THE EFFECTS OF JOB DISPLACEMENT ON CAREER OUTCOMES BY WORKER CHARACTERISTICS*

Jennie E. Brand

Department of Sociology
University of Wisconsin – Madison

This draft: March 2004

Running head: Job Displacement, Difference-in-differences, Career outcomes

* Please direct correspondence to Jennie E. Brand, Department of Sociology, University of Wisconsin - Madison, 1180 Observatory Dr., Madison, WI 53706 USA, (952) 926-1007, or email jlowry@ssc.wisc.edu. This paper was prepared for presentation at the 2004 Boston meeting of the Population Association of America (PAA). The Wisconsin Longitudinal Study (WLS) data are publicly available on line at http://dpls.dacc.wisc.edu/WLS/wlsarch.htm.

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Job displacement is increasingly affecting the security of long-term steady employment breeding an uneasy concern over the ability of workers to sustain a successful career characterized by upward mobility. A worker is defined as being displaced if he or she has lost a job, without being recalled, due to downsizing, restructuring, a plant closing or relocation. It is not the result of a worker quitting or of a worker being fired. Numerous studies have evaluated the economic impact of job displacement for workers. In previous work, I have also examined the impact of job displacement for the aggregate group of displaced workers and found that displaced workers suffer long-term non-employment rates and highly significant wage and earnings losses as much as more than a decade after a worker was displaced. I found that in addition to the widely noted economic losses, displaced workers also have less job autonomy, job authority, and lower occupational status on reemployed jobs (Brand 2004). This study disaggregates the group of displaced workers and examines career outcomes separately: for men and for women; for high school, college, and masters/doctorate degree holders; for upper white collar, lower white collar, and blue collar workers; for manufacturing and non-manufacturing workers; and for a 9-category career classification that includes an interaction of aspects of the sector, industry, and occupation the worker was in. I estimate results using conditional difference-in-differences matching across these worker characteristics for 10 career outcomes including: employment status, earnings, wages, pension, health insurance, occupational education and occupational income, job autonomy and job authority, and job satisfaction.

PREVIOUS FINDINGS ON JOB DISPLACEMENT EFFECTS BY WORKER CHARACTERISTICS

Studies on job displacement have found that outcomes have a high degree of variance. For instance, Seitchik (1991) finds while about ⅓ of all displaced workers are reemployed within 5 weeks, about ⅓ are not reemployed until after more than 6 months. Seitchik (1991) finds that the majority of workers displaced from 1981 to 1986 are earning less in real dollars on reemployed jobs than on the job the worker was displaced from in 1984 and 1986. However, 43% of workers displaced from 1981 to 1986 had higher earnings on reemployed jobs in 1986. Still, over 30% of workers were earning less than ¾ of former wages.

Most studies have found that men are more likely to be displaced than women (Hammermesh 1989; Seitchik 1991). Studies have differed over the question of whether men or women experience greater losses post-displacement. While some have contended that men experience the greatest losses (Ruhm 1987), others contend that there is a greater loss for women (Madden 1987; Podugursky and Swaim 1987; Seitchik 1991). There are undoubtedly definitional issues involved; men may be more likely to be both reemployed and unemployed, while women more likely to exit the labor force following displacement. There is an interaction effect between gender and marital status. Married women are less likely to return to work than unmarried women (Chan and Stevens 2001). Moreover, at least one study has looked at the "added worker effect," i.e. the increased labor supply of wives in response to husband's job losses, reducing the loss of family income (Stephens 2002).

Studies have found that less educated workers are more likely to be displaced than are more educated workers (Farber 1993; Kletzer 1998). Farber (1993) finds that the rate of displacement for college graduates has been roughly half that for high school graduates. While job loss rates were higher for less educated workers than those for more educated workers throughout the period 1982-1991, job loss rates have increased for college educated workers throughout the 1990s (Farber 1997). Most studies have agreed that workers with less education spend more time unemployed and suffer the greatest wage losses after being displaced (Farber 2003; Farber 1993; Hammermesh 1989; Madden 1987; Podgursky and Swaim; Seitchik 1991). More highly educated workers tend to be more mobile (Fallick 1996). Still, as the incidence of displacement for more educated workers has increased, the transition difficulties for such workers have increased as well. The reemployment rate of more educated workers dropped sharply in the 2001 recession (Farber 2003).

Displacement losses are also related to occupation. Firms have replaced low-skill workers as they advance technology. During the 1980s, semiskilled blue collar labor declined by 1.4 million workers. Conversely, higher-skilled precision production workers increased by almost 0.5 million, and white collar occupations remained stable (Levy 1995). Several studies have found that the long-term unemployed are disproportionately semi-skilled blue collar workers (Hammermesh 1989; Seitchik 1991). Moreover, earnings reductions following reemployment are greater for blue-collar workers (Hammermesh 1989; Madden 1988; Podgursky and Swaim 1987). As is true for workers with more education, greater skill transferability is expected for upper white collar workers (Kletzer 1991). The occupational difference, however, narrowed in the

1990s (Farber 1997; Keltzer 1998; Seitchik 1991). Studies have also found that wage losses are higher for workers who change occupations post-displacement (Fallick 1996).

There have been several studies that have examined the impact of pre- and post-displacement industry and industry changes on employment and earnings outcomes of job displacement. Several studies have found that labor market conditions in a displaced worker's industry and local area conditions were important factors in the extent to which displaced workers suffered earnings losses (Howland and Peterson 1988; Jacobson, Lalonde, and Sullivan 1993). Displaced workers have tended to come from industries doing poorly relative to their own trends (Carrington and Zaman 1994). In particular, studies found that manufacturing workers were more likely to be displaced up until the mid-1980s (Hammermesh 1989; Podgursky 1992), and had higher earnings losses than non-manufacturing displaced workers (Carrington and Zaman 1994; Jacobson 1984). Since about 1985, displacement has been considerably less concentrated in manufacturing, and more displacement has been occurring in the trade and finance, insurance, and real estate (FIRE) industries (Farber 1997; Farber 1993; Podgursky 1992).

Several studies have found that workers that change industries after being displaced experienced greater earnings losses (Addison and Portugal 1989; Carrington and Zaman 1994; Jacobson, Lalonde, and Sullivan 1993; Madden 1988; Neal 1995; Podgursky and Swaim 1987; Topel 1990). In particular, while earlier studies focused on the loss of firm specific skills (Hammermesh 1987), Neal (1995) argues that firm specific skills may contribute little to compensation. Rather, it is the industry-specific skills the matter most in determining wages. Moreover, the wage cost of switching industries is correlated with pre-displacement tenure and earnings (Fallick 1993; Neal 1995). The

cost is also associated with gender; Podgursky and Swaim (1987) found that whether or not women stay in the same industry or occupation is insignificant. Union coverage is another important factor. Kuhn and Sweetman (1998) find that even after controlling for firm size and industrial mobility, a significant portion of the wage loss experienced by displaced workers results from the loss of union coverage.

DATA

The most frequently used data to study job displacement has been the Displaced Worker Surveys (DWS) supplements to the Current Population Survey (CPS). The DWS has the advantage of clearly indicating which workers are displaced, includes data on labor force and demographic characteristics, and most significantly, benefits from a large sample of displaced workers. Data on wage losses for displaced workers using the DWS has several limitations. First, the DWS is cross-sectional, making it difficult to study relationships between job attributes and the probability of job loss. There is concern regarding recall bias in the DWS and the distinction between permanent and temporary lay-offs (Seitchik 1991). Second, data on *hourly* wage rates have rarely been available in the data sets used to study displacement to date, including the DWS. Third, a control group is needed to compare displaced workers' wage losses, to represent the "missing counterfactual earnings path" (Fallick 1996, p. 9). The DWS has a retrospective component only for those workers identified as displaced. Since no correction for worker heterogeneity is possible using the DWS, residual variance in post-displacement outcomes can not be confidently attributed to displacement (Seitchik 1991).

Empirical studies of job displacement using longitudinal data have for the most part used the Panel Study of Income Dynamics (PSID) and the National Longitudinal Surveys (NLS). The primary advantage of longitudinal data is the construction of a control group and the primary disadvantage is small sample sizes relative to the DWS. There are other disadvantages in using the PSID and NLS. The PSID isolates plant closings and relocations, but groups lay-offs with firings and lacks the richness of detail found in the DWS. The PSID is a household survey, and is usually analyzed only for household heads. The NLS is better suited for tracking individuals regardless of household status (Seitchik 1991). However, studies using the NLS have had to pool distributions of displaced workers due to small sample sizes. The NLS groups layoffs with firings and temporary/seasonal job loss.

I use the Wisconsin Longitudinal Study (WLS), a panel study of a random sample of 10,317 1957 Wisconsin high school graduates. The WLS sample is limited. Everyone in the sample graduated from high school. Also, the WLS includes predominately white men and women; minorities are not well represented.[1] That said, the WLS also has unique strengths. The WLS solves many of the problems encountered by previous studies of job displacement using aforementioned datasets. The WLS is longitudinal. The data provide a full record of social origins, cognitive ability, educational attainment and performance, employment history, and job characteristics for a large sample of respondents throughout their life course. Moreover, the 1992/3 wave of the WLS

[1] WLS respondents include workers predominantly living in Wisconsin. Displacement has historically been viewed as a "rust belt" phenomenon, i.e. confined to east north central states. Setichik (1991) has argued that while the Midwest states have a higher percentage of all displaced workers (19%), they have a corresponding fraction of the labor force (18%). The WLS, hence, allows for a larger, but proportionate, sample of displaced workers than might otherwise be obtained in a sample originating from a different particular geographic region.

includes a detailed job history record that allows isolation of job displacement at an identified point in time for employment spells spanning almost 20 prime working years. In contrast to the PSID, however, the WLS tracks individuals, and not households, and in contrast to the NLS, the WLS does not combine temporary and seasonal job loss with other displacements. The data, thus, includes strictly comparable life histories for men and for women. Once a control group is constructed, the WLS allows difference-in-differences estimation of long-term effects of job displacement: from 1975 to 1992 job outcomes, where a job displacement occurs between 1975 and 1992. The WLS has data on hourly wages, as well as annual earnings. Also, for all variables gathered with respect to displaced workers, the WLS has corresponding information for non-displaced workers, allowing the construction of a comparable control group. The WLS has had remarkably high rates of response and sample retention; over 80% of the original sample participated in the 1992/3 survey, 35 years after the initial data collection.

This study follows a single cohort through their prime working years (approximately age 35-53) and asks what effects workers that are displaced from jobs endure across their careers. I use survey data that was collected from the original respondents or their parents in 1957, 1964, 1975, and 1992/3 and Wisconsin state records. I include a worker as displaced if that worker reported the termination of an employment spell as a result of downsizing/restructuring or business closing or relocating. I do not include temporary or seasonal lay-offs. I also do not include "other involuntary termination" ("help no longer needed"). This last category likely includes workers who were fired for cause as well as, perhaps, laid-off. Mass lay-offs will likely be included in the categories of "downsizing." However, lay-offs that are the result of

slack work or the abolition of a position or shift not included in these categories may not be captured.[2] I restrict cases to those who responded to the 1992 survey (8,327 cases) and had a least one job spell in the years 1975-1992 (7,972 cases) and had no missing data on reason for employment spell termination (7,878 cases). A total of 1,136 out of 7,878 workers experienced one or more job displacement between 1975 and 1992.

Variables

I examine the effects of job displacement for various classifications of worker characteristics. First, I examine effects using broad education, occupation, and industry classification. For education, I disaggregate into 3 groups based upon highest degree conferred: high school degree, college degree, and masters/doctorate degree. For occupation, I also use 3 groups: upper white collar (professional and managerial workers), lower white collar (sales and clerical workers), and blue collar (including all other workers such as craft workers and laborers). I estimate the effect of job displacement for each of these groups separately for men and for women and by time period. I use three 6-year time intervals, such that I estimate job outcomes for workers that have been displaced for 12-17 years, 6-11 years, and 0-5 years. This classification allows the propensity for displacement to be constructed fluidly, such that for each 6 year period I calculate the probability of displacement based upon both time-invariant covariates and the most recent "pretreatment" time-varying job characteristics.

[2] Studies have shown that when employers have more discretion about laying-off workers, workers with lower ability will be included as displaced (Gibbons and Katz 1991). Hence, not including these workers will likely lead to more conservative estimates of the effects of displacement.

Previous research on job displacement has identified variables that are theoretically and/or empirically related to the probability of job displacement. Almost all studies include the following covariates as controls: job tenure, education, occupational category, industry, sex, race, and age. In addition to these variables, I include several social background variables to estimate the propensity for displacement.[3] These variables include measures of cognitive ability, mothers' education level, father's occupational status, and parent's income. Because sociological studies have found lasting effects of cognitive ability throughout the occupational career (Warren, Hauser, and Sheridan 2002), and because of the frequent reference among economic studies of displacement to the effects of "unmeasured ability," the inclusion of cognitive ability is a valuable addition to the study of job displacement. I also include several 1975 variables: college graduation, labor force experience, residence in the frostbelt states (i.e., the Northeast and Midwest U.S. regions), residence in Milwaukee, union status, and job satisfaction. I also include sex and sex interactions for education and experience. These variables are the time-invariant set of covariates. By dividing displacement into 6 time periods, I am also able to construct time-varying pretreatment covariates that correspond to the year immediately prior to the 3-year displacement period. For each displacement period propensity score equation, I include the following set of time-varying covariates: class of worker (private, government, self-employed), industry (agriculture, goods-producing, trade), occupation (professional/managerial, sales/clerical, blue-collar), tenure (and tenure squared), full-time employment status, pension, occupational earnings, and sex

[3] I do not include age and race. The WLS is a single cohort of 1957 high school graduates and is a predominantly white sample, eliminating the need for the inclusion of either of these "variables."

interactions for most of these variables.[4] The use of tenure squared is intended to capture the diminishing marginal effect of tenure on the probability of job displacement. For each set of worker characteristics I examine, I omit irrelevant variables; e.g., when assessing the effect of job displacement by educational category, I omit education as a covariate.

I also estimate outcomes separately for men and for women by more specific career classification. The multidimensional classification I utilize is an adaptation of Haller, Konig, Krause, and Kurz's (1985) career categories. Haller et al. (1985) simultaneously capture several dimensions of class and stratification, including vertical dimensions of occupational status, horizontal dimensions of sectoral membership, and class of worker. They ultimately generate a classification that includes 23 distinct categories. I aggregate several of these categories and arrive at a 15-category classification. However, due to sample size limitations, partly because I estimate results separately for men and for women, I further aggregate these 15 groupings and arrive at a classification scheme that includes 9 separate career categories, described in Table 4.1. The main difference from my classification and Haller et al.'s is that I aggregate administration workers into one category and combine skilled and unskilled workers.

I estimate the effect of job displacement on ten career outcomes. First, these include current (1992/3) employment status, yearly earnings, hourly wages, pension, and health insurance. Yearly earnings is based on the 1992/3 survey question: "In the last 12 months, how much have you received in wages, salaries, commissions, and tips before taxes and other deductions?" Base hourly wage rate is obtained both from direct reports

[4] The 1990-basis occupational earnings score is the percentage of persons in the 1990 Census in a category who earned at least $14.30 per hour in 1989. Hauser and Warren (1997) recommend that a started logit transformation of this percentage be used to correct for heteroskedasticity: SL(oe) = ln ((oe+1)/(100-oe+1)), where oe is the occupational earnings.

of the hourly wage rate and estimated from reports of other units such as annual salary and hours worked. Pension and health insurance outcomes refer to whether a respondent's current employer offers a pension or retirement plan and health insurance, respectively. If a respondent is not employed in 1992/3, he or she receives a 0 for each for these measures. I also include two measures of occupational status on current or last job, occupational education and occupational earnings (Hauser and Warren 1997). The 1990-basis occupational education score is the percentage of persons in the 1990 Census in an occupation/industry/class-of-worker category who completed one year of college or more; the earnings score is the percentage of persons in the 1990 Census in a category who earned at least $14.30 per hour in 1989. Hauser and Warren (1997) recommend that a started logit transformation of these percentages be used to correct for heteroskedasticity: SL(oe) = ln ((oe+1)/(100-oe+1)), where oe is the occupational education or earnings.

I further include measures of job autonomy and job authority on current or last job. Job autonomy indicates that a worker does not have a boss that supervises what or how much he or she produces; job authority is coded 1 if a worker reports that he or she supervises the work of others and 0 otherwise. I also include an overall measure of subjective evaluation of one's job, "job satisfaction," based upon a 4-point scale where 4 indicates a worker is "very satisfied" with his or her job. All measures that refer to current or last job do not include the job that a worker was displaced from, if that worker had not been reemployed in the observation period. For the entire set of career outcomes described above, I have data in both 1974 and in 1992/3, allowing for a difference-in-differences estimation of effects. Therefore, each outcome variable in the difference-in-

differences estimation takes the difference between the 1992/3 measure and the corresponding 1974 outcome measure.

Descriptive Statistics

Table 4.2 provides descriptive statistics for WLS workers by worker characteristics. For men, the percentage of displaced workers employed in 1992 is far lower than in 1974 and lower than non-displaced workers in 1992, and likewise for percentage employed full-time. For women, there are less displaced workers employed in 1992 than non-displaced, but still more than in 1974. Percentage cumulative employment measures the number of months that a worker was employed across the period 1975-1992. Displaced men were out of work on average almost a year and half more so than non-displaced men; displaced women were out of work only about 3 months more than non-displaced women. As would be expected average tenure levels are far lower for displaced workers in 1992 than non-displaced workers. Both mean and median real earnings have substantially declined for displaced men across the 1974 to 1992 period, while mean earnings have increased for non-displaced men and median earnings have slightly declined. Some of this discrepancy is due to non-displaced high-earner (top 5^{th} percentile) male workers significant earnings increase. For women, earnings have increased for both displaced and non-displaced workers. There are differences by broad occupational classification, specifically for men. In particular displaced upper white collar workers have less earnings losses than lower white collar and blue collar workers. All groups of women have increased earnings from 1974 to 1992; they are also more likely to be working full-time. Figures 4.1 and 4.2 also provide earnings distributions by displacement status in

1975 and in 1992 for men and for women, respectively. Table 4.3 provides another descriptive look at the distribution of displaced workers by worker characteristics across the displacement period. There is a fairly even distribution of workers across this period.

ANALYTICAL APPROACH

An event such as job displacement can be thought of as a "treatment" for which we wish to establish effects. The estimation of a treatment effect (i.e. an effect of job displacement, such as earnings loss) hinges on a counterfactual; that is, inferences must be made about outcomes that would have been observed for displaced workers had they not been displaced (Rosenbaum and Rubin 1983; Rubin 1974). For any single point in time, a person may be in either one of two potential states, but not in both (Heckman, Ichimura, and Todd 1997). Let $w = 1$ indicate a treated unit, i.e. a WLS worker displaced from a job, and $w = 0$ indicate a control unit, i.e. a WLS worker that was not displaced from a job.[5] Two potential outcomes are indicated by Y_1 and Y_0, with Y_1 the value of the outcome, or for example, earnings, that would be observed if a person was displaced from a job and Y_0 the outcome value observed on the same person if he or she was not displaced from a job. The treatment effect is defined as:

$$\Delta = Y_1 - Y_0.$$

The fundamental problem of causal inference is that it is impossible to observe the value of Y_1 and Y_0 on the same person; i.e. we only observe $Y = wY_1 + (1-w)Y_0$. Determining causal effects is essentially a problem of missing data. An average treatment effect

[5] To reduce notation, the individual argument *i* will be dropped throughout this section.

(ATE) is an average partial effect for a binary explanatory variable on a randomly drawn person from the population:

$$\text{ATE} \equiv E(\Delta) \equiv E(Y_1 - Y_0).$$

To address the fundamental problem of causal inference, we must use a comparison group. In observational studies, units are not assigned to treatments at random, so treated and control groups will not be directly comparable. The estimation of a causal effect obtained by comparing a group of units exposed to a treatment with a nonexperimental comparison group that is not exposed to the treatment is likely influenced by evaluation bias, or the difference between the outcomes of the nontreated and the desired counterfactual mean.

While the ATE averages the treatment effect across the entire population, the average treatment effect *on the treated* (ATT) is the mean effect for those who actually received the treatment, i.e. the effect of job displacement *for displaced workers*. Conditioning on the pretreatment characteristics $\boldsymbol{X}$, the estimator for the ATT is:

$$\begin{aligned}\text{ATT} &\equiv E(\Delta \mid w = 1, \boldsymbol{X}) \equiv E(Y_1 - Y_0 \mid w = 1, \boldsymbol{X}) \\ &= E(Y_1 \mid w = 1, \boldsymbol{X}) - E(Y_0 \mid w = 1, \boldsymbol{X}).\end{aligned}$$

We can reliably estimate $E(Y_1 \mid w = 1, \boldsymbol{X})$. This is the outcome for the treated. We do not know $E(Y_0 \mid w = 1, \boldsymbol{X})$. The ATT can be consistently estimated under the assumption that w is independent of Y_0 conditional on pretreatment covariates, without placing any restriction on the relationship between w and Y_1. Letting $\boldsymbol{X}$ denote a vector of observed covariates, the assumption required to estimate an average treatment effect is:

$$Y_0 \perp\!\!\!\perp w \mid \boldsymbol{X}.$$[6]

To evaluate the ATT, it is further assumed that

$$P(w = 1 \mid \boldsymbol{X}) < 1;$$

where $P(w = 1 \mid \boldsymbol{X})$ is the probability of job displacement given the set of observed covariates. This assumption states that there is the possibility of a non-treated analogue for each treated unit. Based on these assumptions, the conditional average treatment effect on the treated can be estimated by the following equation:

$$E(\Delta \mid w = 1, \boldsymbol{X}) = E(Y_1 \mid w = 1, \boldsymbol{X}) - E(Y_0 \mid w = 0, \boldsymbol{X}).$$

There has been some controversy over the plausibility of the above assumptions in the econometrics literature. One of the main concerns is over self-selection into treatment, i.e. if individual *i* predicts his or her expected outcomes and chooses treatment status based upon the largest expected utility. This is a potential source of unobservable (to the researcher) bias.

Conditional Difference-in-Differences Matching

Matching involves pairing displaced and non-displaced workers that are similar in terms of their observable characteristics in an attempt to answer, for example, "What is the effect on earnings for workers displaced from a job compared to what would be the outcome had they not been displaced?" Matching methods are useful for estimating treatment effects as such estimators make no functional form assumptions. Matched control units serve as counterfactuals; the use of observation-specific counterfactuals for each treated observation avoids potential bias due to misspecification of the functional

[6] Heckman, Ichimura, and Todd (1998) show that a conditional mean independence assumption suffices; that is, $E(Y_0 \mid \boldsymbol{X}, w = 1) = E(Y_0 \mid \boldsymbol{X}, w = 0) = E(Y_0 \mid \boldsymbol{X})$.

form in a linear model. If the treatment effect is not constant across all individuals, unconfoundedness does not imply a linear functional relation with (mean) independent errors (Imbens 2003). Matching also highlights the problem of common support in a way that linear regression does not (Black and Smith 2003). Nonoverlapping support means that for some treated/control units there are no comparable control/treated units. If support is not common to treated and control group members, different parameters are (often implicitly) defined and estimated. Regression analysis is not concerned with how similar treated and control groups are in the distribution of covariates. The implied counterfactual for workers outside the region of common support in a linear regression analysis would be the product of the linear functional form assumption (Black and Smith 2003). By using propensity score matching methods, we uncover how many comparison units are in fact comparable and hence, how much smoothing our estimator is expected to perform. Heckman et al. (1997) find that comparing the incomparable, i.e. violating the common support condition, is a major source of evaluation bias.

How can we condition on $\boldsymbol{X}$ in order to perform matching estimation? One method by which to condition on $\boldsymbol{X}$ would be stratify the data into bins each defined by a particular value of $\boldsymbol{X}$. However, as the number of variables increases, the number of bins increases exponentially creating a dimensionality problem. Rosenbaum and Rubin (1983) recommend the use of a propensity score to reduce the dimensionality of the problem and to condition on a scalar variable. A propensity score is defined as the probability of assignment to the treatment group given a set of observed covariates:

$$p(X) = P(w = 1 \mid \boldsymbol{X}).$$

While the propensity value is unobserved (all that is observed is the value $w = 1$ or $w = 0$), it can be estimated using a probit or logit regression model.[7]

Up until this point, I have focused upon estimators that evaluate causal effects at the cross-section. Even if a nonparametric estimation strategy is used, such as propensity score matching, such estimators assume that after conditioning on a set of observable characteristics, mean outcomes are conditionally independent of displacement. This estimation strategy can be problematic due to remaining systematic differences (such as unmeasured characteristics) between treated and control units. To construct a counterfactual in the cross-section, data on non-treated persons is used. There is another source of information that can be used to construct the required counterfactual: data on the treated prior to treatment. A major utilization of panel data for estimating the effects of events is to obtain two or more time-separated measures of selected outcomes and use pre-treatment data to impute counterfactual outcomes for the treated. In the two-period panel data situation, letting t' represent a time period before the event and t a time period after an event, the outcome variable is measured at two distinct points in time, $Y_{t'}$ and Y_t, where the treated experience the event (job displacement) between the two measurements. Several studies of job displacement, especially since the use of the Displaced Workers Survey limits the construction of a comparable control group, have used a simple before-after approach to establish causality. A drawback of the simple before-after estimation strategy is that identification of the causal effect breaks down in the presence of time-specific intercepts, such as life-cycle wage growth or from the business cycle (Smith and Todd 2003). To the extent that the earnings of non-displaced

[7] Rosenbaum and Rubin (1983) prove that when Y_0 outcomes are independent of treatment conditional on $\boldsymbol{X}$, they are also independent of treatment conditional on $p(X)$; that is, $Y_0 \perp\!\!\!\perp w \mid p(X)$.

workers are rising, the simple before-after earnings change for displaced workers will underestimate the true earnings loss displaced workers suffer. A simple before-after estimation of earnings losses will also assume that any change in earnings is the result of displacement. This is a strong assumption, however, considering the multifarious possibilities of earnings trajectories.

A difference-in-differences (DID) estimator measures the effect of the treatment by the difference between the treated and nontreated in the before-after difference in outcomes. It uses both pre- and post-program data (t' and t data, respectively) on $w = 1$ and $w = 0$ units. In contrast to the before-after estimator, the DID estimator allows for time-specific intercepts that are common across groups. The difference-in-differences estimator explicitly takes into account earnings growth displaced workers would have experienced had they not been displaced.[8] The traditional way to accommodate covariates in the DID model is to introduce them linearly in a parametric model. This may not be appropriate if the treatment has different effects for different groups in the population (Abadie 2002). Ideally, covariates should be treated non-parametrically; when the number of covariates required for identification is large, integration such as the propensity score is necessary.

The conditional difference-in-differences matching estimator (CDIDM) formally extends propensity score matching to a longitudinal setting. CDIDM estimators compare the conditional before-after outcomes of displaced and non-displaced workers. The assumptions that justify CDIDM estimation are weaker than the assumptions invoked to

[8] Difference-in-differences estimators have been usefully employed in studies of job displacement that have data that make such estimators feasible (Farber 1993; Jacobson et al. 1993).

justify conventional matching estimators. The less demanding mean independence assumptions are assumptions about differences:

$$E(Y_{0t} - Y_{0t'} \mid \boldsymbol{X}, w = 1) = E(Y_{0t} - Y_{0t'} \mid \boldsymbol{X}, w = 0);$$

i.e., in the absence of treatment, the average outcomes for treated and controls would have followed parallel paths. If we assume that this assumption is true, we can estimate a nonparametric conditional difference-in-differences matching average treatment effect on the treated by the following:

$$ATT_{DD} = E(Y_{1t} - Y_{0t'} \mid p(X), w = 1) - E(Y_{0t} - Y_{0t'} \mid p(X), w = 0).$$

A conditional difference-in-differences estimator is effective in eliminating bias, especially when it is due to temporally-invariant omitted variables (Heckman et al. 1997).

RESULTS

Displacement Centered Non-employment

Before examining the matching results, I graphically evaluate displaced worker's non-employment levels before and after displacement by occupation for men in Figure 4.3 and for women in Figure 4.4, and by education for men in Figure 4.5 and for women in Figure 4.6. For men, there is a striking level of non-employment post-displacement in comparison to pre-displacement levels, such that all 3 occupational categories have significantly higher percentage of non-employed workers even 5 years after the displacement occurs. There is fairly even spread of non-employment levels by broad occupation for male workers before displacement, ranging from approximately 5-8%. Immediately following displacement, upper-white collar workers are the most likely to be reemployed (35% non-employed), followed by lower white collar workers (40% non-

employed) and blue-collar workers the least likely (45% non-employed). This trend generally continues until about year 4, where there is an almost equivalent non-employment level for each occupational category at about 20%. In year 5, there is a switching over such that upper white-collar workers have the highest non-employment level (18% compared to 15.5%). A similar occupational "switching over" story can be told for women (see Figure 4.4). However, for women, lower-white collar and blue-collar women tend to have similar non-employment rates 5 years pre- and 5 years post-displacement. Upper-white collar women's unemployment levels, however, never return to pre-displacement levels.

By education, Figure 4.5 demonstrates that male college graduate eventual displaced workers have a roughly 4% non-employment rate during the 5 years prior to displacement and high school graduates have a roughly 7% non-employment level; 43% of male high school graduates are non-employed in year 1 post-displacement and 38% of male college graduates. By year 4, again, there is a switching over such that college graduates have higher levels of non-employment (16%) than high school graduates (14%). This trend differs for women (Figure 4.6), where female college graduates return to pre-displacement employment levels, but high school graduates do not.

Conditional Difference-in-Differences Matching Results

I estimate the effect of job displacement on career outcomes using ATT nearest neighbor conditional difference-in-differences matching estimation using 4 control units per treated unit. I first estimate results by sex in Table 4.4. CDIDM results for economic and occupational outcomes suggest that both women and men suffer substantial career

losses. Both men and women suffer employment losses. Men's earnings and wage losses are worse than women's, and appear to last longer, but women's authority losses are worse than men's. Men, but not women, also experience substantial losses for pensions and health insurance on reemployed jobs. Results by level of educational attainment can be found in Table 4.5. High school degree holders suffer the most hourly wage losses, while it is the college degree holders who suffer the most yearly earnings losses and benefits losses. However, both groups suffer substantial and long-term economic losses. High school degree holders also lose job authority and some job satisfaction. Masters and doctorate holders appear to be generally unaffected by job displacement, except for some health insurance loss.

Results by occupation, found in Table 4.6, suggest that blue collar workers suffer the greatest wage, earnings, and benefits losses, while upper white collar workers suffer less (although still significant) wage and earnings losses, but also experience occupational status declines, and loss of job authority. Lower white collar workers experience greater wage and earnings loss (about a 50% loss overall compared to a 25% loss for upper white collar workers) and greater health insurance losses. They are about equally as likely to lose pension benefits. Results in Table 4.7, separated by manufacturing and non-manufacturing industry, show that both manufacturing and non-manufacturing workers experience considerable economic losses, but that it is the manufacturing workers who carry a heavy loss in benefits, as much as more than a decade after a worker was displaced from a job.

I estimate results in Table 4.8 by both sex and education and sex and occupation, without respect to time period. Here we see that all except the most educated men

experience employment losses, while no group of women has employment losses. It appears that while education reduces economic losses for women, it does not offer the same protection for men. Men suffer substantial wage, earnings, pension, and health insurance losses across education levels; earnings and pension losses are not significant, however, for male masters/doctorate degree holders. Interestingly, it is the college educated men who experience the largest economic losses. Moreover, college educated men lose job authority on reemployed jobs. Women who do not hold a college degree do lose substantial wage and earnings as a result of displacement. Women, who have a college degree, while not experiencing economic losses, do suffer significant job authority losses on reemployed jobs. College educated men lose job authority as well, but to a lesser extent. By occupation, upper white collar men experience significant career losses for every outcome except job satisfaction, while lower white collar and blue collar workers experience economic losses, but not occupational status or job authority or autonomy losses. Upper white collar women, on the other hand, only show job authority losses, while lower white collar and blue collar women experience significant economic losses.

Table 4.9 provides matching estimates by career classification for men. For self-employed workers, the greatest loss is for job autonomy on reemployed jobs. For professional workers, the loss is for health insurance. Administration workers lose on economic and benefits. Among circulation workers, higher employees lose the least career losses, while lower employees lose a range of losses and skilled/unskilled workers lose the most earnings. Among production workers, skilled/unskilled workers suffer the greatest losses on earnings, wages, and benefits; still, higher employees suffer

significantly. Table 4.10 provides estimates for women. Women's losses are concentrated among lower employee and skilled/unskilled workers. Production workers lose job benefits while circulation workers lose earnings and wages. Women in professional and higher employee production jobs also lose job authority on reemployed jobs. Also self-employed women like men lose job autonomy on reemployed jobs. Many of the cells, unfortunately, suffer from small sample sizes.

DISCUSSION

This study is a causal analysis of the effect of job displacement on both traditional economic outcomes as well as job characteristics that are important components of the sociological literature on job quality and career attainment. It utilizes Wisconsin longitudinal data, which solves many of the problems studies have encountered using other data sets, and allows for a long-term assessment of the effects of job displacement on career outcomes. This study is effective in minimizing evaluation bias, using conditional difference-in-differences matching estimation, and divides displacement into six 3-year time periods controlling for both time-invariant and time-varying covariates. This study is not an analysis of *why* displaced workers are unable to find jobs comparable to the ones they lost. The causal effects literature focuses on first determining that effects exist. Statistically identifying mechanisms means controlling for intervening variables, something the matching tradition never does. Such a study, however, is an important future contribution to the literature on job displacement and career attainment.

I find that displaced workers suffer considerable non-employment levels, such that the average non-employment rate 5 years after displacement is significantly greater

than the rate in the years prior to displacement. Men are more likely to be experiencing elevated non-employment levels in every occupational category and educational attainment level, while women show much more variation by occupation and education. In particular, upper white collar and college educated women appear to return to pre-displacement employment levels within 5 years after the displacement event.

I find that displaced workers suffer considerable economic losses as a result of job displacement, but the results differ by worker characteristics. While studies have differed over the question of whether men or women experience greater losses post-displacement, I find that in general men experience greater economic losses than women. This may be a methodological question. The estimation strategy I employ estimates the causal effect of displacement, i.e., the amount of earnings a worker would have had had he or she not been displaced. Studies that have not used a control group and just taken the difference in post- versus pre-displacement earnings would not be accounting for the extent to which men's earnings have risen in contrast to women's. Another important outcome, however, that has not been estimated is the loss of job authority on reemployed jobs, which is greater for women than for men. Still, these broad generalizations by sex include variation by educational attainment and by occupation. Blue collar women have the same degree of earnings and wages losses as blue-collar men, and even greater benefits losses. However, it is the upper white collar women that have no economic losses, especially in contrast to the large economic losses of upper white collar men. However, upper white collar women do experience substantial loss of job authority.

Most previous studies have found that workers with less education spend more time unemployed and suffer the greatest wage losses after being displaced. I find,

however, that while less educated workers may spend more time unemployed, college educated workers have greater wage, earnings, and benefits losses than high school educated workers. Previous studies have also found that the long-term unemployed are disproportionately semi-skilled blue collar workers, and that earnings reductions following reemployment are greater for blue-collar workers; greater skill transferability is expected for upper white collar workers. My findings generally confirm these findings: blue collar workers do experience the greatest employment, wage, earnings, and benefit losses, followed by lower white collar workers. However, upper white collar workers still experience substantial long-term economic losses, as much as a 50% reduction in earnings as much as 8 years after the displacement event occurred. Moreover, in contrast to lower white and blue collar workers, upper white collar workers also lose occupational status job authority and job autonomy on reemployed jobs.

Previous studies have also found that manufacturing workers had higher earnings losses than non-manufacturing displaced workers, at least up until the mid-1980s. Again, my findings confirm previous studies findings, that economic and benefit losses are greater for manufacturing workers, but not without the important caveat that non-manufacturing workers still suffer substantial losses on wages, earnings, benefits, as well as job quality on reemployed jobs.

Limitation of the Wisconsin Sample

There are two issues with regard to the use of the Wisconsin Longitudinal Study data that warrant further discussion. First, what is the generalizability of results that are based on a Wisconsin cohort consisting of predominantly white, high school graduates? In 1994,

non-Hispanic white high school gradates made up about 75% of the U.S. labor force aged 45-54. The U.S. population that is inadequately represented, namely less-educated ethnic minorities, is likely to have experienced the effects of job displacement more severely than the Wisconsin cohort. Thus, the estimates presented here may underestimate the true national displacement losses. Since 70% of the sample still lived in Wisconsin in 1992, it is also useful to consider how similar Wisconsin's economy is to the national economy. In general, unemployment rates have followed similar trends with the exception of the early 1990s recession; the 1990s recession did not hit Wisconsin as hard as the rest of the U.S. Median hourly wage in 2001 was about $13 an hour in both Wisconsin and the U.S. as a whole. Also, percentage of 2003 non-farm employment is roughly the same: 96% in the U.S. as a whole and 95% in Wisconsin. There are particular strengths in the fact that this is a regional data set, not only in the richness and quality of data, but also in decreased risk of heterogeneity bias.

The second issue is the confounding of age, period, and time since displacement, which stems from the use of a single cohort; this affects the results in which I document effects by 6-year time periods. There are at least 3 possible explanations for trends in the numbers shown. First, one could argue that the effects of displacement are greater in later periods because workers are older, and the effects are lesser in earlier periods because workers are younger. However, at least one study has found that age has little effect on the consequences of displacement under the age of 55 (Ruhm 1987); WLS workers during this period range from approximately age 35-53. The effect of age is bound to have some effect, but this is unlikely to be fully explaining trends. Second, one could argue that period effects will affect the results. Within the period 1975-1993, one

would expect that the effects of displacement would be worst during the two recessions, the early 1980s and early 1990s. But, there is not reason to expect that the declining effect of displacement is attributable to period effects. The main influence on the trend in numbers plausibly seems to be the time since the displacement event occurred.

CONCLUSION

Job displacement is increasingly affecting the security of long-term steady employment breeding an uneasy concern over the ability of workers to sustain a successful career characterized by upward mobility. Beyond individual consequences of unemployment and career losses are the societal consequences, such as the failure to realize the social investment in human capital made through the educational system, a loss of tax revenue, and increased outgoings in unemployment benefits. Job loss might not be such a serious problem if there were many replacement jobs that displaced workers could obtain with similar levels of earnings, benefits, and characteristics. But this is not the case; jobs created are increasingly poorly paid ones in contrast to jobs that workers are displaced from. This does not bode well for displaced workers. It further restricts their ability to replace a lost job with an equivalent position and sustain a rewarding career. Job displacement is affecting the nature of work and opportunity in America. The average worker that is displaced from a job endures a career characterized by years of unemployment, no real earnings growth, and job quality losses on reemployed jobs.

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Table 4.1. Career Classification Class of Worker/Occupational/Sectoral Groupings

Abbreviation	Definition
1 Self-employed	Self-employed workers, not including professional
2 Professional	Professional workers and professional self-employed; Sectoral group V
3 Administration	Sectoral group IV
4 Higher employee, circulation	Occupational group I; Sectoral group III
5 Higher employee, production	Occupational group I; Sectoral group II
6 Lower employee, circulation	Occupational group II; Sectoral group III
7 Lower employee, production	Occupational group II; Sectoral group II
8 Skilled/Unskilled worker, circulation	Occupational group III, IV; Sectoral group III
9 Skilled/Unskilled worker, production	Occupational group III, IV; Sectoral group II

Occupational Groupings

Abbreviation	Definition
I Higher employee	Professional, technical, kindred and managers, officials, proprietors
II Lower employee	Sales and clerical and kindred workers
III Skilled worker	Craftsmen, foreman, kindred and operatives
IV Unskilled worker	Service and private household and laborers

Sectoral Groupings

Abbreviation	Definition
I Agriculture	Agriculture, forestry, fisheries
II Production	Mining, construction, manufacturing
III Circulation	Trade, business, repair, personal, entertainment, recreation services
IV Administration	Public administration, transportation, communications, other public utilities
V Professions	Professional services

Table 4.2. Descriptive Statistics of Workers Before and After Displacement

	Men				Women			
	Displaced		Non-displaced		Displaced		Non-displaced	
	1974	1992	1974	1992	1974	1992	1974	1992
All Workers	n = 558		n = 3293		n = 578		n = 3449	
% Employed	97.1	86	97.6	94.4	63.6	77.3	60.7	85.5
% Full-time emp.	93.8	82.4	95.5	91.5	36.4	57.6	33.2	63.5
% Cumulative emp.	87.1		95.3		76		77.4	
Mean Tenure	6.6	4.9	8.1	17.7	3.1	4.6	3.4	10.5
Mean Earnings	$42,773	$37,282	$45,581	$51,782	$8,519	$15,005	$8,907	$19,178
Median Earnings	$40,000	$30,000	$41,429	$40,000	$3,714	$13,000	$2,571	$16,000
95th Percentile Earnings	$84,286	$90,000	$91,429	$125,000	$29,429	$40,000	$34,286	$47,800
Professional/Managerial	n = 222		n = 1757		n = 156		n = 1651	
% Employed	99	89.6	98.4	95.3	67.4	81.4	67.2	88.6
% Full-time emp.	95.2	84.7	95.7	91.3	37.4	64.5	38.3	69.1
% Cumulative emp.	87.9		94.2		80.3		80.7	
Mean Tenure	5.8	4.2	6.8	15.1	3.2	4	3.5	9.9
Mean Earnings	$48,809	$47,115	$50,817	$63,814	$10,035	$20,427	$11,730	$25,126
Median Earnings	$42,857	$40,000	$45,143	$50,000	$4,571	$18,000	$5,714	$23,000
95th Percentile Earnings	$114,286	$103,000	$102,857	$165,000	$34,286	$50,000	$40,000	$55,000
Sales/Clerical	n = 144		n = 902		n = 357		n = 2213	
% Employed	99.3	85.4	98.4	93.6	61.8	75.4	58.1	83.9
% Full-time emp.	94.7	83.2	96.4	88.1	33.2	53.7	28.1	60.1
% Cumulative emp.	86.7		92.6		75		74.7	
Mean Tenure	6.4	5.1	7.21	13	2.96	4.6	2.85	8.8
Mean Earnings	$41,452	$38,011	$45,691	$48,496	$7,801	$13,658	$6,700	$15,426
Median Earnings	$38,714	$30,000	$40,000	$36,000	$2,857	$12,000	$1,429	$13,000
95th Percentile Earnings	$82,857	$82,000	$97,143	$135,000	$27,714	$35,000	$25,714	$40,000
Crafts/Operatives/Laborers...	n = 199		n = 1213		n = 75		n = 483	
% Employed	93.4	83.9	95.9	93.3	64.2	73.3	58.3	85.3
% Full-time emp.	90.2	80.4	93.9	90.7	49.3	57.3	34.9	64.8
% Cumulative emp.	85.2		94.9		73.8		74.8	
Mean Tenure	7.3	5.4	8.9	17.3	3.4	4.5	3.1	8.6
Mean Earnings	$36,608	$25,889	$38,626	$34,852	$8,507	$11,858	$7,630	$13,933
Median Earnings	$34,429	$25,000	$37,143	$33,000	$7,429	$11,000	$3,714	$12,000
95th Percentile Earnings	$60,000	$50,000	$62,857	$67,000	$21,143	$35,000	$28,571	$35,000

Table 4.3. Education, Industry, Occupation by Displacement Period

	Year of Displacement					
Percentage	**1975-77**	**1978-80**	**1981-83**	**1984-86**	**1987-89**	**1990-92/93**
College Educated	17.4	11.7	22.1	18.2	14.0	21.5
Goods-Producing Ind.	41.3	30.6	36.9	43.5	32.6	38.6
Upper white collar Occ.	29.8	29.6	34.9	34.4	33.1	36.5
Lower white collar Occ.	52.9	46.4	45.6	35.9	41.6	45.1
Blue collar Occ.	22.3	28.1	21.5	30.6	21.9	19.7

Table 4.4. Conditional Difference-in-Differences Matching Estimates of Career Outcomes on Job Displacement: By Sex

	Sex / Year worker was displaced							
Outcome	**Men**				**Women**			
Variables 1992/3	**1987-92/3**	**1981-86**	**1975-80**	**1975-93**	**1987-92/3**	**1981-86**	**1975-80**	**1975-93**
Employment	-0.175***	-0.027	-0.018	-0.074***	-0.200***	-0.07	0.004	-0.046
	(5.01)	(1.09)	(0.62)	(4.05)	(3.53)	(1.39)	(0.08)	(1.45)
Wages	-1.01***	-0.339**	-0.198	-0.501***	-0.661***	-0.225	-0.068	-0.289**
	(7.40)	(3.19)	(1.41)	(6.52)	(3.87)	(1.48)	(0.38)	(2.88)
Earnings	-1.034***	-0.41**	-0.131	-0.576***	-1.017***	-0.494**	0.114	-0.345**
	(6.13)	(2.93)	(0.77)	(5.79)	(4.78)	(2.65)	(0.50)	(2.74)
Pension	-0.325***	-0.034	0.009	-0.145***	-0.148**	0.014	0.079	-0.023
	(6.68)	(0.76)	(0.19)	(5.26)	(2.54)	(0.24)	(1.44)	(0.71)
Health insurance	-0.275***	-0.076*	-0.013	-0.141***	-0.172**	-0.044	-0.015	-0.058
	(6.35)	(2.02)	(0.26)	(5.42)	(2.87)	(0.81)	(0.23)	(1.62)
Occ. Education	-0.053	-0.06	-0.128	-0.084	-0.169	0.149	0.08	-0.003
	(0.50)	(0.64)	(1.12)	(1.32)	(1.35)	(1.37)	(0.63)	(0.04)
Occ. Income	-0.223*	-0.161	-0.08	-0.16**	-0.29*	-0.045	-0.098	-0.089
	(2.07)	(1.56)	(0.68)	(2.45)	(1.69)	(0.31)	(0.59)	(0.88)
Autonomy	0.027	0.088*	-0.099*	0.02	-0.058	-0.019	-0.015	-0.022
	(0.48)	(1.81)	(1.77)	(0.63)	(0.86)	(0.34)	(0.24)	(0.62)
Authority	-0.14**	-0.072	-0.038	-0.077**	-0.209**	-0.151**	-0.04	-0.093*
	(2.61)	(1.42)	(0.71)	(2.41)	(2.86)	(2.48)	(0.61)	(2.31)
Job Satisfaction	-0.036	0.036	0.066	0.012	-0.102	-0.074	0.046	-0.07
	(0.43)	(0.48)	(0.75)	(0.24)	(1.01)	(0.89)	(0.49)	(1.25)

Note: Numbers in parentheses are z-ratios. Treatment effects are conditional upon a set of time-invariant covariates (mother's education, head's occupational status, cognitive ability, educational attainment, labor market experience in 1975, frostbelt residence 1st job spell, Milwaukee residence first job spell, union status for first job spell, and job satisfcation in 1975) and a set of time-varying covariates that for each column indicate "pre-treatment" job characteristics (class of worker, industry, occupation, tenure, full-time employment status, pension, occupational earnings, and tenure squared).

*p <. 05 **p < .01 ***p < .001 (one-tailed tests)

Table 4.5. Conditional Difference-in-Differences Matching Estimates of Career Outcomes on Job Displacement: By Educational Attainment (Highest degree conferred)

	Educational Attainment / Year worker was displaced								
Outcome	High School Degree				College Degree				Masters/ Doc. Degree
Variables 1992/3	1987-92/3	1981-86	1975-80	1975-93	1987-92/3	1981-86	1975-80	1975-93	1975-93
Employment	-0.195***	-0.03	0.007	-0.060**	-0.049	-0.098*	-0.094	-0.075*	-0.033
	(4.70)	(0.87)	(0.19)	(2.63)	(0.74)	(1.77)	(1.20)	(1.89)	(0.75)
Wages	-0.732***	-0.285**	-0.197	-0.404***	-0.786**	-0.462*	-0.015	-0.374*	-0.209
	(5.56)	(2.53)	(1.47)	(5.22)	(2.81)	(2.07)	(0.04)	(2.29)	(0.83)
Earnings	-0.879***	-0.377**	-0.061	-0.425***	-0.963**	-0.893**	-0.755	-0.894***	-0.19
	(5.20)	(2.69)	(0.37)	(4.48)	(2.92)	(2.85)	(1.52)	(3.97)	(0.53)
Pension	-0.230***	-0.013	0.031	-0.080**	-0.384***	-0.11	-0.083	-0.177**	-0.02
	(4.77)	(0.30)	(0.70)	(3.02)	(3.98)	(1.20)	(0.66)	(2.97)	(0.19)
Health insurance	-0.188***	-0.066	-0.026	-0.097***	-0.280***	0	-0.031	-0.125*	-0.158*
	(3.89)	(1.63)	(0.54)	(3.56)	(3.35)	(0.00)	(0.25)	(2.22)	(1.71)
Occ. Education	-0.094	-0.021	-0.039	-0.053	-0.519*	0.349	-0.168	-0.09	-0.027
	(0.94)	(0.28)	(0.40)	(0.94)	(2.31)	(1.41)	(0.46)	(0.53)	(0.08)
Occ. Income	-0.315**	-0.128	-0.114	-0.149*	-0.163	0.054	-0.298	-0.076	0.025
	(2.37)	(1.21)	(0.94)	(2.01)	(0.66)	(0.26)	(0.92)	(0.48)	(0.10)
Autonomy	-0.03	0.039	0.01	0.019	0.016	0.044	-0.228*	-0.08	-0.061
	(0.56)	(0.90)	(0.19)	(0.65)	(0.13)	(0.41)	(1.71)	(1.06)	(0.56)
Authority	-0.125*	-0.105*	0.012	-0.05	-0.169	-0.043	-0.283*	-0.18**	-0.155
	(2.11)	(2.22)	(0.24)	(1.56)	(1.49)	(0.44)	(2.32)	(2.32)	(1.50)
Job Satisfaction	-0.181*	0.029	0.097	-0.026	-0.029	-0.047	-0.031	-0.034	-0.169
	(2.12)	(0.43)	(1.31)	(0.58)	(0.18)	(0.28)	(0.16)	(0.31)	(0.98)

Notes: Numbers in parentheses are z-ratios. Treatment effects are conditional upon a set of time-invariant covariates (sex, mother's education, head's occupational status, cognitive ability, labor market experience in 1975, frostbelt residence 1st job spell, Milwaukee residence first job spell, union status for first job spell, job satisfcation in 1975, and sex interactions) and a set of time-varying covariates that for each column indicate "pre-treatment" job characteristics (class of worker, industry, occupation, tenure, full-time employment status, pension, occupational earnings, sex interactions, and tenure squared).

There were not enough cases to disagregate effects for masters/ doctorate degree holder.

Table 4.6. Conditional Difference-in-Differences Matching Estimates of Career Outcomes on Job Displacement: By Occupation

Outcome Variables	Occupation / Year worker was displaced											
	Upper White Collar				Lower White Collar				Blue Collar			
	1987-92/3	1981-86	1975-80	1975-93	1987-92/3	1981-86	1975-80	1975-93	1987-92/3	1981-86	1975-80	1975-93
Employment	-0.136***	-0.047	0.021	-0.027	-0.197***	-0.008	-0.01	-0.081**	-0.217**	-0.024	-0.04	-0.098**
	(3.31)	(1.16)	(0.51)	(0.89)	(3.71)	(0.19)	(0.21)	(2.52)	(2.90)	(0.46)	(0.69)	(2.53)
Wages	-0.583***	-0.457**	-0.119	-0.268**	-0.884***	-0.268*	-0.199	-0.418***	-1.061***	-0.314*	-0.06	-0.495***
	(3.36)	(3.18)	(0.60)	(2.65)	(5.18)	(1.73)	(1.20)	(4.16)	(5.67)	(2.03)	(0.31)	(4.54)
Earnings	-0.642**	-0.535**	0.04	-0.246*	-0.999***	-0.379*	-0.029	-0.514***	-1.503***	-0.340*	-0.276	-0.676***
	(3.00)	(3.03)	(0.15)	(1.85)	(4.64)	(1.94)	(0.15)	(4.17)	(6.19)	(1.66)	(1.24)	(4.85)
Pension	-0.227***	-0.03	0.067	-0.069*	-0.207***	0.002	0.051	-0.063*	-0.362***	-0.093	-0.054	-0.158***
	(3.55)	(0.56)	(1.04)	(2.06)	(3.44)	(0.03)	(0.99)	(1.92)	(4.79)	(1.32)	(0.77)	(3.82)
Health ins.	-0.132*	-0.092*	-0.018	-0.056*	-0.260***	-0.039	0.015	-0.103**	-0.264***	-0.112*	-0.109	-0.152***
	(2.34)	(1.82)	(0.27)	(1.68)	(4.31)	(0.74)	(0.24)	(2.90)	(3.74)	(1.70)	(1.50)	(3.65)
Occ. Education	-0.243*	-0.004	-0.264	-0.188*	-0.114	-0.048	-0.171	-0.12	0.187	0.267*	0.443**	0.298**
	(1.74)	(0.03)	(1.60)	(2.12)	(0.91)	(0.42)	(1.46)	(1.59)	(1.05)	(2.30)	(2.45)	(3.16)
Occ. Income	-0.298*	-0.247*	-0.293*	-0.269**	-0.297*	0.059	-0.153	-0.091	-0.024	0.04	0.137	0.045
	(1.98)	(1.76)	(1.75)	(2.91)	(1.75)	(0.39)	(0.98)	(0.92)	(0.12)	(0.28)	(0.80)	(0.45)
Autonomy	-0.125*	0.041	-0.114	-0.082*	0.075	-0.019	0.006	0.015	0.109	0.172**	-0.037	0.1*
	(2.03)	(0.70)	(1.54)	(2.07)	(1.04)	(0.33)	(0.11)	(0.40)	(1.29)	(2.66)	(0.48)	(2.27)
Authority	-0.191**	-0.118*	-0.096	-0.152***	-0.118	-0.083	0.067	-0.024	-0.103	-0.066	-0.06	-0.045
	(3.02)	(1.78)	(1.31)	(3.65)	(1.52)	(1.38)	(1.01)	(0.58)	(1.09)	(0.91)	(0.77)	(0.92)
Job Satisfaction	-0.037	-0.018	0.082	0.009	-0.02	0.042	0.041	0.017	-0.05	0.032	0.143	0.065
	(0.46)	(0.20)	(0.77)	(0.17)	(0.22)	(0.55)	(0.49)	(0.33)	(0.37)	(0.34)	(1.36)	(0.95)

Note: Numbers in parentheses are z-ratios. Treatment effects are conditional upon a set of time-invariant covariates (sex, mother's education, head's occupational status, cognitive ability, educational attainment, labor market experience in 1975, frostbelt residence 1st job spell, Milwaukee residence first job spell, union status for first job spell, job satisfcation in 1975, and sex interactions) and a set of time-varying covariates that for each column indicate "pre-treatment" job characteristics (class of worker, industry, tenure, full-time employment status, pension, occupational earnings, sex interactions, and tenure squared).

*p <. 05 **p < .01 ***p < .001 (one-tailed tests)

Table 4.7. Conditional Difference-in-Differences Matching Estimates of Career Outcomes on Job Displacement: By Industry

Outcome Variables 1992/3	Industry / Year worker was displaced: Manufacturing 1987-92/3	Manufacturing 1981-86	Manufacturing 1975-80	Manufacturing 1975-93	Non-Manufacturing 1987-92/3	Non-Manufacturing 1981-86	Non-Manufacturing 1975-80	Non-Manufacturing 1975-93
Employment	-0.175***	-0.051	-0.026	-0.083**	-0.180***	-0.022	0.011	-0.082***
	(3.46)	(1.20)	(0.52)	(2.68)	(4.54)	(0.66)	(0.30)	(4.88)
Wages	-0.966***	-0.247*	-0.134	-0.353***	-0.721***	-0.309**	-0.172	-0.401***
	(6.17)	(1.82)	(0.65)	(3.66)	(5.25)	(2.60)	(1.28)	(5.13)
Earnings	-0.920***	-0.621**	-0.329	-0.584***	-0.993***	-0.366**	0.057	-0.436***
	(4.18)	(3.36)	(1.27)	(4.44)	(5.69)	(2.56)	(0.36)	(4.52)
Pension	-0.420***	-0.202***	-0.023	-0.220***	-0.165***	0.093*	0.046	-0.052*
	(7.14)	(3.46)	(0.35)	(6.33)	(3.46)	(2.13)	(1.08)	(2.05)
Health insurance	-0.319***	-0.213***	-0.138*	-0.216***	-0.181***	0.005	0.056	-0.046*
	(5.87)	(4.10)	(2.03)	(6.35)	(3.93)	(0.12)	(1.16)	(1.75)
Occ. Education	-0.013	-0.132	0.213	0.078	-0.208*	0.022	-0.145	-0.094
	(0.10)	(0.27)	(1.18)	(0.89)	(2.00)	(0.24)	(1.57)	(1.57)
Occ. Income	-0.197	-0.137	0.189	-0.038	-0.298**	-0.077	-0.17	-0.196**
	(1.28)	(0.97)	(1.09)	(0.39)	(2.50)	(0.72)	(1.43)	(2.75)
Autonomy	0.009	0.118*	0.021	0.055	-0.009	0.019	-0.085*	-0.024
	(0.12)	(2.03)	(0.31)	(1.39)	(0.17)	(0.42)	(1.69)	(0.79)
Authority	-0.135*	-0.051	-0.038	-0.059	-0.162**	-0.113*	-0.023	-0.097**
	(1.90)	(0.80)	(0.51)	(1.46)	(2.88)	(2.28)	(0.46)	(3.11)
Job Satisfaction	-0.04	0.158*	0.267**	0.093	-0.04	-0.1	0.095	-0.015
	(0.40)	(1.88)	(2.48)	(1.62)	(0.57)	(1.62)	(1.38)	(0.37)

Note: Numbers in parentheses are z-ratios. Treatment effects are conditional upon a set of time-invariant covariates (sex, mother's education, head's occupational status, cognitive ability, educational attainment, labor market experience in 1975, frostbelt residence 1st job spell, Milwaukee residence first job spell, union status for first job spell, job satisfcation in 1975, and sex interactions) and a set of time-varying covariates that for each column indicate "pre-treatment" job characteristics (class of worker, occupation, tenure, full-time employment status, pension, occupational earnings, sex interactions, and tenure squared).

*p <. 05 **p < .01 ***p < .001 (one-tailed tests)

Table 4.8. Conditional Difference-in-Differences Matching Estimates of Career Outcomes on Job Displacement: By Sex, Occupation, Education

	Sex / Education, Occupation										
	Men						Women				
	Education			Occupation			Education		Occupation		
Outcome Variables 1992/3	High School	College	Masters/ Doctorate	Upper-white	Lower-white	Blue	High School	College	Upper-white	Lower-white	Blue
Employment	-0.049*	-0.095*	-0.043	-0.070**	-0.065*	-0.071*	-0.058	0.052	0.033	-0.062	-0.099
	(1.99)	(2.29)	(1.04)	(2.87)	(2.13)	(1.88)	(1.57)	(0.53)	(0.58)	(1.53)	(1.09)
Wages	-0.446***	-0.455**	-0.454*	-0.465***	-0.405**	-0.439***	-0.289**	0	0.117	-0.441***	-0.416*
	(4.39)	(2.41)	(1.73)	(3.87)	(2.55)	(3.60)	(2.54)	(0.00)	(0.62)	(3.45)	(1.71)
Earnings	-0.374**	-0.888***	-0.371	-0.497**	-0.456**	-0.623***	-0.405**	-0.521	0.261	-0.53***	-0.659*
	(3.00)	(3.32)	(1.02)	(3.18)	(2.36)	(3.96)	(2.89)	(1.30)	(1.12)	(3.35)	(2.10)
Pension	-0.101**	-0.308***	-0.029	-0.127**	-0.135**	-0.101*	-0.047	0.302**	0.031	-0.024	-0.267**
	(2.64)	(4.78)	(0.27)	(3.16)	(2.39)	(2.13)	(1.27)	(2.84)	(0.56)	(0.58)	(2.84)
Health insurance	-0.088**	-0.210***	-0.200*	-0.135***	-0.154**	-0.066	-0.094*	0.167	0.101	-0.097*	-0.328***
	(2.40)	(3.53)	(2.18)	(3.53)	(2.82)	(1.43)	(2.34)	(1.30)	(1.70)	(2.15)	(3.38)
Occ. Education	-0.103	-0.178	-0.193	-0.263**	-0.073	0.241**	-0.028	0.213	0.038	-0.154	0.578**
	(1.28)	(1.09)	(0.61)	(2.44)	(0.60)	(2.42)	(0.36)	(0.45)	(0.23)	(1.62)	(2.35)
Occ. Income	-0.221**	-0.125	-0.154	-0.285**	0.135	-0.117	-0.072	-0.324	-0.067	-0.228*	0.632**
	(2.50)	(0.77)	(0.68)	(2.89)	(1.00)	(1.12)	(0.63)	(0.83)	(0.35)	(1.75)	(2.77)
Autonomy	0.058	-0.077	-0.074	-0.088*	0.064	0.114*	-0.011	-0.113	-0.035	0.003	0.005
	(1.34)	(0.94)	(0.64)	(1.84)	(1.01)	(2.13)	(0.26)	(0.70)	(0.51)	(0.07)	(0.07)
Authority	-0.08*	-0.156*	-0.125	-0.111*	-0.017	-0.068	-0.054	-0.3*	-0.26***	-0.035	0.037
	(1.83)	(2.06)	(1.21)	(2.32)	(0.26)	(1.25)	(1.17)	(2.15)	(3.46)	(0.68)	(0.35)
Job Satisfaction	0.031	-0.064	-0.103	-0.006	0.025	0.005	0.015	0.155	-0.007	0.032	0.172
	(0.54)	(0.54)	(0.73)	(0.09)	(0.29)	(0.06)	(0.27)	(0.97)	(0.08)	(0.52)	(1.20)

Note: Numbers in parentheses are z-ratios. Treatment effects are conditional upon a set of time-invariant covariates (mother's education, head's occupational status, cognitive ability, *educational attainment,* labor market experience in 1975, frostbelt residence 1st job spell, Milwaukee residence first job spell, union status for first job spell, job satisfaction in 1975) and a set of time-varying covariates that for each column indicate "pre-treatment" job characteristics (class of worker, *occupation,* industry, tenure, full-time employment status, pension, occupational earnings, sex interactions, and tenure squared).

*p <. 05 **p < .01 ***p < .001 (one-tailed tests)

Table 4.9. Conditional Difference-in-Differences Matching Estimates of Career Outcomes on Job Displacement: Men

	Career Classification								
1992-1975 Outcomes	**Self-employed**	**Professional**	**Administration**	**HE, circ**	**HE, prod**	**LE, circ**	**LE, prod**	**Worker, circ**	**Worker, prod**
Employment	-0.054	0	-0.113	-0.08	-0.044	-0.100*	-0.021	-0.128*	-0.065
	(1.41)	(0.00)	(1.58)	(1.38)	(1.26)	(2.31)	(0.42)	(1.71)	(1.48)
Earnings	-0.34	-0.29	-0.93**	-0.34	-0.39*	-0.49*	-0.31	-0.85*	-0.60**
	(0.84)	(0.58)	(2.96)	(1.02)	(1.68)	(1.92)	(0.98)	(2.29)	(3.26)
Wages	-0.65*	-0.21	-0.68**	-0.46*	-0.26*	-0.64**	-0.49*	-0.39	-0.48***
	(1.91)	(0.49)	(3.07)	(1.84)	(1.74)	(3.09)	(1.91)	(1.42)	(3.43)
Pension	0.054	-0.25	-0.275**	-0.065	-0.173**	-0.042	-0.066	-0.11	-0.161**
	(0.53)	(1.63)	(3.04)	(0.57)	(2.93)	(0.52)	(0.53)	(0.88)	(2.79)
Heath ins.	0.038	-0.288**	-0.221*	0.04	-0.107*	-0.135*	-0.213*	0.017	-0.180***
	(0.43)	(2.40)	(2.93)	(0.43)	(2.26)	(1.95)	(1.88)	(0.16)	(3.54)
Autonomy	-0.35***	0.04	-0.01	-0.07	-0.03	0.08	0.1	-0.01	0.18**
	(3.40)	(0.29)	(0.07)	(0.59)	(0.47)	(0.84)	(0.90)	(0.12)	(2.95)
Authority	-0.13	-0.04	-0.02	-0.06	-0.07	-0.09	-0.06	-0.19	-0.07
	(1.22)	(0.24)	(0.22)	(0.63)	(1.07)	(1.04)	(0.47)	(1.61)	(1.11)

Note: Numbers in parentheses are z-ratios. Treatment effects are conditional upon the following set of covariates: mother's education, head's occupational status, cognitive ability, educational attainment, frostbelt residence 1st job spell, Milwaukee residence first job spell, union status for first job spell, labor market experience in 1975, job satisfaction in 1975, class of worker, occupation, industry, *tenure and tenure squared* , full-time employment status, *pension,* occupational earnings. All job characteristics pertain to jobs held in 1975.

*p <. 05 **p < .01 ***p < .001 (one-tailed tests)

Table 4.10. Conditional Difference-in-Differences Matching Estimates of Career Outcomes on Job Displacement: Women

	Career Classification								
1992-1975 Outcomes	**Self-employed**	**Professional**	**Administration**	**HE, circ**	**HE, prod**	**LE, circ**	**LE, prod**	**Worker, circ**	**Worker, prod**
Employment	-0.049	-0.039	0.083	0.007	-0.117	-0.175**	-0.182*	-0.151*	-0.15
	(0.58)	(0.44)	(0.68)	(0.08)	(0.82)	(3.00)	(2.20)	(1.79)	(1.36)
Earnings	0.37	0.4	0.28	0.03	-0.57	-0.88***	-0.63*	-1.33***	-0.51
	(0.85)	(1.13)	(0.44)	(0.08)	(0.94)	(3.85)	(2.01)	(4.07)	(1.37)
Wages	-0.13	0.19	0.04	-0.06	-0.41	-0.84***	-0.3	-0.93***	-0.32
	(0.42)	(0.61)	(0.10)	(0.20)	(0.89)	(4.57)	(1.19)	(3.58)	(1.09)
Pension	0.280**	0.105	0.217	0.029	-0.067	-0.006	-0.165	-0.092	-0.311**
	(2.78)	(1.05)	(1.11)	(0.27)	(0.49)	(0.09)	(1.48)	(0.82)	(2.73)
Heath ins.	-0.031	0.145	0.033	0.068	-0.019	-0.138*	-0.07	-0.184*	-0.378***
	(0.28)	(1.61)	(0.19)	(0.63)	(0.13)	(2.28)	(0.67)	(1.66)	(3.34)
Autonomy	-0.34**	0.1	-0.08	0.1	-0.21	-0.02	0.01	-0.05	0.06
	(2.45)	(0.96)	(0.45)	(0.78)	(1.00)	(0.33)	(0.06)	(0.48)	(0.75)
Authority	-0.19	-0.21*	-0.12	-0.19	-0.40*	-0.06	-0.05	-0.14	0.01
	(1.31)	(1.79)	(0.54)	(1.26)	(1.90)	(0.93)	(0.46)	(1.06)	(0.05)

Note: Numbers in parentheses are z-ratios. Treatment effects are conditional upon the following set of covariates: mother's education, head's occupational status, cognitive ability, educational attainment, frostbelt residence 1st job spell, Milwaukee residence first job spell, union status for first job spell, labor market experience in 1975, job satisfaction in 1975, class of worker, occupation, industry, *tenure and tenure squared* , full-time employment status, *pension,* occupational earnings. All job characteristics pertain to jobs held in 1975.

*p <. 05 **p < .01 ***p < .001 (one-tailed tests)

Figure 4.1. Earnings Distributions Before and After Displacement: Men
(0=Non-displaced; 1=Displaced)

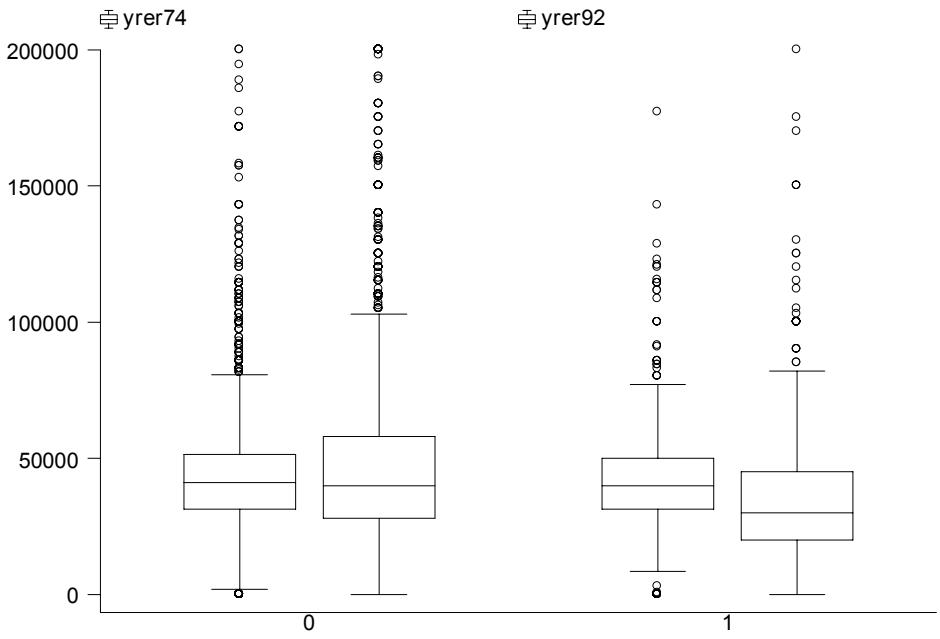

Figure 4.2. Earnings Distributions Before and After Displacement: Women
(0=Non-displaced; 1=Displaced)

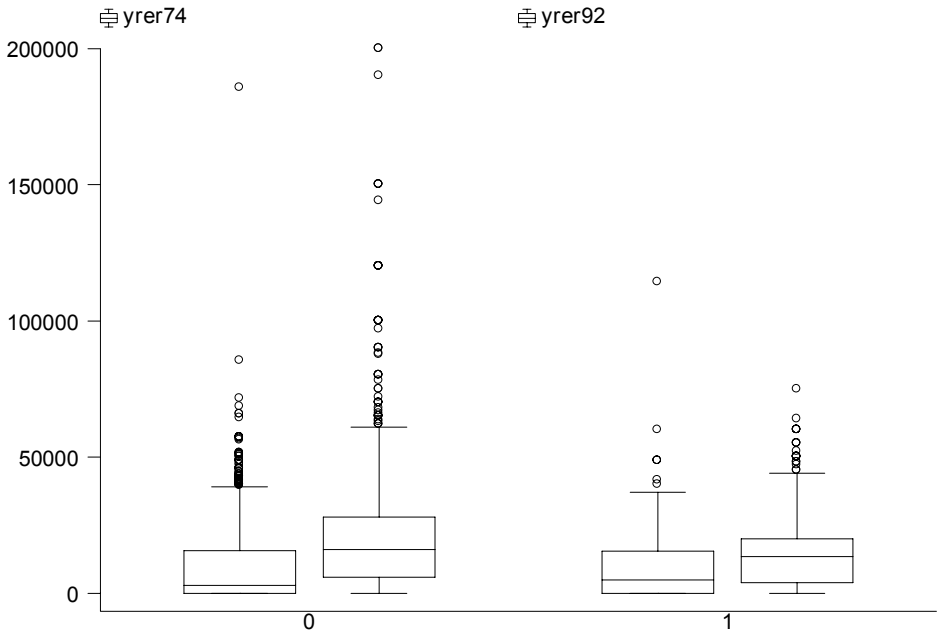

Figure 4.3. Male Displaced Workers' Non-employment by Broad Occupational Category

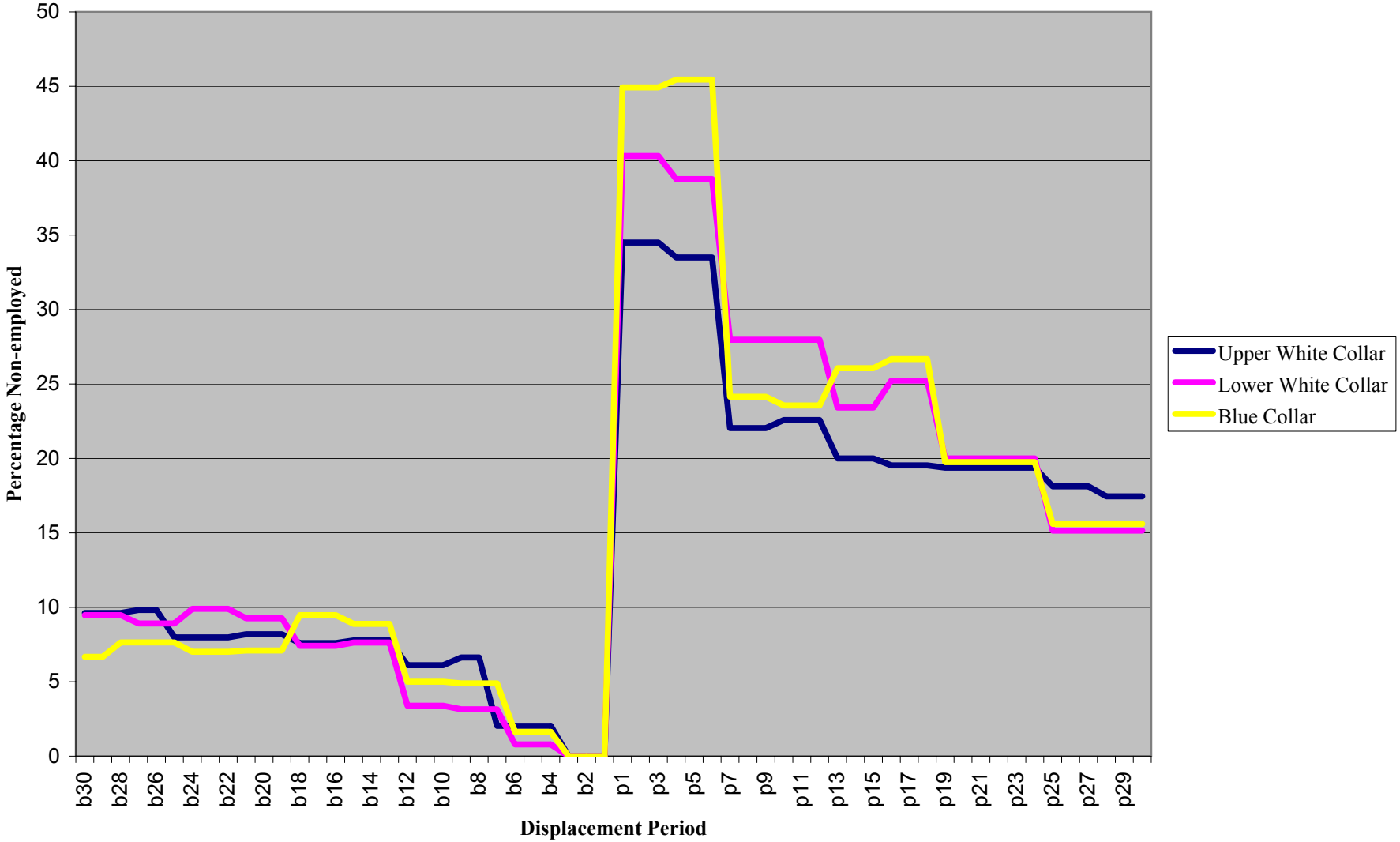

Figure 4.4. Female Displaced Workers' Non-employment by Broad Occupational Category

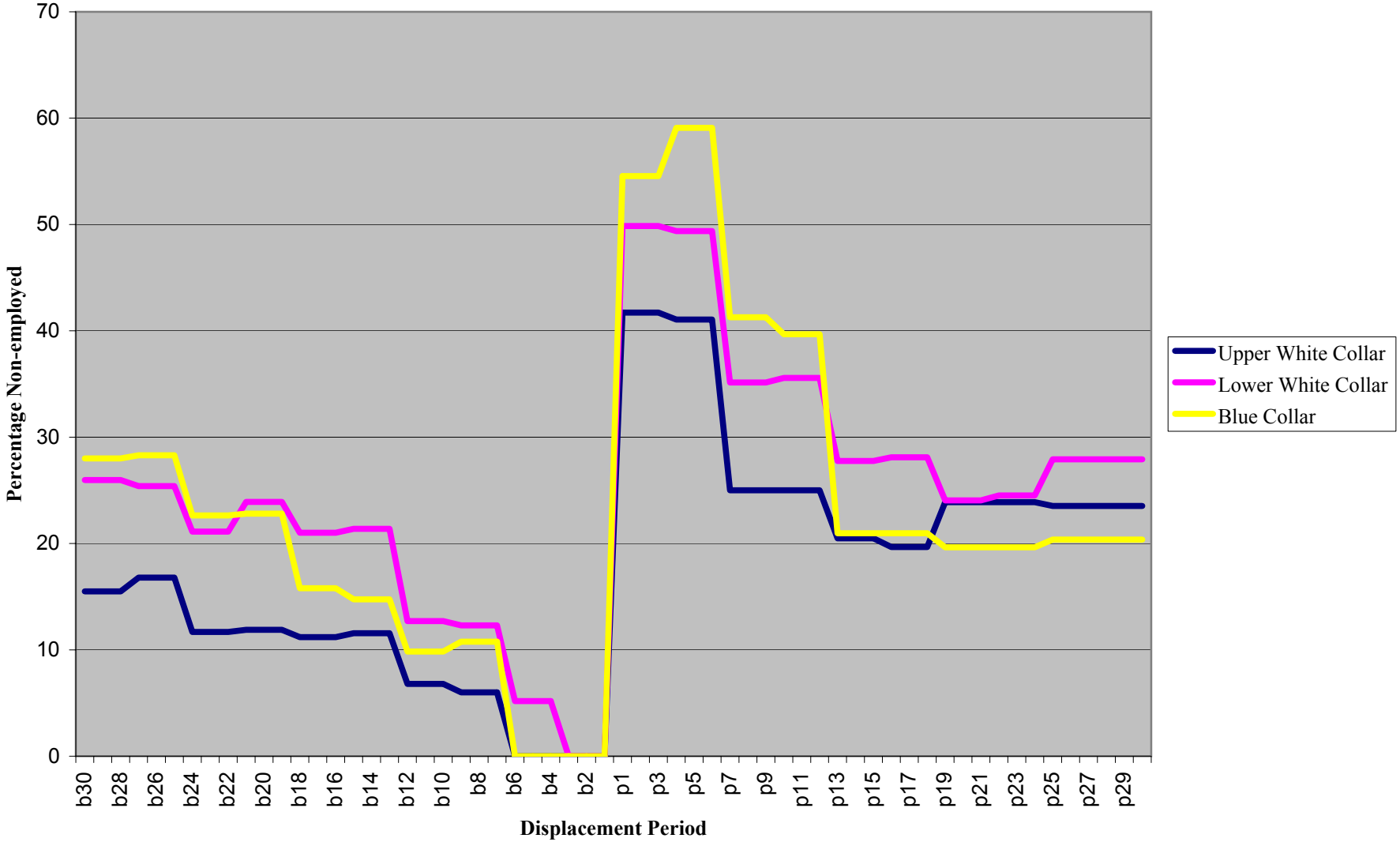

Figure 4.5. Male Displaced Workers' Non-employment by Educational Attainment

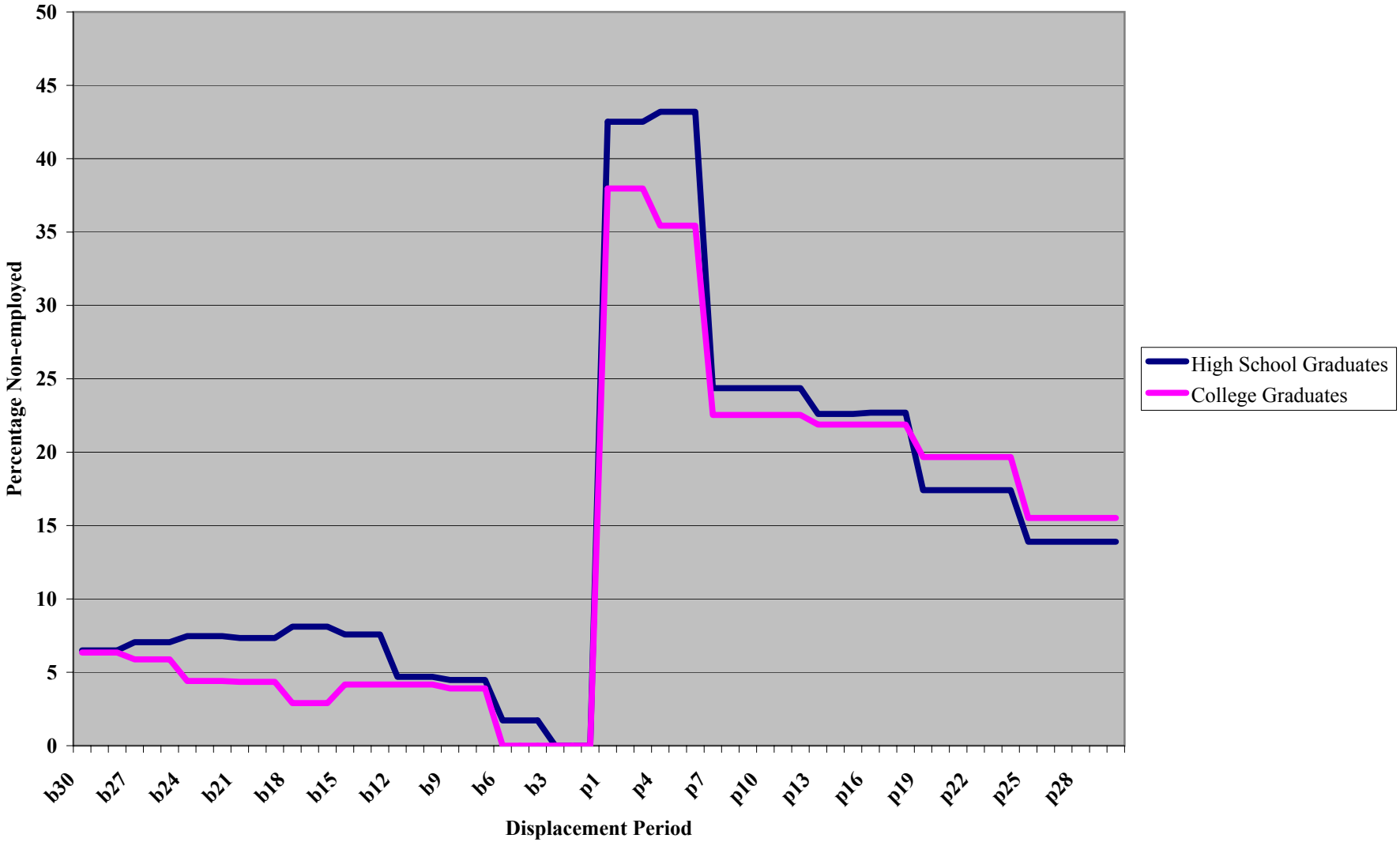

Figure 4.6. Female Displaced Workers' Non-employment by Educational Attainment