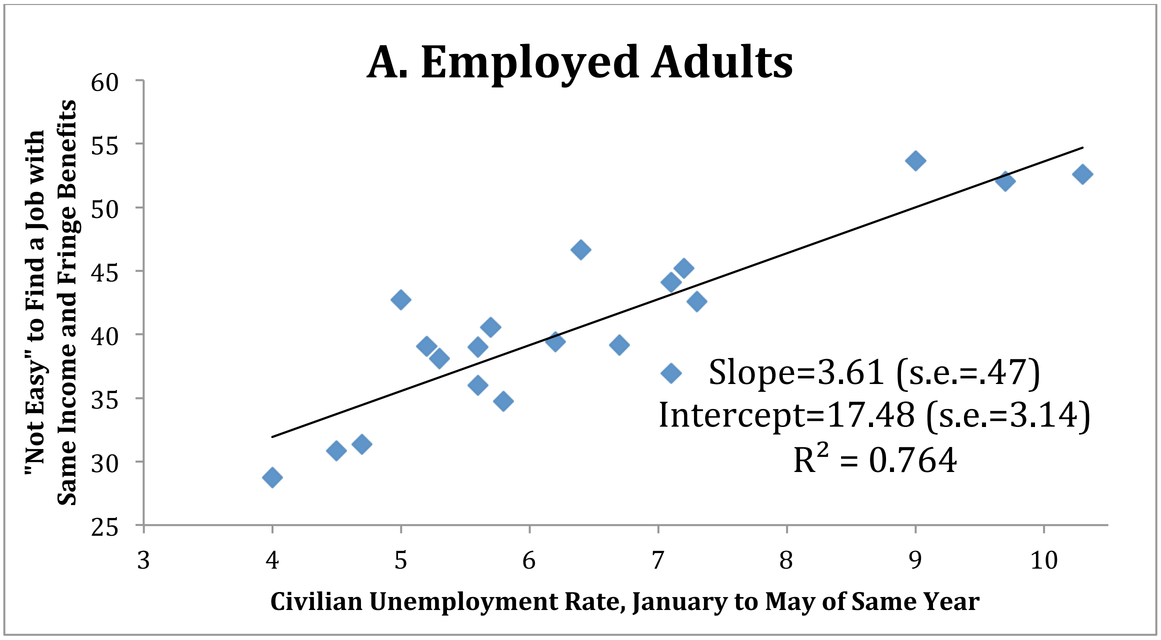
3. The GSS interviews take place in February, March and April of selected years. Data on the perceived probability of job loss are available for 1977, 1978, 1982, 1983, 1985, 1986, 1988, 1989, 1990, 1991, 1993 and every two years from 1994. We use unemployment rates from January to May in each survey year, which extends one month on either side of the GSS interview period.

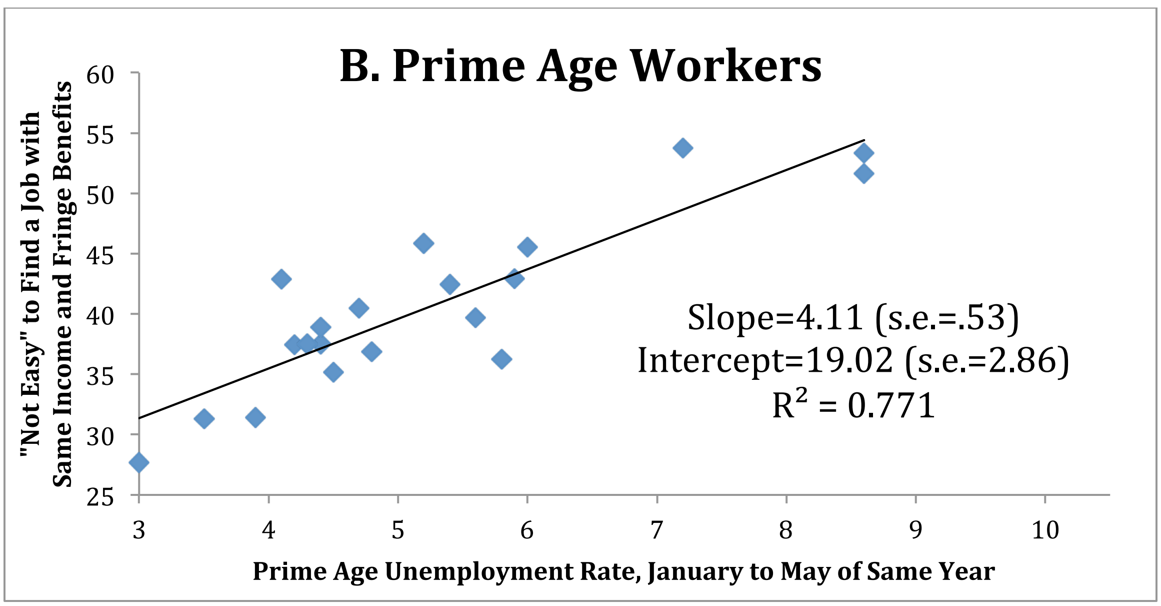
Figure 8 shows, for all available years in the GSS, the percentage of employed persons who consider it "very likely" or "fairly likely" to lose a job or be laid off in the next 12 months. We plot these values against CPS unemployment rates in 5-month windows that bracket the GSS interview months. There is a strong, positive relationship between the perceived likelihood of job loss and the actual unemployment rate. According to the fitted relationship in Figure 8.B, an increase in the prime age unemployment rate from 4% to 8% raises from 10 to 15 the percentage of prime age workers who perceive job loss as fairly or very likely.

Figure 9 shows the percentage of employed persons who perceive it to be "Not Easy" to find a job with income and fringe benefits similar to those in their current jobs. As before, we plot these values against contemporaneous CPS unemployment rates. Again, there is a powerful relationship between perceived and actual labor market conditions. According to the fitted relationship in Figure 9.B, an increase in the prime age unemployment rate from 4% to 8% raises from 31 to 47 the percentage of prime age workers who regard it as hard to find another job with a comparable compensation package. In this regard, it is also worth noting that quit rates are highly pro-cyclical – they have plummeted in the most recent recession and remain extraordinarily low. See, for example, Davis et al. (2011). Extremely low quit rates in the past three years provide another piece of evidence that workers perceive goods jobs as hard to find.

To our knowledge, Gallup polls provide the only other long-running, consistent source of data on perceived labor market conditions. The Gallup data cover a shorter time period than the GSS data, but they pertain to a highly eventful period in terms of economic developments. In addition, one of the Gallup measures is available at a (roughly) monthly frequency, which is useful for assessing the shorter-term relationship between perceived and actual conditions.

Figure 9. Perceived Difficulty of Job Finding, All Available Years in the General Social Survey from 1977 to 2010





Notes:

1. Tabulations of micro data in the General Social Survey and published data on unemployment rates in the Current Population Survey. We report the weighted

percent of GSS respondents who say it is “Not Easy” to find a job with the same income and fringe benefits as his or her current job.

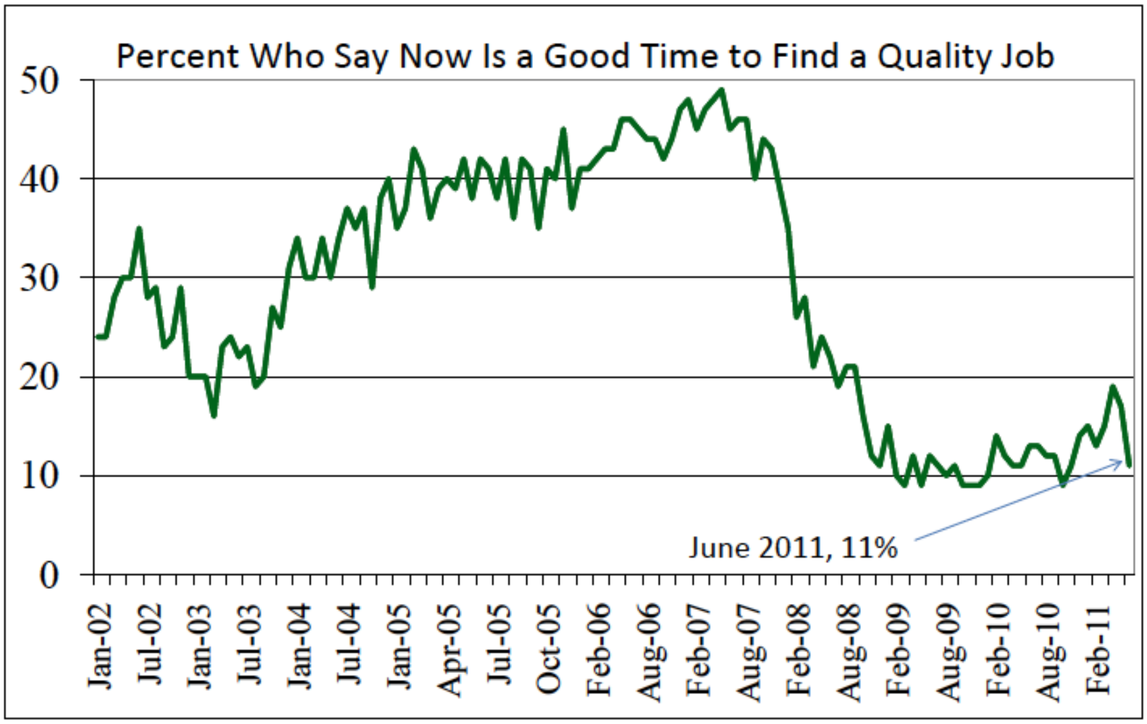
2. Employed adults are persons between 18 and 16 years of age with a job, excluding active-duty armed forces, persons who report self employment as the main job, and institutionalized persons. We exclude the black oversamples in the GSS in certain years, and we weight JOBFIND responses using the WTTSALL variable. Prime age workers are 25-54 years of age.
3. The GSS interview take place in February, March and April of selected years. Data on the perceived probability of job finding are available for 1977, 1978, 1982, 1983, 1985, 1986, 1988, 1989, 1990, 1991, 1993 and every two years from 1994. We report the mean unemployment rate from January to May, which extends one month on either side of the GSS interview period.

Figure 10 draws on Gallup polling data to plot the percentage of adult interviewees who respond yes to the following question: “Thinking about the job situation in American today, would you say that it is now a good time or a bad time to find a quality job?” As seen in the figure, the percentage responding “good time” is highly cyclically sensitive. As the labor market tightened, those responding yes rose from about 20 percent in early 2003 to nearly 50 percent in the first half of 2007. It then dropped to about 10 percent over the next two years, and it has remained at very low levels ever since. This evidence suggests that perceptions about labor market conditions respond very rapidly to changes in actual conditions.

Table 3 reports data from Gallup polls conducted during the month of August in 1997 and 2003 to 2011. The table shows a tremendous increase in worker anxiety levels following the peak of the financial crisis in the latter part of 2008 and early 2009. There were dramatic jumps in the percentages of employed adults who express worries that they personally will experience a cutback in hours, a wage cut, a benefit cut and/or a layoff in the near future. After some lessening of worker anxieties between August 2009 and August 2010, the most recent data for August 2011 show anxiety returning to at peak or near-peak levels.

In summary, the evidence presented in Figures 8-10 and Table 3 indicates that worker perceptions about labor market conditions are closely attuned to actual conditions. The Gallup polling data, in particular, point to a dramatic deterioration in perceptions about labor market conditions and prospects after the financial crisis – one that persists to the present day and that involves widespread concerns about layoff risks, wage and benefit cuts, shorter hours, and the difficulty of finding a good job. Whether or not these fears show up in realized earnings outcomes, they involve psychological costs in the form of heightened anxiety levels for a large segment of the population.

Figure 10. Perceived Ability to Find a Quality Job, March 2002 to June 2011



Notes:

1. Based on telephone interviews with random samples of adults, 18 years and older, living in the 50 U.S. states and the District of Columbia. Gallup conducts the interviews approximately once per month, and each round of interviews takes place over 3 or 4 days. We date each survey according to the first day of interviews.
2. The survey question reads as follows: "Thinking about the job situation in American today, would you say that it is now a god time or a bad time to find a quality job?"

Source: Gallup polling data at www.gallup.com/148121/default.aspx. Click on the link at "View methodology, full question results, and trend data" to obtain the document titled "Gallup News Service, June Wave 1, Final Topline".

Table 3. Worker Anxiety Rose Sharply in the Wake of the 2008 Financial Crisis and Have Remained High

Percent of Employed Adults Who Worry that They Will Experience the Following in the Near Future				
	Hours Cut	**Wage Cut**	**Benefit Cut**	**Lay Off**
August 1997	**15**	**17**	**34**	**20**
August 2003	**15**	**17**	**31**	**19**
August 2004	**14**	**17**	**28**	**20**
August 2005	**13**	**14**	**28**	**15**
August 2006	**16**	**19**	**30**	**17**
August 2007	**12**	**14**	**29**	**14**
August 2008	**14**	**16**	**27**	**15**
August 2009	**27**	**32**	**46**	**31**
August 2010	**25**	**26**	**39**	**26**
August 2011	**30**	**33**	**44**	**30**

Source: Reproduced from Gallup Polling data at www.gallup.com/poll/1720/work-work-place.aspx and www.gallup.com/poll/149261/Worries-Job-Cutbacks-Return-Record-Highs.aspx. Based on polling of workers employed full or part time.

5. The Effects of Job Loss in Leading Theoretical Models of Unemployment and Labor Market Dynamics

Mortensen and Pissarides (1994) present an equilibrium search and matching model that, in various formulations, has become the leading framework for analyzing aggregate unemployment fluctuations. We now evaluate how well certain "MP" models account for our evidence on the magnitude and cyclicality of the earnings losses associated with job displacement.[16] Some preliminary remarks will set the stage and motivate our particular choice of models.

[16] There appear to be few previous efforts to evaluate whether equilibrium search and matching models can account for the earnings losses associated with job displacement. An exception is Den Haan, Ramey and Watson (2000). Davis (2005) provides some back-of-the-envelope calculations.

a. MP Models of Unemployment Fluctuations

Shimer (2005) considers a basic version of the MP model with risk-neutral workers and firms, uniform match quality, Nash bargaining, and a constant rate of job destruction and job loss. Aggregate shocks drive employer decisions about vacancy posting and fluctuations in job creation, job finding and unemployment. Shimer shows that the basic MP model delivers too little volatility in unemployment for reasonable specifications of the aggregate shock process.[17] Under Nash bargaining, the equilibrium wage largely absorbs shocks to labor productivity in the basic model. As a result, realistic shocks have little impact on employer incentives to post vacancies, and the model generates small equilibrium responses in job-finding rates, hiring and unemployment. This unemployment volatility puzzle has motivated a great deal of research in recent years.

One prominent strand of this research stresses the consequences of wage rigidities.[18] Hall and Milgrom (2008), for example, step away from Nash bargaining while retaining privately efficient compensation and separation outcomes. They replace Nash bargaining with the alternating-offer bargaining protocol proposed by Binmore, Rubinstein and Wolinsky (1986). The standard Nash wage bargain treats termination of the match opportunity as the threat point. In contrast, the threat point in Hall and Milgrom's "credible bargaining" setup is a short delay followed, with high probability, by a resumption of bargaining. This change in bargaining regime goes a long way to insulate the equilibrium wage bargain from aggregate shocks and outside labor market conditions.

A key point is that the cost of a small delay during the bargaining process is less cyclical than the value of outside opportunities. Hence, closing the basic MP model in the manner of Hall and Milgrom leads to greater sensitivity of the employer surplus value to aggregate shocks and bigger responses in vacancies, job-finding rates and unemployment. Hall and Milgrom show that their specification of the bargaining environment resolves the unemployment volatility puzzle in a reasonably calibrated version of the basic MP model.

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[17] See also Costain and Reiter (2008).

[18] See, for example, Shimer (2004, 2010), Hall (2005), Gertler and Trigari (2009) and Kennan (2009). Mortensen and Nagypal (2007), Ramey (2008), Pissarides (2009), Burgess and Turon (2010), and Eyigungor (2010), among others, propose alternative resolutions to the unemployment volatility puzzle.

In our analysis below, we adopt Hall and Milgrom's credible bargaining version of the basic MP model and two versions with Nash bargaining. We follow this approach for two reasons. First, Hall and Milgrom offer perhaps the most successful version of the basic MP model in terms of explaining the cyclical behavior of job-finding rates, vacancies and unemployment. Second, by comparing the credible bargaining and Nash versions of the model, we can gain some insight into how a particular form of wage rigidity affects the model's ability to account for the facts about earnings losses associated with job loss.

Despite much attention to the basic MP model in recent work, the model misses some first-order features of labor market fluctuations. The basic MP model cannot reproduce the recessionary spikes in job destruction, job loss, and unemployment inflows depicted in Figures 1 and 2. Moreover, the model has no role for hires and separations apart from job flows. There is no search by employed workers, no job-to-job movements, and no replacement hires. Related, the basic model entails no heterogeneity of productivity, match surplus values or wages. This sort of heterogeneity seems potentially important for generating large earnings losses due to job loss. Given these limitations, we also consider a model of Burgess and Turon (2010) that extends Mortensen and Pissarides (1994) by incorporating search on the job and other changes. The Burgess and Turon version brings the model in line with several first-order features of the data, at least in a qualitative terms.

b. Income and Earnings Losses in the Basic MP Model

Table 4 reports statistics for three versions of the basic MP model: The credible bargaining version of Hall and Milgrom (2008) and two versions with Nash bargaining – a standard calibration similar to Shimer (2005) and another calibration similar to Hagedorn and Manoviski (2008). These two calibrations differ chiefly in the level of income imputed to the unemployed, which we interpret as the sum of unemployment insurance benefits, the value of additional leisure and home production activity, and any savings of work-related costs. Hagedorn and Manovskii set this value to a level nearly as large as the productivity of the employed, thereby amplifying the equilibrium response of unemployment to aggregate shocks. The standard calibration involves a much larger gap between productivity and the imputed income value of unemployment, yielding much smaller equilibrium responses to shocks of a given size. Our calibrations follow Hall and Milgrom (2008) in their choice of parameter values for each version of the basic MP model.

Table 4. Present Value Income and Earnings Losses Associated with Job Loss in the Basic Mortensen-Pissarides Model of Unemployment Fluctuations

	PV Income Losses, Percent of Employment Asset Value			**PV Earnings Losses, Percent**
Model Version	MP-Nash	MP-Nash	MP-CB	MP-Nash
Calibration	Standard	Hagedorn-Manovskii	Hall-Milgrom	Standard
A. Range of Mean Losses Over Five Aggregate States	0.20 - 0.22	0.044 - 0.047	0.20 - 0.23	
B. All Aggregate Paths	*Realized Outcomes*			
Mean Unemployment Rate	0.065	0.066	0.065	
Monthly Job-Finding Rate	0.43	0.43	0.43	
Mean PV Losses	0.21	0.04	0.21	0.78
$10^{th}/90^{th}$ percentile losses	-0.18 / 0.66	-0.13 / 0.21	-0.15 / 0.65	-0.30/2.25
C. Aggregate Boom Paths				
Unemployment Rate	0.064	0.061	0.060	
Monthly Job-Finding Rate	0.44	0.46	0.46	
Mean PV Losses	0.01	-0.11	0.04	0.74
$10^{th}/90^{th}$ percentile losses	-0.30 / 0.43	-0.17 / -0.02	-0.25 / 0.44	-0.33/2.19
D. Aggregate Bust Paths				
Unemployment Rate	0.066	0.072	0.072	
Monthly Job-Finding Rate	0.43	0.40	0.40	
Mean PV Losses	0.43	0.20	0.40	0.81
$10^{th}/90^{th}$ percentile losses	0.13 / 0.83	0.14 / 0.27	0.08 / 0.83	-0.28/2.30
99^{th} percentile losses	1.39	0.37	1.42	4.42
E. Worst Aggregate Paths				
Unemployment Rate	0.067	0.075	0.074	
Monthly Job-Finding Rate	0.42	0.39	0.39	
Mean PV Losses	0.50	0.25	0.46	0.84
$10^{th}/90^{th}$ percentile losses	0.2 / 0.9	0.2 / 0.32	0.14 / 0.91	-0.25/2.33
99^{th} percentile losses	1.42	0.4	1.51	4.47

Notes to Table 4:

1. Table entries report statistics for three versions of the basic Mortensen-Pissarides model of equilibrium unemployment. The two "MP-Nash" versions entail Nash wage bargaining – one with a standard calibration similar to Shimer (2005) and Hall (2005), and one with a calibration similar to Hagedorn and Manoviski (2008). The "MP-CB" version is the credible bargaining model of Hall and Milgrom (2008), which entails sequential bargaining with disagreement costs à la Binmore, Rubinstein and Wolinsky

(1986). All calibrations follow Hall and Milgrom (2008) in their choice of parameter values and the transition matrix of a five-state Markov process for aggregate shocks.

2. We calculate the monthly job-finding rate on a day with job-finding rate $\emptyset$ as $\emptyset \sum_{i=1}^{25}(1-\emptyset)^{i-1}$, assuming 25 job-seeking days per month.
3. We compute the present value income losses in Panel A directly from value functions. For each aggregate state, we calculate the difference between the asset value of employment and the asset value of unemployment. We express this difference relative to the asset value of employment. Performing this calculation for the five aggregate states yields the reported ranges in Panel A.
4. We calculate statistics for the other panels by simulating the indicated model for 1,000 draws of the aggregate path. We simulate each draw for 500 working days, starting from the middle aggregate state (state 3).
5. For present value income losses, we track realized paths for 5,000 individuals who become unemployed on day 1 on each of the 1,000 aggregate paths. An individual receives the imputed income value of leisure if unemployed on a given day, and the annuity value of his wage bargain if employed. At the end of the simulation horizon, we assign each individual the asset value associated with his state on day 500. In this way, we obtain a realized income path plus terminal value for each individual, which we then use to compute the realized present value income stream for an unemployed worker as of day 1. We express this realized present value as a percent of the asset value of employment on day 1, and we then compute the statistics reported in Panels B through E. See the Appendix for a more detailed description of the simulations and calculations.
6. For present value earnings losses, we assign 0 earnings when unemployed and the annuity value of the wage bargain when employed. We then compare the present value of the realized earnings paths for individuals who become unemployed on day 1 to the present value of the mean realized earnings path for 1,000 individuals who remain employed on day 1. Earnings loss statistics are very similar across all three variants of the MP model, so we report only the Nash version with the standard calibration.
7. Panel B reports simulation statistics computed over all 1000 aggregate paths. For Panels C through E, we first rank aggregate paths by the realized mean present value income (or earnings) loss. We then select a subset of paths and calculate the reported statistics. Panel C (Aggregate Boom Paths) considers paths ranked from 90 to 110 by this metric; i.e., the set of paths near the 10th percentile aggregate path. Panel D considers paths ranked from 890 to 910, and Panel E considers the 21 paths with the highest mean income losses.

Panel A in Table 4 highlights one of our main messages: job loss and unemployment is a rather inconsequential event for persons living in an MP world. Job loss reduces the present value of income by about 0.2% in the MP-CB and standard MP-Nash versions of the model and by less that 0.05% in the Hagedorn-Manovskii calibration. We compute these present value income losses directly from value functions. That is, for each aggregate state we calculate the difference between the asset value of employment and the asset value of unemployment, and we express the difference relative to the asset value of employment. Performing this calculation for all five aggregate states yields the reported ranges in Panel A. If these results accurately capture the real world costs of job loss, one might well wonder why all the fuss – why are job loss and unemployment perceived as important economic phenomena and potent political issues?

Recall from Table 1, column (5) that job displacement brings an estimated average present value earnings loss of 11% relative to controls. This empirical earnings loss is 50 times larger than the theoretical income loss implied by the MP-CB and standard MP-Nash versions of the basic model and 200 times larger than those implied by the Hagedorn-Manovskii calibration. The basic MP model fails – in rather spectacular fashion – to account for the costs of job displacement.

One might question this conclusion because it reflects a comparison of earnings losses in the data to income losses in the model. Earnings losses are larger because they omit the imputed income value of unemployment. Another potential concern is that the empirical evidence in Table 1 considers losses associated with "job displacement" events, which by design exclude many job loss events that involve little or no loss of earnings and income. So there is a sense in which we have compared average job loss outcomes in the theoretical models to bad-case outcomes in the data.[19]

To address these concerns, we simulate aggregate and individual paths and use the results to calculate a richer set of theoretically implied outcomes. Specifically, starting in the middle aggregate state, we simulate 1,000 aggregate paths for each version of the model. Along each aggregate path, we simulate paths for large numbers of workers who either lose jobs or remain employed on day 1. Using these artificial data, we compute summary statistics for the distribution of realized income and earnings losses associated with job loss. To compute the realized income loss for someone who loses a job on day 1, we compare the present value of his realized income path to the asset value of employment

[19] While we recognize that this argument has some force, we do not find it entirely persuasive. The estimated earnings losses reported in Section 3 pertain to an ex ante identifiable group of workers (high job tenure at firms with 50 or more employees), and this group accounts for a large share of U.S. employment. We would like a theoretical model that explains the magnitude and cyclicality of the earnings losses associated with job loss for this large group of workers.

on day 1. To compute the realized earnings loss for the individual, we compare the present value of his realized earnings path to the mean present value of realized earnings for individuals living on the same aggregate path who remain employed on day 1.

Consider, first, the results for the MP-CB model in Panel B. Averaging over all day-1 job losers on all aggregate paths yields an average realized income loss of 0.21%. This figure essentially replicates the income loss result for the MP-CB model in Panel A, as it should. However, the simulation approach enables us to compute the full distribution of outcomes for job losers. Continuing to look over all aggregate and individual paths, the 90th percentile income loss in the MP-CB version is only 0.65%, still a rather modest value. Job losers at the 10th percentile of the distribution experience a gain of 0.17% in present value income. The standard MP-Nash version yields very similar results, and the Hagedorn-Manovskii version yields losses that are tightly centered near no meaningful impact.

Turning to earnings losses, we report results only for the MP-CB version because the other two versions yield very similar earnings outcomes. As reported in Panel B, mean present value earnings losses are 0.78% in the basic MP model, less than one-tenth the mean losses reported in Table 1 for persons with 3 or more years of tenure who lose jobs in mass-layoff events. Thus, an earnings-to-earnings comparison shortens the distance between theoretical and empirical outcomes, but the earnings losses in the MP model still miss the data by an order of magnitude. Given the simplicity and extent of homogeneity in the basic MP model, and our averaging over all paths, we can interpret the present value earnings losses in Panel B as pertaining to both a before-and-after comparison for displaced workers and a comparison between the treated (day-1 job losers) and the controls (day-1 employed).

The remaining panels in Table 4 consider selected aggregate paths defined by the mean realized present value income (or earnings) losses. "Boom" paths are those near the 10th percentile of average losses for day-1 job losers, "bust" paths are near the 90th percentile, and the "worst" paths are those in the top 2 percent in terms of average losses. Comparing Panels C, D and E, there is modest countercyclical variation in average present value income losses. However, the mean income losses remain small in all cases, never exceeding half a percent. Even when we isolate the worst 1% of individual outcomes along the worst 2% of aggregate paths, the present value income losses amount to only 1.5% in the MP-CB and standard MP Nash versions of the model and 0.4% in the Hagedorn-Manavoskii calibration. In short, and at least as calibrated by Hall and Milgrom (2008), the basic MP model cannot produce large realized income losses for job losers, even at the extremes of aggregate and individual outcomes.

Although it does not affect our main conclusion, it is useful to clarify the proper interpretation of the results in Panels C, D and E. Recall that we compare the realized income path for day-1 job losers to the asset value of employment. Thus, the income loss results in Panels C, D and E reflect before-and-after comparisons, not treatment-control comparisons. The before-and-after nature of these income loss calculations is the main source of their countercyclical variation. In contrast, we calculate earnings losses by comparing day-1 job losers to day-1 employed persons living on the same aggregate path. Therefore, the earnings loss results in Panels C, D and E reflect treatment-versus-control comparisons. In line with this observation, the countercyclical variation in the present value earnings losses is extremely mild. While both before-and-after and treatment-control comparisons are interesting, the latter corresponds more closely to best-practice empirical methods in research on the costs of job displacement.[20]

In summary, we draw four important conclusions from Table 4. First, job loss is a rather inconsequential event in the basic MP model, even at the extremes of individual and aggregate outcomes. Second, the basic MP model cannot explain the present value earnings losses associated with job displacement. Theoretical earnings losses are an order of magnitude smaller than empirical earnings losses. Third, the basic MP model cannot explain the observed cyclicality of present value earnings losses, an important feature of the data. Fourth, although wage rigidity of the form considered by Hall and Milgrom (2008) greatly improves the ability of the basic MP model to explain aggregate unemployment fluctuations, it does not bring the model closer to the evidence on the magnitude and cyclicality of earnings losses associated with job displacement.

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[20] We could refine the treatment-control comparisons in Table 4 by replicating the employment stability criterion used for controls in Section 3. This type of refinement may make sense in future research. Based on Table 4, however, we do not think the basic MP model can explain the evidence on earnings losses or rationalize strong concerns about job loss and unemployment.

c. Losses in an MP Model with Job Destruction Spikes and Search on the Job

The model of Burgess and Turon (2010) differs from the basic MP model in capturing search on the job, a distinction between job flows and worker flows, heterogeneity in productivity and wages, and job destruction spikes in the wake of negative aggregate shocks. They depart from Mortensen and Pissarides (1994) by allowing search on the job, at a cost, and by adopting a different vacancy creation process that gives meaning to the concept of a job apart from an employer-worker match. Specifically, they assume a finite supply elasticity of potential new job creation each period, so that firms find it optimal to re-fill certain jobs left open by departing workers.

The model is set in continuous time. Idiosyncratic productivity shocks arrive according to independent Poisson processes, and aggregate productivity, *p,* follows a three-state Markov chain. When hit by an idiosyncratic shock, a job draws a new idiosyncratic productivity value in the interval $[-\sigma, \sigma]$, which may be higher or lower than the previous value. Optimizing behavior involves three idiosyncratic productivity thresholds, as shown in Figure 11. If idiosyncratic productivity exceeds S(*p*) in a filled job, the worker's net expected gains to search are negative. For productivity less than S(*p*) in a filled job, the worker's net expected gains to search are positive. If the worker finds a vacant job, he quits and the firm decides whether to search for a replacement. It does so if idiosyncratic productivity exceeds T(*p*); otherwise, it lets the job lapse. If a filled job draws a new idiosyncratic productivity value below R(*p*), the job is destroyed and the worker experiences job loss. As indicated in Figure 11, the productivity thresholds are functions of the aggregate state. A negative shock to *p* shifts R(*p*) to the right, triggering a burst of job destruction.

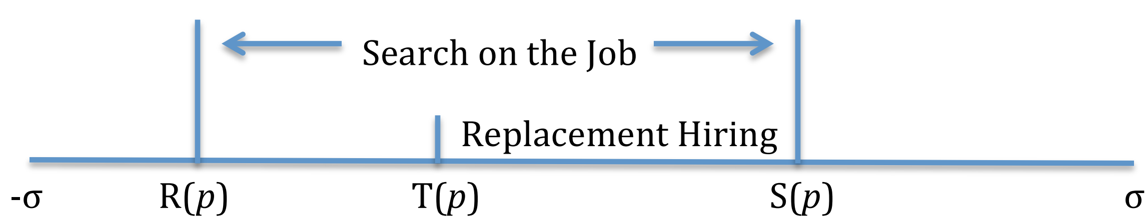

Figure 11. Idiosyncratic Productivity Thresholds for Job Destruction, Replacement Hiring and On-the-Job Search in the Burgess-Turon Model

Table 5 reports statistics for the model of Burgess and Turon. We adopt their calibration, which is meant to match features of the British economy from 1964 to 1999. Rows A and B report results for a period of time corresponding to three months with no change in the aggregate state. The remaining rows involve transitions between states and focus on outcomes for workers who lose jobs in the early part of a downturn, roughly corresponding to the recessionary spikes in job destruction and job loss seen in Figures 1 and 2. As in Burgess and Turon, our calculations ignore sluggish response dynamics for the productivity distribution of filled jobs in the near-term wake of an aggregate shock. All income loss calculations pertain to workers who separate in job destruction/job loss events. That is, we exclude separations that result from search on the job. Given the greater complexity of the Burgess-Turon model, we rely on value function comparisons to implement our loss calculations.

Row A in Table 5 reports present value income losses for job losers in the good, middle and bad aggregate states. These losses are larger than we obtained in the basic MP model, which suggests that search on the job and heterogeneity in match surplus values help move the model closer to the evidence on the losses associated with job loss. However, the quarterly unemployment inflow rates reported in Row B are only about half as large as the U.S unemployment inflow rates plotted in Figure 1. This observation suggests that the model of Burgess and Turon is calibrated to a less dynamic labor market than the models considered by Hall and Milgrom. Thus, at least to some extent, the larger income loss figures in Row A of Table 5 (as compared to Row A of Table 4) simply reflects longer unemployment spells and lower job-finding rates in the Burgess-Turon calibration.

Table 5. Job Loss and Present Value Income Losses in a Mortensen-Pissarides Model with On-the-Job Search and Job Destruction Spikes

Present Value Income Losses as a Percent of Employment Asset Values			
	Aggregate State		
	Good	*Middle*	*Bad*
A. Mean PV Loss Due to Idiosyncratic Shocks that Result in Job Destruction and Job Loss	0.63	0.58	0.54
B. Quarterly Unemployment Inflow Rate	2.78	3.07	3.34
	Aggregate State Transition		
	Good→ Middle	*Middle→ Bad*	*Good→ Bad*
C. Mean PV Loss Due to Idiosyncratic Shocks that Result in Job Loss, Comparison to Own Past	0.85	0.78	1.05
D. Mean PV Loss Due to Aggregate Shock that Results in Job Loss, Comparison to Own Past	0.23	0.21	0.43
E. Mean PV Loss Due to Idiosyncratic Shocks that Result in Job Loss, Comparison to Control Group	0.58	0.54	0.54
F. Mean PV Loss Due to Aggregate Shock that Results in Job Loss, Comparison to Control Group	0	0	0
G. Quarterly Unemployment Inflows Due to Idiosyncratic Shocks that Result in Job Loss	3.06	3.33	3.32
H. Unemployment Inflows Due to Negative Aggregate Shock and Job Destruction Spike	0.33	0.35	0.65
I. Combined Quarterly Unemployment Inflow Rate, Sum of G and G	3.39	3.68	3.97
J. Mean PV Loss Associated with Job Loss, Comparison to Own Past, Using G and H to Compute Inflow-Weighted Average of C and D	0.79	0.73	0.95
K. Mean PV Loss Associated with Job Loss, Comparison to Control Group, Using G and H to Compute Inflow-Weighted Average of E and F	0.52	0.49	0.45

Notes:

1. Table entries report statistics for a search and matching model of Burgess and Turon (2010). Their model differs from the basic Mortensen-Pissarides model in capturing search on the job, a distinction between job flows and worker flows, heterogeneity in wages and match surplus values, and spikes in aggregate job destruction. Their model also adopts a different vacancy creation process that gives meaning to the concept of a job apart from the employer-worker match. Job destruction and job loss arise from negative aggregate shocks and (sufficiently

negative) idiosyncratic shocks. We adopt the calibration of Burgess and Turon, which is meant to match features of the British economy from 1964 to 1999.

2. The model of Burgess and Turon is set in continuous time. Idiosyncratic productivity shocks arrive according to independent Poisson processes, and aggregate productivity follows a three-state Markov chain. Rows A and B report results for a period of time corresponding to three months with no change in the aggregate state. The remaining rows involve transitions between states. As in Burgess and Turon, our calculations ignore the sluggish dynamics of the match quality distribution in response to an aggregate shock.
3. All income loss calculations rely on value function comparisons and pertain to workers who separate in job destruction/job loss/displacement events. That is, the income loss calculations exclude separations that result from search on the job.
4. In Rows A, C and D, we calculate losses for each job-losing worker by comparing his pre-displacement employment value to his post-displacement unemployment value, scale by pre-displacement employment value, and then integrate over the distribution of job-losing workers to get the mean loss. In Row E, we calculate losses for each job-losing worker by first computing the difference between (a) the employment value in the new aggregate state at the same idiosyncratic productivity as the job loser before displacement and (b) the value of unemployment in the new state. We then scale by the employment value in the new aggregate state and integrate over the distribution of job-losing workers to get the mean loss relative to the control group. The loss relative to the control group is zero in Row F, because all workers in the lower tail of the productivity distribution lose their jobs when hit by a negative aggregate productivity shock. Hence, all get the value of unemployment in the new state.
5. The loss calculations in Rows C and D capture the effects of idiosyncratic job destruction events and negative aggregate shock, respectively. Likewise, the loss calculations in Rows and F capture the effects of idiosyncratic job destruction events and negative aggregate shocks, respectively. See the appendix for expressions that precisely define each loss measure.

The other rows in Table 5 characterize outcomes in a recession, especially the early part of a recession associated with spikes in job destruction and job loss. Rows C and E report present value income losses for job destruction/job loss events driven by negative idiosyncratic productivity shocks, as in Row A. These events involve job losers previously employed along the entire productivity distribution of filled jobs. Rows D and F, in contrast, involve job losers displaced by a negative aggregate shock and are drawn from the lower tail of the productivity distribution. For example, when the economy is hit by a negative shock that lowers the aggregate state from “Good” to “Middle”, all workers at jobs with idiosyncratic productivity in the range [R(Good), R(Middle)] lose their jobs and become unemployed. Note that Rows C and D pertain to before-and-after comparisons of a worker's unemployment asset value in the new aggregate state to his own employment asset value in the previous, higher aggregate state. In contrast, Rows E and F pertain to a treatment-control comparison of a worker's unemployment asset value in the new aggregate state to the employment value of an identical worker in the new aggregate state.[21] In our recessionary scenario, the treatment-control comparisons yield smaller income losses because the controls experience the deterioration in aggregate labor market conditions.

One of the key points in Table 5 shows up in Rows D and F. In particular, the job loss events caused by a negative aggregate shock and a burst of job destruction yield relatively small income losses. These job losses involve the destruction of marginal jobs with little surplus value in any event. Thus, the mix of job destruction and job loss tilts toward marginal, low value jobs in the early part of a recession, according to the model. This composition effect diminishes the size of the model-implied income losses. Because of this composition effect, the treatment-control comparisons in Row K are actually smaller than the ones reported for the same column of Row A. In other words, the model-implied treatment-control comparison yields smaller present value income losses for the average job loser in the early part of a recession than for the average job loser in the previous and better aggregate state. Thus, the source of job destruction spikes in the model of Burgess and Turon (and in Mortensen and Pissarides (1994)) works against finding larger losses in recessions.

The more important point is that the average income losses due to job loss remain very small in the model of Burgess and Turon. This holds for the values reported in Row A for a "steady" economy and in Rows J and K for an economy in the early stages of a recession. For the treatment-control comparisons in the recessionary economy, the

[21] Our treatment-control loss calculations compare a given worker's current unemployment asset value to the current employment asset value of a job with the same idiosyncratic productivity value as the unemployed worker had in his former job. One can think of this comparison as corresponding to highly similar job losers and controls in an empirical study. Alternatively, we can compare the unemployment asset value to the average asset value of employed persons. This comparison corresponds to less similarity of job losers and controls in an empirical study. This alternative version of the treatment-control calculation yields values in Row F similar to Row E. Under this approach, Row K is essentially the same as Row J.

present value income losses are about the same size as in the basic MP model. Regardless of whether we consider persistence differences across aggregate states (Row A) or the transition from better times to worse times (Row K), a treatment-control comparison in the model generates *pro-cyclical* movements in the present value income loss due to job loss. Although we have not simulated earnings outcomes for the model of Burgess and Turon, the analysis summarized in Table 5 suggests that their richer model is also unable to explain the empirical evidence on the magnitude and cyclicality of job loss. In any event, job loss in only marginally more consequential in the model of Burgess and Turon than in the basic MP model.

6. Concluding Remarks

High-tenure workers who lose jobs in mass-layoff events experience large and persistent earnings losses compared to otherwise similar workers who retain their jobs. That is the central message of a now-sizable literature on the earnings losses due to job displacement. For men with 3 or more years of prior tenure on the job, we estimate that job loss in mass-layoff events lowers the present value of future earnings by 11%. We also show that present value losses rise steeply with the unemployment rate at the time of displacement. For high-tenure workers who experience job displacement in a recession, the losses amount to about three years of earnings at pre-displacement levels and 19% of the present value earnings of otherwise similar workers who retain jobs.

The evidence in Tables 1 and 2 and Figures 5 to 7 says that tight labor market conditions strongly improve the earnings prospects of displaced workers in the medium term and long term. The highly pro-cyclical behavior of job-finding rates for unemployed workers implies that tight labor market conditions strengthen near-term earnings prospects as well. Seen in this light, economic policies that set the stage for strong growth and low unemployment are highly beneficial to displaced workers. Indeed, pro-growth policies may be the most efficient and cost-effective means available to policymakers to alleviate the hardships experienced by displaced workers.

Previous work also develops evidence that job displacement has negative consequences for employment and earnings stability, household consumption expenditures, health and mortality outcomes, children's achievement levels, and subjective wellbeing. We present evidence that worker perceptions about layoff risks, job-finding prospects, and the likelihood of wage cuts closely track cyclical fluctuations in actual labor market conditions. Perception measures point to a tremendous increase in worker anxieties about labor market prospects after the financial crisis of 2008, an increase that persists through August 2011. It seems likely that these high anxiety levels produce important stresses and psychological costs for a large segment of the population.

We also consider whether models in the DMP class along the lines of the canonical contribution by Mortensen and Pissarides (1994) account for the facts on earnings losses associated with job displacement. They do not. A basic version of the MP model featured in much recent research implies theoretical earnings losses an order of magnitude smaller than empirical losses. The full income loss due to job loss in the basic MP model is smaller yet, amounting to about 0.2% of present value income in a standard calibration. Extending the basic model to encompass heterogeneity in match productivities, aggregate job destruction spikes, search on the job, and worker flows apart from job flows raises the theoretical income losses only modestly. Moreover, neither basic nor extended versions of the MP model explain the high sensitivity of present value earnings losses to the unemployment rate at the time of job loss.

In our view, a major weakness of MP models is their implication that job loss is a rather inconsequential event for the affected workers. As a result, the models are unable to address the large and persistent earnings losses associated with job loss and the intensification of those losses in recessions and periods of high unemployment. The negative consequences of job displacement, and fears of job displacement, are among the main reasons that recessions and high levels of unemployment create so much concern in the general population and among politicians. The negative consequences of job displacement are why unemployment is such a potent political issue. We also think that the consequential nature of job displacement is a key reason why unemployment and unemployment fluctuations have attracted so much attention from economists.

It is important to put our criticism of MP models in proper context. We see MP models, in particular, and the larger class of DMP models as a great advance over earlier work. DMP models deliver a coherent theory of frictional unemployment and its determinants. They provide tools for analyzing search and matching behavior by employers and job seekers. They provide an analytical framework for studying cyclical movements in unemployment, vacancies, job-finding rates, and the joint dynamics of workers flows and job flows. These tools are put to frequent use to study the effects of policies, wage-setting arrangements and other economic institutions on unemployment and a wide variety of other labor market outcomes.

We hope to see these models develop in directions that encompass major roles for the accumulation of specific forms of human capital and other sources of rents in long-lived employment relationships. In light of evidence that earnings losses due to job loss rise with pre-displacement tenure, it seems important to incorporate into DMP models a an explanation for how and why match surplus and wages rise with tenure on the job. A theory with this feature is also likely to deliver the implication that present value earnings losses are higher in recessions, when negative shocks bite more deeply into the distribution of valuable employment relationships.

Of course, economists have long recognized the importance of specific human capital. And some economists have introduced specific forms of human capital into models in the DMP class. However, mainline macroeconomic models of unemployment fluctuations, including those in the DMP class, largely omit any role for forms of human capital that are specific to particular jobs, employers, occupations or industries. As a result, the models are unable to address the facts about the earnings losses associated with job loss, and they fail to grapple with one of the main reasons that job loss, unemployment and recessions matter to people and policymakers.

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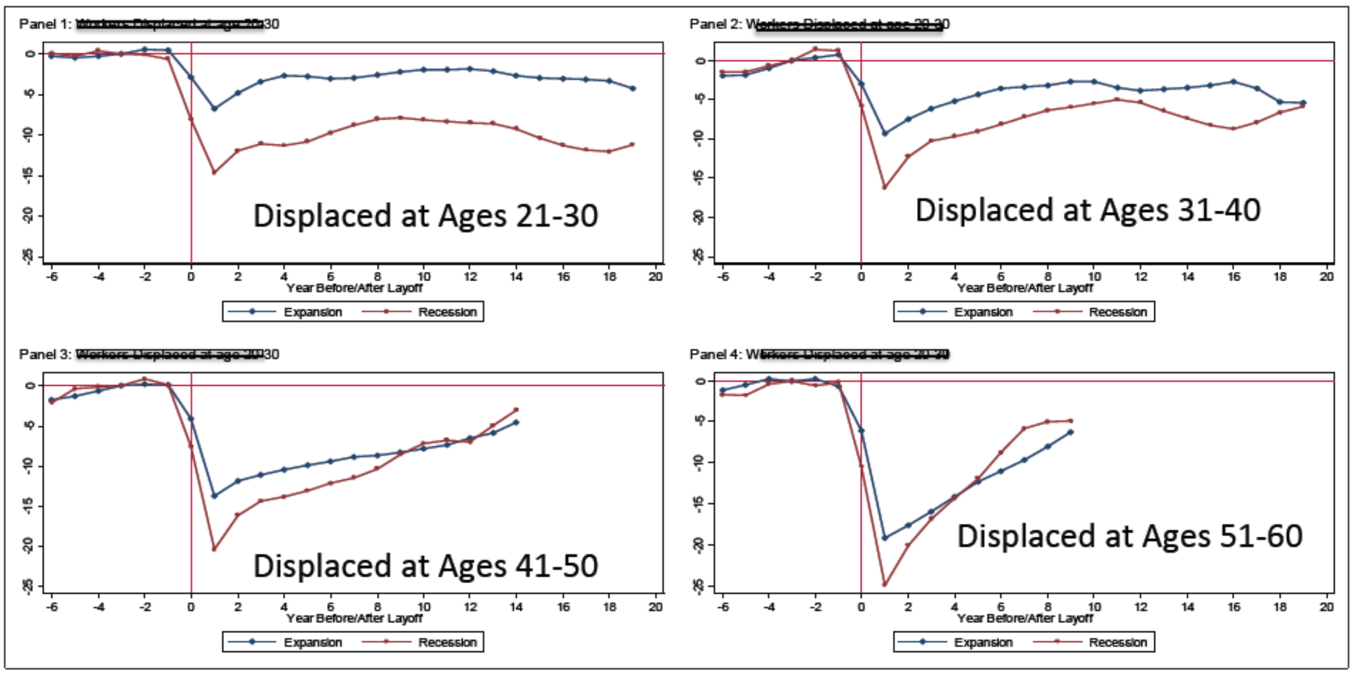
Supplemental Material for Appendix

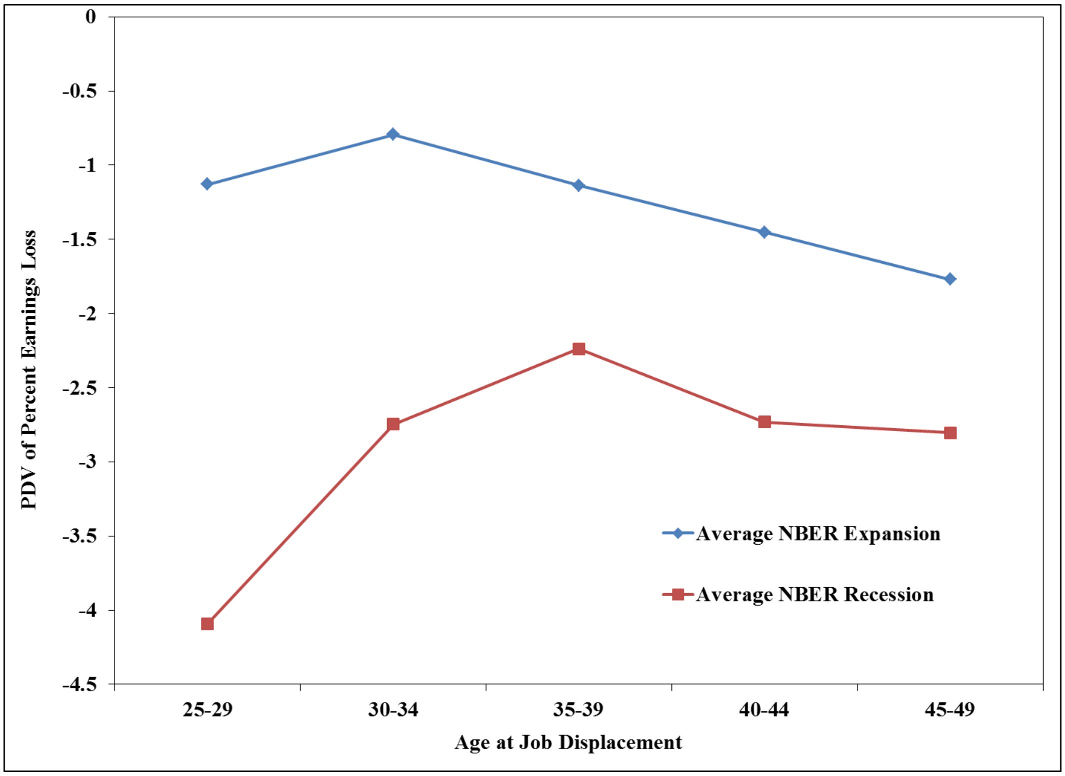
I. Additional Empirical Results

Figure A1: Earnings Losses at By Age at Displacement, Men with at Leasst 3 Years of Job Tenure Displaced in Mass-Layoff Events, Averages in NBER Recessions and Expansions (As of Displacement Year)



Source: 1% Files of Social Security administrative data (see text).

Figure A2: Present Discounted Value of Earnings Losses By Age at at Job Displacement, Men with At Least 3 Years of Job Tenure



Notes:

1. The present discounted value of percent earnings losses are defined as in Table 1 (column 3). For each year of displacement, we take the discounted sum of earnings losses in a range of years after a job displacement that varies by age of displacement using a discount rate of 5%. For workers displaced up to age 39, we calculate the present discounted value over 20 years after job displacement. For workers displaced 40-49 we calculate it over 15 years. To extrapolate for years beyond our sample window, we use the average rate of decay in the respective ranges of years after job displacement observed in the remainder of the sample.
2. The earnings losses are calculated using administrative earnings data from W2 earnings records used in von Wachter, Song, and Manchester (2011) and described in the text.

II. Detailed Explanation of Model Simulations and Calculations (To Be Written)