Recessions and the Costs of Job Loss

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1. Introduction

Major economic downturns 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 displacement. Previous research shows that job displacements lead to large and persistent earnings losses for the affected workers.[1] The available evidence also indicates that job displacement leads to less stability in earnings and employment, worse health outcomes, higher mortality, lower achievements by children, and other unwelcome consequences.[2]

We develop new evidence on the cumulative earnings losses associated with job displacement and the role of labor market conditions at the time of displacement. In present value terms, men lose an average of 1.4 years of pre-displacement earnings if displaced in mass-layoff events that occur when the national unemployment rate is below 6 percent. They lose a staggering 2.8 years of pre-displacement earnings if displaced when the unemployment rate exceeds 8 percent. These results reflect discounting at a 5% annual rate over 20 years after displacement. We also document large cyclical movements 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 economic conditions. Finally, we confront leading models of unemployment fluctuations in the tradition of work by Peter Diamond, Dale Mortensen and Christopher Pissarides with evidence on the present value earnings losses associated with job displacement.

Our study builds on 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 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 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

[1] See, for example, Jacobson, Lalonde, and Sullivan (1993), Couch and Placzek (2010) and von Wachter, Song, and Manchester (2011).
[2] We review the evidence and provide citations to the relevant literature in Section 4. See also Wachter (2010).

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 future earnings by 12 percent in an average year. The present value losses are high in all years, but they rise steeply with the unemployment rate in the year of displacement. Present value losses for displacements that occur in recessions are nearly twice as large as for displacements 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. These findings also imply that workers are well aware of and concerned about the costly nature of job loss, especially in recessions.

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, 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 do not account for our evidence on the present value earnings losses associated with job displacement. The empirical losses are an order of magnitude larger than those implied by basic versions of the Mortensen-Pissarides model. 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 evidence on the earnings losses associated with displacement. The model of Burgess and Turon (2010) generates larger present value losses, because most job-losing workers in the model do not immediately recover pre-displacement wage levels upon re-employment. Instead, unemployed persons tend to flow into jobs on the lower rungs of the wage distribution and move up the distribution over time. Yet, when calibrated for consistency with U.S. unemployment flows, the model of Burgess and Turon yields present value earnings losses due to job loss less than one-fourth as large as the empirical losses. Moreover, present value losses in the model vary little with aggregate conditions at the time of displacement, unlike the pattern in the data.

Present value income losses associated with job loss are even smaller in the search models we consider. Indeed, a fundamental weakness of these models is their implication that job loss is a rather inconsequential event from the perspective of individual welfare. In this sense, and despite many virtues and attractions, this class of models fails to address a central reason that job loss, unemployment and recessions attract so much attention and concern from economists, policymakers and others. For the same reason, care should be taken in using this class of models to form conclusions about the welfare effects of shocks and government policies.

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 the losses vary with conditions at 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 earnings and income losses associated with job loss. Section 6 concludes.

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

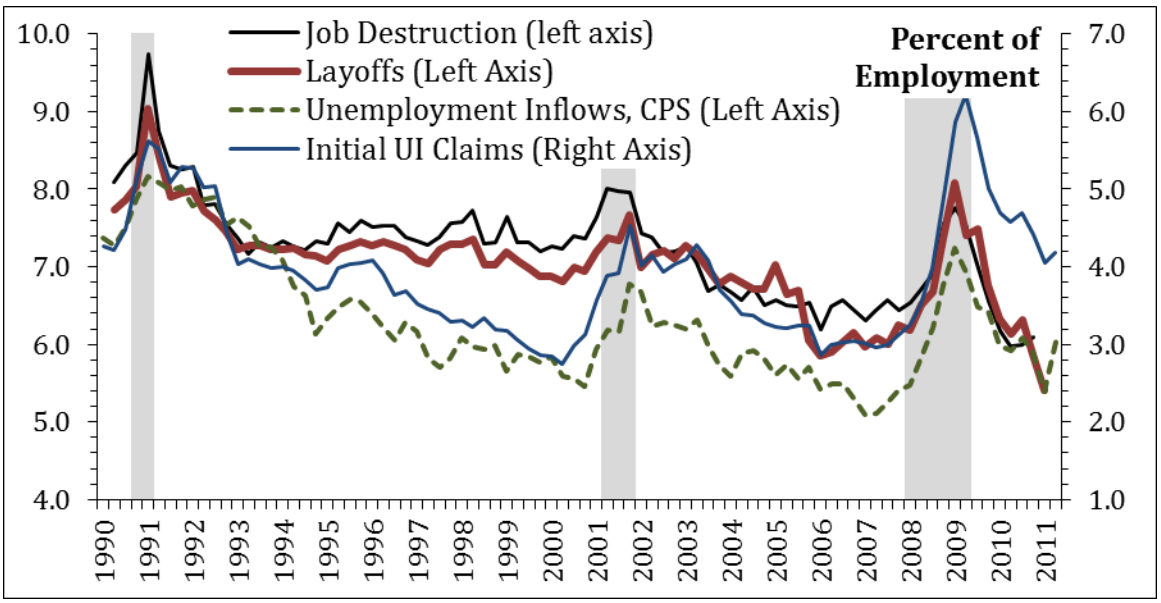
Figure 1 displays four time series that draw on distinct sources of data and pertain to different concepts of job loss. The job destruction measure captures gross employment losses summed over shrinking and closing establishments in the Business Employment Dynamics (BED) database.[3] The layoff measure 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).[4] 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 payroll 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 payroll employment in 2011 yields about 9 million layoffs per quarter. 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.

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

[4] 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, expressed as a percent of nonfarm payroll employment in the Current Employment Statistics. Weekly new claims data are available at www.ows.doleta.gov/unemploy/claims.asp. We sum weekly claims in the month, rescale the sum to represent 4 and 1/3 weeks worth of claims, and divide by CES employment in the month. We then 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.[5] 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.[6] 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.[7]

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 an annual job displacement measure for men constructed from the SSA data and compares it to annual measures of job destruction and initial claims for unemployment insurance benefits.[8] Here, we report displacement rates in the population of male employees 50 years or younger with at least 3 years of prior job tenure, excluding government workers and certain service sectors not covered by the Social Security system throughout our full sample period.

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

[6] 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).

[7] As an example, the Conference Board uses new claims for unemployment insurance benefits in constructing its "Leading Economic Index." See www.conference-board.org/data/bcicountry.cfm?cid=1.

[8] 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.

We regard a worker as displaced in year y if he separates from his employer in y, *and* the employer experiences a mass-layoff event in y. We say a worker "separates" from an employer in year y when he has earnings with the employer in y-1 but not in y. To qualify as a mass-layoff event in year y, the employer must meet the following criteria: (i) 50 or more employees in y-2; (ii) employment contracts by 30% to 99% from y-2 to y; (iii) employment in y-2 is no more than 130% of employment in y-3; (iv) employment in y+1 is less than 90% of employment in y-2. The 99% cutoff in condition (ii) ensures that we do not capture spurious firm deaths due to broken longitudinal links. Conditions (iii) and (iv) exclude temporary fluctuations in firm-level employment. While these criteria miss some displacements of high-tenure workers at larger employers, they help ensure that the separations we identify as job displacement events are indeed the result of permanent layoffs.[9] To qualify as a job displacement event in y, we also require that the separation be from the worker's main job, defined as the one that accounts for the highest share of his earnings in y-2. For additional details on the data, sample, and measurement procedures, see von Wachter, Song, and Manchester (2011), hereafter VSM.

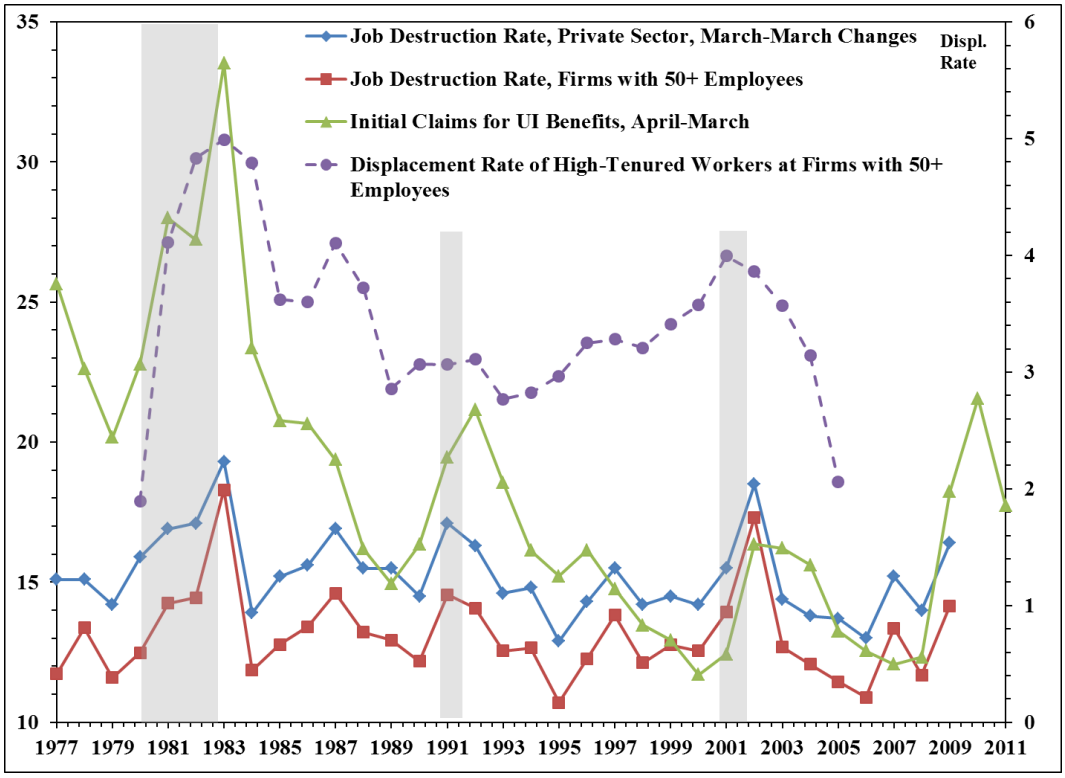
To express job displacements in year y as a rate in Figure 2, we divide by the number of male workers 50 or younger in y-2 with at least 3 years of job tenure at firms with 50 or more employees in the industries covered by Social Security throughout our sample period. These workers comprise 31 to 36 percent of all male workers 50 or younger in industries continuously covered by the SSA from 1980 to 2008, depending on year, 40 to 48 percent when we also restrict attention to those with 3 or more years of job tenure, and 70 to 74 percent when we further restrict to firms with 50 or more employees.

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

[9] Tabulations in Davis et al. (2006) based on BED and JOLTS data indicate that most employment reductions are achieved through layoffs when firms contract by 30% or more.

rate rose from 1.9% in 1980 to 5.0% in 1983.[10] 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.

Figure 2. Job Displacement, Job Destruction, and Initial Claims for Unemployment Insurance Benefits, Annual Rates, 1977 to 2011



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 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

[10] The very high rates of Initial UI Claims in the early 1980s should be interpreted with 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. Since few temporary layoff spells last more than a full year, and given that our mass-layoff definition excludes temporary firm-level fluctuations, temporary layoffs play little role in our job displacement measure. For similar reasons, temporary layoffs have little impact on the annual job destruction measures.

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 is the rate of job loss in mass-layoff events among male workers 50 years or younger with at least 3 years of prior job tenure, expressed as a percent of all male employees 50 or younger 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, y-2 to y, we mean one in which EIN employment at y+1 is no more than 90 percent of employment of its employment at y-2. Similarly, we require that EIN employment grow by no more than 30% from y-3 to y-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.

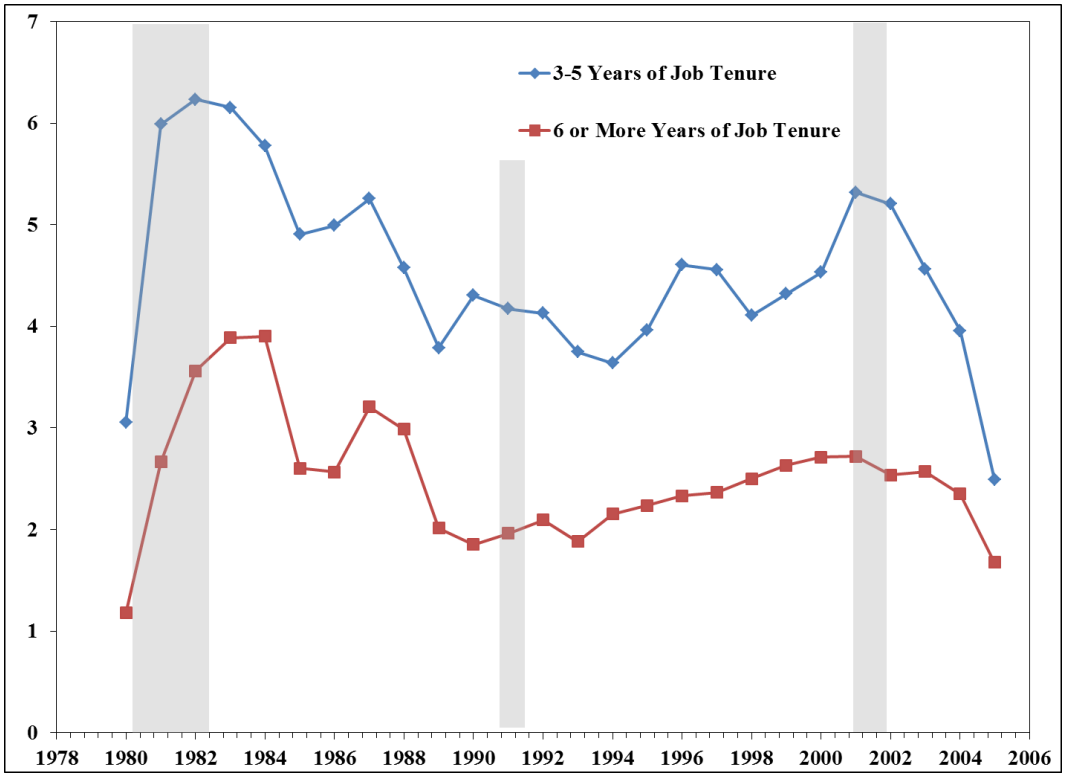
The incidence of job displacement might seem modest in any given year, but it cumulates to a large number during severe downturns. For example, summing the job displacement rates in Figure 2 from 1980 to 1985 yields a cumulative displacement rate of more than 20%.[11] This figure translates to about 2.7 million job displacement events over the six-year period among men 50 years or younger with 3 or more years of prior job tenure, and working in industries with continuous SSA coverage. This figure is conservative, given our restrictive criteria for mass-layoff events. 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). This figure includes women and does not impose our mass-layoff criteria. BLS also reports that an additional 8.5 million persons were displaced in 2007-2009 from jobs held less than 3 years.

Figure 3 shows displacement rates for men with 3-5 years of prior job tenure and with 6 or more years. We impose the same requirements for age, firm size, industry coverage, and mass-layoff events as before. 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 displacement rates for men in three broad age groups. The basic pattern is clear: younger men

[11] In calculating this figure, we allow the at-risk population to change from year to year. For some purposes, it is more appropriate to consider the cumulative displacement rate for a fixed at-risk population. Consider, for example, the population of male workers younger than 50 with 3 or more years of job tenure at firms with at least 50 employees as of 1979, and working in industries with continuous SSA coverage. 16% of this fixed population experienced a job displacement event from 1980 to 1985 by our criteria.

tend to be more exposed to negative firm-specific and aggregate shocks that lead to job destruction.

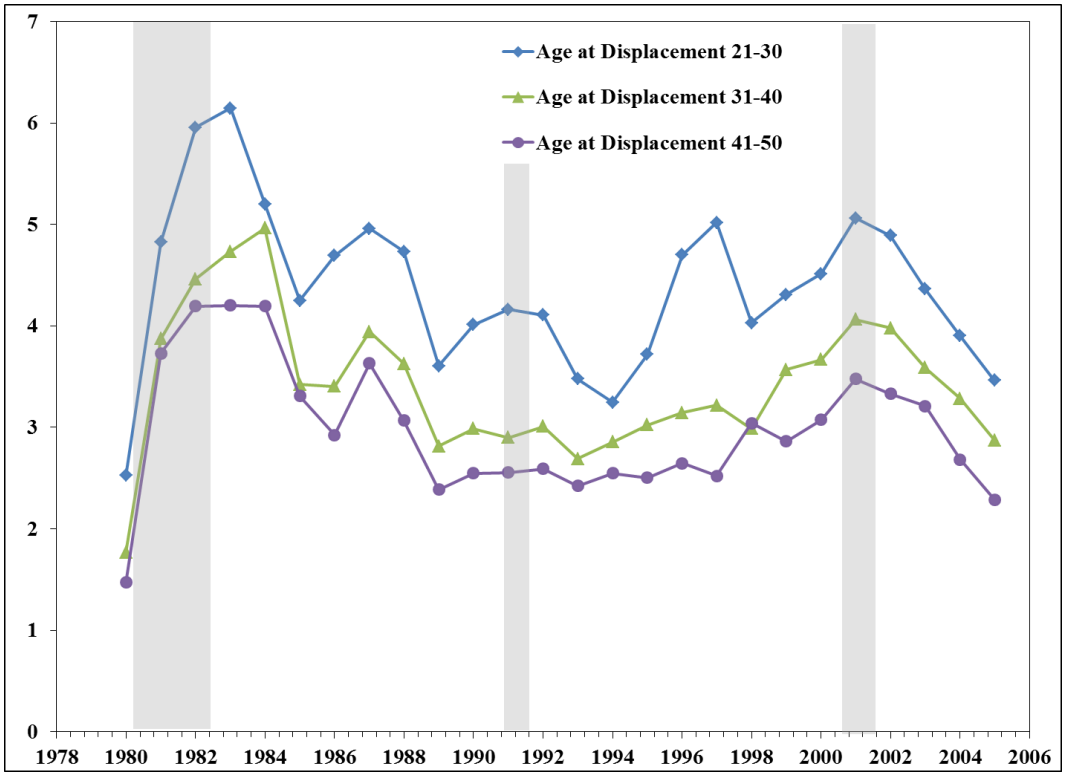
Figure 3: Annual Displacement Rates in Mass-Layoff Events by Prior Job Tenure, Men 50 or Younger at Firms with at Least 50 Employees, 1980 to 2005



Notes to Figure 3: See notes 4, 5 and 6 to Figure 2.

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 supports this view as well.

Figure 4: Annual Displacement Rates in Mass-Layoff Events by Age Group, Men at Firms with at Least 50 Employees, 1980 to 2005



Notes to Figure 4: See notes 4, 5 and 6 to 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 large, persistent earnings losses. Most studies estimate the causal effect as the earnings change before and after job loss relative to the contemporaneous earnings change of comparable workers who did not lose jobs. Studies differ somewhat in how they measure job loss and how they define the control group of non-displaced workers.

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. VSM also require the employer to have at least 50 employees in the baseline period before the mass layoff. They exclude workers in 2-digit industries not covered by SSA in the early 1980s, chiefly the public sector.

VSM compare the evolution of annual earnings for displaced workers with that of a control group of similar workers who did not separate in the displacement year or the next two years. They find that displacements in the early 1980s led to average annual earnings losses relative to the control group of more than 30% of pre-displacement annual earnings. Despite some recovery over time, even after 20 years the earnings of displaced workers remain 15-20% below the level implied by control group earnings.

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 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 Kodrzycki (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 large and long lasting even in regions and periods with stronger labor markets. 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-tenure workers suffer persistent losses in 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 earnings of job losers to a control group, which typically do not focus on depressed areas or periods, also find large earnings and wage losses that persist up to five to ten years (e.g., Topel, 1990, 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, and that most job losers returning

to the labor force find full-time jobs (e.g., Farber 1999), suggest that the bulk of earnings losses after job displacement reflects a reduction in wage rates or hours worked per employed.

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 mass layoffs, 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 panel survey data that do not impose restrictions on firm size or firm events yield results for earnings similar to results based on administrative data.

Overall, a central finding in previous research is that job displacement leads to large and long-lasting earnings losses, especially under weak labor market conditions. This observation suggests that workers who have experienced job displacement 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 data 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 with 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 in all major industries. Older workers tend to have larger immediate 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. Estimated Earnings Losses Associated with Job Displacement

We now follow VSM in estimating the earnings effects of job displacement and their sensitivity to economic conditions at the time of displacement. We define job displacement as in Section 2 – the separation of high-tenure men, 50 years or younger, from firms with at least 50 employees at baseline in mass-layoff events. We also provide some results for women and older men. To estimate the effects of job displacement, we compare the earnings path of workers who experience job displacement to the path of similar workers who did not separate during the same time period, while controlling for individual fixed effects and differential earnings trends.

We implement this comparison by estimating the following distributed-lag model separately for each displacement year y from 1980 onwards:

$$e_{it}^{y} = \alpha_i^y + \gamma_t^y + \bar{e}_i^y \lambda_t^y + \beta^y X_{it} + \sum_{k=-6}^{20} \delta_k^y D_{it}^k + u_{it}^y \qquad (1)$$

where the outcome variable e_{it} is real annual earnings of individual *i* in year *t* in 2000 dollars (using the Consumer Price Index), α_i^y are coefficients on worker fixed effects, γ_t^y are coefficients on calendar year fixed effects, X_{it} is a quartic polynomial in the age of worker *i* at *t*, and the error u_{it} represents random factors. To allow further differences in annual earnings increments by a worker's initial level of earnings, the specification includes differential year effects that vary proportionally to the worker's average earnings, $\bar{e}_i^y$, in the five years prior to the displacement year. The D_{it}^k are dummy variables equal to one in the worker's k-th year before or after his displacement, and zero otherwise**.**

We estimate (1) by displacement year using annual individual-level observations in the SSA data from 1974 to 2008. The sample for displacement year y contains data on workers displaced in y, y+1 and y+2 plus data on workers in a control group described below.[12] The evolution of earnings of the control group over time helps identify the year effects γ_t^y and

[12] We include displacements that occur in *y+1* and *y+2* in the sample for displacement year *y* to raise the number of observations on displaced workers, and to align the inclusion windows for displaced and control group workers. Note that this approach smooths the estimated earnings effects of job displacement from one displacement year to the next, which works against finding differences between recessions and expansions.

λ_t^y. Given the presence of the year effects and worker fixed effects in (1), the coefficients δ_k^y on the dummies D_{it}^k measure the time path of earnings *changes* for job separators from six years before and up to 20 years after a displacement -- relative to the baseline and relative to the change in earnings of the control group.[13] The baseline consists of years seven and eight before displacement.[14] To interpret the estimated effects δ_k^y as the causal effect of job displacement on earnings requires that, conditional on worker fixed effects and the other control variables, the counterfactual earnings of displaced workers in the absence of job displacement is captured by workers in the control group. To obtain the counterfactual earnings path of a displaced worker *i* absent displacement, we evaluate (1) at D_{it}^k =0 for all *k*.

For workers displaced in year *y*, the control group consists of workers not separating from in y, y+1, and y+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 y to y+2 from the control group. Non-mass layoff separators comprise workers who quit their jobs and workers laid off by firms with an employment drop of less than 30%. We impose the same restrictions with restrict to firm size, worker age and job tenure, gender, and industry as for displaced workers. We discuss the impact of alternative control groups and concerns related to potential selection bias in the earnings loss estimates in Section 3.d below.

Figure 5 reports results for men 50 or younger with at least 3 years of prior job tenure as of the displacement year. 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, respectively. If a peak or trough 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. Panel A shows these average earnings loss profiles relative to the mean earnings of displaced workers, normalized to reflect changes relative to mean earnings in years t-4 to t-1 prior to displacement. Panel B shows the average time paths of mean raw earnings before and after displacement for

[13] Since our sample window stops in 2008, for displacement years after 1988 we do not observe 20 years of earnings data after a displacement. For these years, the post-displacement dummies are included up to the maximum possible number of years.

[14] For 1980 (1981), the baseline is years five and six (six and seven) before displacement. We also drop the dummy variable for the first calendar year in each regression. These zero restrictions, two for the baseline and one for the first calendar year, resolve the potential collinearity among the dummy variables in (1).

workers displaced in recessions and expansions. Panel C in Figure 5 shows the Panel A losses as a fraction of pre-displacement mean earnings.

Earnings losses at displacement relative to the control group are very large initially, 40% in the first year after displacement for displacements that occur in recessions and 23% for displacements that occur in expansions. They are also long lasting. The average earnings losses are about 20% from 10 to 20 years out for displacements that occur in recessions and about 10% for those that occur in expansions. These estimates are robust to many specification checks, as discussed below and in VSM. For example, the earnings losses are similar if one defines a mass-layoff event as a firm-level employment decline of at least 80%. They are slightly larger for workers with 6 years or more of job tenure (the main comparison group of JLS and others), and slightly smaller for 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 t+2 for a job displacement in t, as estimated from equation (1), divided by displaced workers' pre-displacement mean earnings in years t-4 to t-1. The figure displays a clear inverse relationship. If we regress the percentage loss on the unemployment rate at displacement, we obtain an R^2 of 0.22 and a slope coefficient of -0.022 (standard error of 0.008). That is, a rise in the unemployment rate from 5% to 9% at the time of displacement implies that the earnings loss in the third year of displacement increases from 18% to 26% of average annual pre-displacement earnings. Since the earnings recovery pattern in Figure 5C is approximately parallel in 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.

Figure 5A: Average Annual Earnings Before and After Job Displacement Relative to Control Group Earnings, Men 50 or Younger with at Least 3 Years of Job Tenure

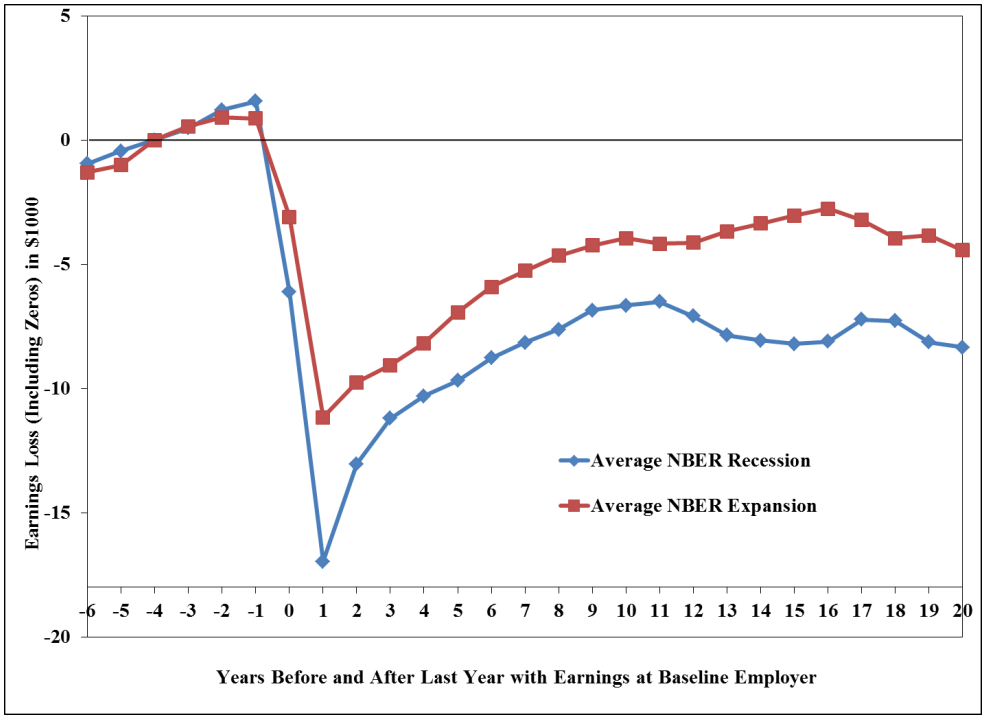


Figure 5B: Average Annual Earnings Before and After Job Displacement, Men 50 or Younger with at Least 3 Years of Job Tenure

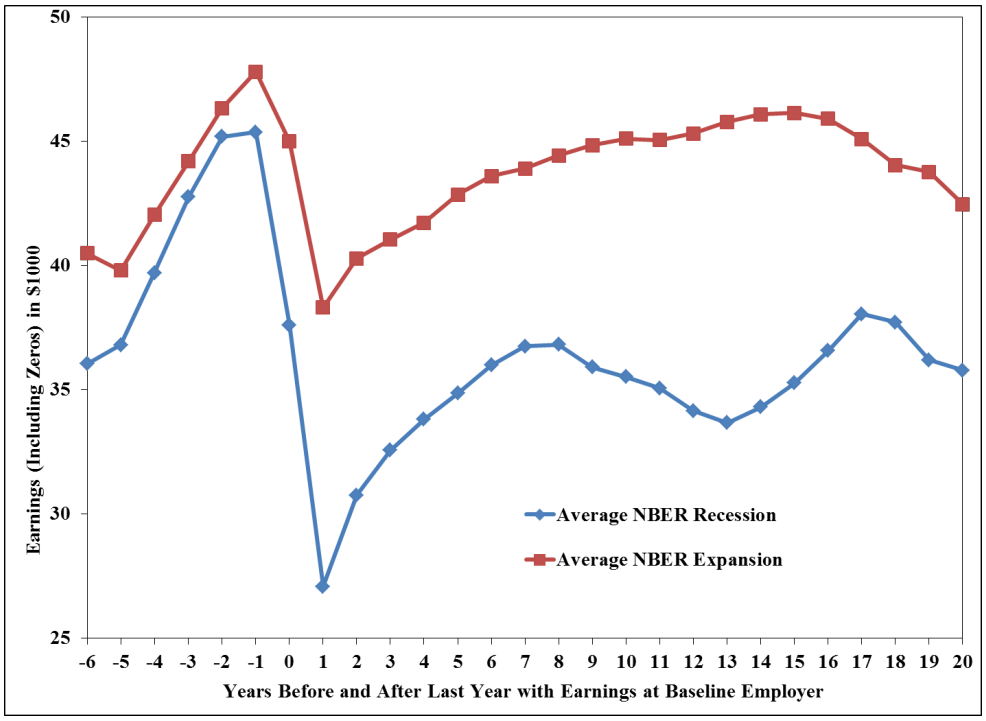
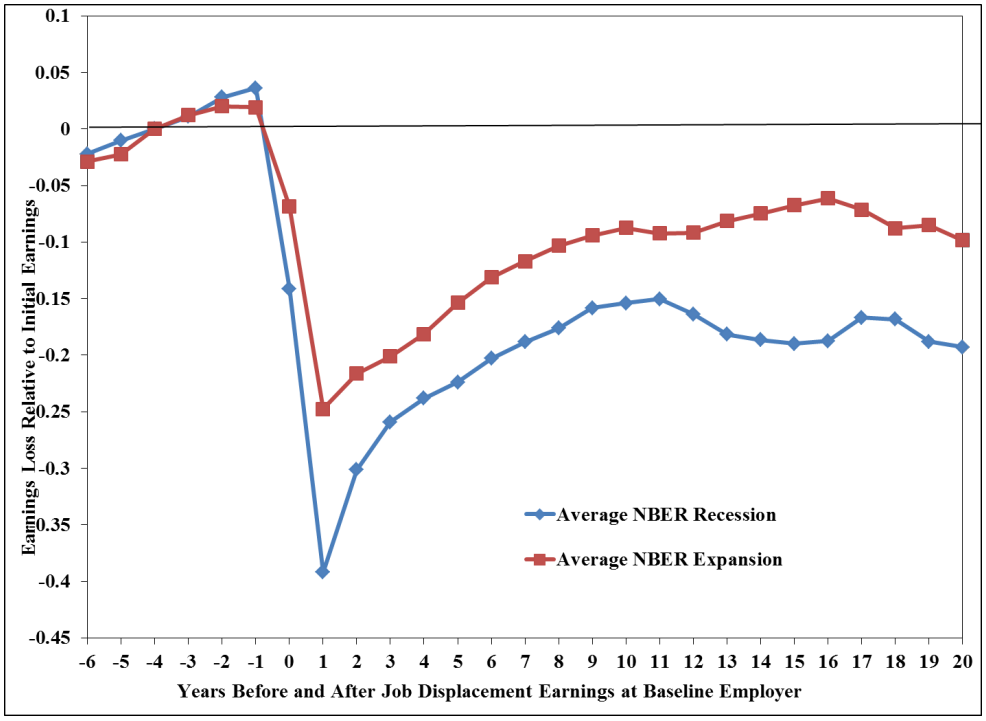


Figure 5C: Average Annual Earnings Losses Before and After Job Displacement Relative to Control Group Earnings As Percentage of Pre-Displacement Earnings, Men 50 or Younger with At Least 3 Years of Job Tenure



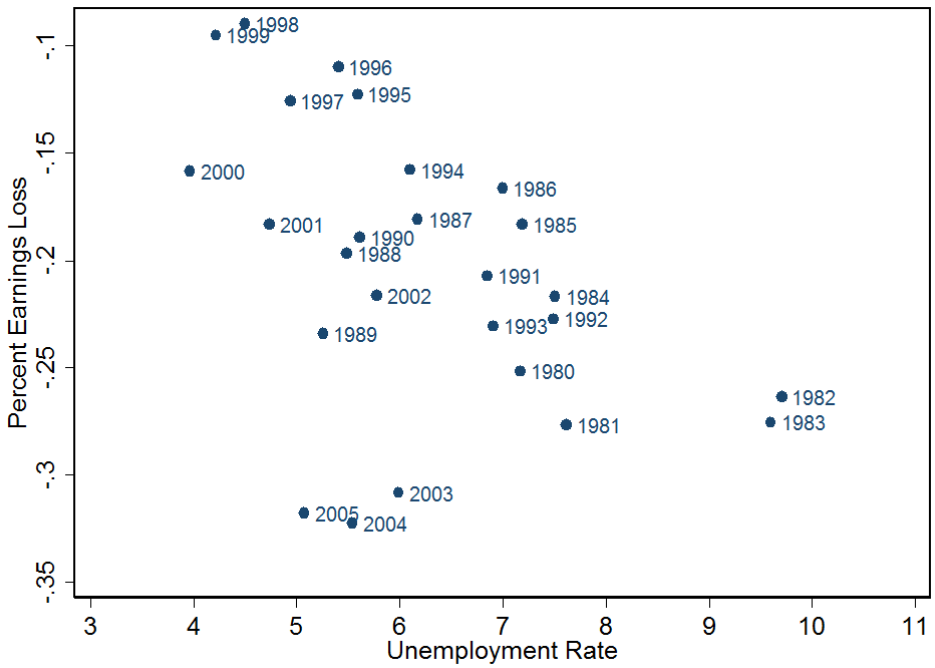
Notes to Figures 5A, 5B and 5C:

1. Year 1 on the horizontal axis is the displacement year. Year 0 is the last year of earnings from the main employer before displacement.
2. Panels A show average annual earnings losses relative to pre-displacement earnings for male workers, 50 years or younger at the time of displacement, with 3 or more years of tenure prior to job loss. The earnings losses reflect differences in the path of mean annual earnings between displaced workers and control group workers. Panel B, which does not involve a control group comparison, shows average annual earnings rather than earnings losses. Panel C shows the figures of Panel A, divided by pre-displacement average annual earnings from t-4 to t-1.
3. One curve in each panel shows average outcomes for workers displaced in recession years from 1980 to 2005, and the other shows average outcomes for those displaced in expansion years. When a given displacement year straddles recession and expansion periods, we apportion that year's values based on its number of months in each category. For example, if 3 months of the year are in recession, we allocate its values to recession and expansion categories with weights 0.25 and 0.75, respectively.
4. 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 who separate from their main employers in mass-layoffs events, expressed as a difference relative to a pre-displacement baseline from t-4 to t-1 and relative to workers who did not separate from employers. The underlying regression includes controls for worker effects, calendar year effects, age, and interacts calendar year fixed-effects with individual average earnings in

the five years preceding displacement. The earnings levels in Panel B are constructed in a similar manner. See the text discussion of equation (1) for additional details.

5. The earnings losses and levels are estimated using administrative data on W2 earnings following von Wachter, Song, and Manchester (2011), as described in the text.

Figure 6: Annual Earnings Losses in the Third Year of 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 of displacement, expressed as a fraction of displaced workers' mean annual earnings in the four years before displacement. The figure plots this earnings loss measure 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.

c. Present Value Earnings Losses Associated with Job Displacement

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

$$PDV_{\text{Loss}}^{R} = \sum_{s=1}^{10} \bar{\delta}_{s}^{R} \frac{1}{(1+r)^{s-1}} + \sum_{s=11}^{20} \bar{\delta}_{10}^{R} \frac{(1-\bar{\lambda})^{s-10}}{(1+r)^{s-1}} \tag{2}$$

where $\bar{\delta}_{s}^{R}$ 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 displacement years), and $\bar{\delta}_{10}^{R}(1-\bar{\lambda})^{s-10}$ is the extrapolated earnings loss using the rate of decay $\bar{\lambda}$. The evolution of earnings losses is roughly parallel for displacements in expansions and recessions, so we use the average decay rate of earnings losses over all periods. If the rate of decay is faster in booms, this choice understates the cyclical differences in the cost of job loss.

In principle, we could use the actual earnings path for those displacement cohorts that we follow more than ten years after job loss. In practice, however, as the sample of workers displaced in a given year ages and labor force participation declines, the estimates for long after the displacement year may be affected by changes in composition and greater sampling error in smaller samples. Similarly, using actual estimates for the long-run follow up period may put weight on cohorts that have particularly long-lasting effects. Given our aim to approximate the average PDV loss for a typical worker in boom and recession years, we chose a common decay rate for all displacement cohorts. 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 to years 11 to 15 after displacement. This approach balances the influence of displacements in the early 1990s, which reflect a strong recovery in the high-pressure labor market of the mid to late 1990s, and the influence of displacements in other periods.

Since earnings levels change over time and may differ between displacements that occur in expansions and recessions, we consider three ways of normalizing the absolute earnings losses. First, we scale the PDV earnings loss by displaced workers' mean annual earnings in years t-4 through t-1 prior to displacement. This approach expresses the PDV loss as the number of earnings years lost at the previous level of earnings. Second, we express the PDV earnings loss as percent of the average pre-displacement earnings from t-4 to t-1. Third, we express the

PDV earnings losses as a *percentage* of PDV earnings along the counterfactual earnings path in the absence of displacement. To do so, we first construct a counterfactual earnings path absent 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 obtain $\bar{e}_t^{cf,y} = \bar{\alpha}^y + \gamma_t^y + \beta^y \bar{X}_t^y$. Using the mean earnings of displaced workers as a benchmark ensures that we average over the right worker fixed effects and obtain the right earnings levels. We then take the average of the counterfactual in years belonging to NBER recessions and expansions, respectively.[15] Using these averages, we divide the PDV earnings loss by the resulting PDV of counterfactual earnings in booms and recession, respectively.

Table 1 reports these alternative measures of the PDV earnings loss after a job displacement – again for men 50 years or younger with at least three prior years of positive earnings at an employer with at least 50 workers. The definition of displacement is the same as in Figure 5. The first row shows estimated PDV earnings losses, averaged over all displacement years. The average PDV earnings loss is about $77,557 (Column1), which amounts to 1.71 times average annual pre-displacement earnings (column 2) and 11.9% of the PDV of counterfactual earnings absent job displacement (Column 3).

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 losses are much larger in recessions than expansions. A worker displaced in a recession experiences PDV losses of $109,567, which amounts to 2.50 years of average pre-displacement earnings, and to 18.6% decline relative to counterfactual earnings absent displacement. In contrast, the PDV of earnings losses experienced by workers displaced in an expansion is $72,487, which amounts to 1.59 of pre-displacement earnings. In short, job displacements lead to very large declines in PDV earnings, and the loss is much larger for displacements that occur in recessions.

[15] 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 2005, Men 50 or Younger with at Least Three Years of Job Tenure Before Displacement

		(1)	(2)	(3)
		Present Discounted Value (PDV) of Average Loss at Job Displacement		Ratio of PDV of Loss and PDV of Counterfactual Earnings in Absence of Displacement
	Fraction of Years Covered by Row Category	Dollar Value	Multiple of Pre-Displacement Annual Earnings	
Average All Years	--	-77,557	-1.71	-11.9
Avg. in NBER Expansion Years	*0.88*	-72,487	-1.59	-11.0
Avg. in NBER Recession Years	*0.12*	-109,567	-2.50	-18.6
Average in Years with:				
UR< 5%	*0.23*	-50,953	-1.06	-9.9
5%<=UR<6%	*0.35*	-71,460	-1.56	-10.9
6%<=UR<7%	*0.13*	-71,006	-1.58	-10.7
7%<=UR<8%	*0.21*	-89,792	-2.07	-14.4
UR>=8%	*0.08*	-121,982	-2.82	-19.8

Notes:

1. See note 5 to Figure 2 and Section 2 of the text for definition of mass-layoff events.
2. To compute the entries in this table, we averaged earnings losses by displacement year from VSM (2011) over recession and expansion years. When a given displacement year straddles recession and expansion periods or multiple unemployment intervals, we apportion that year's values based on its number of months in each category. For

example, if 3 months of the year are in recession, we allocate its values to recession and expansion categories with weights 0.25 and 0.75, respectively.

3. We calculate the estimated PV earnings losses over 20 years after job displacement, using a 5 percent annual discount rate. See text for an explanation of how we impute earnings losses in the out years for which we lack direct estimates.

Recall from Figure 1 that the incidence of job displacement is also much greater in recessions. Given that displacements have more severe consequences in recessions, the un-weighted averages over years in row 1 understate average PDV earnings losses taken over displaced workers.[16] Similarly, because we weight all recession years equally, while recessions with higher displacement rates also involve higher earnings losses, Table 1 understates the average PDV earnings losses taken over job displacements that occur in recessions.

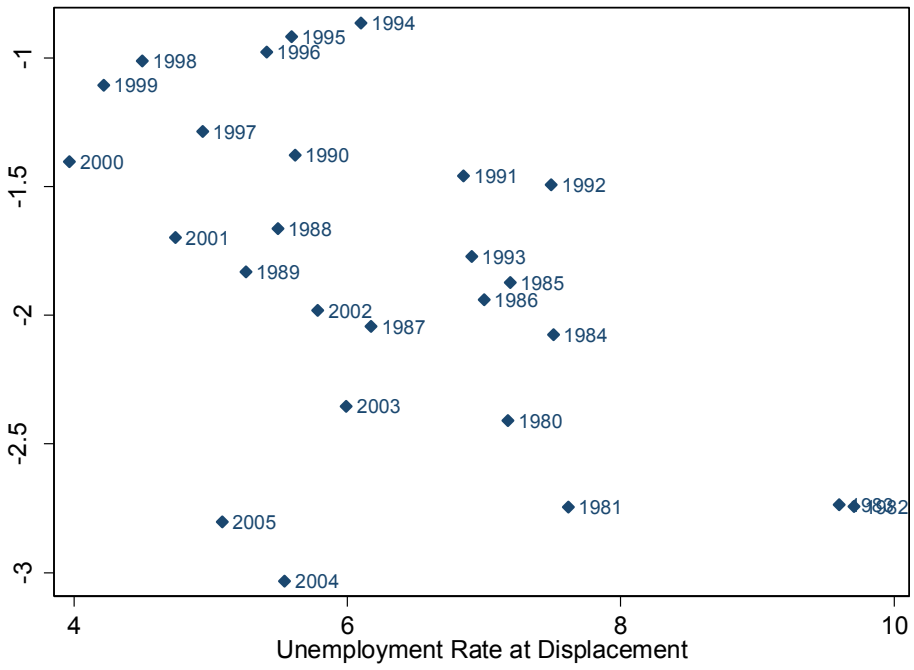
The lower panel of Table 1 shows how estimated PDV earnings losses vary by the unemployment rate in the year of displacement. The unemployment rate reflects contemporaneous labor market conditions at the time of displacement in a different way than NBER business cycle dating. As before, to calculate the table entries, we first estimate PDV earnings losses by year of 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 steeply with the unemployment rate in the year of job displacement. This important finding strongly reinforces and extends the evidence in Figure 6.

To take this result one step further, we repeat our procedure for calculating PDV earnings losses by year of displacement. We now depart from working with averages over multiple displacement years and consider a separate earnings loss path for each displacement year. 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 same 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.

[16] Row 1 in the Table 1 effectively gives less weight to persons displaced in recessions as compared to those displaced in expansions.

Figure 7 plots the resulting PDV earnings losses (expressed as multiples of average annual pre-displacement earnings) against the unemployment rate in the year of displacement. The figure again shows an approximately linear relationship, which is not surprising given the roughly linear relationship in Figure 6 and our use of a common decay rate beyond the tenth year after displacement. Even allowing for different post-displacement recovery patterns, the figure suggests that PDV earnings losses increase approximately linearly with the unemployment rate in the year of displacement. A linear regression of the PDV loss measure on the unemployment rate in the year of displacement yields an R^2 of 0.27 with a slope coefficient of -0.23 (0.08). Thus, an increase from 5% to 9% in the unemployment rate at displacement implies that PDV earnings losses rise from 1.6 to 2.5 years of pre-displacement earnings. When we add the NBER recession indicator to this descriptive regression model, it is not statistically significant.

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 20 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 shows PDV earnings losses for men with at least 6 years of tenure, for women, and for four age groups.[17] The PDV earnings losses due to job displacement are large for all groups. Comparing Tables 1 and 2, the losses are larger for men with higher job tenure prior to displacement. They are smaller for women, but not dramatically so once we control for differences in average earnings levels between men and women. For example, the average losses for women 50 or younger with 3 or more years of prior job tenure amount to 1.5 years of pre-displacement earnings (Table 2), as compared to 1.7 years for the corresponding group of men (Table 1). Except for workers displaced near the end of their working lives, PDV earnings losses are much larger for displacements that occur in recessions.

d. 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 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, which we discuss below, and obtain results very similar to the ones we report. After considering various estimators, VSM confirm the conclusion in previous research that the 'true' loss at displacement is closer to the estimates that exclude non-mass layoff separators from the control group.

[17] The online appendix contains additional results by age group.

Table 2. Magnitude and Cyclicality of Present Value Earnings Losses Associated with Displacement in Mass-Layoff Events from 1980 to 2005: Various Subgroups

Sub-Group		(1) Present Discounted Value (PDV) of Average Loss at Job Displacement: Dollar Value	(2) Present Discounted Value (PDV) of Average Loss at Job Displacement: Multiple of Pre-Displacement Annual Earnings	(3) Ratio of PDV of Loss and PDV of Counterfactual Earnings in Absence of Displacement
Men with 6 or More Years of Job Tenure at Displacement	Average All Years	-106,900	-2.0	-12.9
	Avg. in NBER Expansion Years	-100,543	-1.8	-11.9
	Avg. in NBER Recession Years	-148,400	-3.0	-20.0
Women with 3 or More Years of Job Tenure at Displacement	Average All Years	-38,033	-1.5	-10.9
	Avg. in NBER Expansion Years	-33,164	-1.3	-9.5
	Avg. in NBER Recession Years	-68,782	-3.3	-20.6
Men with 3 or More Years of Job Tenure and age 21-30 at Displacement	Average All Years	-50,240	-1.6	-9.8
	Avg. in NBER Expansion Years	-39,639	-1.3	-7.8
	Avg. in NBER Recession Years	-117,322	-3.7	-22.0
Men with 3 or More Years of Job Tenure and age 31-40 at Displacement	Average All Years	-49,599	-1.2	-7.7
	Avg. in NBER Expansion Years	-42,555	-1.1	-6.5
	Avg. in NBER Recession Years	-93,833	-2.5	-16.0
Men with 3 or More Years of Job Tenure and age 41-50 at Displacement	Average All Years	-98,519	-1.9	-15.9
	Avg. in NBER Expansion Years	-95,716	-1.8	-15.1
	Avg. in NBER Recession Years	-116,515	-2.8	-21.9
Men with 3 or More Years of Job Tenure and age 51-60 at Displacement	Average All Years	-99,288	-2.4	-24.0
	Avg. in NBER Expansion Years	-97,934	-2.3	-23.1
	Avg. in NBER Recession Years	-108,248	-3.2	-31.1

Notes to Table 2 :

1. See notes to Table 1. This table differs from Table 1 in its focus on different groups of workers.
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.

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 earnings growth rates in different parts of the earnings distribution (e.g., Autor and Katz, 1999). 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 industry 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 industry-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 *unobserved* earnings trends *within* firms, VSM replicate equation (1) using the mass-layoff event at the firm level as an instrumental variable for displacement. That is, they use 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, to instrument for the dummy of the individual layoff (D^k_{it}). Hence, the comparison is now between the earnings of *all* workers at firms undergoing mass layoffs and the evolution of earnings among all workers at non-mass layoff firms. Using this type of firm-level indicator to instrument for displacement, and controlling for differential trends by pre-mass layoff characteristics at the firm level, VSM obtain results very similar to

those based on (1). This IV estimator is also robust to the presence of non-mass layoff separators, since the instrument should be orthogonal to the rate of retirement or voluntary mobility.

To also address the potential concern that workers with lower potential earnings trends sort into firms more likely to experience mass layoffs, VSM follow previous work and consider a version of (1) that includes firm fixed effects. This specification yields somewhat smaller estimated earnings losses, because the losses of workers remaining at firms with mass layoffs are now subtracted from the losses of 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 (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 our calculations based on estimated versions of (1) 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 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 20 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 and 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). These studies find higher mortality rates in the years following job displacement, but they contain 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 divorce incidence, reduce fertility, reduce home ownership, and increase the rate of application to and entry into disability insurance programs.[18] 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 value earnings losses we estimate nor estimated consumption responses capture the full measure of costs associated with job displacement.

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

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 several respects. First, if recessions or high unemployment rates 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.[19] 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.

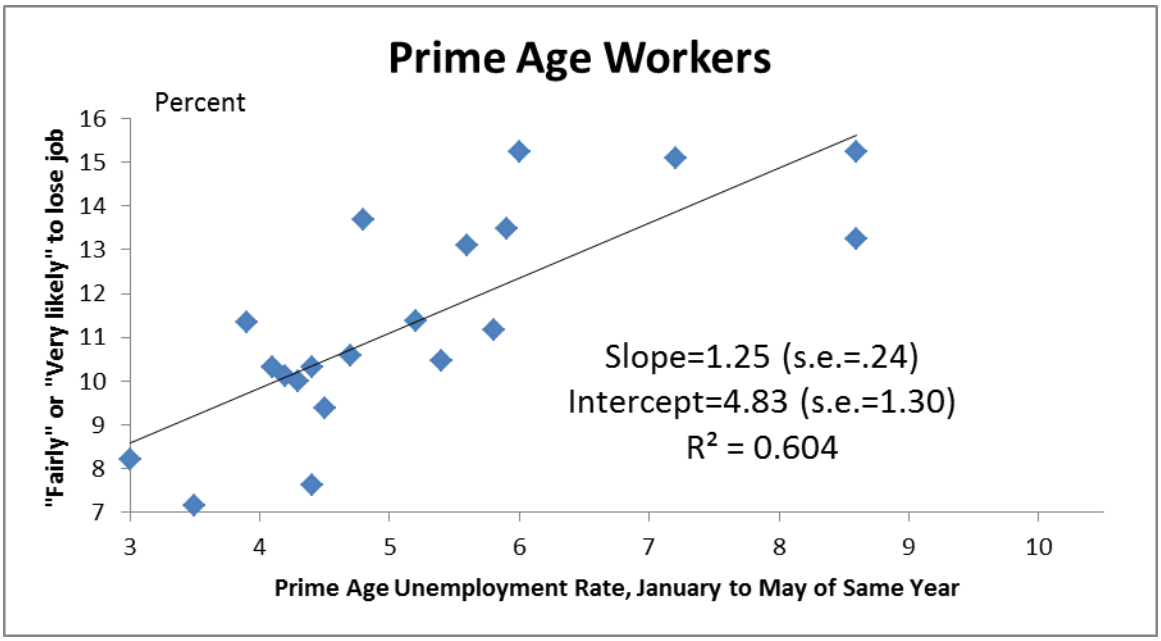
For a long-running source of data on perceptions about labor market conditions, we turn to the General Source Survey (GSS). The GSS is a repeated cross-sectional household survey conducted since 1972. It includes two categorical response questions that are useful for gauging cyclical movements in perceptions 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 the perceived difficulty of finding a job with the same income and fringe benefits as the respondent's current job.

Figure 8 shows, for all available years in the GSS, the percentage of prime age workers 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, an increase in the prime age unemployment rate from 4% to 8% raises from 10 to 15 the percentage

[19] 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.

of prime age workers who perceive job loss as fairly or very likely. The online appendix shows a very similar pattern for all employed workers 18-64 years of age.

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



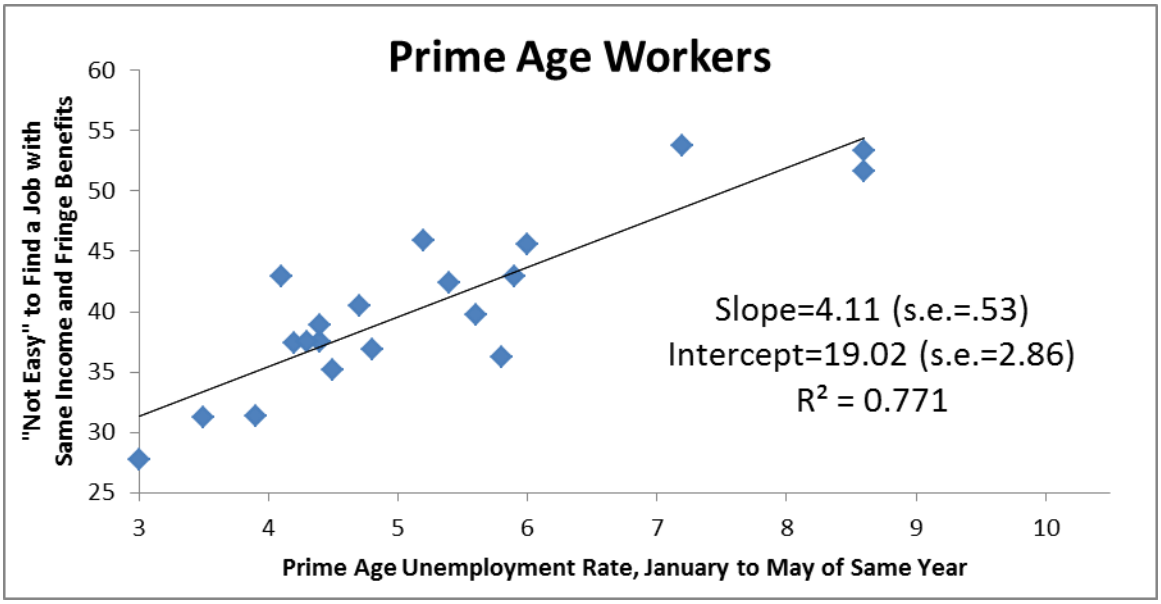
Notes:

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. Prime age workers are employed adults between 25 and 54 years of age, 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.
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 9 shows the percent of prime age workers 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 unemployment rates. Again, there is a strong relationship between perceived and actual labor market conditions. According to the fitted relationship in

Figure 9, 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 – see, for example, Davis et al. (2011). Quit rates plummeted in the most recession and remain extraordinarily low, another indication that workers perceive goods jobs as hard to find.

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



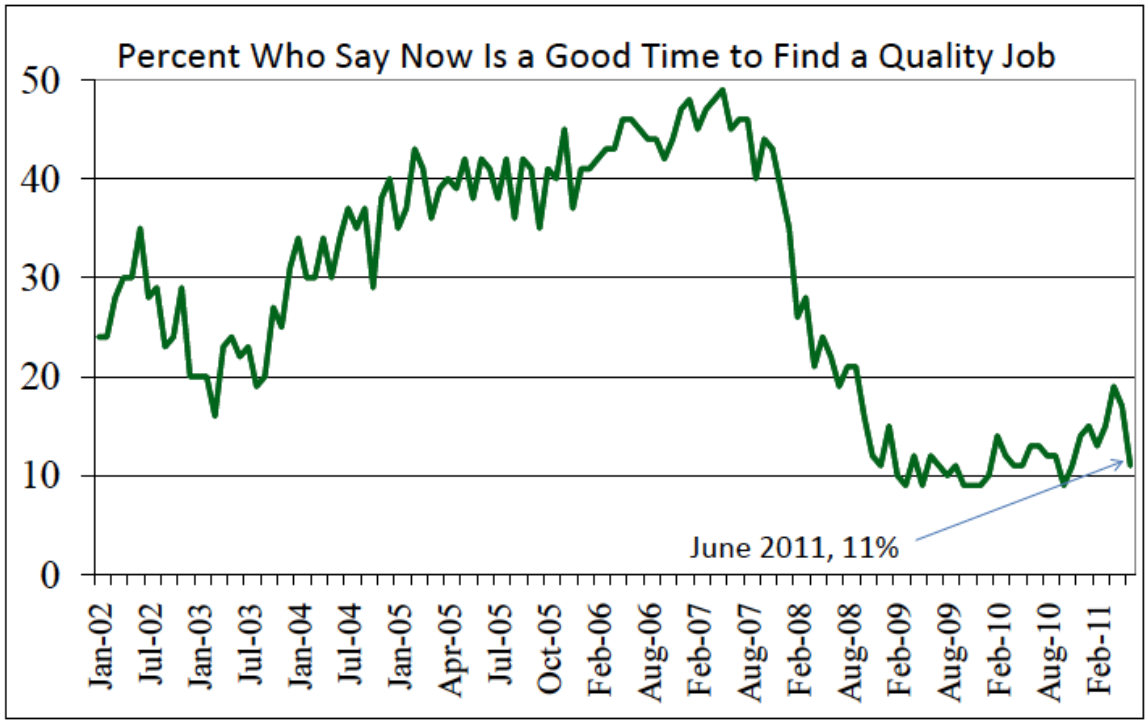
Notes:

1. 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. We weight JOBFIND responses using the WTTSALL variable.
2. See notes to Figure 8.

Gallup polls provide another 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 10 draws on Gallup data to plot the percent 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 percent responding "good time" is

highly cyclically sensitive. As the labor market tightened, yes responses 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 has remained at very low levels ever since. This evidence suggests that perceptions about labor market conditions respond rapidly to actual conditions.

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 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 between August 2009 and August 2010, the most recent data for August 2011 show worker anxiety returning to peak or near-peak levels.

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.

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.

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.[20] Some preliminary remarks will set the stage and motivate our particular choice of models.

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.[21] 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.[22] 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

[20] 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. The loss of earnings potential upon job loss is an important element in the theoretical model of high European unemployment rates developed by Ljungqvist and Sargent's (1998).

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

[22] 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.

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.

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 determine whether a particular form of wage rigidity improves 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 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 model of Burgess and Turon produces hires and separations apart from job flows and recessionary spikes in job destruction, job loss and unemployment inflows.

There are also good reasons to anticipate that the model of Burgess and Turon will generate larger earnings losses associated with job loss than the basic MP model. As in Burdett and Mortensen (1998), Postel-Vinay and Robin (2002) and other models with search on the job, their model generates persistent heterogeneity in match surplus values and wages for workers of a given quality. As a related point, the model delivers a job ladder whereby newly re-

employed workers tend to obtain jobs in the lower rungs of the wage distribution initially, and to move up the wage distribution over time through search on the job. This job ladder feature prolongs the period of earnings recovery after displacement. Finally, Hornstein, Krusell and Violante (2010) show that plausibly parametrized versions of basic search models yield very modest levels of frictional wage dispersion, which implies little scope for earnings losses due to job loss when unemployment spells are short. Hornstein et al. also consider several extensions to basic search models and, among those they consider, the only ones that offer much scope for cross-sectional wage dispersion are models with search on the job.

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. See the online appendix for a detailed discussion of the model simulations and our calculations for the present value losses associated with job loss.

Panel A in Table 4 highlights an important message: job loss and unemployment is a rather inconsequential event for persons living in the basic MP world. Using a 5% annual discount rate, 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, expressing 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 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?

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	Hall-Milgrom
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	0.066	0.067	0.067	
Monthly Job-Finding Rate	0.43	0.43	0.43	
Mean PV Losses	0.23	0.05	0.23	1.28
$10^{th}/90^{th}$ percentile losses	-0.55 / 1.07	-0.29 / 0.40	-0.51 /1.04	-2.62/5.72
C. Aggregate Boom Paths				
Unemployment Rate	0.065	0.064	0.064	
Monthly Job-Finding Rate	0.43	0.44	0.44	
Mean PV Losses	-0.19	-0.26	-0.12	1.14
$10^{th}/90^{th}$ percentile PV losses	-0.84 / 0.56	-0.39 / -0.11	-0.75 / 0.60	-2.73/5.53
D. Aggregate Bust Paths				
Unemployment Rate	0.067	0.07	0.070	
Monthly Job-Finding Rate	0.43	0.41	0.42	
Mean PV Losses	0.66	0.37	0.59	1.42
$10^{th}/90^{th}$ percentile PV losses	0.02/ 1.38	0.26 / 0.51	-0.08 / 1.35	-2.49/5.87
99th percentile PV losses	2.18	0.66	2.20	10.81

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. All present value calculations reflect discounting at a 5% annual rate.

4. We calculate statistics for the other panels by simulating the indicated model for 1,000 draws of the aggregate path, with each draw starting from the middle aggregate state (state 3) and evolving according to the aggregate transition matrix. We simulate each draw for 5,000 working days, which corresponds to 20 years at 250 working days per year. We track realized paths for 5,000 day-1 job losers and 1,000 day-1 employed persons on each of the 1,000 aggregate paths.
5. For present value income losses, 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 5,000. 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 mean realized income present value of the day-1 employed persons on the same aggregate path. We then compute the statistics reported in Panels B through D. The online appendix provides 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. To focus on present value earnings over a 20-year horizon comparable to our empirical estimates in Section 3, we set the terminal value to 0 at the end of the 5,000-day simulation horizon. We then compare the present value of the realized earnings paths for individuals who become unemployed on day 1 to the mean realized present value earnings paths for 1,000 individuals who remain employed on day 1 on the same aggregate path. Earnings loss statistics are very similar across all three variants of the MP model, so we report results only for the MP-CB version. See the online appendix for a more detailed description of the earnings loss simulations and calculations.
7. Panel B reports simulation statistics computed over all 1,000 aggregate paths. For Panels C and D, 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.

The remaining panels of Table 4 report statistics on unemployment, job finding, and the distribution of present value income and earnings losses. To compute these statistics, we simulate aggregate and individual paths. Specifically, starting in the middle aggregate state, we simulate 1,000 aggregate paths for each version of the model, letting each simulation run for 20 years (5,000 days at 250 working days per year). Along each aggregate path, we simulate paths for large numbers of workers who either lose jobs or remain employed on day 1. Flow income equals the annuity value of the wage bargain when employed and the imputed flow value of unemployment otherwise. Present value income includes the discounted asset value of the individual's realized terminal state. To compute the realized income loss for a day-1 job loser, we compare the present value of his realized income path to the mean realized present value

income for persons who remain employed on day 1 on the same aggregate path. By comparing day-1 job losers to persons who remain employed along the same aggregate path, we obtain a comparison between the treated (day-1 job losers) and the controls (day-1 employed).

To compute the realized earnings loss for a day-1 job loser, we compare the present value of his realized earnings path over the 20-year horizon to the mean present value of realized earnings for individuals living on the same aggregate path who remain employed on day 1. Earnings equal the wage when employed and zero when unemployed. We set the terminal value to zero to match the 20-year horizon in our empirical estimates of present value earnings losses. Thus, the earnings losses in Table 4 are larger than the corresponding income losses for two reasons: earnings exclude the imputed income value of unemployment, and we set terminal values to zero in the earnings comparisons.

Consider 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 present value income loss of 0.23%. 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. Continuing to look over all aggregate and individual paths, the 90th percentile income loss in the MP-CB version is only 1.04%, still a rather modest value. Job losers at the 10th percentile of the distribution experience a gain of 0.51% in present value income.

Turning to earnings losses, we report results only for the MP-CB version because the other two versions yield very similar results. Mean present value earnings losses are 1.28% in the basic MP model – an order of magnitude smaller than the 10.7% figure in the first column and first row of Table 1. One potential concern about this earnings loss comparison is that 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 basic MP model to bad-case outcomes in the data. While we recognize that this argument has some force, we do not find it persuasive. The estimated earnings losses reported in Section 3 pertain to an ex ante identifiable group of workers (men, 50 or younger, with 3 or more years of 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 present value earnings losses associated with job loss for this large group of workers.

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, and "bust" paths are near the 90th percentile. Mean present value income losses remain small along boom and bust paths. Even when we isolate the worst 1% of individual outcomes along the bust paths, the present value income losses amount to only 2.2% in the CB and standard Nash versions of the model and only 0.7% in the Hagedorn-Manavoskii calibration. In short, the basic MP model cannot produce large welfare losses for job losers, even at the extremes of aggregate and individual outcomes. The model can produce large present value earnings losses at the extremes of the distribution of individual outcomes. For example, the worst 1% of individual outcomes reported in Panel D yield earnings losses comparable to the mean loss reported in Table 1.[23] This result, however, hardly amounts to a success for the model.

Why are the consequences of job loss so modest in the basic MP model? Two aspects of the model deliver the result almost immediately. First, wages are uniform in the cross section, so that unemployment spells are the only source of earnings loss upon job loss. Second, when calibrated to job-finding rates typical of the postwar U.S. experience, expected unemployment durations are short, about two or three months. Short unemployment spells coupled with uniform wages in the cross section imply small earnings losses associated with job loss.

The basic MP model also implies a close relationship between the cost of job loss to the worker and the vacancy supply condition, as stressed to us by Bob Hall. Given free entry, the zero-profit condition for job-creating employers says that the daily vacancy-filling rate times the asset value of a filled job equals the daily flow cost of maintaining a vacancy. JOLTS data imply a vacancy-filling rate of about 5% per day. Drawing on Silva and Toledo (2009) and Hagedorn and Manovskii (2008), Hall and Milgrom conclude that the daily flow cost of a vacancy is about one-half of a worker's daily output. Thus, the asset value of a newly filled job for the employer is about ten days output generated by a (newly hired) worker. If employer and worker share equally in the surplus generated by a new match, then the worker's value of transitioning from unemployment to employment is also about ten days' worth of output. In other words, not much

[23] 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. Given the uniformity of wages and the small consequences of job loss in 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.

value is at stake in the creation and destruction of employment relationships in the basic MP model. Richer models in the MP class need not imply such a tight relationship between the cost of filling a new job and the surplus value of the average existing job.

In summary, we draw three conclusions from Table 4 and the related discussion. First, job loss is a rather inconsequential event for individual welfare in the basic MP model, even at the extremes of individual and aggregate outcomes. Second, the basic MP model cannot rationalize the empirical evidence on the present value earnings losses associated with job displacement. Third, 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.

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

Burgess and Turon (2010) depart from Mortensen and Pissarides (1994) by introducing 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. Like MP (1994), their model also differs from the basic MP model in capturing cross-sectional heterogeneity in match products and surplus values. These extensions lead to cross-sectional wage dispersion, a distinction between job flows and worker flows and endogenous job destruction spikes in the wake of negative aggregate shocks. The model also gives rise to a job ladder that prolongs the recovery of pre-displacement earnings for job-losing 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 $[-\sigma, \sigma]$, possibly higher or lower than the previous value. Optimizing behavior yields 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. An important implication of these assumptions is that job losses due to idiosyncratic shocks occur throughout the distribution of productivities, while job losses due to aggregate shocks occur at low-value jobs.

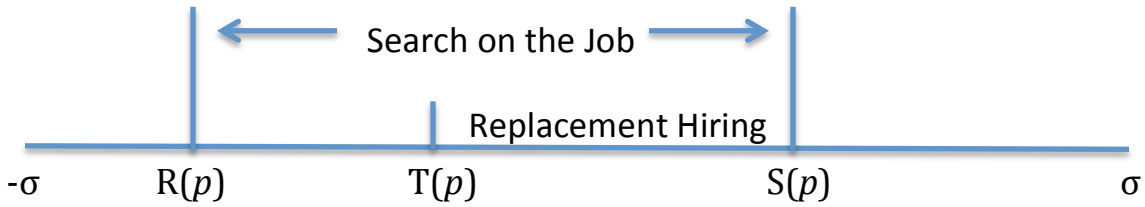


Figure 11. Idiosyncratic Productivity Thresholds for Job Destruction, Replacement Hiring and On-the-Job Search in the Burgess-Turon Model

Table 5 reports statistics for the model of Burgess and Turon. We modify their calibration to generate job-finding rates and unemployment spell durations comparable to postwar U.S. experience.[24] 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. All loss calculations pertain to workers who separate in job destruction/job loss events and exclude separations that result from search on the job.

Row A in Table 5 reports present value income and earnings losses for job losers in the good, middle and bad aggregate states. We compute the income losses using differences in value functions at each level of the idiosyncratic productivity level, ε, then integrate over the distribution of ε that prevails in the indicated aggregate state to obtain the mean present value income losses in Row A. For earnings losses, we adopt a simulation approach similar to the one used for Table 5. However, we now compare the realized present value earnings of workers who lose jobs with a given ε to the mean realized present value of earnings among workers who remain employed (in the displacement period) at the *same* value of ε. Once we

[24] See the online appendix for a version of Table 5 that adopts their calibration, which is meant to match features of the British economy from 1964 to 1999.

obtain the comparison for each ε, we integrate with respect to the appropriate distribution to obtain the mean realized present value earnings loss. As before, we use a 20-year horizon for the earnings calculations. The online appendix describes the model simulations and present value calculations in detail.

Table 5. Present Value Losses Due to Job Loss in a Mortensen-Pissarides Model with Search on the Job, Heterogeneity in Match Values, and Job Destruction Spikes

Present Value Losses, Percent of Employment Asset Value for Income Losses and Percent of Present Value Earnings Over a 20-Year Horizon for Earnings Losses				
	Aggregate State	*Good*	*Middle*	*Bad*
A. Mean PV Loss Due to Idiosyncratic Shocks that Result in Job Loss	***Income***	0.39	0.35	0.32
	Earnings	2.44	2.54	2.71
B. Quarterly (Monthly) Job Finding Rate		82.5 (44.1)	73.7 (35.9)	64.9 (29.5)
		Present Value Income Losses		
	Aggregate State Transition	*Good→ Middle*	*Middle→ Bad*	*Good→ Bad*
C. Mean Loss Due to Idiosyncratic Shocks that Result in Job Loss, Comparison to Own Past		0.63	0.57	0.84
D. Mean Loss Due to Aggregate Shock that Results in Job Loss, Comparison to Own Past		0.25	0.22	0.47
E. Inflow-Weighted Average of Rows C and D		0.61	0.55	0.80
F. Mean Loss Due to Idiosyncratic Shocks that Result in Job Loss, Comparison to Control Group		0.35	0.32	0.32
G. Mean Loss Due to Aggregate Shock that Results in Job Loss, Comparison to Control Group		0	0	0
H. Inflow-Weighted Average of Rows F and G		0.33	0.30	0.29
		Present Value Earnings Losses		
I. Mean Loss Due to Idiosyncratic Shocks that Result in Job Loss, Comparison to Own Past		2.85	3.08	3.26
J. Mean Loss Due to Aggregate Shock that Results in Job Loss, Comparison to Own Past		2.15	2.57	2.57
K. Inflow-Weighted Average of Rows I and J		2.81	3.05	3.19
L. Mean Loss Due to Idiosyncratic Shocks that Result in Job Loss, Comparison to Control Group		2.54	2.71	2.71
M. Mean Loss Due to Aggregate Shock that Results in Job Loss, Comparison to Control Group		0	0	0
N. Inflow-Weighted Average of Rows L and M		2.39	2.55	2.42

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 content to the concept of a job apart from the employer-worker match. Job destruction and job loss arise from negative aggregate shocks and sufficiently bad idiosyncratic shocks.

2. Burgess and Turon set their model 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. The calibration of Burgess and Turon is meant to match features of the British economy from 1964 to 1999. We depart from their calibration by increasing the arrival rate of idiosyncratic shocks (from 0.15 to 0.25) and the efficiency of the matching function (from 0.6 to 1.1). These parameter changes yield more rapid flows through the unemployment pool and higher monthly job-finding rates, roughly in line with U.S. outcomes. The unemployment rate is 5.2% in the middle state for our calibration.
4. Income loss calculations rely on value function comparisons and pertain to workers who separate in job destruction/job loss events. The PV income losses are expressed relative to the asset value of employment. Earnings loss calculations rely on simulated aggregate and individual paths over 20-year horizons (80 quarters), where we set earnings to the wage if employed and to 0 if unemployed. The wage when employed depends on the aggregate state and the idiosyncratic productivity level of the job. The PV earnings losses are expressed relative to the present value of earnings over a 20-year horizon; i.e., we assign a continuation value of 0 at the 20-year horizon in the earnings loss calculations. All loss calculations exclude separations that result from search on the job.
5. For "Comparison to Own Past" we calculate losses relative to the job loser's pre-displacement employment value evaluated at the old aggregate state, and expressed relative to that same employment value. For "Comparison to Control Group" we instead evaluate the employment value at the new aggregate state. Either way, we evaluate the unemployment value at the new aggregate state. The "Control Group" comparison yields zero loss in Row G and M, 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. The "Own Past" and "Control Group" benchmarks yield the same loss values in Row A because the aggregate state is held constant. See the online appendix for a detailed explanation of the loss calculations and the underlying simulations.
6. Rows E, H, K and N report inflow-weighted averages of present value losses associated with idiosyncratic and aggregate shocks. The weights are given by the flow of job losers due to idiosyncratic shocks during the quarter the flow of job losers triggered by a negative aggregate shock.

Present value income losses due to job loss are larger than in the basic MP model, but they remain quite modest – about 0.3% to 0.4% in Row A. The entries in Rows C through H consider job loss events that occur in the quarter when the economy gets hit by a negative

aggregate shock. Job loss events now arise for two reasons. As before, a flow of negative idiosyncratic shocks produces a stream of job loss events. In addition, the negative aggregate shock erases the surplus value of marginal jobs, producing a burst of job destruction and job loss. *All* workers at jobs below the new, higher destruction threshold R become unemployed in the wake of a negative aggregate shock. That is, for treatment-control comparisons conditional on the idiosyncratic productivity value ε, all workers below the new destruction threshold are in the same position. Thus, we set losses to 0 in Rows G and M.[25] For control group comparisons, job loss produces present value income losses of about 0.3% in these "recession" periods (Row H). The disproportionate loss of marginal jobs in the wake of a negative aggregate shock pulls down the average present value income loss. So the model of Burgess and Turon does not shed much light on why job loss events in recessions are more consequential.

Turning to earnings, our calibrated version of the Burgess and Turon model produces nontrivial present value losses. For a given aggregate state, the losses reported in Row A range from 2.4% to 2.7% of present value earnings. These losses amount to about one quarter of the empirical present value earnings losses reported in Tables 1 and 2. Thus, search on the job and heterogeneity in match surplus values clearly helps move the model closer to the evidence on the present value earnings losses associated with job loss.

In this respect, the job ladder feature of the model plays an important role. The online appendix displays the cross-sectional wage function, the density of all filled jobs, and the density of first jobs for newly re-employed workers who leave unemployment. For our calibrated version of the model, the maximum wage in the good aggregate state exceeds the minimum wage by 49%. The density of first jobs is much more concentrated at the low end of the wage distribution than the density of all jobs. The average difference between the pre-displacement wage and the wage on the first post-displacement job is 10% in the good aggregate state, 8.4% in the middle state and 6.7% in the bad state. These observations and statistics are different ways of saying that the model incorporates a significant job ladder.

A few additional remarks are in order. First, in generating the results for Table 5, we do not impose a job tenure requirement on for displaced workers or control group workers. Doing

[25] In practice, empirical treatment-control comparisons do not perfectly condition on the idiosyncratic component of jobs and match values. However, as long as the empirical specification at least partly captures a disproportionate loss of marginal jobs in the wake of a negative aggregate shock, the composition effect we highlight here will also be present in the empirical estimates of earnings losses associated with job loss in a recession.

so may increase the earnings losses. Second, search intensity is a binary decision variable in the model of Burgess and Turon. Variable search intensity for employed workers, as in Hertweck (2010), may generate an elongated climb up the job ladder after displacement and, as a result, produce larger present value earnings losses.[26] We conclude that job ladder models can produce nontrivial earnings losses due to job displacement but are unlikely to account for the bulk of the empirical losses. For one thing, they do not explain why the earnings of displaced workers remain well below that of control group workers 10 or more years after displacement. Moreover, it does not appear that a pure job ladder model can rationalize the striking cyclical pattern in the present value earnings losses that we documented in Section 3.

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 associated with job displacement. We focus on displacements from 1980 to 2005 among men 50 or younger with 3 or more years of prior job tenure. For this group, job loss in mass-layoff events reduces present value earnings by an estimated $77,557 (2000 dollars) over 20 years at a 5% annual discount rate, equivalent to 1.7 years of pre-displacement earnings. Losses are larger for men with greater job tenure. They are smaller for women, even as a multiple of pre-displacement earnings.

Present value losses rise steeply with the unemployment rate at the time of displacement. The average loss equals 1.4 years of pre-displacement earnings if unemployment at displacement is less than 6%, and 2.8 years if unemployment exceeds 8%. More generally, the evidence in Tables 1 and 2 and Figures 5 to 7 says that tight labor market conditions at displacement strongly improve the medium- and long-term future earnings prospects of displaced workers. The highly pro-cyclical behavior of job-finding rates among the unemployed implies that tight labor market conditions strengthen near-term re-employment and

[26] Postel-Vinay and Robin (2002) consider a different model with search on the job and productivity heterogeneity on both sides of the labor market. Employers have all the bargaining power, and newly re-employed workers start at the bottom of the wage distribution after an unemployment spell. When an employed worker finds an attractive outside opportunity, the incumbent employer may respond with a successful counter offer, i.e., a wage increase. Thus, the model of Postel-Vinay and Robin also yields a prolonged earnings recovery path after job loss that is tied to search on the job, but wage gains may or may not coincide with job changes.

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 shows that job displacement also has negative consequences for employment and earnings stability, household consumption expenditures, health and mortality outcomes, children's achievement, 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 of unemployment fluctuations along the lines of the canonical contribution by Mortensen and Pissarides (1994) can account for the earnings losses associated with job displacement. Basic versions of the MP model featured in much recent research imply theoretical earnings losses an order of magnitude smaller than empirical losses. The explanation is straightforward. The basic model has uniform wages in the cross section and, when calibrated to U.S. job-finding rates, short unemployment spells. Thus, job loss has little impact on present value earnings. Because so little is at stake in the destruction of employment relationships in the basic MP model, it cannot rationalize the earnings losses associated with job displacement.

Lastly, we evaluate an MP model of Burgess and Turon (2010) with search on the job and replacement hiring. Unlike the basic MP model, the model of Burgess and Turon is at least qualitatively consistent with several first-order features of the data: cross-sectional wage dispersion, worker flows in excess of job flows, and recessionary spikes in job destruction and unemployment inflows. The model also exhibits a job ladder that prolongs the earnings recovery path after displacement. When calibrated to match U.S. job-finding rates, job loss in the model produces present value earnings losses that, on average, are about one quarter of the mean empirical losses due to job displacement. This is a sizable improvement over the basic MP model, but it leaves a very large gap between theory and evidence. Moreover, the model

cannot explain larger losses for displacements that occur in recessions, because negative aggregate shocks trigger the destruction of lower value jobs.

In our view, a major shortcoming of existing MP models of unemployment fluctuations is their implication that job loss is a rather inconsequential event for the affected workers. The consequences of job displacement, and fears of displacement, are among the main reasons that recessions and high unemployment create so much concern in the general population. The negative consequences of job displacement are why unemployment is such a potent political issue. We also think the consequential nature of job displacement is a major reason that unemployment and unemployment fluctuations attract 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. These models deliver a coherent theory of frictional unemployment and its determinants. 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. They provide tools for analyzing search and matching behavior by employers and job seekers, and for studying the implications of search and matching frictions for wage dispersion and individual wage dynamics. These tools are widely used to study the effects of policies, wage-setting arrangements and other economic institutions on unemployment and a variety of other labor market outcomes.

We hope to see these models taken in directions that can explain large and lasting earnings losses at job displacement. There are potentially several ways to bring MP-type models closer to the evidence on the earnings losses associated with job displacement. Learning about match quality over time as in Jovanovic (1979), the acquisition of specific skills through learning-by-doing on the job, and investments in specific training as in Becker (1962) can yield substantial earnings losses at job loss. These three mechanisms influence match durability and the evolution of surplus values in ongoing matches. It would be useful to integrate these mechanisms into MP models of unemployment fluctuations, which have thus far devoted much greater attention to the forces governing match formation. Topel (1990) and Neal (1995), among others, argue that specific forms of human capital play a central role in determining the magnitude of earnings losses associated with job displacement. Ljungvist and Sargent (1998) build an equilibrium search model that hard wires a link between job loss and the destruction of human capital, and that includes further human capital depreciation during unemployment.

Workers may also enjoy rents for reasons apart from search and matching frictions and returns on specific human capital. Explanations for worker rents include fairness norms and concerns about pay equity (Akerlof and Yellen, 1982), high pay as a device to deter shirking (Bulow and Summers, 1986), the appropriation of quasi-rents generated by sunk investments (Grout, 1986 and Caballero and Hammour, 2005), and worker sharing of product market rents. Beaudry and DiNardo (1992) stress the role of long-term contracting and one-sided commitment as a source of downward wage stickiness. Schmieder and von Wachter (2010) consider workers who receive higher wages due to tight labor market conditions in the past. They find evidence that these workers experience higher layoff rates and lose their wage premiums upon job loss, a pattern of results that supports the presence of rents. Whether this pattern accounts for larger earnings losses in recessions, when displacements are more widespread, is an open question.

Workers who enter the labor market in periods of slack conditions suffer negative effects on future earnings that persist for ten years or more (e.g., Kahn, 2010). Both lasting declines in employer quality and lasting effects of low starting wages on wage growth within firms contribute to the persistent negative earnings effects of slack conditions at entry (e.g., Oreopoulos, von Wachter, and Heisz, 2010). These results are interesting, in part, because new entrants have not accumulated job-specific rents and are unlikely to have accumulated much in the way of specific human capital. Apparently, weak conditions at the time of labor market entry slow the accumulation of rents and specific human capital for many years thereafter. Similar forces could lower the future earnings prospects of workers who are displaced in recessions and slumps.

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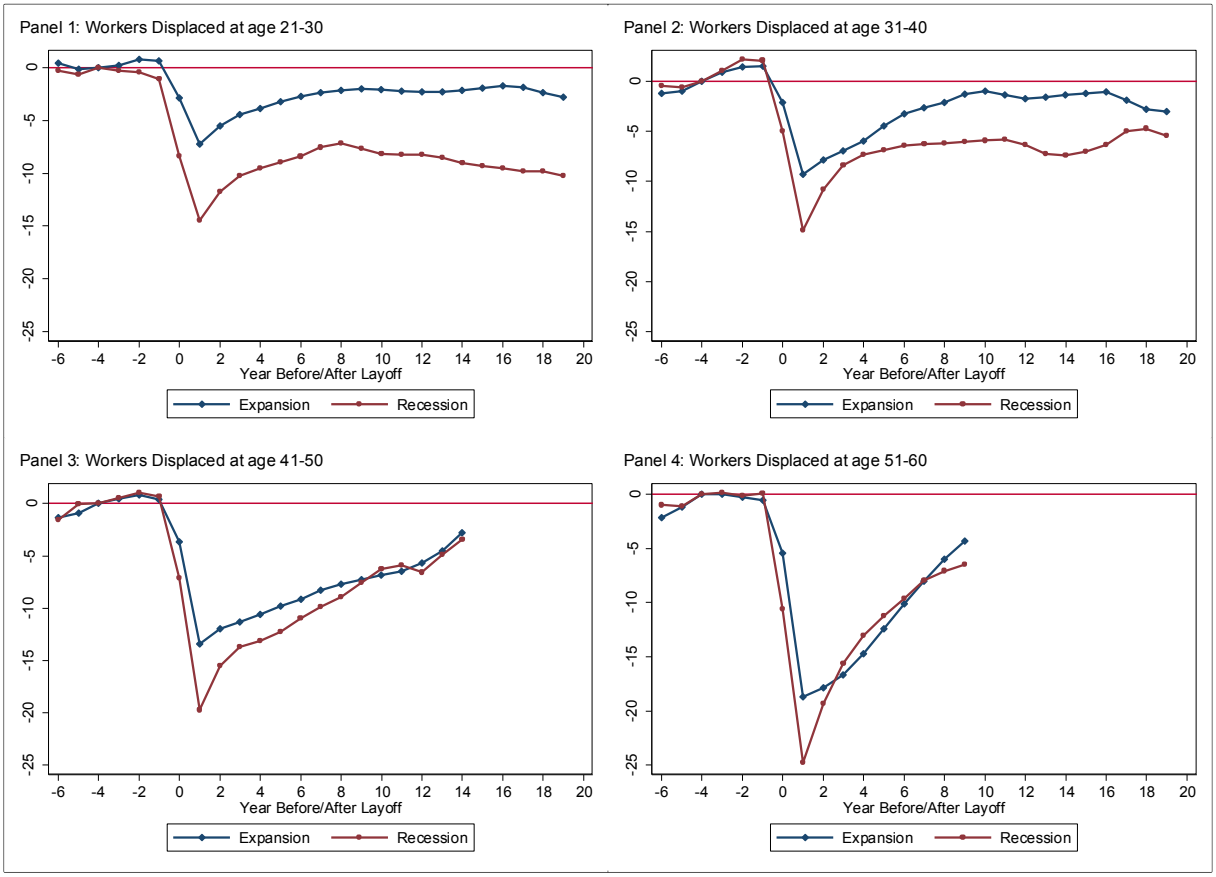
Supplemental Material for Online Appendix

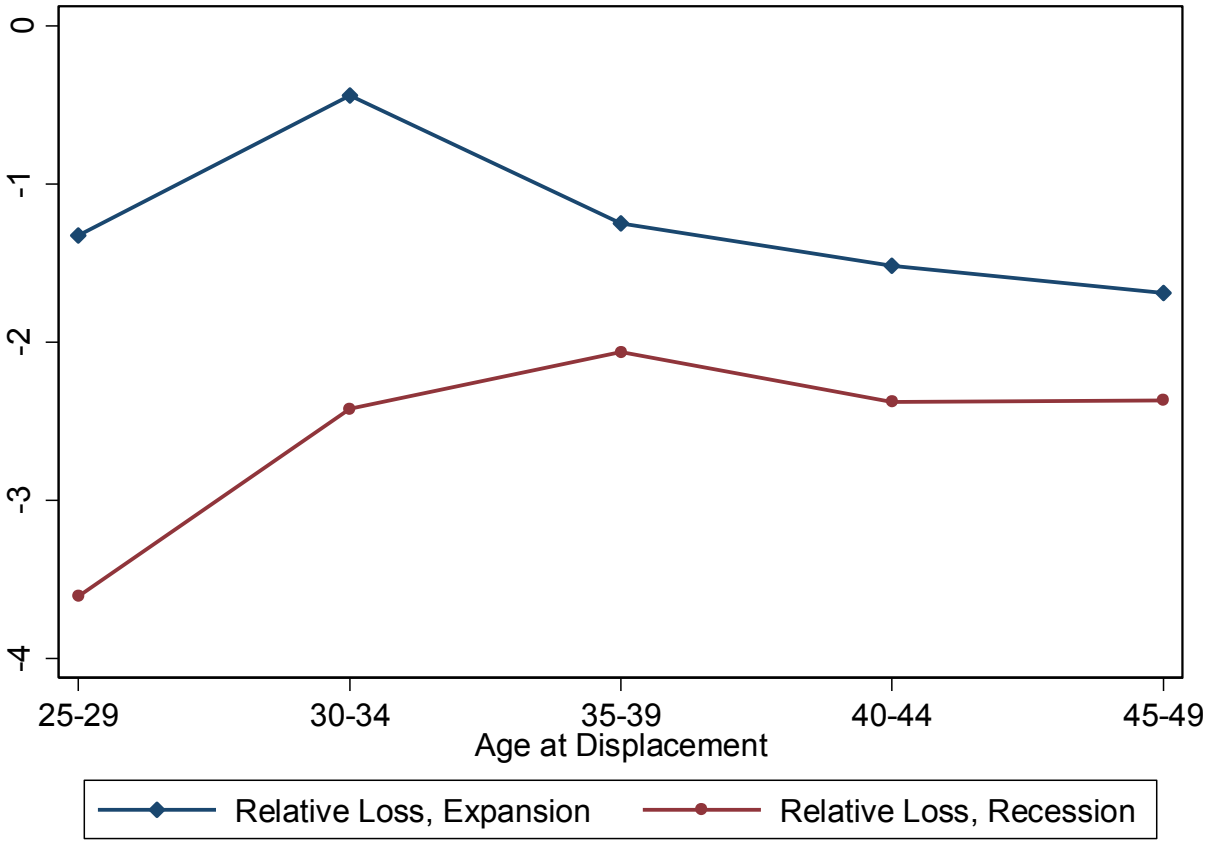
A. Additional Empirical Results

Figure A1: Annual Earnings Losses By Age at Displacement, Men with at Least 3 Years of Job Tenure Displaced in Mass-Layoff Events.



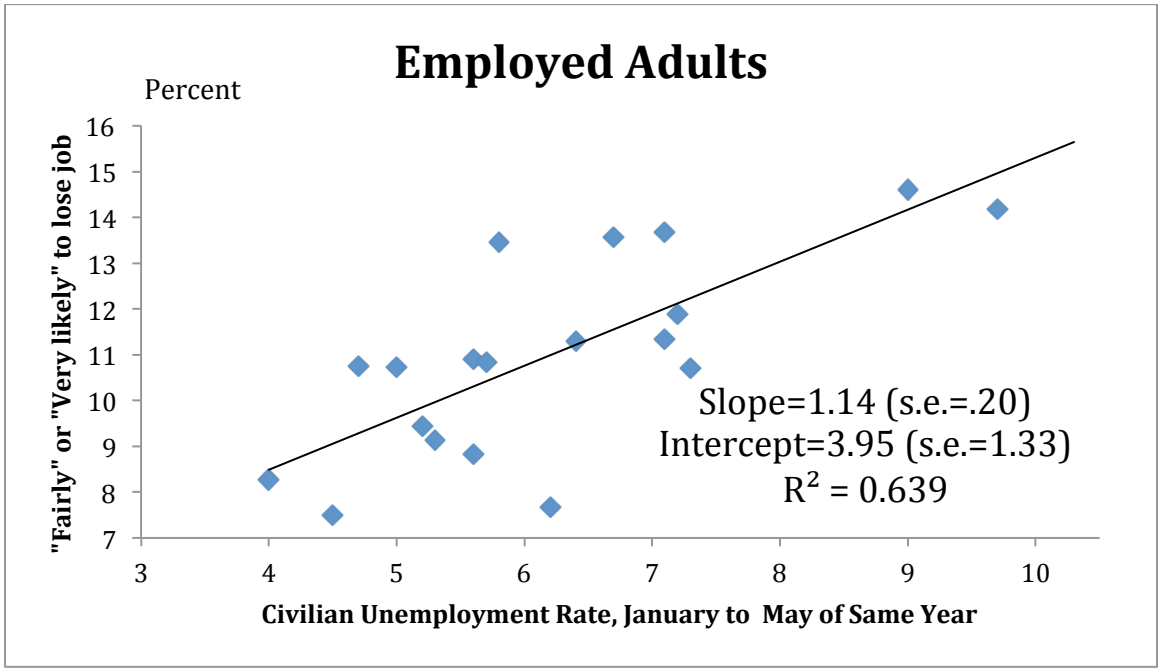
Note: See notes to Figure 5A in the main text.

Figure A3: Present Value Earnings Losses By Age at Displacement, Expressed as a Multiple of Average Annual Pre-Displacement Earnings in the Four Years Prior to Displacement, Men with at Least 3 Years of Job Tenure Displaced in Mass-Layoff Events.



Note: See notes to Tables 1 and 2 in the main text.

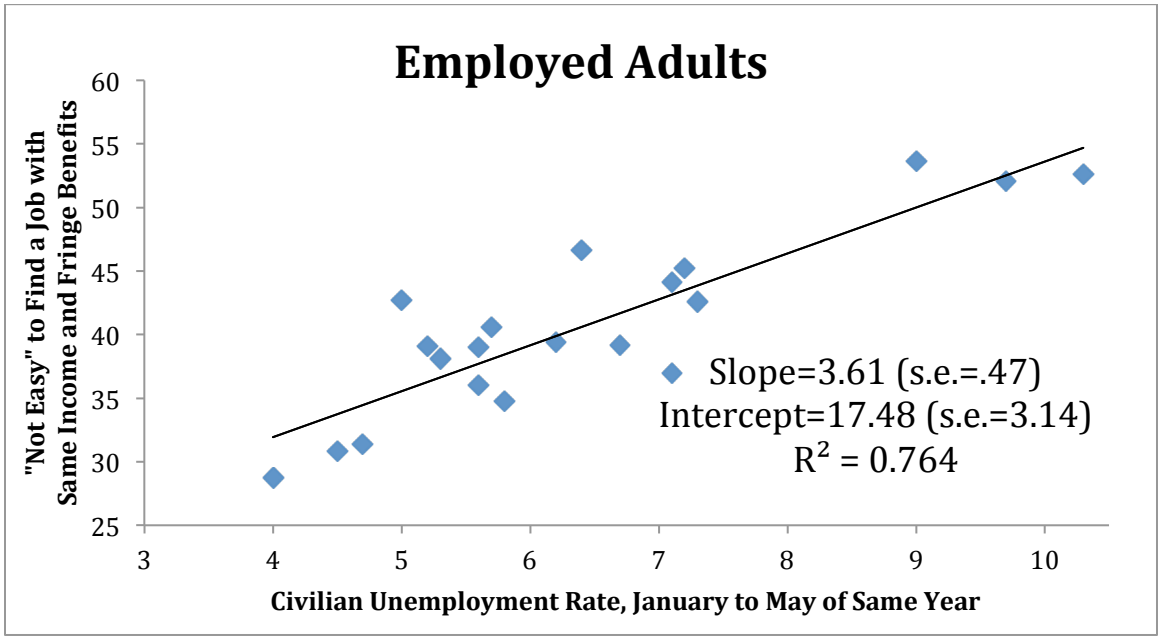
Figure A.3. Perceived Likelihood of Job Loss or Layoff in the Next 12 Months, All Available Years in the General Social Survey from 1977 to 2010



Notes:

1. See notes to Figure 8 in the main text.
2. This figure considers samples of workers 18-64 years of age, whereas Figure 8 considers samples restricted to prime age workers 25-54 years of age.

Figure A.4. Perceived Difficulty of Job Finding, All Available Years in the General Social Survey from 1977 to 2010



Notes:

1. See notes to Figure 9 in the main text.
2. This figure considers samples of workers 18-64 years of age, whereas Figure 9 considers samples restricted to prime age workers 25-54 years of age.

B. Model Simulations and Calculations

1. Model of Hall and Milgrom (Table 4)

Following Hall and Milgrom (2008), define the asset value of unemployment as

$$U_i = z + \frac{1}{1+r}\sum_{i'} \pi_{i,i'}\left[\phi(\theta_i)(W_{i'} + V_{i'}) + \left(1-\phi(\theta_i)\right)U_{i'}\right],$$

where:

- z is the income value of leisure and other nonmarket activity, inclusive of unemployment benefits
- r is the daily rate of interest
- $\phi(\theta_i)$ is the daily job-finding probability for unemployed workers in aggregate state *i,* a function of the vacancy-unemployment ratio θ
- $\pi_{i,i'}$ is the daily probability of transitioning from state *i* to state i', and
- W_i is the worker's value of the wage bargain in state *i.*

The asset value of employment, net of the value of the wage bargain, is given by

$$V_i = \frac{1}{1+r}\sum_{i'} \pi_{i,i'}\left[(1-s)V_{i'} + sU_{i'}\right],$$

where *s* is the daily rate at which workers separate from jobs.

Let w_i be the annuity value of the wage bargain for an employed worker in aggregate state *i.* This annuity value solves the system of equations,

$$W_i = w_i + \frac{1-s}{1+r}\sum_{i'} \pi_{i,i'}W_{i'}, \text{ for } i = 1,\ldots,5.$$

In matrix notation, we can write the vector of annuity values as

$$w = \left[I - \left(\frac{1-s}{1+r} \right) \Pi \right] W.$$

For Panel A in Table 4, we work directly with value functions and calculate the percentage loss in present value income due to job loss in aggregate state *i* as

$$Inc\_Loss_i = 100 \left[\frac{W_i + V_i - U_i}{W_i + V_i} \right].$$

Each entry in Panel A reports the range of these loss values across the 5 aggregate states for the indicated model and calibration.

The remaining panels rely on simulated aggregate and individual-level outcomes for each model. Panel A tells us that mean present value income losses differ very little across aggregate states for a given model and calibration. Partly for this reason, and partly for the sake of brevity, we start all simulations in the middle aggregate state.

The simulations for the income loss calculations proceed as follows:

1. Set the initial aggregate state to *i*=3, the middle state.
2. Draw 1,000 aggregate daily paths using the transition matrix Π. Let each aggregate path proceed for 5,000 days, which corresponds to 20 years at 250 days per year. The evolution of the aggregate state along a given aggregate path determines the evolution of the daily job-finding probability $\phi(\theta_i)$.
3. On each aggregate path, track realized income flows for 5,000 persons who become unemployed on day 1. After day 1, persons transition between unemployment and employment according to the probabilities $\phi(\theta_i)$ and *s*. An individual's realized income flows are given by

$$Flow_{i,t} = \begin{cases} w_{i,t}, & \text{if employed at } t \text{ in state } i; \\ z, & \text{if unemployed.} \end{cases}$$

4. At the terminal date T=5,000, assign each individual the asset value of his employment status, either $W_i + V_i$ if employed or U_i if unemployed.

5. Compute the day-1 present value of the realized income path for persons who lose jobs on day 1 as

$$\tilde{U}(\text{Income, Day 1}) = z + \sum_{t=1}^{T} \left(\frac{1}{1+r} \right)^{t-1} flow_{i,t} + \left(\frac{1}{1+r} \right)^{T} A_{i,T},$$

   where $A_{i,T}$ is the terminal asset value of the individual's employment status.

6. The foregoing simulations produce 5,000 values of $\tilde{U}(\text{Income, Day 1})$ for each aggregate path. The corresponding realized present value income losses due to job loss, expressed as a percentage of the asset value of employment, are given by

$$R\_Inc\_Loss = 100 \left[\frac{W + V - \tilde{U}(\text{Income, Day 1})}{W + V} \right],$$

   where the asset values are evaluated at the initial aggregate state i=3.

The realized income loss calculations in Table 4 report summary statistics on the individual-level values of *R_Inc_Loss* for all aggregate paths (Panel B) and subsets of aggregate paths (Panels C to D). These panels also report mean values taken over aggregate paths for the unemployment rate and the monthly job-finding rate.

The simulations for the earnings loss calculations proceed as follows: Steps 1 and 2 are the same as above. Step 3 is also the same, except that z=0. In Step 4, we set the terminal asset value to 0 to focus on 20-year earnings horizons. We modify Step 5 to obtain

$$\tilde{U}(\text{Earnings, Day 1}) = 0 + \sum_{t=1}^{T} \left(\frac{1}{1+r} \right)^{t-1} flow_{i,t}(z=0),$$

where $flow_{i,t}(z=0)$ is the realized path of earnings for the individual in question.

Along each aggregate path, we also simulate the earnings paths for 1,000 persons who remain employed on day 1. Following the same approach as for day-1 job losers, we calculate the present value of their earnings over a 20-year horizon,

$$\tilde{E}(\text{Earnings, Day 1}) = w_i + \sum_{t=1}^{T} \left(\frac{1}{1+r} \right)^{t-1} flow_{i,t}(z=0),$$

where, again, $flow_{i,t}(z=0)$ is the realized earnings path for the individual in question. We then compute the mean over employed persons on Day 1 to obtain $\bar{E}(\text{Earnings, Day 1})$ for each aggregate path. Thus, we have one value of $\bar{E}(\text{Earnings, Day 1})$ and 5,000 values of $\tilde{U}(\text{Earnings, Day 1})$ for each aggregate path.

Lastly, we compute a realized present value earnings loss measure for each individual in a manner analogous to step 6 above, obtaining

$$R\_Earn\_Loss = 100 \left[\frac{\bar{E}(\text{Earnings, Day 1}) - \tilde{U}(\text{Earnings, Day 1})}{\bar{E}(\text{Earnings, Day 1})} \right].$$

Table 4 reports statistics for the distribution of individual-level values of *R_Earn_Loss* for all aggregate paths (Panel B) and subsets of aggregate paths (Panels C and D).

2. Model of Burgess and Turon (Table 5)

As before, we calculate present value income losses due to job loss as a percent of employment asset values. We also calculate present value earnings losses over a 20-year horizon, expressed as a percent of present value earnings over 20 years.

Before describing the simulation details, it will be helpful to define the objects we calculate. Let $f^p(\varepsilon)$ denote the density function of filled jobs in aggregate productivity state *p,* where ε is the idiosyncratic productivity value, and let F^p be the corresponding distribution function. Following Burgess and Turon, we ignore the short-term dynamics of $f^p(\varepsilon)$ for a given aggregate productivity state and, in solving the model, calculate the "stationary" distribution of filled jobs that prevails when aggregate productivity remains constant for a period of time. Employers and workers know the stochastic processes governing aggregate and idiosyncratic shocks and how the distribution F^p shifts in response to aggregate productivity. They account for the stochastic elements of the environment when making choices about job creation, recruitment, search and wages. Burgess and Turon show that wages can be expressed as a function of *p* and ε.

Let $E^p(\varepsilon;z,T)$ denote the present value of expected future income or earnings flows for a worker currently employed in a job with idiosyncratic productivity ε when the aggregate state is *p.* Evaluating $E^p(\varepsilon;z,T)$ at z = income value of leisure and $T=\infty$ yields the expected present value of income. Evaluating at z=0 and T=80 quarters yields the expected present value of earnings over a 20-year horizon. Similarly, $U^p(z,T)$ is the present value of expected future income or earnings for an unemployed worker in aggregate state *p.*

Panel A in Table 5 reports present value loss measures in the Good, Middle and Bad aggregate states. Specifically,

$$\text{Panel A:} \quad \int \left\{ \left[E^p(\varepsilon;z,T) - U^p(z,T) \right] / E^p(\varepsilon;z,T) \right\} f^p(\varepsilon) d\varepsilon,$$

where *p* indexes the aggregate state, and we evaluate *z* and *T* to recover the present value loss of income or earnings, as discussed above. For the income loss calculations, the

relevant $E^p(\varepsilon)$ and U^p objects are value functions. For the earnings loss calculations, we construct the relevant $E^p(\varepsilon)$ and U^p objects by simulating aggregate and individual-level earnings paths as described below. The Panel A calculation can be interpreted as the present value loss due to job loss relative to the worker's pre-displacement situation (own past) and relative to the situation for workers who remain employed in a job with the same value of ε as the pre-displacement job (control group). These two benchmarks – own past and control group – yield the same loss calculation in this case.

Rows C through N in Table 5 report present value income and earnings losses for workers who lose jobs in the wake of a negative shock to aggregate productivity. Job destruction and job loss now arise because of (sufficiently) negative idiosyncratic productivity shocks, as in Panel A, and because the negative aggregate shock generates a burst of job destruction at the lower end of the match productivity distribution. We describe the present value calculations for the Good(G) to Middle(M) transition; i.e., in the wake of a shock that shifts aggregate productivity from Good to Middle. Analogous calculations hold for the Good→Bad and Middle→Bad transitions. The present value loss expressions for the Good→Middle transition are given by

Panel C and I: $\int \left\{ \left[E^G(\varepsilon;z,T) - U^M(z,T) \right] / E^G(\varepsilon;z,T) \right\} f^G(\varepsilon) d\varepsilon,$

Panel D and J: $\left[F^G\left(R(M)\right) \right]^{-1} \int_{R(G)}^{R(M)} \left\{ \left[E^G(\varepsilon;z,T) - U^M(z,T) \right] / E^G(\varepsilon;z,T) \right\} f^G(\varepsilon) d\varepsilon,$ and

Panel F and L: $\int \left\{ \left[E^M(\varepsilon;z,T) - U^M(z,T) \right] / E^M(\varepsilon;z,T) \right\} f^M(\varepsilon) d\varepsilon,$

where $R(p)$ is the job destruction threshold in aggregate productivity state *p*.

The expression for Panels C and I gives the mean PV loss in the Middle aggregate state relative to own past PV positions in the Good state for workers who lose jobs due to idiosyncratic shocks. The expression for Panels D and J gives the mean PV loss for workers who become unemployed in the burst of job destruction triggered by the aggregate productivity transition from Good to Middle. This negative aggregate shock destroys all jobs with $\varepsilon \in [R(G), R(M)]$. Panels D and J express the PV loss relative to the worker's own past situation in the Good aggregate state. The expressions for Panels F and L give the mean PV loss for job-losing workers relative to control groups of workers who remain employed in the new Middle state. The loss expression in the Good→Middle transition for Panels F and L is identical to the loss expression in the Middle state for Panel A.[1] Because all workers with $\varepsilon \in [R(G), R(M)]$ lose jobs when the economy transitions from Good to Middle, Panels G and M report zero losses for these workers relative to controls. Finally, Panels E, H, K and N report inflow-weighted averages of PV earnings losses due to the two types of job destruction shocks – negative aggregate shocks and sufficiently negative idiosyncratic shocks. At the quarterly frequency and chosen calibration, idiosyncratic shocks drive most of the job-loss events.

The simulations for the earnings loss calculations proceed as follows:

1. Set the initial aggregate state to Good, Middle or Bad.
2. Draw 2,000 aggregate paths using the transition matrix for *p.* Let each aggregate path proceed for 80 quarters (20 years). Calculate the implied paths for the distribution function $F^p(\varepsilon)$, wage function $w(p,\varepsilon)$, and job-finding probability.

[1] We integrate with respect to $f^M(\varepsilon)$ in Panels F and L rather than $f^G(\varepsilon)$, but that matters little for the results.

3. Partition $[-\sigma,\sigma]$, the range of possible productivity values, into 200 subintervals of equal length. In the first quarter of each aggregate path, choose 1,000 unemployed persons and 100 employed persons per subinterval in the support of $F^p(\varepsilon)$. The support of $F^p(\varepsilon)$ covers at least 150 subintervals for each aggregate state.
4. Follow the initially employed and initially unemployed persons forward in time for the 80-quarter duration of each aggregate path. Track each person's realized earnings path given optimal search and allowing for the stochastic arrival of job opportunities when searching and idiosyncratic productivity shocks when employed. Track and store each person's realized earnings path, where earnings equal $w(p,\varepsilon)$ when employed and 0 when unemployed.
5. Consider all simulated individual outcomes along a given aggregate simulation path. Calculate the realized PV of earnings for each initially unemployed and each initially employed person living on that aggregate path. Compute the mean PV over initially unemployed persons to obtain $U^p(0,80)$ and the mean by subinterval to obtain $E^p(\varepsilon;0,80)$. Plug these objects into the integral expressions above to obtain the desired PV earnings loss expression for the given aggregate path.
6. Repeat Step 5 for all aggregate paths and compute the simple mean of the PV loss expressions to obtain the results reported in Table 5.

As remarked in the main text, the calibration used for Table 5 departs from that of Burgess and Turon to obtain job-finding rates in line with U.S. experience in recent decades. For comparison purposes, Table B1 below reports results for a version of Table 5 based on the calibration of Burgess and Turon. As indicated by the entries in Panel B, the

Burgess-Turon calibration involves much lower job-finding rates than the ones considered in Table 5. As a result, the PV income and earnings losses associated with job loss are substantially larger in the Burgess-Turon calibration.

Section 5.C in the main text also reports the average difference between the pre-displacement wage and the wage on the first post-displacement job for persons who lose jobs due to idiosyncratic shocks. We calculate this statistic as follows. For initially unemployed persons in Step 4 above, store the wage in their first post-displacement job. Compute the mean of this wage over all aggregate and individual-level paths, and call it $\overline{w}_1^p$. The wage-change statistic we report in the text is $1-\int\left[\overline{w}_1^p / w(p,\varepsilon)\right]f^p(\varepsilon)d\varepsilon$.

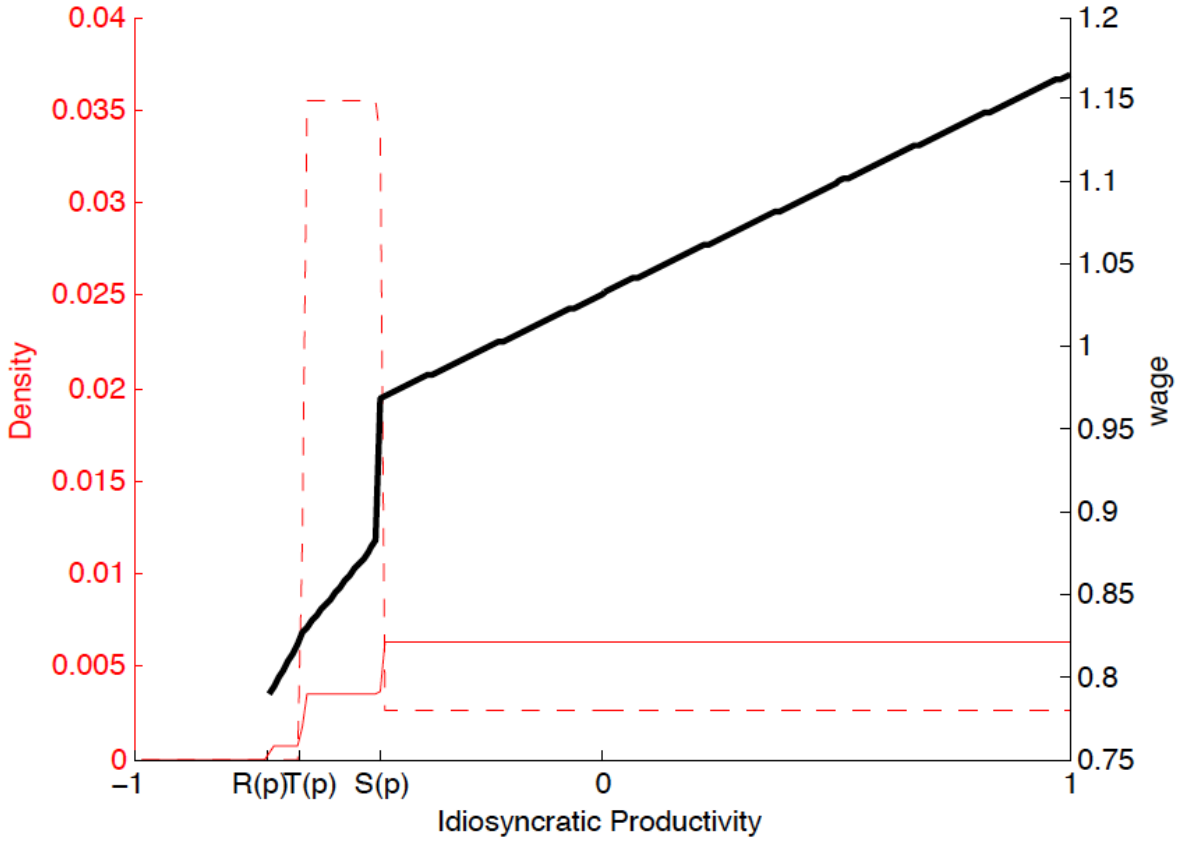
Figure B1 shows the wage function, the density of all filled jobs, and the density of first jobs for workers who exit unemployment after losing their jobs in the model of Burgess and Turon. The figure is constructed for the Good aggregate state using the same calibration as Table 5 in the main text. Wages in filled jobs vary from about 0.79 to 1.16. As seen by a comparison between the dashed and solid red lines, the distribution of filled jobs for recent job losers is more concentrated at the low end of the wage distribution than the distribution of all filled jobs. This comparison illustrates the job ladder in the model: Following a job loss event, newly reemployed workers tend to start near the bottom of the job ladder and to move up the ladder over time through search on the job.

Table B1. Present Value Losses Due to Job Loss in the Model of Burgess and Turon with their Calibration

Present Value Losses, Percent of Employment Asset Value for Income Losses and Percent of Present Value Earnings Over a 20-Year Horizon for Earnings Losses				
	Aggregate State	*Good*	*Middle*	*Bad*
A. Mean PV Loss Due to Idiosyncratic Shocks that Result in Job Loss	***Income***	0.62	0.58	0.53
	Earnings	4.38	4.68	4.98
B. Quarterly (Monthly) Job Finding Rate		39.4 (15.4)	35.3 (13.5)	31.5 (11.9)
		Present Value Income Losses		
	Aggregate State Transition	*Good→ Middle*	*Middle→ Bad*	*Good→ Bad*
C. Mean Loss Due to Idiosyncratic Shocks that Result in Job Loss, Comparison to Own Past		0.84	0.77	1.04
D. Mean Loss Due to Aggregate Shock that Results in Job Loss, Comparison to Own Past		0.23	0.21	0.43
E. Inflow-Weighted Average of Rows C and D		0.78	0.72	0.94
F. Mean Loss Due to Idiosyncratic Shocks that Result in Job Loss, Comparison to Control Group		0.58	0.53	0.53
G. Mean Loss Due to Aggregate Shock that Results in Job Loss, Comparison to Control Group		0	0	0
H. Inflow-Weighted Average of Rows F and G		0.52	0.48	0.44
		Present Value Earnings Losses		
I. Mean Loss Due to Idiosyncratic Shocks that Result in Job Loss, Comparison to Own Past		5.44	5.80	6.09
J. Mean Loss Due to Aggregate Shock that Results in Job Loss, Comparison to Own Past		4.48	5.10	5.23
K. Inflow-Weighted Average of Rows I and J		5.34	5.73	5.95
L. Mean Loss Due to Idiosyncratic Shocks that Result in Job Loss, Comparison to Control Group		4.68	4.98	4.98
M. Mean Loss Due to Aggregate Shock that Results in Job Loss, Comparison to Control Group		0	0	0
N. Inflow-Weighted Average of Rows L and M		4.21	4.51	4.14
Average Relative Wage Loss Due to Idiosyncratic Shocks That Result in Job Loss		5.17	4.00	4.58

Notes: The calculations in this table follow those of Table 5 in the main text. Here, we use the calibration of Burgess and Turon, which involves substantially smaller job-finding rates.

Figure B1. Wage Function and Density of Filled Jobs in the Model of Burgess and Turon for the Table 5 Calibration



Notes:

1. The bold black line shows the wage as a function of the idiosyncratic productivity value, ε, in the Good aggregate state.
2. The solid red line shows the density function of filled jobs in the Good aggregate state.
3. The dashed line shows the density function of first post-displacement jobs for workers leaving unemployment after losing their former jobs.