# Earnings Losses of Displaced Workers in Connecticut

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# EARNINGS LOSSES OF DISPLACED WORKERS IN CONNECTICUT


## EXECUTIVE SUMMARY

This study examines the experiences of prime age workers who have lived and worked in Connecticut for six continuous years and lose their jobs due to a reduction in employment of 30 percent or more at their place of work. Their experiences are compared to a group of workers who also initially are observed working for the same employer for six continuous years but who retain their original jobs.

Key findings from the study include:

- Workers who lose jobs at firms where there are mass layoffs and are re-employed within a year have sustained earnings losses six years later of 13 to 15%.

- The corresponding quarterly reductions in earnings for the average re-employed worker in the study six years after the job loss are estimated $1,699 to $1,923.

- In a sample of all laid-off workers, whether re-employed or not, earnings losses six years after job loss are estimated to be as large as 33%.

- Six years following a mass layoff, older workers have sustained earnings losses more than 3 times those of the youngest.

- The largest earnings losses occur among the long-term workers displaced due to mass layoff in manufacturing and business and professional services.

- Long-term workers displaced from one industry that find new employment in a different sector of the economy have systematically larger sustained earnings losses. This is presumably due to many of the skills built up with their former employer not being as relevant for their new position.

**ABSTRACT**

Most would agree that workers who have had steady employment histories and been active in the labor market should not be left to fend for themselves when they lose jobs due to events beyond their control such as plant closures or large scale layoffs. In this paper, longitudinal administrative data on employees and firms collected by the State Department of Labor (DOL) in Connecticut from 1993 through 2004 are used to calculate earnings losses of workers affected by mass layoffs. Estimated earnings reductions are more than 30% at the time of job loss for those who are later re-employed. Six years later, the estimated earnings losses for those workers range from 13 to 15%. Estimated earnings losses are largest for men, older workers, and those losing jobs in the manufacturing sector and business and professional services. The paper also demonstrates that laid off workers who have difficulty in finding new employment in the same industry where they used to work have larger sustained earnings losses than others.

## I. INTRODUCTION

Gains from free trade materialize in the form of lower prices and technological innovation. A natural consequence of economic competition is the deterioration and failure of uncompetitive firms. Typically, those firm level failures impact individual workers due to events beyond their control. Most would agree that, as our society reaps the benefits of free and open trade, individual workers should not be left to bear the costs of that progress. A highly relevant question in this context is: what are the economic consequences for individuals? This paper examines this question for workers in the State of Connecticut by examining the impact of large-scale layoffs on the subsequent earnings of workers who lose their jobs in that context.

Recent literature reviews conclude that job displacement does result in sustained earnings losses (Fallick 1996 and Kletzer 1998). Estimates of the size of those losses have varied with the type of data used and the industry within which displacement occurs (Carrington and Zaman 1994). The largest estimated losses were obtained using administrative data similar to those used in this study from Pennsylvania during the 1970s and 80s (Jacobson, Lalonde, and Sullivan 1993a). Their data covered a period of high unemployment in a heavily industrialized state characterized by disproportionate job losses in manufacturing. Thus, the ability to generalize those results to more favorable economic times and states with a greater reliance on service sector employment such as Connecticut has been questioned. To address these issues, administrative data are again assembled here to similarly examine the impact of job displacement on earnings losses of workers in the State of Connecticut from 1993 to 2004.

The results presented here for Connecticut differ from those found in Jacobson, Lalonde, and Sullivan (JLS) using data for Pennsylvania. In the period immediately following job loss, regardless of the technique employed, earnings reductions for workers displaced through mass layoff range from 32 to 33%. JLS reported immediate losses of more than 40%. Six years later using the same estimators as JLS, earnings reductions in Connecticut range from 13 to 15%. They report sustained losses of 25%. The smaller long-term impacts in Connecticut demonstrate that under more ordinary economic times, estimated losses from administrative data lie within the range observed using panel surveys. This finding resolves a longstanding conflict among the results of high quality panel studies that have used differing data sources to study earnings reductions following job loss.[1]

## II. PRIOR LITERATURE

The empirical literature on the earnings impact of job displacement is well established.[2] While there is consensus that displacement leads to sustained earnings losses, the magnitude of those estimates vary systematically with the data source largely due to the availability of a comparison group for use in the analysis (Madden 1998).

The well-known Displaced Workers Supplements (DWS) to the Current Population Survey (CPS) are retrospective and only ask respondents about pre-displacement employment and subsequent work histories if individuals report losing a job due to plant closure or layoff. Thus, the data do not contain a readily available comparison group. Estimates using it misstate losses by the amount of earnings growth the displaced workers would have experienced had they remained employed (Kletzer 1998). Estimates based on the DWS not employing a comparison group commonly report earnings losses around 12 or 13% the year of the survey (Carrington and Zaman 1994, Farber 1997, Kletzer 1998).[3] Madden (1998, p.101) reports larger losses using the DWS employing a comparison group of respondents matched across rotation groups in the CPS.

Longitudinal data more readily address the need for a comparison group; workers who meet definitions of being at risk of displacement can be selected and followed over time; and as some of them lose their jobs, their experiences can be contrasted with workers who remained employed. One well-known longitudinal survey, the Panel Study of Income Dynamics, has regularly been used (Ruhm 1991 and Stevens 1997) in the literature.[4] Using these data Ruhm (1991) finds that earnings declined by 16 percent in the initial year following a job loss and remained at 14 percent four years later. Stevens (1997) reports a drop in earnings at the time of displacement of 30 percent but by the sixth year the deficit is less than 10 percent.

[1] Kornfield and Bloom (1999) similarly conclude that UI data and surveys yield similar program impacts in the evaluation of manpower training programs.

[2] For a full discussion see the literature reviews by Fallick (1996) and Kletzer (1998).

[3] When estimates are calculated using the Connecticut data without the comparison group no earnings losses are observed for the mass layoff sample at the fourth year after separation.

[4] Similarly, NLSY data have been used to examine displacement among younger workers (Fairlie and Kletzer 2003). HRS data have been used in studies of older workers (Chan and Stevens 1999). Experiences of workers in other countries have also been examined using panel data such as the GSOEP (Couch 2001).

The only published study of earnings losses following job displacement using administrative data similar to those used in this study that appear to be representative of most workers in a state is the research of Jacobson, LaLonde, and Sullivan (1993a) on Pennsylvania.[5] They consider the impact of large-scale layoffs on long tenure workers. The administrative data used in their analysis are drawn from wage records states keep for the purpose of calculating unemployment insurance (UI) benefits if a worker loses employment. They match these individual-level records to data from the Quarterly Census of Employment and Wages (QCEW), which are initially collected for the purpose of calculating employer UI tax liability and are enhanced for use in producing statistical reports. One advantage of these administrative records is that the wage data are from firm payrolls so they are more reliable than survey measures requiring individual recall.

Jacobson, LaLonde, and Sullivan (1993a) report earnings losses of more than 40 percent the year of displacement. Six years after the original job is lost, earnings are found to still be 25 percent below their pre-displacement level. These calculations apply to those workers who are observed re-employed.[6]

The Jacobson, LaLonde, and Sullivan study is important. It introduced the use of program evaluation techniques into the job displacement literature. More importantly it used actual payroll data and finds the largest estimates of earnings losses associated with displacement in the literature. While the authors assert their findings are due to the superior quality of the data used in the study, reasonable doubts about the scale of the estimates exist because of location and timing.

The late 1970s and early 1980s were characterized by changes in industrial structure in the United States due to mine exhaustion, high energy prices, and resulting import penetration. Pennsylvania was heavily impacted by this restructuring. Moreover, workers in the study were continuously employed through 1979 and experienced job separations beginning in 1980. The period from January to July of 1980 was the first of the twin recessions, the second occurring from July 1981 to November 1982. Thus, the first three years of the period during which workers' earnings could potentially recover were characterized by recession.

Statistics regarding the Pennsylvania economy during the JLS study confirm that the displacements came at a difficult time. The average rate of unemployment in Pennsylvania in the time period covered by their sample was 8.3%. In the years when displacements would

[5] Schoeni and Dardia (2003) examine displaced workers in defense related industries in California and draw similar conclusions to the JLS study. Lengermann and Vilhuber (2002) consider the pattern of individual departures from firms that subsequently have mass layoffs using data for Maryland; however, they do not consider the pattern of losses following displacement. Abowd, McKinney, and Vilhuber (2005) also consider the relationship between worker attributes, mass layoffs, and firm closure but do not consider patterns of earnings loss afterwards. Stevens, Crosslin, and Lane (1994) examine trade sensitive employment sectors in three states. They consider a representative sample of UI claimants in their analysis.

[6] JLS have gone on to study the impact of retraining on long-tenure workers who lose their jobs in the state of Washington (Jacobson, LaLonde, and Sullivan 2005a, 2005b). They compare individuals who filed unemployment claims and were retrained in community colleges to those who were not.

occur and workers would be searching for new jobs, the average unemployment rate was 9.4 and, in many months, exceeded 12%.[7] Thus, the magnitudes of their estimated earnings losses as well as weakness in the pattern of recovery could have been driven by the unusually poor economic conditions at that time.

It is also worth noting that the relative increase in employment in the service sector throughout the United States was accelerated by the restructuring that occurred in the 1980s. Prior studies have found that earnings losses in services are much smaller than in manufacturing (Carrington and Zaman 1994). Thus, the relative composition of employment may also have a large influence on estimated earnings losses. This implies that a more contemporary examination of similar data could result in smaller estimates.

To answer the question of whether the results from JLS for Pennsylvania are an artifact of unique circumstances at that time, a similar analysis is conducted here for the State of Connecticut. In conducting the study, every effort was made to construct a data set similar to that used by JLS and to use the same estimation methodologies.[8] The data used in the study are more recent, covering the period from 1993 through 2004. Workers in the sample are screened to be continuously employed for the first six years of the sample and can be separated from employment beginning in 1999.

The 2001 recession occurred from March to November. Thus, the first two recovery years for the earnings of job separators are prior to the peak of the 1990s business cycle. Despite the 2001 recession, comparisons of conditions across the two states at important points in the analysis show that Connecticut had a more robust economy than Pennsylvania did at the time of the JLS study.

Compared to the average rate of unemployment in Pennsylvania from 1974 to 1985 (8.3), Connecticut's (4.5) was about half that level in the period from 1993 to 2004. In the six years before job separations are examined, the average unemployment rate in PA was 7.2 versus 5.1 in CT. In the important period where job separations are examined, the unemployment rate in CT averaged 3.8 percent compared with 9.4 in PA. Peak unemployment during the period where workers would be recovering from job loss was 12.9 percent in PA versus 5.7 in CT. The economic conditions at any important juncture of the sample one might care to examine were more favorable in CT than PA. For those who have questioned whether the results of JLS are simply due to the difficult economic conditions at the time, the relatively favorable conditions in CT during the period of this study provide the type of variation one would like to see to critically examine their results.

[7] These numbers are calculated using seasonally adjusted monthly rates from 1974 through 1985 available at: www.paworkstats.state.pa.us.

[8] The paper drew both from JLS (1993) as well as their monograph JLS (1993b) in producing a data set with a similar structure.

## III. ESTIMATION METHODOLOGY

Estimates of earnings loss are calculated using techniques described in Jacobson, LaLonde and Sullivan (1993a). The estimators used in the JLS study are well-known by researchers in fields that employ program evaluation methods. The first estimation equation makes use of the longitudinal administrative panel data in an individual fixed-effects model as follows.

$$Y_{it} = \alpha_i + \gamma_t + \sum_{k \geq -6} D_{is}^k \delta_k + \varepsilon_{it}(1) \quad \textbf{(1.)}$$

$Y_{it}$ equals earnings of worker $i$ at time $t$ and $D_{is}$ is a dummy variable indicating if a worker is displaced at date $s$. Here, the parameters, $\alpha_i$, represent the individual fixed-effects. The $\gamma_t$ variables represent a set of quarterly dummy variables. $X$ is a matrix of demographic and firm characteristics. $k$ indexes a set of dummy variables, D, that begin 20 quarters prior to separation. The parameters $\delta_k$ capture the impact of displacement before, during, and after the event. is a stochastic error term.

The second model adds an individual time trend to equation (1.). The resulting equation is often referred to as a random growth model. The second estimation equation is

$$Y_{it} = \alpha_i + \gamma_t + w_i t + X_{it}\beta + \sum_{k \geq -20} D_{it}^k \delta_k + \varepsilon_{it} \quad \textbf{(2.)}$$

The parameters, $w_i$, capture individual specific time trends in earnings. When estimated without the individual and firm characteristics ($X$), the individual parameters, $\delta_k$, from equations (1.) and (2.) are plotted to show the path of earnings differences over time. In the text, equation (1.) is called a fixed-effects estimator and (2.) a time trend estimator.

For each model, JLS provide an alternative formulation in which a spline that captures the earnings impact of job loss is estimated relative to the individual period categorical variables. The elements of the spline are interacted with analysis variables primarily to demonstrate how the earnings of specific demographic or industry groups track relative to others. For the three years prior to job loss, they estimate a separate slope parameter; for all of the quarters after separation, a parameter which captures the average loss of earnings; and from the 7th quarter through the end of the sample, a separate slope.[9] They refer to these as dip, drop, and recovery parameters. Similar estimates are conducted here.

## IV. DATA

The data used in this study are drawn from state administrative files from the Connecticut Department of Labor. The unemployment insurance (UI) wage file contains a code

[9] The reformulated equations are presented on page 695 of JLS (1993a).

that identifies employers of each individual. Those codes are used to match the wage data to firm information from the Quarterly Census of Employment and Wages (QCEW). Wages are converted to real 2000 values using the CPI-U.[10] Further, the wage files contain social security numbers, which are used to link them to CT Department of Motor Vehicle records in order to obtain demographic information.[11] The resulting file contains information on 63 percent of all workers in CT. More information on this matching process is available in Appendix Sections A through E. Detailed analyses reveal that the data are highly representative of workers in the State. A brief discussion of the demographic matching and quality of the analysis file is provided here.

In July of 2002, the Connecticut DMV began requiring that social security numbers be obtained and/or verified for license applications and renewals. Normally, licenses expire on a six-year clock. One would expect that a process of systematic checking would result in a fairly random selection of license holders since most obtain them near their 16th birthday. Further, if workers are proportionately distributed among license holders, matches to the wage file should yield a representative sample of workers.

For this analysis, a file containing social security numbers for 70.1 percent of licenses is matched to the UI wage records. The only workers systematically excluded are those who commute to Connecticut for work; thus, the matches and the study are representative of the resident worker population.[12] In 2004:1, the matching resulted in coverage of 63 percent of all wage records. This is a match rate of 90 percent (63/70.1).

The original JLS study required that individuals report some positive wages each year.[13] Thus, whether matches are made at the beginning or end of the sample period, the same group of individuals will be selected. If the screening criteria that a person reports positive wages in 1993:1 and that they have some positive earnings every year are applied to the CT data, 1,009,876 individuals pass through these filters. Matching them to DMV files yields 615,973 persons or coverage of 60.99%. To be clear, there is 63 percent coverage of all

[10] Because the data were top coded at $100,000 1987 dollars in the original JLS study (1993b, p. 57, footnote 2), after adjusting for inflation and rounding up to the nearest $5,000, they are similarly top coded here at the censoring value of $155,000. Removing the top code results in earnings losses that are typically 4 to 6 percent larger than reported in the paper although this result and associated volatility are due to a relatively small number of observations.

[11] These data are highly confidential, and all calculations were performed by DOL staff within the Office of Research.

[12] The JLS data would have had matches for these individuals, as they used Social Security records to obtain demographic information. Data from the 2000 Census indicates this is 3.5% of workers in CT. The matches for both CT and PA also exclude workers who commute to work out of the State. Again, based on Census data, this is 3.5% of CT workers.

[13] When workers do not meet the earnings criteria, they are dropped from the study. 2,751 observations are lost from the mass layoff sample because of a lapse of a complete year in reporting earnings following job separation. This represents an attrition rate of 14.8 percent. Estimates that include those observations as zeros result in earnings losses as much as 18 percentage points larger than those reported in the text. The largest estimated impact is an earnings loss of 33 percent six years after separation in the mass layoff sample. JLS report that they similarly lose 25 percent of their sample observations for this reason (p. 689) and that including them results in estimated losses which are 15 percentage points larger than the 25 percent sustained loss after six years found in their primary analysis. It is likely that the attrition rates are somewhat understated here since demographic information is obtained at the end of the study period.

records in the UI wage file. The 60.99% coverage reported here is relevant to records once the sample selection criteria of this study have been imposed. Again, given the expectation of proportional matching to the 70.1% DMV file, the match rate is 87% (60.99/70.1). The match rates across the DMV records and the UI wage file for CT compare well with information provided in Lengermann and Vilhuber (2002, pp. 5-6) who report that the match rate between the Maryland UI wage file and social security records is 89%.[14]

In addition to the high match rates, additional tabulations show a close correspondence between the distributions of wages for matched records relative to the entire UI file. This is true even though commuters who work in the State that cannot be matched are known to have higher earnings. For example, the difference in median quarterly earnings for matched individuals and the entire wage file in 1993:1 is only $265. The average difference is $390. Examining the group of individuals who meet the criteria to be included in this study and for whom matches are obtained, median quarterly earnings are $359 lower and average earnings are $405 less than in the entire UI file.[15]

In examining distributions of industry sector employment in 1993:1 for the entire wage file relative to all individuals for whom DMV information could be obtained, they are quite similar. Differences in the percentage distribution of employment across two-digit sectors are less than 2-tenths of a percentage point for 14 of the 21 industry groups examined. The largest deviation occurs for manufacturing, where there is a 1-percentage point understatement (6 percent understatement) of employment in that sector.[16] When matched observations are screened to select those meeting key sample selection criteria of this study, again, 14 of the 21 sectors have employment distributions that differ by 2-tenths of a percentage point or less. The understatement of manufacturing employment is 7 percent.

Just as matches to social security records do not give researchers perfect information, neither does matching to DMV records.[17] Nonetheless, examination of the distribution of wages and employment among matched individuals and the entire UI file for CT does not reveal differences that indicate troubling levels of selection in the resulting samples. Combined with the primary study criterion that individuals report some earnings each year of the analysis, the use of DMV records and the UI wage file provide a valid basis to study the topic of interest in this paper. Researchers may wish to explore this combination in other contexts.

Employment separations in the study are identified by tracking changes in employer codes. The validity of the coding over time is important. Internal files from the Connecticut

[14] Similar information on the match rate for the Pennsylvania UI data to social security files is not presented in their 1993b monograph of JLS.

[15] Additional information on percentiles of these distributions is contained in Appendix Section E.

[16] Percent distributions of employment by sector are contained in Appendix Section E.

[17] Matching wage data to demographic information in social security record is problematic because the social security records do not contain information on state and federal workers. The omitted workers are around 10 percent of all employees.

Department of Labor regarding the reason for the change in coding were used to determine whether the lapsing of a particular employer identification number was due to plant closure or not. The Connecticut Department of Labor keeps information on these changes in order to correctly calculate UI risk ratings.[18]

In the simplest case, an individual has a sole employer in a particular quarter and is observed working for a different firm the following period. This is considered a job separation in this study if it occurs after 1998. If the individual's change in employment occurred within a year (before or after) of a drop in the firm's employment to 30 percent or more below its maximum level prior to 1999, it is considered a displacement due to mass layoff.[19] When calculating these employment changes, the figures are volatile for small employers. For this reason, those working for employers with less than 50 employees are removed from the sample.

There are individuals in the sample with multiple employers and the changes between them do not always progress in a smooth manner. If there is a transition from one employer to another, the change is assumed to occur in the last quarter in which the code of the prior job is observed. The separation is coded at that time and the determination is made of whether this change was associated with a mass layoff event. Appendix Sections A through E contain more information on data construction.

### V. DESCRIPTIVE INFORMATION AND PARAMETER ESTIMATES

Table 1 contains descriptive information on the sample in 1998, the last year before job separations. 95,126 individuals meet screening criteria for the sample. Of those, 60,670 (64%) were continuously employed. 34,456 (36%) separated from jobs after 1998. 15,855 (17%) were displaced in mass layoffs.

The average continuously employed worker earned $14,577 per quarter in 1998; the average separator not in the mass layoff sample earned $13,174; and the average separator in the mass layoff sample earned $13,228. Within the group of separators, women are earning far less than men ($11,166 versus $15,314 respectively). Manufacturing workers have the highest earnings ($13,756) among separators.[20]

When the date of birth screening is combined with the requirement that sample members work six continuous years, the analysis file in 1998 represents prime age workers.

[18] The calculations involved in assembling these data are very complex. The data are confidential and cannot be directly accessed by any individual not employed by the Connecticut Department of Labor. However, individual arrangements for collaborative research can be made with the Director, Office of Research, as was done for this analysis.

[19] Consistent with Stevens, Crosslin, and Lane (1994), varying the rule for determining the event of mass layoff was found to have a large impact on estimated losses. For example, using a rule that mass layoff occurs when the drop in employment is 30 percent or more below the 1998 average results in sustained losses 10 percentage points larger than those reported here.

[20] A figure that shows the path of earnings for separators relative to the continuously employed identical to figure 1 from JLS is available in Appendix Section F.

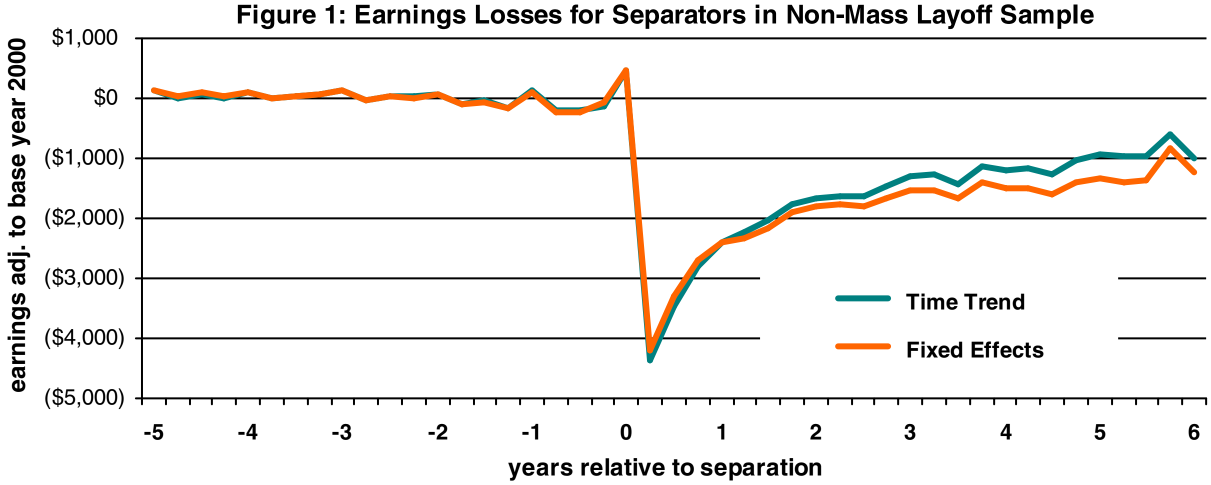
The 10th percentile of the age distribution is 31 and the 90th is 48.

**Table 1: Sample Characteristics**

| Workers | Observations | Mean | Std. Dev. | Median | 10th %tile | 90th %tile |
|---|---|---|---|---|---|---|
| **A. Age in 1998** | | | | | | |
| **Entire Sample:** | **95,126** | **39.74** | **6.11** | **40** | **31** | **48** |
| Separators: | | | | | | |
| All | 34,456 | 38.92 | 6.45 | 39 | 30 | 47 |
| Males | 16,883 | 39.02 | 6.36 | 39 | 30 | 47 |
| Females | 17,573 | 38.83 | 6.54 | 39 | 30 | 47 |
| Non-manufacturing | 25,511 | 38.75 | 6.59 | 39 | 30 | 47 |
| Manufacturing | 8,945 | 39.42 | 6.02 | 40 | 31 | 47 |
| Non-mass layoffs | 18,601 | 38.82 | 6.60 | 39 | 30 | 47 |
| Mass layoffs | 15,855 | 39.04 | 6.27 | 39 | 30 | 47 |
| **Continuously Employed:** | **60,670** | **40.20** | **5.86** | **41** | **32** | **48** |
| **B. 1998 Earnings** | | | | | | |
| **Entire Sample:** | **95,126** | **$14,078** | **$9,857** | **$12,457** | **$6,580** | **$21,313** |
| Separators: | | | | | | |
| All | 34,456 | $13,199 | $9,637 | $11,455 | $5,829 | $20,779 |
| Males | 16,883 | $15,314 | $11,113 | $13,167 | $7,443 | $23,160 |
| Females | 17,573 | $11,166 | $7,417 | $9,843 | $4,919 | $18,101 |
| Non-manufacturing | 25,511 | $13,003 | $9,560 | $11,255 | $5,476 | $20,783 |
| Manufacturing | 8,945 | $13,756 | $9,831 | $11,941 | $6,808 | $20,769 |
| Non-mass layoffs | 18,601 | $13,174 | $9,450 | $11,510 | $5,783 | $20,721 |
| Mass layoffs | 15,855 | $13,228 | $9,851 | $11,393 | $5,894 | $20,855 |
| **Continuously Employed:** | **60,670** | **$14,577** | **$9,946** | **$13,026** | **$7,097** | **$21,548** |

Figure 1 provides a graphical presentation of the estimated parameters for the fixed-effects and time trend models estimated for separators who are not part of the mass layoff sample. The figure contains similar patterns to those found in JLS. Using either estimator,

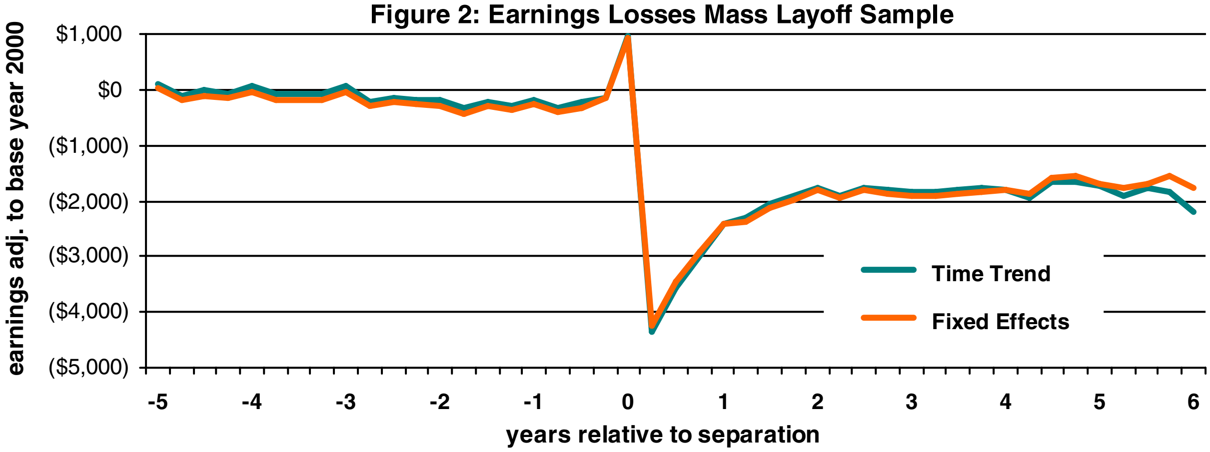
**Figure 1: Earnings Losses for Separators in Non-Mass Layoff Sample**



there is little difference between the regression-adjusted earnings of the continuously employed and those who later separate prior to job loss. In the quarter after the job separation, there is a sharp drop in earnings. The estimates of earnings reductions for separators using the fixed-effects and time trend estimators the first quarter following displacement are $4,185 (32%) and $4,361 (33%) respectively. In the sixth year following separation, substantial recovery occurs and the estimated quarterly impacts average $1,204 (9%) and $887 (7%) respectively.[21] The one substantive difference found here relative to the equivalent analysis in JLS is that in their samples, earnings of separators had recovered fully to their prior level within six years.[22]

Figure 2 contains an equivalent analysis for the sample of workers in the mass layoff sample. Prior to job loss, relative earnings are observed trending downwards with both estimators although they do not exhibit the sharp dip reported by JLS.[23] In the final period prior to job loss, the workers experiencing mass layoff, on average, receive about $950 in their final pay. This result is due to the receipt of what appear to be sizeable severance payments for a small portion of the sample.[24]

Figure 2: Earnings Losses Mass Layoff Sample




In the period immediately following job loss, using the fixed-effects and time trend models, the estimated reductions in earnings are $4,254 (32%), and $4,341 (33%) respectively. Six years later, the average quarterly earnings losses for that year are $1,699 (13%) and $1,923 (15%) respectively.[25] The initial losses reported here for the mass layoff

[21] The earnings of the group of separators in 1998:4 averaged $13,174. This figure is used in calculating the percentage losses.

[22] This analysis is contained in Figure 3 of JLS on page 698.

[23] Three working papers using administrative data to track earnings of workers who experience mass layoff also do not find a substantial dip in earnings in pre-displacement periods (Lengermann and Vilhuber (2002), Shoeni and Dardia (2003), and Hildreth, Von Wachter, and Handwerker (2005). Hildreth et al. additionally find upward spikes in earnings in the year prior to separation as reported here. Results from Lengermann and Vilhuber also indicate that it is unlikely that the larger size of the spike observed here relative to JLS is due to the impact of the WARN Act.

[24] 2,532 workers in the mass layoff sample have increases in earnings the last period prior to separation of more than $5,000. 187 workers have increases of more than $50,000.

[25] The earnings of the group of displaced workers in 1998:4 averaged $13,228. This amount was used in calculating the percentage earnings losses in the text.

sample are similar to those of other separators; however, their earnings recover more slowly. It is important to note that the earnings losses of the mass layoff sample using administrative data for Connecticut are similar in magnitude to the range of estimates obtained by other researchers using panel data such as the Panel Survey of Income Dynamics (PSID).

Estimation results for the mass layoff sample using equation (2.) and including other available variables were also calculated.[26] For each variable available in the analysis, a spline was formed as described in the methods section. The spline is estimated first for specific groups of individual or industrial characteristics and then controlling for all of the interactions simultaneously. The results of those estimates are used to calculate the magnitude of earnings losses in the fifth year after job loss. Table 2 (see next page) contains those results. Ordering of the estimated impacts is similar across the two sets of estimates.

Notable patterns include larger earnings losses for workers from Business and Professional Services than from Manufacturing five years after job loss. Workers who separate from jobs in Education and Health Care have the smallest earnings losses five years following job loss. The largest earnings reductions are found among older individuals (born in the 1950s). Their estimated losses are more than three times those of the youngest generational cohort in the study (born in the 1970s). Employees in the largest firms also have smaller losses than other workers who experience mass layoff.

Past research (Carrington and Zaman 1994 and Neal 1995) has also investigated the importance of being re-employed in the same specific industry code or in the broader industry group versus transitioning to another sector in terms of influence on the earnings loss associated with displacement. Table 3 contains estimates of the earnings losses of workers re-employed in the same six-digit North American Industry Classification System (NAICS) code, re-employed outside the identical NAICS code but within the broad industry aggregate, and for those who move across major industry groupings.

Both in manufacturing and non-manufacturing, those re-employed in a firm with the same NAICS code have the smallest earnings losses; those who are re-employed in a firm in the same sector have larger losses; and those who move outside the sector have the largest losses. The primary difference across industry groupings is that earnings losses for manufacturing workers are

**Table 3. Estimates of Earnings Losses and Re-Employment in Other Sectors**

| Qtrs since separation | New job in same sector | | New job in other sector |
|---|---|---|---|
| | Same NAICS | Different NAICS | |
| ***A. Displaced Manufacturing Sector Workers*** | | | |
| -8 | (331.92) | (282.95) | (474.53) |
| | [0.78] | [0.64] | [3.11] |
| 12 | (865.40) | (2,294.62) | (3,180.75) |
| | [10.01] | [10.71] | [12.39] |
| 20 | (1,414.53) | (2,371.36) | (2,835.75) |
| | [4.04] | [3.84] | [3.17] |
| ***B. Displaced Non-Manufacturing Sector Workers*** | | | |
| -8 | 513.25 | 267.95 | 104.08 |
| | [2.15] | [2.57] | [2.51] |
| 12 | 428.45 | (1,157.25) | (1,377.26) |
| | [1.09] | [14.52] | [14.79] |
| 20 | 165.47 | (746.35) | (1,593.67) |
| | [0.42] | [6.05] | [11.02] |

Note: Parameter estimates entered in parentheses are negative in value. The terms in brackets are t-statistics calculated using Huber-White standard errors based on one-fifth of the sample used for the estimates.

[26] These estimates are similar in form to those contained in the JLS paper (Table 2).

## Table 2. Earnings Loss Estimates for Demographic and Industrial Characteristics

Estimates of Equation (2.) Using Splines Defined as in Jacobson, LaLonde, and Sullivan (1993b)

| Group | without other controls | | | | | | with other controls | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | # Displaced Workers | Pre | During | Post | 5th Year Diff | 5th Year Loss | Pre | During | Post | 5th Year Diff | 5th Year Loss |
| **Overall:** | 15,855 | ***** | ***** | ***** | ***** | ***** | 122,27 | (1,878.99) | 193.40 | ***** | (6,022.55) |
| | | | | | | | [6.90] | [6.06] | [1.00] | | [7.61] |
| **Gender:** | | | | | | | | | | | |
| Male | 8,181 | (24.42) | (519.08) | 17.40 | (1,206.50) | (8,649.49) | (19.28) | (500.33) | 23.89 | (806.99) | (6,829.54) |
| | | [5.79] | [10.05] | [1.76] | [3.12] | [9.12] | [3.48] | [9.36] | [2.20] | [1.82] | [7.50] |
| Female | 7,674 | 30.30 | 553.40 | (18.55) | 1,286.21 | (6,156.69) | 20.56 | 533.41 | -25.47 | 860.34 | (5,162.21) |
| | | [5.79] | [10.05] | [1.76] | [3.12] | [9.12] | [3.48] | [9.36] | [2.20] | [1.82] | [5.62] |
| **Decade of Birth:** | | | | | | | | | | | |
| 1950's | 7,848 | (2.03) | (560.98) | (19.54) | (3,221.09) | (10,992.29) | 1.30 | (548.67) | (22.45) | (3,315.94) | (9,338.50) |
| | | [-0.47] | [-9.85] | [-2.09] | [8.92] | [12.06] | [0.30] | [9.54] | [2.43] | [9.09] | [10.24] |
| 1960's | 6,786 | 8.03 | 502.63 | 17.50 | 2,885.38 | (4,815.81) | 4.57 | 485.54 | 20.06 | 2,944.96 | (3,077.60) |
| | | [1.69] | [7.56] | [1.62] | [7.00] | [7.38] | [0.96] | [7.17] | [1.86] | [6.99] | [3.65] |
| 1970's | 1,221 | (31.59) | 812.48 | 28.38 | 4,668.89 | (3,032.30) | (33.75) | 828.30 | 32.69 | 4,947.40 | (1,075.15) |
| | | [-3.73] | [6.82] | [1.56] | [7.17] | [3.67] | [4.01] | [6.87] | [1.72] | [6.99] | [0.98] |
| **Industry:** | | | | | | | | | | | |
| Manufacturing | 5,359 | (23.83) | 633.90 | (56.87) | (308.22) | (7,920.57) | (16.03) | 1,197.08 | (78.09) | 883.92 | (5,138.63) |
| | | [3.94] | [8.41] | [3.72] | [0.55] | [8.28] | [2.30] | [14.69] | [4.76] | [1.43] | [5.30] |
| Trade | 2,410 | (0.87) | (118.06) | 26.19 | 837.26 | (6,775.09) | 8.41 | (77.66) | 29.51 | 1,164.78 | (4,857.77) |
| | | [0.11] | [1.14] | [1.32] | [1.04] | [6.04] | [1.04] | [0.72] | [1.40] | [1.38] | [3.87] |
| Financial/Real Estate | 1,569 | 178.69 | 1,357.01 | (48.77) | 2,989.46 | (4,622.90) | 160.15 | 794.23 | (43.08) | 1,023.09 | (4,999.47) |
| | | [7.26] | [6.76] | [1.34] | [2.10] | [2.80] | [6.24] | [3.91] | [1.17] | [0.71] | [3.10] |
| Prof./Business Services | 1,570 | 39.57 | 271.92 | (63.68) | (2,096.39) | (9,708.74) | 35.58 | (81.57) | (43.51) | (2,501.63) | (8,524.19) |
| | | [1.99] | [1.58] | [2.52] | [1.97] | [8.58] | [1.94] | [0.51] | [1.78] | [2.39] | [6.34] |
| Edu./Health Services | 2,426 | 2.83 | 664.80 | 24.93 | 3,905.63 | (3,706.72) | (5.19) | 431.67 | 27.13 | 3,082.96 | (2,939.59) |
| | | [0.37] | [5.48] | [1.37] | [5.84] | [5.3] | [0.64] | [3.46] | [1.49] | [4.22] | [3.08] |
| All Other Industries | 2,521 | (87.12) | (2,888.61) | 141.90 | (4,459.50) | (12,071.84) | (92.72) | (3,329.61) | 165.60 | (5,038.56) | (11,061.12) |
| | | [7.99] | [26.56] | [6.98] | [5.49] | [11.08] | [8.25] | [28.91] | [8.19] | [6.51] | [9.31] |
| **Firm Size:** | | | | | | | | | | | |
| Emp Level 1: 50-500 | 6,215 | (22.28) | (228.83) | (2.80) | (1,055.26) | (8,645.28) | (16.59) | (133.61) | (8.65) | (966.87) | (6,989.43) |
| | | [3.86] | [3.11] | [0.23] | [2.32] | [10.64] | [2.78] | [1.90] | [0.73] | [2.10] | [7.71] |
| Emp Level 2: 501 to 2,000 | 5,169 | 8.80 | 10.28 | 8.94 | 405.69 | (7,184.33) | 10.53 | (189.69) | 16.21 | 51.56 | (5,979.99) |
| | | [1.54] | [0.13] | [0.64] | [0.85] | [8.49] | [1.92] | [2.39] | [1.19] | [0.11] | [6.00] |
| Emp Level 3: 2,001 to 5,000 | 2,204 | (3.39) | 119.99 | (24.04) | (721.82) | (8,311.33) | 2.87 | 215.99 | (44.79) | (1,375.53) | (7,398.05) |
| | | [0.33] | [1.09] | [0.97] | [0.68] | [6.76] | [0.28] | [1.93] | [1.92] | [1.41] | [5.53] |
| Emp Level 4: > 5,000 | 2,267 | 44.61 | 537.84 | 10.74 | 2,688.32 | (4,901.70) | 18.82 | 592.90 | 30.51 | 3,897.21 | (2,125.34) |
| | | [3.63] | [4.49] | [0.45] | [2.71] | [4.20] | [1.53] | [5.04] | [1.31] | [3.87] | [1.99] |
| **Local Labor Market:** | | | | | | | | | | | |
| Trend | 15,855 | (37.58) | (933.05) | 96.38 | 1,086.70 | ***** | (70.09) | (1,193.27) | (49.37) | (7,241.51) | ***** |
| | | [4.63] | [9.12] | [6.81] | [1.88] | | [4.40] | [6.70] | [1.41] | | |
| Deviation | 15,855 | 22.75 | 605.79 | (75.98) | (1,375.63) | ***** | (19.65) | 666.74 | (165.25) | (5595.80) | ***** |
| | | [3.94] | [6.89] | [5.73] | [2.49] | | [1.88] | [4.58] | [4.86] | | |
| Unemployment Rate | 15,855 | 9.38 | (319.89) | 54.44 | 1,442.48 | ***** | 15.42 | 281.37 | (5.09) | 970.77 | ***** |
| | | [2.86] | [9.07] | [7.41] | [4.83] | | [4.30] | [8.45] | [0.75] | | |

Note: Parameter estimates in parentheses are negative in value. T-Statistics are in brackets and are calculated using bootstrapped standard errors obtained using a 20 percent sample of the primary analysis file. The Trend, Deviation, and Unemployment Rate Variables are expressed relative to the average for the mass layoff sample.

larger on average when compared to all non-manufacturing workers, and the pattern of earnings losses across the three transitions considered is more severe. This finding is similar to that contained in the table 2 which contains calculations of earnings the fifth year after mass layoff by industry group. When only the characteristic of experiencing a mass layoff in manufacturing is considered, earnings losses of those workers are larger than most other categories of employment.

The relative difference in the importance of being re-employed in the same industry or the same sector of the economy for manufacturing workers relative to those in non-manufacturing sectors suggests that specific skills may be more important in determining their earnings. If transitioning to a firm with a different NAICS code but in the same sector of the economy is thought of as distance from the original occupation, manufacturing workers appear to lose more as they transition further away from their original occupations. This is consistent with specific skills being a more important determinant of their earnings.

## VI. CONCLUSION

The research presented in this paper indicates that it is likely that the estimates of earnings losses associated with job displacement contained in the JLS study are large relative to the rest of the empirical literature due to the particularly severe economic circumstances that existed in Pennsylvania in the time period examined rather than because of properties unique to administrative data. Using similar data from Connecticut during a period of moderate economic conditions estimated earnings losses the quarter following job loss using the same techniques as JLS range from 32 to 33 percent for workers who experience mass layoff and by the same amount for other job separators. Similarly, six years after the typical worker separates from an employer in this study when it is not due to mass layoff, they continue to experience an earnings deficit of 7 to 9 percent. When an individual separates due to mass layoff, the earnings losses are sustained six years later at 13 to 15 percent. These estimates are similar in magnitude to those reported by Ruhm (1991) and Stevens (1997) using the PSID as the basis for their research. Thus, the larger sustained losses reported by JLS appear to be more unique to circumstances in Pennsylvania at the time than to administrative data in general.

Only a few papers exist which have used administrative data to study worker experiences after job loss. Nonetheless, the estimates contained in them differ in a manner that appears to be systematic. Studies using data from periods with difficult economic conditions (Jacobson, LaLonde, and Sullivan 1993a) or using demographic information only on individuals who filed unemployment claims (Jacobson, LaLonde, and Sullivan 2005a and 2005b) would be expected to yield larger estimated earnings losses. Studies, such as this one, using data that is more representative of the typical worker who experiences a mass layoff in ordinary times are likely to find moderated impacts. To date, this is the pattern observed in the available evidence.

## A. Data Construction of Matched Wage and Firm Information

The combined individual and firm level data used in the study are constructed by combining Connecticut Unemployment Insurance (UI) program reports and the state QCEW data on employment of firms. The UI report includes quarterly earnings for each employee (wage record) and identifies the employer with a UI identification number. The earnings data are top-coded for this study at the level of $155,000 in 2000 dollars. The age and gender information used in the study were obtained from matches to Connecticut Department of Motor Vehicle (DMV) records. Those matches are described in section E.

Components of the QCEW data provide information on employment of firms used to calculate the Bureau of Labor Statistics (BLS) industry employment and wage reports. These QCEW data contain the employer's UI identification number that can be used to attach information regarding the firm to the individual's UI wage record. After this merge, the analysis file contains information on quarterly earnings from 1993 through 2004, the principal employer's UI identification number each quarter, the employer's six-digit industry (NAICS) code, and the employment level of the principal firm.

## B. Dating Worker Separations

In the UI file, an employer's UI identification number is attached to each earnings source. Changes in this employer identifier over time are used to track employment changes for individuals in the file. These employer identification numbers may change for administrative reasons, and making certain that the changes observed were genuine was important to the analysis. Fortunately, the Connecticut DOL maintains files that detail the nature of the change of identification numbers when they occur. These files are usually referred to as predecessor-successor files. The identifiers for employers were coded using these sources of information so that they would be consistent over time.

Changes in the employer identification number from one quarter to the next along with earnings information from different employers were used to date separations from firms. There were two basic rules followed. First, if an employee had a principal employer this quarter but not the next and their recorded earnings from the original employer stop this quarter, then the separation is dated as occurring this quarter. Second, in cases where earnings from multiple employers overlap, the date of the separation is the quarter when the person last receives earnings from the previous employer.

This dating procedure may miss the timing of separations, for example, in the case where a person receives severance payments several quarters after employment ends. Also, a worker might have had a continuous job with a third employer. This dating procedure does not account for such circumstances. To the extent that the dating procedure is incorrect, it will contribute to earnings declines prior to separation. The graph in this Appendix (Section F) tracing the evolution of earnings for separators demonstrates that this is not a large problem.

The earnings of separators trend upwards with those of the continuously employed prior to separation. Also, there is no sign of significant earnings loss among the separators in the figures presented in the text prior to job loss. This can be seen in Figures 1 through 3 where adjusted earnings of the non-mass layoff and mass layoff samples also are essentially equal to those of the continuously employed prior to job separation.

### C. SAMPLE RESTRICTIONS

The sample was restricted to workers born between 1949 and 1979. They had to have six years of continuous employment with the same employer from 1993 through the end of 1998. They had to report some positive earnings in each year of the panel from 1993 through 2004. Individuals were only included in the analysis if information regarding age and gender were available for them. For small firms, minor changes in employment might result in a firm appearing to have a large percentage layoff. For this reason, employees of firms with less than 50 employees were omitted from the analysis.

Finally, the sample restrictions imply that anyone who separated and subsequently did not have earnings would be removed from the analysis. Information is contained later in this appendix on how many observations are lost both from no additional reports of earnings after job loss as well as intermittent years of zero reported earnings.

### D. LOCAL LABOR MARKET CONDITIONS

The Connecticut Department of Labor produces and maintains files on the employment and unemployment status of the state's residents through the Local Area Unemployment Statistics (LAUS) program. These data have geographic identifiers that were used to match to the firm locations in the employer records. The LAUS data on area resident employment and unemployment rates were attached to the analysis file using the location identifiers. Wherever a match was not possible, the state average was attached to the record.

The unemployment rate was attached as an analysis variable. The trend of the employment rate by location was calculated along with the deviation from that trend. These variables were included to control for local labor market conditions.

### E. MATCHING ON DMV RECORDS TO OBTAIN DEMOGRAPHIC INFORMATION

One of the drawbacks of administrative data drawn from state Departments of Labor is that demographic information is typically not available unless an individual has made use of the state's employment services in searching for a job or when filing an Unemployment Insurance claim. One would naturally be concerned that using a sample built on that basis would result in a highly selected analysis sample. In the original JLS study the UI wage files were matched by the state of Pennsylvania to the social security master file in the second year of their sample (1976) to obtain information on date of birth and gender. This would give them good coverage of most individuals at the beginning of their study period. The file would be limited in its research uses as individuals who entered the wage file at a later date would not have matching demographic information.

An alternative method of obtaining demographic data is to match to DMV records. In the state of Connecticut, procedures for obtaining motor vehicle operators' licenses were altered effective July of 2002. Those procedures now require that social security numbers be obtained and verified for licenses. For this study, a file which cumulatively covers 70.1 percent of licenses issued in the state was used to match to the UI wage records. The match covers 63 percent of all wage records in 2004, the last year of the study. Assuming that workers are randomly distributed in DMV records, this represents an effective match rate of 90 percent in 2004. In raw numbers, this process yields 1,180,053 workers with demographic information.

If the data from the UI wage file are instead screened to meet the sample criteria that there are both positive earnings in the first quarter of the sample and some positive earnings every year, 1,009,876 individuals pass that screen. Of them, 615,973 successful matches are made to the DMV file for demographic information. This gives 60.99% coverage of the relevant records. Again, if the matches were proportionate to the proportion of DMV records for which validated SSNs are available, 70.1 percent coverage would be expected. Thus, the effective match rate for those who could possibly be included in the study is 87 percent. This compares well with match rates for individual states using the social security master file. For example, Lengermann and Vilhuber (2002), based on data in their paper (pp. 5-6) report an 89 percent match rate between UI records and the social security file for Maryland.

In this study as well as in the original research by JLS, all individuals are required to have positive earnings information in each year. Thus, whether demographic information is matched at the beginning or end of the study period does not matter for any of the core calculations in the analysis. The question that remains is how well do the individuals for whom demographic information is obtained represent the workers in Connecticut?

Table A-1 presents the quarterly distribution of employment at the 2-digit NAICS level for the sample used in the analysis relative to the entire wage file at the point the sample is drawn, 1993:1. The distribution of employment at the 2-digit level is very similar between those for whom demographic information is obtained and the entire set of wage records. The largest exception is in manufacturing where the file constructed for this study will under-represent employment in that sector by one percentage point or 5.7 percent.

Overall, the employment distributions among individuals for whom demographic information was obtained provide a fairly accurate picture of the distribution of employment in 1993. Of the 21 categories of employment considered, 14 of the categories differ by two-tenths of a percentage point or less when comparing the entire wage file with those for whom matches were obtained.

Unemployment Insurance records contain information on payroll for persons who work in a state. Relative to DMV records, citizens who have always worked in another state cannot be matched, nor can out-of-state residents who work in Connecticut. This is consistent with the definition of the resident worker population of Connecticut, those who both live and work in the state.

Census data allow one to obtain information on the resident worker population by using cross border migrant data to construct the population of individuals who both live and work in Connecticut. Further, they can be compared to those who commute from another state to work in Connecticut. Generally, 2000 Decennial Census data show that approximately 3.5 percent of the workforce of the state of Connecticut at any point in time is represented by commuters from surrounding states. Commuting workers typically have significantly higher incomes. This shows up when one considers the distribution of earnings in 1993 for those for whom demographic information is obtained relative to the entire wage file.

**Table A-1: Percent Distribution of Employment 1993:1 in Connecticut**

| NAICS Code | Industry | UI File | DMV Matches |
|---|---|---|---|
| 11 | Agriculture, Forestry, Fishing, and Hunting | 0.2 | 0.2 |
| 21 | Mining | 0.0 | 0.0 |
| 22 | Utilities | 0.4 | 0.4 |
| 23 | Construction | 3.2 | 3.5 |
| 31 | Manufacturing | 17.4 | 16.4 |
| 42 | Wholesale Trade | 4.1 | 3.9 |
| 44 | Retail Trade | 11.2 | 11.9 |
| 48 | Transportation and Warehousing | 2.5 | 2.9 |
| 51 | Information | 2.7 | 2.6 |
| 52 | Finance and Insurance | 7.5 | 7.1 |
| 53 | Real Estate and Rental and Leasing | 1.3 | 1.3 |
| 54 | Professional and Technical Services | 5.3 | 4.9 |
| 55 | Management of Companies | 2.4 | 2.3 |
| 56 | Administrative and Waste Services | 5.1 | 5.2 |
| 61 | Education Services | 8.9 | 8.7 |
| 62 | Health Care and Social Assistance | 12.1 | 12.2 |
| 71 | Arts, Entertainment, and Recreation | 1.5 | 1.5 |
| 72 | Accommodation and Food Services | 6.7 | 6.7 |
| 81 | Other Services | 4.2 | 4.0 |
| 92 | Public Administration | 3.6 | 4.0 |
| 99 | Unclassified Establishments | 0.1 | 0.1 |

Table A-2 shows the mean, median, and various percentiles of the wage distribution from the UI file as a whole relative to those who could be matched to the DMV files for demographic data. For example, in 1993:1, average earnings for the entire file of wage earners is $390 higher than for the sample containing demographic information. Similarly, median earnings for the entire file are $265 higher than for the subset for which demographic information is available. The columns in table A-2 such as P-10 refer to the dollar value equivalent to the 10th percentile of the distribution.

**Table A-2: Reported Qtrly. Wage Distribution in Connecticut 1993:1**

| | Median | Mean | P-10 | P-25 | P-75 | P-90 |
|---|---|---|---|---|---|---|
| UI File | $5,110 | $6,665 | $494 | $1,813 | $8,848 | $13,225 |
| DMV Matches | $4,845 | $6,280 | $450 | $1,657 | $8,456 | $12,600 |

Table A-3 reports the percentage distribution of employment by 2-digit industry code in Connecticut in 1993:1 for those individuals who met the major screening criteria of the analysis sample that positive wages be reported that quarter and that some wages have to be reported every year. Again, in 14 of the 21 employment categories considered, the deviation in the percentage distribution of employment among those with demographic data and the entire file who meet major screening criteria of the study is two tenths of a percentage point or less. The overall distributions are fairly similar with the one outlier being manufacturing. Manufacturing workers are under-represented in the sample by 7 percent.

**Table A-3: Percent Distribution of Employment for those meeting sample screening criteria in 1993:1 in Connecticut**

| NAICS Code | Industry | UI File | DMV Matches |
|---|---|---|---|
| 11 | Agriculture, Forestry, Fishing, and Hunting | 0.2 | 0.2 |
| 21 | Mining | 0.0 | 0.1 |
| 22 | Utilities | 0.4 | 0.5 |
| 23 | Construction | 3.1 | 3.3 |
| 31 | Manufacturing | 18.2 | 16.9 |
| 42 | Wholesale Trade | 3.9 | 3.8 |
| 44 | Retail Trade | 10.7 | 11.4 |
| 48 | Transportation and Warehousing | 2.4 | 2.9 |
| 51 | Information | 2.7 | 2.6 |
| 52 | Finance and Insurance | 7.7 | 7.2 |
| 53 | Real Estate and Rental and Leasing | 1.2 | 1.2 |
| 54 | Professional and Technical Services | 4.9 | 4.7 |
| 55 | Management of Companies | 2.4 | 2.3 |
| 56 | Administrative and Waste Services | 4.4 | 4.7 |
| 61 | Education Services | 9.4 | 9.0 |
| 62 | Health Care and Social Assistance | 12.9 | 12.7 |
| 71 | Arts, Entertainment, and Recreation | 1.4 | 1.5 |
| 72 | Accommodation and Food Services | 5.4 | 6.1 |
| 81 | Other Services | 3.9 | 3.8 |
| 92 | Public Administration | 4.1 | 4.3 |
| 99 | Unclassified Establishments | 0.8 | 0.8 |

Similarly, table A-4 provides information regarding the distribution of reported wages from the entire UI wage file relative to those who meet the same major screening criteria for the analytical sample. Mean earnings differ across the two samples by $405 and median earnings differ by $359. More detail on percentiles can be found in the table.

While the earnings and employment distributions for the analysis file match the total wage file fairly well, a further question worth considering is attrition in the sample. In the original JLS study, they report that they lose 25 percent of the mass layoff group because of workers who do not report positive earnings beyond the point where they lose their jobs. Similar calculations are performed on the matched analysis file here. A total of 2,751 people drop out of the mass layoff sample beyond the point where a job is lost because of failure to report some positive earnings in at least one of the years examined. A person could enter this total because they had just one calendar year where they did not report earnings. 397 of the 2,751 people never report any positive earnings beyond the point of job loss.

**Table A-4: Reported Qtrly. Wage Distribution in Connecticut 1993:1 For Those Meeting Sample Screening Criteria**

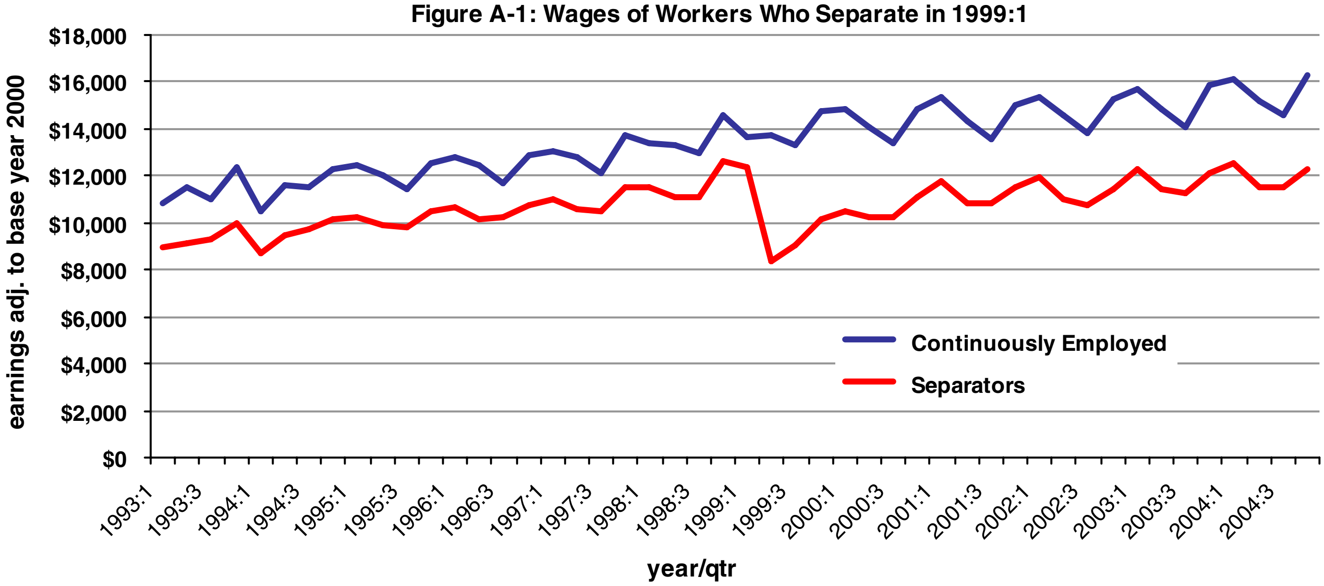
| | Median | Mean | P-10 | P-25 | P-75 | P-90 |
|---|---|---|---|---|---|---|
| UI File | $5,595 | $6,958 | $646 | $2,315 | $9,213 | $13,314 |
| DMV Matches | $5,236 | $6,553 | $551 | $2,000 | $8,785 | $12,777 |

If the 2,751 people who do not meet this criterion but otherwise would be in the study are added to the total sample of mass layoffs reported in the table in the next section of this appendix, the total available number of individuals who experienced mass layoff would be 18,606. Thus, attrition because of unreported earnings in the mass layoff sample is 14.8 percent. It is likely this number somewhat understates the true degree of attrition since matches are obtained based on information available at the end of the sample period. Nonetheless, like JLS, when the earnings losses presented in the paper are recalculated and zero earnings are assigned to these individuals, the earnings losses (as a percentage) using the fixed-effects and time-trend estimators are 30 and 33 percent respectively. Including individuals with intermittent earnings reports following displacement more than doubles the largest estimated earnings loss presented in the Occasional Paper.

### F. SAMPLE CHARACTERISTICS AND WAGE PATHS FOR SEPARATORS IN 1999:1 RELATIVE TO THE CONTINUOUSLY EMPLOYED

The figure presented here is equivalent to figure 1 in the original JLS study. It shows the earnings path of individuals who separate from employment in 1999:1 relative to the group of continuously employed workers. It is notable that both before and after job separation, earnings trend similarly relative to each other. There appears to be a simple intercept difference in the starting point of the wage paths of the continuously employed and separators at the start of the sample period. Thus, estimators such as the fixed-effect and time trend estimators used in the paper which control for individual specific intercepts would be expected to effectively equalize earnings prior to job separation. This turns out to be true as can be seen in Figures 1 and 2 in the text.

Figure A-1: Wages of Workers Who Separate in 1999:1



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