Labor Displacement, Unemployment, and Health:
A Consideration of Alternative Causal Pathways and Sociodemographic Variation

Kate W. Strully
New York University
Department of Sociology
269 Mercer Street, 4th Floor
New York, NY 10003
kate.strully@nyu.edu

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Associations between job loss, unemployment, and poor health have been documented across several decades and national contexts (Arnetz et al 1991; Bartley and Fagin 1990; Beal and Nethercott 1985; Clark 2003; D'Archy and Siddique 1985; Dooley et al 1996; Ferrie 2005; Jahoda et al 1933; Kessler et al 1987; Smith 1987). The resilience of this association—particularly when it is supplemented with ethnographic and narrative accounts of the economic deprivation and psychological struggles of displaced workers (Jahoda et al 1933; New York Times 1996)—provide a compelling case for the argument that unemployment has true negative effects on health. However, across most historical and national contexts, there may also be several labor market-related "sorting" processes that can provide alternative explanations for associations between job loss, unemployment, and poor health. First, there is the possibility that sicker or otherwise disadvantaged people tend to select (or be selected) into less stable work situations. In this case, the association between job loss, unemployment, and poor health may be explained by the concentration of the least resilient workers in the highest risk areas of the labor market. Second, there is the possibility that sicker or otherwise disadvantaged people tend to select (or be selected) out of their jobs. This could result from sicker people being more likely to quit their jobs because of health problems, or from employers laying off or firing their sicker, less productive workers. In this scenario, the association between job loss, unemployment, and poor health may be explained by the least resilient workers within a workplace facing the highest risk of displacement. Finally, there is the possibility that after a job loss, it is the sickest or otherwise least advantaged individuals who faced the highest risk of a prolonged period of unemployment, which will likely have more significant health consequences that a shorter period of unemployment. In this scenario, the association between unemployment and poor health may be explained by the selection of more resilient displacement workers back into employment, and the concentration of the least resilient displaced workers in unemployment.

In this paper, I use nationally representative panel data from the U.S. Panel Study of Income Dynamics and attempt to untangle the true health consequences of job loss/unemployment and the relative impacts of these different selection processes. Using questions about why a person's last job ended (e.g. laid off/fired, plant closed, company folded, quit, etc) along with random effects and individual-level fixed effects models, I hold constant in varying combinations the contexts around job displacement and unobserved heterogeneity across individuals that is likely associated with various labor market selection processes. Results suggest that, holding constant unobserved variation and focusing on job losses that should be exogenous to health status (e.g. "no fault" instances: companies folding, relocating, closing plants), unemployment is associated with a 12 percent increase in the risk of poor health. Results also suggest, however, that associations between poor health and unemployment when job loss may have been dependent on a person's health status (e.g. the person was fired or laid off) can be largely explain by unobserved variation across individuals. Therefore, while the results appear to document true health consequences of unemployment, they also suggest that labor market selection processes may account for unemployment-health associations in several situations.

After having established that there are significant health effects of unemployment, net of selection, I move on to consider the possibility that the health consequences of unemployment vary across sociodemographic groups. In this preliminary analysis (which will be expanded in the near future), I am concerned with whether being in a sociodemographically-disadvantaged group (and potentially facing barriers to reemployment) increases the health costs of being unemployed. Using a fixed effects framework and focusing on displacements that should be exogenous to health status (e.g. "no fault" cases: companies folding, relocating, closing plants), I compare the health effects of unemployment across gender, race, education, and marital status. Factoring out selection, it does appear that being in a relatively disadvantaged group (being female, less educated, or single) is associated with larger health consequences of unemployment. (However, the precise magnitudes of these differences remain a bit unclear because of small N problems.) An examination of how long individuals in these different sociodemographic groups have been out of work, and their labor market attachment at the time of the survey, provides some evidence to suggest that elevated health risks may results from a combination of having difficulty becoming reemployed and becoming discouraged with the market.

Health and Employment

There are several reasons why job loss and unemployment may pose a threat to health. First is a simple economic explanation. Job loss and unemployment typically imply a significant drop in earnings (from 20 to 40 percent according to Ruhm 1991; Jacobson, LaLonde et al. 1993; Stephens 2003), which in turn may translate into a drop in household consumption. Stephens (2003), for instance, finds that a household's annual food consumption falls by roughly 16 percent with a job loss. It is not difficult to imagine that such tightening of a household's budget may translate into health problems related to either stress or changes in behavior.

However, even without significant economic deprivation, it is still relatively easy to see how job loss and unemployment may harm health. As far back as 1893, Durkheim discussed the importance of employment for integrating individuals into a diverse and specialized society (Durkheim 1984). In this respect, unemployment may translate into an anomic state as a person looses important social roles, such as employee, family breadwinner, etc. Widespread associations between unemployment and suicide may further be interpreted as lending empirical support to this possibility if we invoke models of anomic suicide from Durkheim's later work (Durkheim 1979; see Smith 1987 for review of associations with suicide). However, putting to the side any loss of purpose and social integration that may accompany loosing social roles, it is also possible to see that unemployment may harm health through much more mundane mechanisms. For instance, job loss and unemployment may harm health simply by disrupting the rhythms of daily life. Without a regular work schedule a person's time and behaviors may be largely unstructured and this may make it difficult to maintain a health lifestyle (e.g. regular diet and exercise) and outlook (e.g. avoid depression and anxiety). In short, there are several reasons to believe that there is a causal pathway running from job loss and unemployment to poor health.

However, if we think more carefully about the paths that may lead people into different (un)employment situations, there are also several reasons to anticipate an alternative causal pathway running from health to job loss and unemployment. First, there is the somewhat obvious possibility that sicker employees in a given workplace may face an increased risk of displacement precisely because they are sick. Being in poorer health may make it difficult to get to work everyday and a person may simply become discouraged and quit their job. Alternatively, it is not a stretch to imagine that sicker workers face a higher risk of being laid off or fired. During a downsizing, for instance, employers likely target for layoffs those employees with the most sick days or with generally lower productivity. Such a selection of the sickest employees out of work and into unemployment has been documented by Kessler et al (1987) and Arrow (1996). In the following analysis, I address this possibility of health-based selection out of jobs with a strategy inspired by community-level studies of plant closures (see most notably Kessler et al 1987). I separate sample members based on the contexts surrounding the end of their last job and I focus my attention on instances of "no fault" displacement (e.g. companies folding, relocating, closing plants, employers dying, etc). In these cases, in which an entire worksite was closed, virtually all employees should be let go and the risk of job displacement should be unassociated with underlying variation among employees.

Health-based selection out of jobs poses a very feasible explanation for why we might expect an alternative causal relationship in which poor health leads to unemployment. However, additional attention needs to be paid to the question of why people might end up in more or less stable jobs. For decades, researchers have paid considerable attention to the fact that coming from a relatively disadvantaged childhood environment tends to lead one toward a similarly disadvantaged adult socioeconomic position. More recently, authors have begun to consider the simultaneous influence of early childhood environmental and health risks in this inheritance of wellbeing. Conley et al. (2003) and Case et al. (2003), for instance, document significant impacts of both early childhood environment and early childhood health (e.g. birth weight, chronic conditions at age seven) on levels of adult human capital. This evidence, suggesting that not only early socioeconomic disadvantage, but also early health disadvantage, may lead people toward particular labor market positions, raises the additional possibility of health-based selection into different (potentially less stable) sorts of jobs. That is, the most physically frail workers may select into the least desirable—and likely least stable—sectors of the labor market, and in this respect, poor health may lead to job loss/unemployment by increasing the likelihood that one ends up in an unstable job. Associations between early childhood health risks and unemployment have been documented by Montgomery et al (1996) and Caspi et al (1998). Caspi et al (1998), further, shows that early childhood risk factors (e.g. growing up in a single parent household, global health status in childhood) continue to predict later unemployment even net of controls for educational attainment and pre-displacement health status. This suggests that typical controls for human capital and pre-displacement health may not be able to adequately factor out such health-related selection within the labor market.

In the following analysis, I address this possibility of unobserved variation across people in different employment situations with an individual-level fixed effects framework. In an individual-level fixed effects framework, I will be comparing observations on the same individuals over time, and considering how changes in a person's employment status predict changes in a person's health status. Examining such changes at the individual level (rather than comparing observations across a random sample of individuals as is the case in random effects models), factors out unobserved characteristics of individuals that remain stable over time (e.g. early childhood environment, genetics, etc). In this respect, a fixed effects model should factor out unobserved heterogeneity associated with both health status and labor market position. Combining this modeling strategy with an emphasis on no-fault causes for displacement (e.g. plant closings, company relocations, etc) should address both health-based selection out of jobs and health-based selection into more or less stable jobs. I know of two other studies that use an individual level fixed effects frameworks when examining the relationship between unemployment and health (Clark 2003; Bjorklund, 1985). However, neither of these studies have information on why individuals became unemployed, and therefore they cannot rule out endogeneity from declines in health. That is, while these analyses can hold constant stable unobserved heterogeneity across individuals, they cannot eliminate the possibility that fixed effects associations between unemployment and poor health reflect declines in health status leading to unemployment. While these fixed effects results likely reflect a causal relationship, the direction of that relationship remains unclear.

In addition to considering health-based selection out of jobs and health-based selection into more or less stable jobs, we finally need to consider the possibility of health-based selection out of unemployment and into reemployment. Healthier individuals, who may be advantaged and resilient in other respects as well, will likely have an easier time finding work after a job loss and/or spell of unemployment. In this respect, associations between unemployment and health may be upwardly biased because of the most resilient displaced workers selecting out of the state of unemployment. Empirical evidence on this question of selection into reemployment is somewhat mixed. Stewart (1999) finds that good health predicts shorter unemployment spells, and therefore appears to documents a health-based selection into reemployment. Kessler et al (1989), on the other hand, find no such predictive power of health status, and their results alternatively suggest true health costs to remaining unemployed. (This disparity in results may be explained by the different labor market contexts of these studies—see Kessler et at (1989) for a discussion of how the strong local labor market in their study may explain their results.) In the following analysis, the fixed effects framework will also address this possibility of unobserved heterogeneity across the unemployed and reemployed. The fixed effects framework will hold constant unobserved, time-invariant variation in physical robustness and other factors that may be associated with a displaced worker's employability.

In sum, focusing on instances of no-fault displacement within a fixed effects framework in the following analysis should address the possibilities (1) selection into more or less stable jobs, (2) selection out of jobs, and (3) selection out of unemployment and into reemployment. Examining estimates across both random and fixed effects frameworks that separate workers into different categories depending on why their last job ended and whether they are reemployed at the time of the survey may further offer some purchase on the question of which of these potential selection processes has the most influence on existing estimates of health-unemployment relationships.

Review of the Literature: Problems of Causality and Heterogeneity

The literature on health and unemployment can be roughly organized into two camps. The first camp has tended to use community-level studies of plant closures to document mental and physical health consequences of unemployment. The community-level designs of these studies have generally been effective at addressing issues of causality. But, such community-level designs also raise questions about the generalizability of findings, and tend to limit the possibilities for examining variation in treatment effects. The second camp within the literature has tended to use nationally-representative survey data to examine associations between unemployment and well-being. While using such data tends to yield more widely generalizable results, and further allows for greater exploration of variation in treatment effects, these data sources have typically limited authors' abilities to address issues of causality. In short, within the existing literature, there seems to be something of a trade-off between addressing issues of causality and considering diverse, nationally-representative situations. In the following analysis, I attempt to integrate the strengths of these two camps and consider questions of causality, while also working with a nationally-representative, diverse sample.

Community-Level Studies of Plant Closures

Within the literature on unemployment and health, several authors have attempted to gain estimates of the true health consequences of displacement and unemployment with community-level studies of plant closures (Arnetz et al. 1991; Dew et al. 1987; Gore 1978; Hamilton et al. 1990; Kasl et al 1975; Levi et al. 1984; Keefe et al. 2002; Kessler et al 1989; Kessler et al. 1987). In these projects, researchers typically focus on small geographical areas in which the local labor market is dominated by a single plant, company, or industry. While there is of course variation, these studies have generally found that workers' health tends to decline when plants close.

These findings generally provide strong evidence of a causal effect of job loss and unemployment on health. In these studies, where an entire workplace was shutdown and all the employees were displaced, it can be assumed that job loss is independent of variations in employees health (i.e., there is no health-based selection out of jobs). Further, since a single plant, company, or industry tends to supply most of the jobs in these community-level studies, there is relatively little concern about other sources of selection bias as well. Because of the relative homogeneity of employment opportunities within these community-level studies, there should be relatively little bias resulting from selection of less resilient workers into less stable jobs or from selection of more resilient workers into reemployment. Overall, community-level plant closure studies are rather effective at factoring out sources of endogeneity, and we can be fairly confident that the associations they document reflect a causal impact of unemployment on health.

However, these studies also remain significantly limited by their community-level designs. The homogeneity of the job markets in these studies offer clout in debates over causation by factoring out large amounts of variation. However, this homogeneity also raises questions about generalizability and typically limits authors' abilities to explore variation in treatment effects. It is unclear whether the effects of job displacement and unemployment documented in these community-level studies will be applicable to the more varied contexts of a national labor market. Community-level plant closure studies tend to deal primarily with manual labor jobs in manufacturing industries that are going through economic difficulties. Job loss and unemployment in this context may pose a particular type of threat to health, and consequently these studies may under or overstate more general health effects of job loss/unemployment. In the following analysis, only approximately 35 percent of the workers in the "no-fault" displacement category (e.g. company folded, relocated, plant closed, employer died, etc) come from manual labor jobs, the remaining come from a combination of administrative, sales, service and professional occupations. Further, only about 30 percent come from manufacturing industries, the rest come from a combination of wholesale and retail industries, construction industries, transportation industries, and business/repair industries. In this respect, results based on the "no fault" group in the following analysis may be more confidently applied to the heterogeneity of a national labor market

When considering the generalizability of community-level plant closure studies, it is also necessary to note the problem of geographic concentration of job loss and unemployment. The shutting down of a single plant in these studies may wipe out most of the jobs in an area. Such a concentration of unemployment, and such poor prospects of quick reemployment within a community, may lead to more pronounced health consequences than we would witnessed in a more diverse labor market. Ethnographic and narrative evidence suggests, for instance, that when people become unemployed they tend to stop many of their civic and community activities (e.g. stop volunteering with the boy scouts or the local church) (Jahoda et al 1933; New York Times 1996). When unemployment is widespread in a given area, this tendency may have a significant impact on a town's civic infrastructure and its levels of social capital (Jahoda et al 1933). This possibility, along with the simple fact that a plant closure can significantly limit reemployment opportunities in these studies, suggests that these analyses may overstate the health effects of job loss and unemployment. Borrowing the underlying logic of these studies by focusing on "no fault" displacements, but working with a nationally representative sample, one of the contributions of the following analysis will be to test whether findings from these unique community-level studies are applicable to a more diverse national context.

In addition to raising questions about generalizability, the homogeneity of the local labor markets in these community-level plant closure studies also limits opportunities to consider variation in effects of unemployment by sociodemographic, occupational, or geographical characteristics. While a selection of community-level plant closures studies have considered variation in effects by individuals' social support and coping strategies (e.g. Turner et al. 1991), the relatively small geographic contexts of these studies, combined with the emphasis on a single or small number of workplaces, have generally limited the chances to consider variation along other dimensions. Only one plant closure study that I know of examines variation in effects by sociodemographic characteristics (race, education, marital status, etc). This study of General Motors plant shutdowns examines psychological health outcomes (e.g. depression, anxiety, etc) and suggests that less educated black workers fared worse following displacement than other workers (Hamilton et al 1990). This study provides important and compelling evidence of heterogeneous treatment effects of unemployment. However, its results are limited to psychological outcomes of blue-collar workers within a single industry and geographical area. In the following analysis, I also consider the problem of sociodemographic variation in the consequences of unemployment, but this preliminary analysis is applicable to a more diverse nationally-representative population and applies to indicators of physical rather than psychological well-being. In future versions of this paper, I plan to expand this analysis by considering the possibility of varying unemployment consequences by occupation (e.g. blue-collar versus white-collar), industry (e.g. shrinking versus growing industries), and geography (e.g. by region, rural versus urban). Such an analysis may speak to differences in unemployment effects based on characteristics of work and local labor market contexts.

Nationally-Representative Survey Research

Analyses of nationally-representative survey data have typically raised fewer questions about the generalizability of results, and have typically allowed for greater exploration of varying treatment effects (see D'Archy and Siddique 1987; Dew et al 1992; Payne et al 1984; Leeflang et al 1992; Turner 1995). However, analyses of nationally-representative surveys have typically not allowed authors to consider the possibilities of endogeneity and unobserved variation. That is, in most analyses of nationally-representative data, the various labor market-related selection processes discussed above (e.g. selection out of jobs, selection into more or less stable jobs, etc) could be at least partially responsible for associations between unemployment and poor health. Further, to the extent that these processes work in varying ways across different sociodemographic groups and contexts, evidence of heterogeneous treatment effects may not reflect differences in true causal effects, but rather differences in how people sort themselves within the labor market.

For instance, if individuals who are sociodemographically disadvantaged are in worse health to begin with, they may face a higher risk of selecting out of jobs because of declines in health. This, of course, could lead to larger risks for upwardly biased estimates within sociodemographically-disadvantaged groups. Such a risk may be particularly pronounced for less educated workers given the evidence discussed above of associations between poor health in early childhood and low educational attainment in later life. Further, within certain sociodemographic categories, or occupational and geographical contexts, there may be relatively stronger or weaker associations between unobserved heterogeneity, employment status, and health. This may be particularly true in the case of gender. Since women tend to have less consistent and strong labor market attachment than men, it is possible that unobserved characteristics (potentially associated with health) have a stronger influence on women's selection out of and into employment and the labor market. Again, such a possibility may upwardly bias estimates for more sociodemographically-disadvantaged groups. In short, working with nationally-representative survey data, it has typically been difficult for authors to consider such possibilities when examining heterogenous treatment effects. This implies that existing evidence of variation in the health consequences of unemployment may be biased because unobserved heterogeneity and health statuses pose varying risks to employment depending on people's characteristic and/or occupational and geographic contexts. In the following analysis, I address this possibility by comparing estimates across different groups using only fixed effects specifications and focusing on instances of no-fault displacement. With this strategy, selection out of jobs and unobserved variation within sociodemographic categories should be held constant.

Data and Variables

Data for this project come from the U.S. Panel Study of Income Dynamics (PSID). The PSID is a nationally representative, longitudinal sample of American families, who were first interviewed in 1968. The PSID initially surveyed a total of 4,800 families and consisted of two independent samples: a broadly representative, cross-sectional national sample, supplemented by a more focused, national sample of low-income families. The PSID has grown since its inception as it follows new households that have formed out of the original 4,800. Among those tracked are the children in the initial sample and those subsequently born or moved into a sample household. As a result of its success in following young adults as they form their own families, the PSID includes more than 7,000 families as of 2001(Institute for Social Research University of Michigan 2002).

The PSID is well suited to this project because, in addition to collecting information on socioeconomic status and multiple indicators of health, it has also collected information about heads of households' and wives/cohabiters' last and current employment. It is these questions about employment that provide the main framework for this analysis. Questions about the start dates and end dates of employment allowed me to determine whether a sample member experienced a job disruption over the past several months. Further questions about the reasons why jobs ended allowed me to separate sample members who report reasons that should be independent of health (e.g. the company folded/changed hands/moved out of town, etc) from those reporting other reasons for displacement and those experiencing no displacement.

This analysis is limited to the survey years 1999 and 2001. I choose to work with these years because they provide two separate health measures—self-assessed global health status and self-reports of chronic health conditions. Having two separate health outcome measures allows me to assess the robustness of results across more subjective and objective self-reports of health. In order to work with both random and fixed effects models, data for this analysis are structure as a person-year file (multiple observations per individual are contained in a single file). This implies that the relevant unit for this analysis is a person-year.

When inquiring about a person's last employment, the PSID generally limited the number of eligible sample members. In order for the PSID to ask a head of household or wife/cohabiter about a previous job, the person had to have been in that job in January of the year prior to the survey (e.g. for 2001 survey, person had to be in job in January of 2000). Putting this another way, in order for labor displacement to be detected in this survey, it had to have taken place in January of the year prior to survey or later (e.g. left job in January 2000 or later). This restriction has two implications for this analysis. First, it means that I am only going to be considering relatively recent displacement events—more specifically, those taking place since January of the year prior to the interview date. Second, it means that for any head of household or wife/cohabiter to be included in the analysis, s/he must have been employed in January of the prior year. If not employed at that time, s/he is not at risk of experiencing a job displacement during the period of observation. Working with the years 1999 and 2001 and limiting the sample to heads and wives/cohabiters who were employed in January of the year prior to the survey, but were not self-employed, yields a sample size of 11,797 individuals and 21,007 records. Descriptive statistics for this sample, broken down by reasons for displacement and employment status at the time of the survey, can be found in Table 1.

Variables

Health in this project is measured using two separate variables. First, I work with a simple self-assessment of *global health status*. In this variable, heads of households and wives/cohabiters are asked to evaluate their health as excellent, very good, good, fair or poor (with lower values indicating a more positive assessment). This variable is dichotomized so that individuals who report their health as fair or poor are coded as one and individuals who report their health as excellent, very good, or good are coded zero. This dichotomization scheme was chosen in an effort to make the interpretation of results for this measure more comparable to the chronic health measure.

Second, I work with a series of questions about *chronic health conditions*. In the 1999 and 2001 surveys of the PSID, heads of households and wives were asked whether a doctor had ever told them that they had a variety of conditions.[1] For the purposes of this analysis, I combine these different indicators of specific health conditions into a single dichotomous variable in which one indicates having one or more of the relevant conditions and zero indicates having none of the conditions. The questions that this measure is based on ask whether a doctor *ever* told someone they had a given condition. Given such wording, the timing of the onset of a given condition is unclear and, in the random effects models that follow, it is ambiguous whether a condition began before or after a given incident of displacement. The fixed effects model that follow, however, should address this ambiguity by considering changes in chronic health status, and consequently holding constant a person's baseline chronic health status. In the following analysis estimates of "no fault" displacement effects on chronic health status are frequently slightly larger in the fixed effects models than the random effects models. This pattern can likely be attributed to ambiguity in the random effects models, that is corrected in the fixed effects models, surrounding the ordering of displacement and the on-set of a condition. Given that both these dependent variables are dichotomized, the following analysis is based on linear probability models.[2]

Displacement Status in this analysis is measured with a series of dichotomous variables. First, is a single dichotomous variable indicating a person's displacement status. This variable, called *Displaced,* is coded one if a person left a job since January of the year prior to the survey, and is coded zero if a person has been in the same job since January of the year prior to the survey.

[1] Questions were specifically asked about stroke, high blood pressure/hypertension, diabetes/high blood sugar, cancer, lung disease, heart attack, coronary heart disease, angina, or congestive heart failure, emotional, nervous, or psychiatric problems, arthritis or rheumatism, asthma, or permanent loss of memory or loss of mental ability.
[2] Here I am working with a linear probability model simply so that non-discordant cases may be included in the FE model. When working with a logit model, such non-discordant cases are dropped from FE models. Results based on logit models were overall very similar to those I report based on linear probability models.

Second, is a series of dichotomous variables that distinguish people by the contexts surrounding the end of their last job. In the first of these variables, called *No Fault Displacement,* individuals who report that their last job ended because of a company folding, relocating, closing a plant, an employer dying, etc are coded one, and all other individuals are coded zero. In the second of these variables, called *Involuntary Displacement*, individuals who report that their last job ended because they were fired or laid off are coded one and all other individuals are coded zero. In the third of these variables, called *Voluntary Displacement*, individuals who report that their last job ended because they quit, retired, became pregnant, the work was only temporary, etc are coded one and everyone else is coded zero. This voluntary displacement group is admittedly a rather heterogeneous group, but given the PSID's coding scheme, I am unable to differentiate this group much further. In the following analysis, I do however make an effort to distinguish the different types of situations captured in this category by breaking it down by employment status at the time of the survey.

Finally, I work with a series of dichotomous variables that further distinguish the above displacement categories depending on whether individuals were reemployed or not at the time of the survey. Individuals in the No Fault displacement group are recoded so that those who are working at the time of the survey are coded one in the variable called *No Fault-Employed* and those who are not working at the time of the survey are coded one in the variable called *No Fault-Not Employed.* Similarly, individuals in the Involuntary Displacement group are recoded so that individuals working at the time of the survey are coded one for the variable *Involuntary-Employed* and individuals who are not working at the time of the survey are coded one for the variable *Involuntary-Not Employed.* Finally, individuals in the Voluntary Displacement group are recoded so that individuals working at the time of the survey are coded one for the variable *Voluntary-Employed* and individuals who are not working at the time of the survey are coded one for the variable *Voluntary-Not Employed.* The suppressed category in all the following models includes individuals who have not experienced a recent job displacement.

Control variables for this analysis are as follows: *age* (a series of dummy variables with less than 30 as the suppressed category); *gender* (a dichotomous variable in which one indicates female); *race* (dichotomous variables indicating either 'black" or "other" racial identity, white is the suppressed category); *education* (a series of dummy variables indicating degree status, having less than a high school diploma is the suppressed category); *income* (a continuous measure of total family income from the year prior to the survey, this measure is logged to account for skewdness); *occupational prestige* (hierarchically-ranked prestige scores based on Hodge et al (1966) were attached to all the 1970 three-digit census occupational codes); *marital status* (a series of dichotomous variables indicating whether a person was never married, divorced/separated, or widowed in a given year, currently married is the suppressed category); *year* (a variable indicating each survey year 1999 and 2001 to account for possible period effects).

Results

Part One:

Turning to Tables 2 and 3, we can begin to explore results from the first part of the analysis. Table 2 summarizes the main results by expressing all of the displacement coefficients in terms of percentage changes in the probability of poor health (either poor self assessed health or having one or more chronic health condition). Meanwhile, Table 3 provides coefficients and standard errors for the full models.

Models 1 and 2 in these tables mark a first pass at considering the relationship between health, unemployment, and job loss. Based on these models, which do not account for possibilities of unobserved variation and health based selection, it appears that recently leaving a job is associated with an increased risk of poor health. Individuals who recently left a job face a three percent higher risk of poor self-assessed health and four percent higher risk of chronic health conditions than individuals who have been stably employed over the past one to two years. This pattern suggests that job displacement, and possible unemployment post-displacement, is slightly bad for one's health. . However, as discussed above, a variety of typically unobserved selection processes may be at work in this association. As mentioned previously, three possibilities pose particular concerns in this analysis:

-First, is the possibility that associations between poor health and job displacement may be upwardly biased because of sicker, or otherwise disadvantaged, people selecting into less stable work situations with higher risks of (varying types of) displacement.

-Second is the possibility that, after people in relatively advantaged or disadvantaged positions sort into varying work situations, upward bias may result from sicker, or otherwise disadvantaged people, facing a higher risk of job loss within a given workplace (e.g., employers letting go of their less productive employees).

-Third, after people are differentially selected into job displacement through the above two processes, there may be differential selection into unemployment and reemployment. More specifically, there is the possibility of bias resulting from healthier, or otherwise advantaged people, finding new and relatively better employment more quickly.

In short, the processes that lead someone into given job, out of that job, and then into either unemployment or another job may translate into a variety of subtle (likely unobserved) differences across people in different (un)employment situations. The estimates in models 1 and 2 likely reflect some combination of a "true" health consequence of job loss and unemployment along with various unobserved differences across and within the categories of displaced, non-displaced, employed, and non-employed workers. In the following models I attempt to parcel out a "true" health consequence of job loss/unemployment and the variety of potential biases that may result from these unobserved selection processes.

In Models 3 and 4, I differentiate displaced workers depending on the contexts surrounding the end of their last job in order to consider the possibility of upward bias resulting from health-based selection out of jobs. According to models 3 and 4, if people loose jobs through no fault of their own, they face a five percent higher risk of poor self assessed health and/or chronic health problems than people who have been with the same employer for a year or more. If people are alternatively fired or laid off, they face a six percent higher risk of poor self-assessed health and a five percent higher risk of chronic health problems than people not experiencing such a recent job loss. Finally, people who leave their jobs voluntarily for a variety of reasons face a three percent higher risk of poor self-assessed health and a four percent higher risk of chronic health problems, compared to people who have been stably employed for the past year or more.

Examining these models, one of the first points to note is the similarity of the estimates for the no-fault and involuntary displacement groups. This provides little preliminary evidence of upward bias because of employers choosing to fire or layoff sicker employees—if this process were at work, we should be seeing larger estimates for involuntary displacement group. We can further note that the estimates for the voluntary displacement group are slightly smaller than those for no fault and involuntary groups. This also presents little evidence of upward bias from sicker people selecting themselves out of jobs (e.g. early retirement, quitting because of disability). However, in interpreting this result, the heterogeneity of this voluntarily displaced group needs to be kept in mind. Several people in this group may be voluntarily leaving one job for a better, higher paying job; such upwardly mobile people are probably particularly healthy or otherwise advantaged, and therefore may be counteracting the alternative scenario of sicker people selecting out of work.

Overall, the displacement estimates in models 3 and 4 provide little evidence of upward bias because of the sickest employees in a given workplace selecting (or being selected) out of jobs. However, there is still the possibility of bias resulting from sicker, or otherwise disadvantaged, people selecting into less stable work situations with higher risks of varying types of displacement. In other words, there may be unobserved differences among workers who experience no-fault, involuntary, and voluntary displacement. As mentioned previously, the community-level plant closure studies that have most effectively used this strategy of no-fault displacement to address health-based selection out of jobs have tended to deal with local labor markets that are dominated by a single company and industry. In such situations where one plant is supplying most of the jobs in a community, there is relatively little concern about selection into a situation of no-fault displacement. However, when we apply the strategy of focusing on no-fault displacement to the more heterogeneous context of a national labor market, we need to consider the possibility that individuals who loose their jobs because of companies folding, relocating, etc. are different from those who loose jobs for other reasons.

For instance, it is possible that sicker or otherwise disadvantaged people tend to be employed in smaller companies that are not doing as well, or in industries that are on the decline. In this case, the no fault group in the analysis may have an overrepresentation of disadvantaged/sicker individuals. Second, it is possible that, as a company beings to do poorly and faces the possibility of closing a plant or going out of business, advantaged or healthier people with better job prospects leave for alternative employment before the company actually closes the plant or goes under. Again, this would imply an overrepresentation of disadvantaged/sicker people in the no-fault group in this analysis.

In models 5 and 6, I address this possibility of unobserved heterogeneity across the different displacement groups with an individual-level fixed effects model. In this modeling strategy, in which multiple observations of the same individual over time are compared, stable unobserved characteristics (such as those that might lead people into different employment situations; e.g., underlying biological frailty, attitudes toward work, early childhood environment) are held constant.[3] To the extent that the coefficients for any of the displacement categories are reduced in the fixed effects models, it is likely the case that part of the relationship between these displacement situations and health is explained by unobserved differences across the individuals experiencing these different types of job separation.

Turning to models 5 and 6, we see that the coefficients for the voluntary and involuntary displacement groups are reduced to the point of non-significance for both the self-assessed health and chronic health measures. The coefficients for no fault displacement, however, remain somewhat more resilient. When predicting self-assessed health in a fixed effects framework, the no fault coefficient is statistically significant at the $p<.10$ level and suggests that loosing a job through no fault of your associated with a five percent increase in the risk of poor health. When predicting chronic health status in a fixed effects framework, the coefficient is significant at the $p<.05$ level and suggests that loosing a job through no fault of your own is associated with a seven percent increase in the risk of a chronic health condition. At first pass, these results suggest that associations between no fault displacement and health are not explained by unobserved heterogeneity, but associations between voluntary and involuntary displacement are. However, it needs to be kept in mind that, as the model is currently specified, there is significant heterogeneity in people's current employment situations. That is, some of the people in the displacement categories are reemployed, while others are not. Consequently, the possibility of better health among the reemployed (resulting from either true health returns to employment or selection bias) may be significantly downwardly biasing these estimates.

In models 7 and 8, the individuals in the different displacement categories are further differentiated based on whether or not they were reemployed by the time of survey. Here we see

[3] A Hausman test confirms the appropriateness of fixed effects estimates for predicting both self assessed and chronic health status. As mentioned previously, the wording of the chronic health questions in the PSID also make a fixed effects framework highly appropriate.

significant differences in well being across employment status. When predicting chronic health status, none of the reemployed individuals, regardless of the context surrounding the end of their last job, face a statistically significant difference in health status when compared to the non-displaced reference group. When predicting self-assessed health, it is only reemployed individuals who were laid off or fired who face a higher risk of poor self assessed health (a five percent higher risk compared to the suppressed non-displaced group). People who are still not working at the time of survey, on the other hand, all face an elevated risk of poor health, regardless of the contexts surrounding the end of their last job. Currently non-employed individuals in the no fault category face a 12 percent higher risk of poor self-assessed health and a nine percent higher risk of a chronic health condition, compared to the non-displaced reference group. People who are currently not working and were fired or laid off face a seven percent higher risk of poor self-assessed health and a nine percent higher risk of a chronic health condition, compared to the stably employed suppressed group. Finally, people who voluntarily left their jobs and are not working at the time of survey face a seven percent higher risk of poor self-assessed health and a nine percent higher risk of chronic health conditions, compared to those who have been in the same job for the past year or more.

These results clearly suggest that most of the relationship between job displacement and poor health is driven by people who remain out of work for a period of time post-displacement. (This is consistent with existing evidence; see Kessler et al 1987.) This could be because there are true health costs to unemployment and true health returns to reemployment. However, in the random effects framework in models 7 and 8, unobserved variation across individuals is being allowed to vary freely. This implies that there could be unobserved differences across individuals in each of the displacement categories, along with unobserved differences between those who remain not working at the time of the survey and those who have begun working by the time of the survey. In short, the estimates in models 7 and 8 may be biased by health-based selection into the different displacement categories and health-based selection out of unemployment and into reemployment.

Turning to models 9 and 10, I present the final specification and again use an individual-level fixed effects framework. In this model, individuals are differentiated depending on the contexts surrounding the end of their last job and their employment statuses at the time of survey. Further, unobserved individual-level variation is held constant in this model with the use of a fixed effects specification. In sum, this final specification should address: 1) health-based selection out of job, 2) health-based selection into different employment situations with varying risks of different types of displacement, and 3) health-based selection out of unemployment and into reemployment.

In this model, being displaced through no fault of your own and remaining without work at the time of the survey is associated with a 12 percent higher risk of poor health (both self-assessed and chronic), compared to people not experiencing a recent displacement. Leaving a job voluntarily and remaining without work at the time of the survey is associated with a 4 percent higher risk of poor health (both self-assessed and chronic), compared to people not experiencing a recent displacement. Holding constant unobserved variation in this model, currently not working individuals who were laid off or fired from their last jobs are no longer in significantly worse health than the stably employed reference group. Similarly, none of the currently employed individuals in this model face an elevated risk of poor health.

Comparing models 7 and 8 to models 9 and 10, we can note that estimates for the no-fault-not-employed displacement group are quite resilient to the fixed effects specification. The coefficient predicting global self-assessed health remains unchanged, and the coefficient predicting chronic health status increases slightly. This suggests that estimates for this group cannot be attributed to unobserved characteristics. The larger health risks in this group cannot be explained by unobserved differences between those experiencing no fault displacement and those experience other forms of displacement. And further, cannot be explained by unobserved differences between those who remain without work and who become reemployed by the time of survey. Overall, this result provides strong evidence of a causal effect of current unemployment on health.

Estimates for the involuntarily-displaced-not-working group do not fare as well in the fixed effects framework—they are reduced to the point of statistical non-significance. This suggests that much of the relationship between unemployment and health after being laid off or fired can be explained by the unobserved characteristics of this group. It is unclear, though, whether these unobserved differences result from 1) employees choosing to lay off only their sickest employees, 2) selection of frail employees into work situations with higher risks of layoffs, or 3) selection of the healthiest member of this displacement group into reemployment.

All of these sources of unobserved heterogeneity could be responsible for the significant estimates for this group in models 7 and 8.

Finally, estimates for the voluntarily-displaced-not-working group are reduced in magnitude, but remain statistically significant in the fixed effects specification. This suggests that part of the relationship between poor health and voluntary displacement and unemployment may be explained by stable unobserved characteristics of this group. The 4 percent higher risk that remains in the fixed effects specification for this group, however, is somewhat difficult to interpret. Given the voluntary nature of displacement for this group, it could reflect a true health consequence of voluntary displacement/unemployment, but it could also reflect declines in health status that may cause one to voluntarily leave a job. Unlike with the estimates for the no fault group, we cannot necessarily assume that displacement in this category is independent of changes in health status.

Overall, the 12 percent higher risk faced by the no-fault-not-employed group in this final specification suggests the existence of true and significant health consequences of unemployment. However, the drop in the coefficient for the involuntarily-displaced-not-employed group raises concerns about unobserved heterogeneity between the employed and not-employed in more common job loss situations.

Before moving on to consider the possibility of variation in the effects of unemployment by sociodemographic characteristics, it is necessary to briefly consider the types of health conditions that are being captured with the chronic health measure. The specific conditions that are asked about in this measure are: stroke, high blood pressure/hypertension, diabetes/high blood sugar, cancer, lung disease, heart attack, coronary heart disease, angina, or congestive heart failure, emotional, nervous, or psychiatric problems, arthritis or rheumatism, asthma, or permanent loss of memory or loss of mental ability. Some of these conditions may be a feasible response to job loss and or unemployment. However, others—such as asthma or diabetes—typically develop either early in life or over very long periods of time. If these are the sorts of conditions that sample members in the no-fault displacement group are developing post-job loss, we should probably be concerned about endogeneity in the above estimates (even despite all the efforts that went into the final specification).

An examination of the types of conditions that sample members developed between 1999 and 2001, by displacement category, suggests that the most common health condition that was developed in the no-fault displacement group was arthritis or rheumatism. Of the individuals who experienced no fault displacement between 1999 and 2001 and also developed a chronic health condition, 50 percent of them reported arthritis or rheumatism as their chronic health problem. Alternatively, very few of the members of this group reported either asthma or diabetes in 2001. This association between job loss and arthritis conforms to existing findings (Kasl et al 1975; D'arcy and Siddique 1987), and is further be explained by hormonal responses to stress. The hormone interleukin-6 has been found to be to elevated amongst those experiencing chronic stress and has further been found to be associated with inflammation and rheumatoid arthritis (see Seplaki 2004 for a review of stress-related biomarkers). In short, the onset of arthritis amongst those in the no-fault displacement group does not significantly challenge the above causal explanation of the results, and further suggests that prolonged stress may play an important mediating role in the above associations between unemployment and health.

Part Two

Having found a 12 percent higher risk of poor health amongst the no-fault-not-employed sample members, it is time to briefly consider whether that result varies by sociodemographic characteristics. In Table 5, the final specification of models 9 and 10 is replicated, but this time I run separate models for gender, education (more than high school degree, high school degree or less), race (white, non-white), and marital status (married/cohabiting, single) groups. That is, I re-run the fixed effects specification including distinct categories for reason of displacement and employment status, but this time I run separate models for different sociodemographic groups. Table 4 summarizes these results by presenting the coefficients for the three currently not working groups in terms of percentage changes in the probability of poor health.

Turning to Table 4, we can begin to examine these results. Considering first gender, we can note that women appear to be experiencing stronger associations between unemployment and health than men. Women in the no-fault-not-employed group face a 16 percent higher risk of a chronic health condition and a 17 percent higher risk of poor self-assessed than women who have been continuously employment. Meanwhile, men in the no-fault-not-employed group do not appear to face a higher risk of poor health than continuous employed men. The statistical insignificance of estimates for the men in this analysis, and for several of the other sociodemographic groups in this analysis, need to be interpreted somewhat loosely. There are relatively few cases of no fault displacement in this sample, and in this analysis I am dividing this group up even further into smaller segments. Consequently, I don't have a great deal of statistical power. Statistical insignificance in this analysis should probably not be interpreted as decisive evidence of no effect of unemployment, but rather should be seen as evidence of a smaller (possibly insignificant) effect. The statistically insignificant coefficients for the no-fault-not-employed men reported in Table 5, however, really are quite minimal in magnitude compared to the equivalent coefficients for women. The men's coefficients are -.000 when predicting self-assessed health and .043 (4 percent) when predicting chronic health status. This does suggest far more modest effects of unemployment for men.

A rather obvious reason for why women may be facing larger consequences of unemployment than men is that they are having more difficulty becoming reemployed. Examining descriptive statistics of the number months men and women in the no-fault-not-employed group have been without work, it does appear that women have on average been out of work for about two months longer than men. However, part of this pattern may be explained by women dropping out of the labor market entirely. Women in no-fault-not-employed group appear to be about 25 percent less likely than men to report themselves as unemployed and searching for work. Alternatively, they are more likely to report their post-displacement employment status as "homemaker." This gendered pattern is certainly not surprising, but its association with health is intriguing. It is unclear, for instance, whether women are suffering larger health declines than men because of unemployment, and are therefore not actively searching for work. Or, alternatively, whether women are choosing to withdraw from the labor market, and then (perhaps as a result of withdrawal) experiencing larger health declines.

Moving on, it appears that less educated worker experience larger health declines with unemployment than more educated workers. Sample members in the no-fault-not-working group holding a high school degree or less face a 12 percent higher risk of chronic health conditions and 13 percent higher risk of poor self-assessed health than similarly educated, but stably employed, sample members. Meanwhile, more educated unemployed sample members in the no fault group do not appear to face a significantly higher risk of poor health than stably employed, similarly educated workers. The statistically insignificant coefficients for the more educated no-fault-unemployed group reported in table 5 are .105 (11 percent) when predicting chronic health status and .078 (8 percent) when predicting self-assessed health. Unlike the case with gender, where the men's coefficients were really quite minimal compared to the women's, these coefficients (while still statistically insignificant) are only somewhat smaller than the coefficients for the less educated group.

It is again interesting to consider whether this larger effect of unemployment among the less educated may have to do with barriers to reemployed. Less educated workers in the no-fault-not-employed group have on average been out of work only about a month longer than the more educated workers in this group. But, the less educated workers in this group are slightly more likely (about six percent more likely) to report that they are unemployed and searching for work. This could imply that less educated workers who want to go back to work are spending more time looking for work than more educated workers who want to go back to work. Overall, however, these differences between the more and less educated sample members in the no-fault-not-employed group are small. (This pattern for instance seems less clear than what we witnessed in the comparison across gender.)

Results across the racial categories white and non-white are rather ambiguous. In fact, they are entirely contradictory across the two health indicators. Whereas non-white sample members in the no-fault-no-employed group face a higher risk of poor self-assessed health than white people in this group, white sample members in this group face a higher risk chronic health conditions than non-white people in this group. This pattern is quite unclear and does show any real evidence of a race interaction in the relationship between unemployment and health.

Moving on, we can note much larger associations between unemployment and health for single sample members, compared to married and cohabiting sample members. Single sample members in the no-fault-not-employed group face a 22 percent higher risk of chronic health conditions and a 29 percent higher risk of poor self-assessed health, compared to similarly single, but stably employed, sample members. Meanwhile, differences between the stably employed and the no-fault-not-working groups for the married sample members are not statistically significant. Statistically insignificant coefficients for the no-fault-not-working married sample members reported in Table 5 are .084 (8 percent) when predicting chronic health status and .062 (6 percent) when predicting self-assessed health. Somewhere between the large differences that we saw in the gender comparison and the rather modest differences we saw in the education comparison, these coefficients are about half the magnitude of the coefficients for single individuals.

Larger effects of unemployment among single sample members may result from less availability of social support during unemployment. Or, it could be that single individuals face larger financial strain with unemployment since there is no possibility of an additional income in the household. In future versions of this paper, I will explore this possibility by examining whether the spouses/partners of unemployed sample members responded to respondent's job loss by increasing work hours. In the meantime, though, it is interesting to again consider whether the disparities in effects across these categories may be attributed to larger hurdles to reemployment. Comparing descriptive statistics across the married/cohabiting and single members of the no-fault-not-working group, it seems that single individuals have only been out of work for about a month longer then their married counterparts. Single individuals in this group are, however, about 10 percent more likely than married/cohabiting individuals to report that they are unemployed and looking for work. This could imply greater difficulty finding work for single individuals than married individuals. But, explanations addressing social support and spousal income need to be considered further here.

In sum, this preliminary examination of variation by sociodemographic characteristics provides some evidence suggesting that sociodemographically-disavantaged groups (women, less educated, and single people) face larger health consequences of unemployment. Disparities across gender and marital status appear the most salient, while disparities by educational status were more modest. Variation by racial status was largely ambiguous. In future versions of this paper, I will also consider variation in unemployment-health associations by consequences by occupation (e.g. blue-collar versus white-collar), industry (e.g. shrinking versus growing industries), and geography (e.g. by region, rural versus urban).

Conclusion

Using nationally representative panel data, individual-level fixed effects models, and information about the why people left their jobs, this analysis has attempted to disentangle a causal effect of unemployment on health from various labor market-related selection processes. Holding constant unobserved heterogeneity, and focusing on people who lost jobs for reasons that should be exogenous to health (e.g. plant closed, company relocated, employer died, etc), I document a 12 percent higher risk of poor health for currently unemployed individuals, compared to stably employed individuals. This suggests that there are true and significant health consequences to unemployment.

Similarly holding constant unobserved heterogeneity, but focusing on people who were laid off or fired from their last job, alternatively yielded a non-significant association between unemployment and health. Therefore, while the results document true health consequences of unemployment, they also suggest that labor market selection processes and unobserved heterogeneity may at work in unemployment-health associations in more common job loss situations.

A preliminary analysis of interactions between sociodemographic characteristics and unemployment status suggests that the health consequences of unemployment may be larger for sociodemographically-disadvantaged groups (women, less educated, and single displaced workers). An examination of how long displaced workers in these groups had been out of work, and how they classified their employment status at the time of the survey, provided only mixed evidence on the question of whether these disparities in effects could be attributed to greater barriers to reemployment.

Before concluding, it is necessary to briefly contextualize these findings within the national labor markets of 1999 and 2001. These years were marked by economic expansion and low unemployment rates (averaging only about 4 percent) (Helwig 2004). This suggests that, overall during this period, the risk for labor displacement should have been low and reemployment prospects should have been good. There is some evidence from Finland suggesting that relationships between unemployment and mortality are larger during economic expansions (Martikainen and Valkonen 1996). To the extent this pattern holds in the United States, this might suggest that the current analysis would overstate the relationship between unemployment and poor health in a weaker economic context.

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Table 1: Sample Means and Standard Deviations, by Displacement Status (standard deviations between individuals in parentheses, standard deviations within individuals in brackets)

	Total Sample	No Fault-Employed	Involuntary-Employed	Voluntary-Employed	No Fault-Not Employed	Involuntary-Not Employed	Voluntary-Not Employed
Chronic Health Status	.430 (.461) [.190]	.321 (.469)	.361 (.477)	.305 (.457)	.427 (.497)	.446 (.495)	.464 (.496)
Global Health Status	.153 (.327) [.159]	.096 (.281)	.127 (.334)	.078 (.267)	.214 (.412)	.19 (.393)	.18 (.387)
Displaced	.274 (.416) [.219]	1 (0)	1 (0)	1 (0)	1 (0)	1 (0)	1 (0)
No Fault Displ	.016 (.117) [.072]	1 (0)	--------	--------	1 (0)	--------	--------
Involuntary Displ	.044 (.193) [.107]	--------	1 (0)	--------	--------	1 (0)	--------
Voluntary Displ	.214 (.382) [.209]	--------	--------	1 (0)	--------	--------	1 (0)
No Fault Displ-Employed	.010 (.089) [.057]	1 (0)	--------	--------	--------	--------	--------
Involuntary Displ-Employed	.020 (.129) [.079]	--------	1 (0)	--------	--------	--------	--------
Voluntary Displ-Employed	.135 (.307) [.188]	--------	--------	1 (0)	--------	--------	--------
No Fault Displ-Not Employed	.007 (.080) [.045]	--------	--------	--------	1 (0)	--------	--------
Involuntary Displ-Not Employed	.023 (.145) [.079]	--------	--------	--------	--------	1 (0)	--------
Voluntary Displ-Not Employed	.078 (.270) [.124]	--------	--------	--------	--------	--------	1 (0)
Age 31-35	.116 (.289) [.148]	.129 (.336)	.171 (.378)	.153 (.352)	.155 (.364)	.134 (.337)	.108 (.306)
Age 36-40	.143 (.312) [.163]	.129 (.336)	.151 (.359)	.143 (.347)	.117 (.322)	.178 (.381)	.135 (.338)
Age 40-45	.139 (.304) [.166]	.2 (.401)	.144 (.349)	.112 (.317)	.175 (.382)	.117 (.316)	.108 (.311)
Age 46-50	.118 (.285) [150]	.114 (.319)	.070 (.249)	.077 (.266)	.155 (.364)	.108 (.308)	.075 (.257)
Age 51-55	.078 (.268) [.123]	.036 (.186)	.060 (.236)	.037 (.193)	.058 (.235)	.058 (.238)	.066 (.243)
Age 56-60	.044 (.180) [.095]	.021 (.145)	.023 (.153)	.014 (.114)	.029 (.169)	.017 (.133)	.049 .215
Age 61-65	.033 (.160) [.083]	.021 (.145)	.013 (.117)	.007 (.082)	.029 (.169)	.012 (.109)	.055 (.225)
Age 66-70	.036 (.064) [.082]	.014 (.119)	.003 (.059)	.002 (.041)	.039 (.194)	.009 (.095)	.029 (.168)
Age 71-75	.034 (.163) [.079]	.007 (.085)	0	.001 (.033)	.01 (.099)	.006 (.077)	.012 (.113)
Age 76-80	.024 (.138) [.061]	.007 (.085)	0	0	0	.012 (.095)	.005 (.074)
Age 80+	.023 (.150) [.032]	0	0	0	0	0	.002 (.043)
Female	.060 (.497) [-----]	.45 (.499)	.421 (.494)	.516 (.5)	.65 (.479)	.531 (.5)	.702 (.459)
Black	.284 (.452) [----]	.287 (.454)	.294 (.457)	.249 (.433)	.404 (.493)	.528 (.5)	.321 (.465)
Other	.087 (.284) [-----]	.118 (.323)	.078 (.273)	.088 (.284)	.121 (.328)	.081 (.276)	.105 (.305)
High School	.328 (.466) [.052]	.254 (.437)	.305 (.462)	.298 (.459)	.442 (.499)	.325 (.466)	.272 (.447)
Some College	.242 (.426) [.051]	.3 (.46)	.261 (.44)	.284 (.451)	.2 (.402)	.261 (.439)	.25 (.432)
College Degree	.139 (.344) [.034]	.162 (.369)	.121 (.331)	.153 (.36)	.063 (.245)	.07 (.259)	.106 (.31)

Table 1 (Continued)

Graduate Education	.081 (.270) [.029]	.092 (.291)	.04 (.191)	.076 (.268)	.032 (.176)	.032 (.178)	.06 (.242)
Income (logged)	10.573 1.084) [.520	10.629 (.923)	10.432 (.779)	10.524 (.954)	10.335 (.919)	10.134 (1.115)	10.323 (1.091)
Occupationa Prestige	40.870 3.814) [4.60	38.935 (12.606)	36.870 (13.059)	38.609 (14.39)	33.903 (12.888)	33.289 (12.863)	35.639 (14.035)
Never Marri	.115 (.318) [.081]	.214 (.412)	.187 (.395)	.211 (.406)	.146 (.354)	.254 (.434)	.181 (.378)
Widowed	.056 (.224) [.059]	0	.013 (.117)	.009 (.099)	.019 (.139)	.026 (.154)	.023 (.154)
Divorced/ Separated	.130 (.318) [.115]	.171 (.378)	.211 (.408)	.13 (.334)	.175 (.382)	.175 (.385)	.137 (.345)
Year	2000.03 (.461) [.938]	2000.171 (.989)	2000.037 (.987)	2000.031 (.952)	2000.068 (1.003)	2000.184 (.966)	2000.085 (.961)
N	21,417	140	299	1984	103	343	1154
n	12,003	291	291	1815	103	332	1079

Table 2: Risk of Poor Health Relative to Continuously Employed Workers, by Displacement and Employment Categories (See Table 3 for complete models)

	Model 1 Chronic RE (1)	Model 2 Global RE (2)	Model 3 Chronic RE (3)	Model 4 Global RE (4)	Model 5 Chronic FE (5)	Model 6 Global FE (6)	Model 7 Chronic RE (7)	Model 8 Global RE (8)	Model 9 Chronic FE (9)	Model 10 Global FE (10)
Displaced	4%	3%								
No Fault Displacement			5%*	6%	7%	5%*				
Involuntary Displacement			5%	6%	NS	NS				
Voluntary Displacement			4%	3%	NS	NS				
No Fault-Employed							NS	NS	NS	NS
Involuntary-Employed							NS	5%	NS	NS
Voluntary-Employed							NS	NS	NS	NS
No Fault-Not Employed							9%	12%	12%	12%
Involuntary-Not Emplloyed							9%	7%	NS	NS
Voluntary-Not Empl							9%	7%	4%	4%*
Addresses selection into:										
work situations and displ categories	No	No	No	No	Yes	Yes	No	No	Yes	Yes
out of jobs	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
into unemployment and reemployment	No	No	No	No	No	No	No	No	Yes	Yes

*Significant and p<.10 level, all other percentage changes are significant at p<.05
**All RE models include controls for age, gender, race, education, income, occupational prestige, marital status, and year of the survey. FE models include these same controls with exception of time invariant characteristics (i.e., gender and race).

Table 3: Unstandardized Regression Coefficients from Linear Probability Models (Standard Errors in Parentheses)

	Model 1 Chronic RE (1)	Model 2 Global RE (2)	Model 3 Chronic RE (3)	Model 4 Global RE (4)	Model 5 Chronic FE (5)	Model 6 Global FE (6)	Model 7 Chronic RE (7)	Model 8 Global RE (8)	Model 9 Chronic FE (9)	Model 10 Global FE (10)
Displaced	.038*** (.008)	.034*** (.005)	--------	--------	--------	--------	--------	--------	--------	--------
No Fault Displ	--------	--------	.049 (.027)	.056* (.017)	.072* (.035)	.046 (.025)	--------	--------	--------	--------
Involuntary Displ	--------	--------	.048* (.017)	.062*** (.011)	-.007 (.024)	.023 (.017)	--------	--------	--------	--------
Voluntary Displ	--------	--------	.035*** (.009)	.027*** (.006)	.002 (.012)	.000 (.007)	--------	--------	--------	--------
No Fault Displ-Employed	--------	--------	--------	--------	--------	--------	.019 (.035)	.008 (.023)	.032 (.045)	.002 (.032)
Involuntary Displ-Employed	--------	--------	--------	--------	--------	--------	.011 (.024)	.053* (.016)	-.051 (.032)	.020 (.022)
Voluntary Displ-Employed	--------	--------	--------	--------	--------	--------	.010 (.01)	.005 (.007)	-.010 (.013)	-.012 (.01)
No Fault Displ-Not Employed	--------	--------	--------	--------	--------	--------	.087* (.041)	.124*** (.027)	.115* (.055)	.115* (.039)
Involuntary Displ-Not Employed	--------	--------	--------	--------	--------	--------	.088*** (.023)	.073*** (.015)	.050 (.032)	.029 (.023)
Voluntary Displ-Not Employed	--------	--------	--------	--------	--------	--------	.089*** (.014)	.069*** (.009)	.040 (.021)	.037* (.015)
Age 31-35	.023 (.013)	.031*** (.009)	.023 (.013)	.031*** (.009)	.002 (.026)	.033 (.018)	.023 (.013)	.031*** (.009)	.002 (.026)	--------
Age 36-40	.059*** (.014)	.043*** (.009)	.058*** (.014)	.043*** (.009)	-.042 (.036)	.009 (.025)	.057*** (.014)	.042*** (.009)	-.043 (.036)	-.027 (.016)
Age 40-45	.146*** (.014)	.065*** (.009)	.145*** (.014)	.064*** (.009)	-.040 (.044)	.000 (.031)	.144*** (.014)	.063*** (.009)	-.040 (.044)	-.037 (.023)
Age 46-50	.202*** (.015)	.093*** (.009)	.202*** (.015)	.092*** (.009)	-063 (.052)	.021 (.037)	.2*** (.015)	.091*** (.009)	-.630 (.052)	-.019 (.030)
Age 51-55	.309*** (.017)	.118*** (.01)	.308*** (.017)	..118*** (.01)	-.030 (.061)	.041 (.043)	.305*** (.017)	.115*** (01)	-.028 (.061)	.001 (.036)
Age 56-60	.342*** (.022)	.111*** (.014)	.342*** (.022)	.111*** (.014)	-.022 (.074)	.063 (.052)	.336*** (.022)	.106*** (.014)	-.023 (.074)	.017 (.460)
Age 61-65	.395*** (.028)	.093*** (.018)	.395*** (.028)	.093*** .018	-.059 (.093)	.042 (.066)	.382*** (.029)	.083*** (.018)	.065 (.093)	-.013 (.060)
Age 66-70	.499*** (.039)	.178*** (.025)	.499*** (.039)	.175*** (.025)	.031 (.124)	.186* (.088)	.485*** (.039)	.164*** (.025)	.022 (.124)	.127 (.084)
Age 71-75	.577*** (.055)	.172*** (.035)	.577*** (.055)	.172*** (.035)	.209 (.160)	.247* (.113)	.565*** (.055)	.163*** (.035)	.195 (.160)	.182 (.120)
Age 76-80	.533*** (.096)	.230*** (.060)	.532*** (.096)	.226*** (.060)	.144 (.260)	.201 (.184)	.514*** (.096)	.216*** (.060)	.124 (.260)	.129 (.182)
Age 80+	.143 (.167)	.187 (.105)	.143 (.167)	.188 (.105)	.115 (.484)	.178 (.342)	.125 (.167)	.175 (.105)	.057 (.484)	.068 (.341)

Table 3 (Continued)

Female	.026	.010	.026*	.010	--------	--------	.022*	.007	--------	--------
	(.009)	(.006)	(.009)	(.006)			(.009)	(.006)		
Black	.009*	.044***	.009	.043***	--------	--------	.006	.042***	--------	--------
	(.011)	(.007)	(.011)	(.007)			(.011)	(.007)		
Other	-.095***	.033*	-.095***	.033*	--------	--------	-.096***	.032*	--------	--------
	(.017)	(.011)	(.017)	(.011)			(.017)	(.011)		
High Schoo	-.037*	-.080***	-.037*	-.079***	-.110	.006	-.034*	-.077***	-.111	.010
	(.015)	(.009)	(.014)	(.009)	(.090)	(.064)	(.014)	(.009)	(.090)	(.064)
Some Colleg	-.028	-.082***	-.028	-.081***	-.077	-.180	-.025	-.079***	-.078	-.014
	(.015)	(.009)	(.015)	(.009)	(.092)	(.065)	(.015)	(.01)	(.092)	(.065)
College Deg	-.061*	-.010***	-.060*	-.099***	-.142	-.006	-.057**	-.096***	-.137	.001
	(.018)	(.011)	(.018)	(.011)	(.120)	(.085)	(.018)	(.011)	(.120)	(.085)
Graduate	-.057**	-.108***	-.057*	-.108***	-.256*	.008	-.054*	-.105***	-.245	.023
Education	(.021)	(.013)	(.021)	(.013)	(.127)	(.090)	(.021)	(.013)	(.127)	(.090)
Income	-.014**	-.018***	-.014*	-.018***	-.010	-.002	-.013*	-.017***	-.010	-.002
(logged)	(.005)	(.003)	(.005)	(.003)	(.007)	(.005)	(.005)	(.003)	(.007)	(.005)
Occupationa	-.001**	-.001***	-.001*	-.001***	-.001	.000	-.001*	-.001***	-.001	.000
Prestige	(.000)	(.000)	(.000)	(.000)	(.001)	(.000)	(.000)	(.000)	(.001)	(.000)
Never Marri	.015	-.001	.015	-.002	.019	-.017	.016	.000	.022	-.012
	(.014)	(.009)	(.014)	(.009)	(.034)	(.024)	(.014)	(.001)	(.034)	(.024)
Widowed	.126***	.001	.126***	.001	.044	-.118*	.130***	.004	.050	-.115*
	(.036)	(.022)	(.036)	(.022)	(.078)	(.055)	(.036)	(.022)	(.078)	(.055)
Divorced/	.065***	-.004	.064***	-.004	.089***	.004	.067***	-.002	.090***	.006
Separated	(.013)	(.008)	(.013)	(.008)	(.024)	(.017)	(.013)	(.008)	(.024)	(.017)
Year	.014***	.003	.014***	.003	.026***	.004	.013***	.003	.025***	.005*
	(.003)	(.002)	(.003)	(.002)	(.004)	(.003)	(.003)	(.002)	(.004)	(.002)
N	13,764	13,764	13,764	13,764	13,764	13,764	13,764	13,764	13,764	13,764
n	8,459	8,459	8,459	8,459	8,459	8,459	8,459	8,459	8,459	8,459

*** p<.001, ** p<.01, * p<.05

Table 4: Risk of Poor Health Relative to Continuously Employed Workers, by Displacement and Sociodemographic Characteristics (See Table 5 for complete models)

	Total Sample		Men		Women		More than HS		HS or Less		White		Non-White		Married		Single	
	Chronic	Global	Chronic	Global	Chronic	Global	Chronic	Global	Chronic	Global	Chronic	Global	Chronic	Global	Chronic	Global	Chronic	Global
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
No Fault-Not Empl	12%	12%	NS	NS	16%	17%	NS	NS	12%*	13%	15%	NS	NS	16%	NS	NS	22%	29%
Involn-Not Empl	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS	NS
Voln-Not Empl	4%	4%	NS	9%	5%*	NS	NS	3%*	NS	4%*	NS	NS	NS	9%	NS	5%	NS	NS
N	13,759	13,759	6,768	6,768	6,991	6,991	6,875	6,875	6,419	6,419	8,725	8,725	5,034	5,034	9,410	9,410	3,313	3,313
n	8,457	8,457	4,122	4,122	4,335	4,335	4,107	4,107	3,932	3,932	5,277	5,277	3,185	3,185	5,717	5,717	2,142	2,142

*Significant and p<.10 level, all other estimates are significant at p<.05
**All models presented here are equivilant to the final specification (models 9 and 10) in Table 2. They are fixed effects models that include controls for age, education, income, occupational prestige, marital status, and year of the survey.

Table 5: Unstandardized Regression Coefficients from Fixed Effects Linear Probability Models (Standard Errors in Parentheses), by Sociodemographic Characteristics

	Total Sample		Men		Women		More than HS		HS Degree or Less		White		Non-White		Married	
	Model 1 Chronic (1)	Model 2 Global (2)	Model 3 Chronic (3)	Model 4 Global (4)	Model 5 Chronic (5)	Model 6 Global (6)	Model 7 Chronic (7)	Model 8 Global (8)	Model 9 Chronic (9)	Model 10 Global (10)	Model 11 Chronic (11)	Model 12 Global (12)	Model 13 Chronic (13)	Model 14 Global (14)	Model 15 Chronic (15)	Model 16 Global (16)
No Fault Displ-	.032	.002	.031	.037	.014	-.037	.054	.052	.010	-.087	.037	.070*	.010	-.138*	.044	.033
Employed	(.045)	(.032)	(.060)	(.042)	(.068)	(.049)	(.061)	(.037)	(.068)	(.055)	(.054)	(.034)	(.081)	(.066)	(.059)	(.041)
Involuntary Displ-	-.051	.020	-.064	.057	-.040	-.017	-.082	.033	-.045	.009	-.056	.010	-.052	.032	-.037	.018
Employed	(.032)	(.022)	(.045)	(.030)	(.047)	(.033)	(.046)	(.028)	(.045)	(.036)	(.040)	(.026)	(.051)	(.042)	(.045)	(.031)
Voluntary Displ-	-.010	-.012	-.001	.013	-.016	-.033*	-.009	.010	-.012	-.033*	.009	-.010	-.046	-.012	-.010	-.003
Employed	(.013)	(.01)	(.020)	(.014)	(.019)	(.013)	(.018)	(.011)	(.020)	(.016)	(.016)	(.010)	(.024	(.020)	(.017)	(.012)
No Fault Displ-	.115*	.115*	.043	-.000	.156*	.169**	.105	.078	.120	.129*	.154*	.077	.066	.162*	.085	.062
Not Employed	(.055)	(.039)	(.094)	(.065)	(.069)	(.049)	(.107)	(.065)	(.065)	(.052)	(.078)	(.049)	(.081)	(.066)	(.067)	(.047)
Involuntary Displ-	.050	.029	.074	.039	.030	.029	.067	.006	.035	.043	.064	.025	.031	.039	.041	.017
Not Employed	(.032)	(.023)	(.046)	(.032)	(.046)	(.033)	(.054)	(.032)	(.042)	(.034)	(.050)	(.032)	(.045)	(.037)	(.045)	(.031)
Voluntary Displ-	.040	.037*	.024	.087**	.045	.015	.031	.031	.033	.041	.041	.005	.039	.089**	.035	.052**
Not Employed	(.021)	(.015)	(.037)	(.026)	(.025)	(.018)	(.030)	(.018)	(.030)	(.024)	(.026)	(.017)	(.034)	(.028)	(.026)	(.018)
Age 31-35	.002	--------	-.033	-------	.041	--------	.014	------	-.020	--------	.003	-------	.004	--------	.014	------
	(.026)		(.035)		(.037		(.033)		(.040)		(.030)		(.046)		(.032)	
Age 36-40	-.043	-.027	-.049	-.054*	-.030	-.006	-.049	.011	-.052	-.063*	-.084	-.024	.015	-.035	-.041	-.033
	(.036)	(.016)	(.051)	(.023)	(.051)	(.022)	(.048)	(.019)	(.054)	(.026)	(.044)	(.019)	(.061)	(.030)	(.043)	(.019)
Age 40-45	-.040	-.037	-.024	-.076*	-.044	-.005	-.029	-.020	-.070	-.051	-.083	-.039	.013	-.041	-.034	-.026
	(.044)	(.023)	(.063)	(.034)	(.062)	(.032)	(.060)	(.028)	(.066)	(.038)	(.055)	(.027)	(.075)	(.044)	(.053)	(.027)
Age 46-50	-.630	-.019	-.069	-.056	-.043	.016	-.039	-.015	-.109	-.009	-.115	-.021	.003	-.027	-.066	-.005
	(.052)	(.030)	(.074)	(.042)	(.073)	(.041)	(.070)	(.035)	(.078)	(.049)	(.064)	(.033)	(.089)	(.057)	(.062)	(.034)
Age 51-55	-.028	.001	.014	-.025	-.058	.024	.005	.003	-.100	.017	-.083	-.033	.043	.057	-.024	.020
	(.061)	(.036)	(.087)	(.052)	(.086)	(.051)	(.082)	(.042)	(.092)	(.061)	(.075)	(.040)	(.107)	(.073)	(.072)	(.042)
Age 56-60	-.023	.017	-.001	.045	-.020	-.019	-.006	.026	-.074	.027	-.064	-.022	.018	.086	-.052	.033
	(.074)	(.460)	(.104)	(.064)	(.104)	(.066)	(.100)	(.034)	(.109)	(.077)	(.089)	(.049)	(.132)	(.095)	(.086)	(.052)
Age 61-65	.065	-.013	.024	-.043	-.110	-.009	-.016	.059	-.124	-.035	-.080	-.026	-.089	-.001	-.089	-.013
	(.093)	(.060)	(.133)	(.085)	(.130)	(.085)	(.135)	(.077)	(.132)	(.096)	(.111)	(.064)	(.168)	(.127)	(.109)	(.069)
Age 66-70	.022	.127	.269	.070	-.181	.119	.188	.327**	-.110	.020	.033	.026	-.060	.272	.080	.191
	(.124)	(.084)	(.180)	(.119)	(.173)	(.117)	(.185)	(.108)	(.174)	(.131)	(.151)	(.091)	(.219)	(.171)	(.159)	(.106)
Age 71-75	.195	.182	.536*	.260	-.056	.102	.406	.481**	.039	-.007	.183	.096	.222	.236	.478*	.405**
	(.160)	(.120)	(.241)	(.163)	(.216)	(.149)	(.238)	(.141)	(.221)	(.170)	(.189)	(.115)	(.312)	(.249)	(.211)	(.143)
Age 76-80	.124	.129	.956*	.195	-.542	.122	.664*	.444*	-1.153*	-.165	.445	.070	-1.022	.197	.881*	.353
	(.260)	(.182)	(.381)	(.262)	(.360)	(.255)	(.335)	(.201)	(.487)	(.387)	(.301)	(.187)	(.537)	(.437)	(.356)	(.246)
Age 80+	.057	.068	-------	-------	-.586	.096	--------	--------	-1.235	-.220	.358	.043	-------	---------	---------	--------
	(.484)	(.341)			(.543)	(.386)			(.640)	(.511)	(.502)	(.341)				

Table 5 (Continued)

	Total Sample		Men		Women		More than HS		HS Degree or Less		White		Non-White		Married	
	Model 1 Chronic (1)	Model 2 Global (2)	Model 3 Chronic (3)	Model 4 Global (4)	Model 5 Chronic (5)	Model 6 Global (6)	Model 7 Chronic (7)	Model 8 Global (8)	Model 9 Chronic (9)	Model 10 Global (10)	Model 11 Chronic (11)	Model 12 Global (12)	Model 13 Chronic (13)	Model 14 Global (14)	Model 15 Chronic (15)	Model 16 Global (16)
High School	-.111	.010	-.082	-.012	-.145	.038	--------	--------	-.351**	.005	-.047	-.035	-.237	.079	.064	.019
	(.090)	(.064)	(.134)	(.094)	(.123)	(.088)			(.119)	(.096)	(.114)	(.072)	(.156)	(.128)	(.402)	(.280)
Some College	-.078	-.014	-.101	-.002	-.086	-.038	--------	-.057	-------	--------	-.039	.045	-.193	-.049	-------	-------
	(.092)	(.065)	(.132)	(.092)	(.130)	(.093)		(.066)			(.116)	(.073)	(.165)	(.135)		
College Degree	-.137	.001	-.118	.086	-.121	-.126	-.058	-.030	-------	-------	.129	.102	-.497*	-.146	--------	--------
	(.120)	(.085)	(.184)	(.128)	(.166)	(.119)	(.094)	(.058)			(.156)	(.098)	(.202)	(.166)		
Graduate	-.245	.023	-.531**	.066	-.070	-.129	-.216*	-------	-------	--------	-.030	.010	-.567*	-.139	--------	--------
Education	(.127)	(.090)	(.182)	(.127)	(.182)	(.131)	(.109)				(.157)	(.097)	(.230)	(.188)		
Income	-.010	-.002	-.016	-.003	-.004	.001	-.014	.001	-.003	-.002	-.020*	-.005	.034	.008	-.012	-.003
(logged)	(.007)	(.005)	(.010)	(.007)	(.012)	(.008)	(.012)	(.007)	(.010)	(.008)	(.009)	(.005)	(.015)	(.012)	(.010)	(.007)
Occupational	-.001	.000	.000	.001	-.001	-.000	-.001	.001	-.000	.000	-.000	.000	-.002	.000	-.001	.000
Prestige	(.001)	(.000)	(.001)	(.001)	(.001)	(.001)	(.001)	(.000)	(.001)	(.001)	(.001)	(.000)	(.001)	(.001)	(.001)	(.000)
Never Married	.022	-.012	.013	-.013	.035	-.017	.082	.014	-.023	-.041	.047	-.008	-.005	-.012	--------	--------
	(.034)	(.024)	(.048)	(.033)	(.048)	(.035)	(.048)	(.029)	(.050)	(.040)	(.045)	(.028)	(.053)	(.044)		
Widowed	.050	-.115*	-.198	-.332***	.203	.080	-.029	-.182**	-.108	-.100	.100	-.159**	-.131	.005	--------	--------
	(.078)	(.055)	(.118)	(.082)	(.105)	(.076)	(.115)	(.070)	(.131)	(.105)	(.093)	(.059)	(.152)	(.125)		
Divorced/	.090***	.006	.123***	-.015	.062	.039	.105**	-.037	.070	.029	.079*	-.017	.119**	.045	--------	--------
Separated	(.024)	(.017)	(.033)	(.023)	(.036)	(.026)	(.036)	(.022)	(.036)	(.029)	(.031)	(.019)	(.040)	(.033)		
Year	.025***	.005*	.026***	.003	.024***	.006	.026***	.002	.025***	.007	.026***	.005	.024***	.006	.027***	.006*
	(.004)	(.002)	(.005)	(.003)	(.005)	(.003)	(.005)	(.002)	(.005)	(.004)	(.004)	(.003)	(.006)	(.005)	(.004)	(.003)
N	13,764	13,764	6,768	6,768	6,991	6,991	6,875	6,875	6,419	6,419	8,725	8,725	5,034	5,034	9,410	9,410
n	8,459	8,459	4,122	4,122	4,335	4,335	4,107	4,107	3,932	3,932	5,277	5,277	3,185	3,185	5,717	5,717

*** p<.001, ** p<.01, * p<.05