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ABSTRACT

Does Job Loss Cause Ill Health?*

This study estimates the effect of job loss on health for near elderly employees based on longitudinal data from the Health and Retirement Study. Previous studies find a strong negative correlation between unemployment and health. To control for possible reverse causality, this study focuses on people who were laid off for an exogenous reason – the closure of their previous employers' business. I find that the unemployed are in worse health than employees, and that health reasons are a common cause of job termination. In contrast, I find no causal effect of exogenous job loss on various measures of physical and mental health. This suggests that the inferior health of the unemployed compared to the employed could be explained by reverse causality.

JEL Classification: I12, J63

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1. Introduction

Unemployment is a major cause of economic insecurity for working-age Americans. Loss of employment is often linked with a loss of income and employer provided health insurance, as well as the loss of valued relationships, status, and identity. There is a well-documented negative correlation between health and unemployment (see discussion in Catalano et al. 2000). However, as will be discussed below, the direction of causality has proved difficult to establish. In this study I look at business closures as a natural experiment that can be used to test for a causal relationship from job loss on health.

I use data from the Health and Retirement Study (HRS), a nationally representative survey of near elderly Americans. For the purpose of examining the causal effects of job loss on health the HRS offers several advantages: 1) The HRS includes detailed information on the causes of the termination of employment contracts. In this paper, I only consider individuals who lost their job because of business closure, which is arguably exogenous to employees' health. This definition of job loss sets this study apart from most previous studies that don't control for the cause of unemployment. 2) The HRS is a panel data set. 3) The HRS includes detailed information on demographics, health, income, education, health behaviors, job characteristics, and the ex-ante subjective probability of involuntary job loss. This information can be used to control for differences between the characteristics of people who are affected by job loss and those who are not affected by job loss.

This study uses a differences-in-differences estimation approach. It follows a cohort of initially employed individuals and compares the subsequent changes in health of those who lose their job due to business closure with a control group of those who don't lose their jobs. I test the robustness of my results by performing estimations for various measures of physical and mental health, various sets of covariates, and by including other reasons of job termination that might not be exogenous to health, such as being laid off for any reason, quitting a job, or explicitly leaving for health reasons. Further, I test if there is a difference in the effect of job loss for people who anticipated a lay-off compared to those who are dismissed unexpectedly, and I examine how the health effects of job loss vary by gender, race, marital status, income, and education level, as well as previous working conditions. I also examine the effect of job loss on health over different time periods, and finally, I look at a possible effect of a spousal job loss on health.

In contrast to most previous studies that use cross-sectional datasets or broader definitions of job loss, I find no significant effect of exogenous job loss on health for any of my specifications. This finding is robust for different definitions of health and for various subgroups of the population. In contrast, I find that causes of unemployment that are endogenous to health, such as leaving a job for bad health, are common and associated with a substantial deterioration in health. While a lack of statistically significant results does not prove that job loss has no effect on ill health, my results suggest that the negative correlation between health and unemployment could be explained by reverse causality.

The paper proceeds as follows: Section 2 discusses the previous literature with a focus on the problem of causal inference. Section 3 outlines the identification strategy, and discusses the estimation methods. Section 4 describes the data. Section 5 presents and discusses the estimation results. Section 6 concludes the paper.

2. Previous literature

This study is part of a literature that examines the effects of job loss and unemployment on health. Some previous studies in the economics literature examine this relationship (Bjorklund 1985, Mayer et al. 1991, Gerdtham and Johannesson 2003, Browning et al. 2006, Boeckerman and Imakunnas 2006, and Sullivan and von Waechter 2008), and there is also a large literature on this topic in the epidemiology, psychology, public policy, and sociology literatures. Most of these studies compare various measures of physical and mental health between the employed and unemployed, often with a focus on how the effects of unemployment differ for specific racial and ethnic groups (Rodriguez et al. 1999, Catalano et al. 2000), gender, family role, and social class (Artazcoz et al. 2004, Price, Choi and Vinokur 2002, Dew et al. 1992), unemployment benefit type (Rodriguez 2001), and community characteristics (Turner 1995). These studies mostly find that the unemployed are in worse physical and mental health than the employed. However, such an association does not necessarily imply a causal relationship from unemployment to ill health if people in ill health are more likely to become or remain unemployed. There is some empirical evidence that people in ill health are more likely to lose their jobs and become unemployed (Arrow 1996), and that unemployment spells are longer for people with health problems (Stewart 2001). In order to study the causal relationship from unemployment to health it is necessary to control for the cause of entry into unemployment, and also to account for the fact that unemployment spells might be longer for people in ill health.

One strategy to address reverse causality is to account for the cause of the loss of employment. For example, Catalano et al. (2000) look only at people who had been fired or laid off. However, the estimation results could still be biased, if lay-offs are related to health, if for example some people are laid off because of sickness related work absences. This bias can be avoided by studying the health effects of job loss for a cause that is exogenous to employees' health. Several studies have examined the effect of mass layoffs on health (Dew et al. 1992, Browning et al. 2006 and Sullivan and von Wachter 2008), with contradictory findings: Dew et al. (1992) compare the mental health of a group of 141 women before and after layoffs at a plant in semi-rural Pennsylvania. During the twelve months following the first interviews, 73 of these women had been laid-off. They find a significant effect of lay-offs on mental health. Sullivan and von Wachter (2008) also find a large effect of mass lay-offs in Pennsylvania on subsequent mortality. In contrast, Browning et al. (2006) examine the effect of mass layoffs in Denmark on hospitalization for diseases of the cardiovascular and digestive system, and they find no significant effect of displacement on hospitalization. My study accounts for reverse causality by looking including only individuals who lost their job, because their previous employer's business closed. My study adds to the previous literature on the effect of lay-offs on health by considering a broad range of physical and mental health outcomes that have not been examined before. One advantage of this study compared to previous studies is that I control for a more detailed list of individual characteristics, including the ex-ante subjective probability of job loss. Without controlling for detailed individual characteristics, differences in the subsequent health of workers affected by lay-offs and workers who are not laid off might reflect not the effect of lay-offs on health, but could be explained by different individual characteristics. Such a bias could possibly explain differences in the findings of my study and the study by Sullivan and von Wachter (2008).

Another cause of reverse causality is that not only the reason of entry into unemployment, but also the length of stay in unemployment could be related to health. My study includes people who have been laid-off because of business closure at any point of time within a two-year period, independent of their unemployment status at the time of the second interview. This approach allows the consistent estimation of the causal effect of job loss on health.

Job loss can have potentially lasting effects on the socio-economic situation and the health of workers even if laid-off workers face no or only brief periods of unemployment. Job loss can cause a substantial reduction of income and consumption (Chan and Stevens 2002, Stephens 2004). This is true not only for the unemployed, but also for many laid-off workers who start a new job. Chan and Stevens (2002) find that job loss reduces earning for near elderly employees one year after job loss by between 20% and 33%, and lower income might be a cause of deteriorating health (Adams et al. 2003). Also, job loss can cause a loss of health insurance, at least for those laid-off employees who were covered by employment based health insurance. Although health insurance is usually also available in the individual health insurance market, it tends to be more expensive. Loss of health insurance could also cause worsening health (Haudley 2003, Levy and Meltzer 2004).

3. Identification strategy

The main parameter of interest in this study is the average effect of job loss on the health of those who lost their job. A formal definition of this effect, similar to Heckman et al. (1997) is:

$$\alpha = E(Y(i,1) - Y(i,0) \mid D(i,1) = 1) - E(Y(i,1) - Y(i,0) \mid D(i,1) = 0) \qquad (1)$$

where $Y(i, t)$ is the health of individual i at time t. The population is observed in a pre-treatment period t = 0, and a post-treatment period t = 1. I denote $D(i, 1)$ = 1 if individual i has been affected by job loss between periods t = 0 and t = 1, and $D(i, 1)$ = 0 otherwise.

The parameter α represents the difference between the health change of people affected by job loss and their hypothetical (counterfactual) health change if they had not been affected by job loss. Unfortunately, the counterfactual is never observed. Therefore, I need to assume that without job loss the health of people who in fact have been laid off would have evolved in the same way as it did for people with the same observed characteristics who have not been laid off. If i' is an individual in the control group (not laid off) with the same observed characteristics as i, an individual in the treatment group (laid off), then this assumption can be stated as:

$$E(Y(i, 1) - Y(i, 0) \mid X(i), D(i, 1) = 0) = E(Y(i', 1) - Y(i', 0) \mid X(i'), D(i', 1) = 0)$$

where $X(i)$ is a vector of observed characteristics predetermined at t = 0. It is necessary to control for a sufficiently detailed set of relevant characteristics $X(i)$, because on average people affected by job loss do not have the same characteristics as people who are not laid off. Not controlling for differences between these groups would lead to biased estimation results. If for example the average laid-off employee is poorer or less educated than the average employee who is not laid-off, one might expect their health to evolve unfavorably compared to the health of the control group even in the absence of job loss. Observed characteristics in this study include information on demographics (age, gender, race), social situation (marital status, education, income, wealth), health behaviors (smoking, obesity, and health insurance), and job characteristics (part-time employment, firm size, and industry). I also control for the ex-ante subjective probability of involuntary lay-off. Stephens (2004) finds that the subjective probability of involuntary lay-off includes information about the likelihood of subsequent job loss even after controlling for other characteristics, and that it is a good predictor of subsequent actual job loss. Including the subjective probability of involuntary lay-off controls for unobserved heterogeneity between people affected by job loss and others, which other observed characteristics could not detect. The average treatment effect can be estimated by the following linear differences-in- differences regression equation:

$$Y(i, 1) - Y(i, 0) = \delta + X(i)' \pi + D(i, 1)\alpha + \varepsilon(i) \tag{2}$$

where the dependent variable is the change in health between period 0 (before the treatment) and period 1 (after the treatment), and $X(i)$ are assumed to be exogenous to the random error term $\varepsilon(i)$. The equation above can be estimated by standard regression methods such as least squares or ordered probit. I estimate the effects of job loss on several measures of health, and for alternative causes of job termination. These variables are described in the following section.

4. Data and descriptive statistics

I use data from wave two to six of the Health and Retirement Study (HRS) which cover the time period from 1994 to 2002[1]. The HRS includes a sample of initially 7600 households (12654 individuals), with at least one household member born between 1931 and 1941, and their spouses, who could be any age. The survey was subsequently repeated every two years. In 1998, a new sample was added to the survey which consists of `war babies' born between 1942 and 1947, and the data also include new spouses of previous wave respondents. The baseline estimation sample in this study consists of all persons who were working for pay at the time of the interviews for waves 2 to 5 and who were age 63 or below at this time. This sample excludes persons who are self employed and can include multiple observations for the same person. This leaves a sample of 20,396 observations. Of these, 4697 observations do not include information on subjective probability of involuntary job loss, 221 observations do not include information on industry sector, 92 observations have missing information on smoking, 59 observations do not include information on household income, and 9 observations have no information on household wealth. The final sample for the baseline regression (table 3, column 4) consists of 15218 observations on 6867 individuals.

For each observation, I use information from two waves, before and after treatment. Before treatment, all respondents work for pay. At the following interview two years later, some respondents do not work any more for their previous-wave employer. These individuals might be retired, unemployed, or work for a different employer. All respondents who did not work for their previous-wave employers were asked why they

[1] For a detailed description of the HRS see Juster and Suzman (1995) and the HRS homepage (www.hrsonline.isr.umich.edu).

had left that employer. Possible answers included ‘business closed’, ‘laid off / let go’, ‘poor health / disabled’, and ‘other reasons’. Respondents could give multiple reasons. My definition of exogenous job loss includes 369 observations (2.4% of the baseline sample) who answered that their previous employers’ business closed. This definition excludes 17 observations who also stated that they quit by themselves or left for health reasons. 720 respondents stated that they were laid off / let go, 544 quit, and 507 left for health reasons. One concern with respect to the timing of job transitions is that respondents stopped working for their previous employers at different point of time during the two year period between interviews, and it could make a difference whether for example the previous employers’ business closed just after the first interview or just before the second interview. This study estimates average effects.

Outcome variable is the change of health between waves, which is measured by various subjective and self-reported objective measures of health. One measure for change of health is the answer to a question how self-assessed health has changed since the last interview two years ago. Possible answers include ‘much better’, ‘somewhat better’, ‘about the same’, ‘somewhat worse’, and ‘much worse’. The answer ‘much better’ is coded as 1 and ‘much worse’ is coded as 5. Another measure of health change is the change in limitations in activities of daily living (ADL’s) since the previous interview. Activities of daily living include the ability to walk across a room, dress, eat, bath, use a toilet, and get in and out of bed without help. Another measure of health change is the change in longevity expectations. Longevity expectations are measured as the subjective probability to live to age 75 or longer, and changes in answers between waves are measured relative to life-table averages. I also use two measures of change in mental health, the first of which is the change in CESD scores (Center for Epidemiologic Studies Depression Scale). Respondents are asked whether they agree or disagree with eight statements about their emotions during the past week, such as whether they felt depressed much of the time. The CESD score is based on the answers to these questions and ranges from 0 (good mental heath) to 8 (bad mental health). The second measure of mental health change is a binary variable that indicates whether there was a first incidence of a doctor diagnosed mental health condition between interview waves. Further, in one regression I use a measure of same-period self-reported overall health as dependent variable. Possible answers range from 'excellent' (codes as 1) to 'very good' (2), 'good' (3), 'fair' (4), and 'poor' (5).

One concern with respect to self-reported change of health is that the differences between categories might not be equal. For example the difference between 'much better' health and 'somewhat better' health might not be the same as the difference between 'somewhat better' health and 'about the same health'. One solution to this potential problem is to use ordered probit estimation, which allows for different distances between categories.

Another question is whether self-reported health measures provide meaningful indicators of health status. Idler and Benyamini (1997) documented in a review of 27 studies that self-reported health measures are strongly correlated with mortality. Bath (2003) and Remle (2004) also find that self reported changes in health predict future mortality both for British data and the HRS. Another concern about self-reported health measures that has received a lot of attention in the literature is that self-reports of health might be biased depending on labor force status, if people out of work are more likely to report ill health in order to justify economic inactivity. Several previous studies found evidence for such a justification bias, while others found no evidence (see review by Currie and Madrian 1999, and discussion in McGarry 2004). This study uses several measures of health change. Some of those, such as subjective longevity expectations and doctor diagnosed psychological conditions, are not likely to be affected by justification bias. For other measures such as self-reported health change, it is possible that the estimates of the negative effect of job loss on health change are upward biased.

Explanatory variables include respondents' age, and binary variables for respondents who are female, black, married, have a high school degree, and for respondents who have a college degree. Further explanatory variables are total household net wealth, and the logarithm of the total household income. Income and wealth are adjusted for consumer price inflation (CPI) and represent real 1982-1984 prices. Also included are binary variables about health behaviors, whether the respondent is currently smoking, is obese, which is defined as a body mass index (BMI) in excess of 30, or is covered by health insurance. Explanatory variables also include information on job characteristics such as a binary indicator for part time work, and five binary indicators for firm size, which is measured by the total number of employees at all locations (5-14 employees, 15-24 employees, 25-99 employees, 100-499 employees, and 500+ employees, less than five employees is omitted category), as well as twelve binary indicators for industry sector (agricultural sector including forestry and fishery is omitted category). The subjective probability of job loss is based on the following question: 'Sometimes people are permanently laid off from jobs that they want to keep. On the scale from 0 to 100 where 0 equals absolutely no chance and 100 equals absolutely certain, what are the chances that you will lose your job during the next year?' One limitations of this study is that this question refers to the probability of involuntary job loss during a one year period after the interview, while this study examines lay-offs during a two year period after the first interview.

[Table 1 about here]

Table 1 shows sample statistics for both the overall population and those affected by job loss. Table 1 is based on the sample included in the baseline regression (Table 3, column 4). To some degree, people anticipate being laid off. For job losers, the average subjective probability of being laid off was 31% compared with 15.4% for the total population. However, a substantial fraction of laid-off persons did not previously expect to lose their employment. The fraction of laid-off respondents, who had previously stated that their probability of involuntary job loss was zero, amount to 37.1%, as compared to 54% for the full sample. Compared to the full sample people who are affected by job loss due to business closing are more likely to be female, married, and have a high-school degree, but much less likely to have a college degree. On average, people, who will lose their job, live in households with somewhat lower incomes, and substantially lower wealth, and they are more likely to work part time. They are more likely to smoke and be obese, and somewhat less likely to be covered by health insurance. Compared to the full sample, the sample of laid-off employees differs little in terms how stressful jobs are and how much physical effort they require. However, laid-off employees are more likely to receive low pay, which is defined as an hourly wage below $4.72 in 1982-1984 prices. Laid-off employees also tend to work at smaller firms, and are more likely to work in manufacturing and retail sales and less likely to work in public administration and professional services.

Laid-off respondents face a 10.8% probability to be unemployed at the time of the second interview, while this probability is only 1.6% for the entire sample. The probability that laid-off respondents will not be working at the time of the second interview is 39.2%, as compared to 19.5% for the full sample. Thus, many of the laid-off respondents in the sample leave the labor force. People who lose their job suffer a substantial drop in household income, on average –12.9% between waves, while average income stays constant in real terms for the entire sample. For respondents who don't work again after being laid off, the average drop in household income is -17.8%, while for people who work for pay in the interview after the job loss, the average reduction in household income is -9.7%. Thus, laid-off workers face on average a substantial drop in household income even if they find new employment.

5. Results

A. Cross-section estimation of the relationship between unemployment and health

The regression results in Table 2 show the association between being unemployed and self-reported overall health. Unemployment status and self- reported overall health are both measured at the same time. The sample differs from the samples used in the following regressions by including not only respondents who work for pay at the time of the first interview, but also those who are unemployed. The regression presented in table 2 replicates the cross-sectional approach taken in much of the previous literature on unemployment on health (for example Turner 1995, Rodriguez 2001, Artazcoz et al.

2004). In line with previous studies, I find a significant negative association between unemployment status and self-reported health. However, this does not establish a causal link from unemployment to ill health, if people who are ill in the first place are also more likely to become and/ or remain unemployed. The coefficient of the effect of unemployment on health is 0.21.[2] This implies that unemployment increases the probability of higher health categories, which represent worse health. The signs of the other dependent variables are as one might expect. Higher education, higher income, being female and having health insurance coverage are associated with better health, while higher age, being black, working part-time, smoking and obesity correlate with worse health.

[Table 2 about here]

B. The average effect of job loss on health

Table 3 shows the estimated average effect of job loss on health for laid-off persons. Column 1 to column 4 show estimation results for different sets of covariates. None of the specifications shows a significant effect of job loss on health change. The negative estimation coefficient for the business-closed indicator actually points toward a positive, but insignificant effect of job loss on health. The estimation coefficient of business-closed becomes even more negative if additional covariates are added to the regression. The signs of the coefficients for the other covariates are mostly as expected. Higher education, income, and wealth are associated with improving health, while age, smoking and obesity are associated with worsening health. Black race is associated with improving health. This result could reflect different standards of black respondents in

[2] The values of coefficients from ordered probit estimations do not have a straightforward intuitive interpretation, because the size of the marginal effect of unemployment on health varies with the values of the other explanatory variables.

answering questions about self-reported change of health. The subjective probability of job loss is associated with a significant subsequent deterioration in health. This can be explained either if the risk of being laid off itself is harmful to health, or if the subjective probability of job loss is correlated with other characteristics that cause ill health.

[Table 3 about here]

One concern with respect to interpreting the results in Table 3 is that respondents might use different scales for answering questions about self-reported change of health. Such scales could also vary systematically between subgroups of the population. One approach to account for different scales across subgroups (index sifting) is to include variables for demographic and socio-economic characteristics. The specifications in column 3 and 4 of Table 3 include a detailed range of such characteristics.[3]

In summary, the results in Table 3 show no significant causal effect of job loss on ill health. One concern is that the sample size (369 individuals lose their job due to business closure) is insufficient to determine a significant effect. In order to test for the robustness of the result that job loss does not cause ill health I estimate additional specifications for various measures of physical and mental health. I also estimate the effect of job loss on health separately for subgroups based on demographics, job characteristics, and on previous expectations about the probability of involuntary job loss. Further, I examine whether there is any effect of job loss on health for a longer time period, and I also estimate the effect of spousal job loss on the health of respondents.

[Table 4 about here]

[3] One approach to control for different distances between cutoff points across subgroups of the population (cutoff-point shifting) is to use a generalized ordered probit model. In analysis not shown I estimate a generalized ordered probit for the baseline specification in column 4 of Table 3, and I find that. business-closed is not significantly different from zero at any of the cutoff points.

In addition to testing for the robustness of the result that job loss does not cause ill health, I also examine whether the observed correlation between unemployment and health can be explained by reverse causality. Table 4 compares how subsequent health changes vary by different reasons of job termination. Previous studies differ in what reasons for unemployment they include in their analysis. For example, Bjorklund (1985) and Rodriguez et al. (1999) include all reasons for unemployment, while Catalano et al. (2000) include only those who were involuntarily laid off. A simple test on how the definition of job loss influences the estimated effects of job loss on health is to estimate the effect of job loss on health for various reasons of job termination and compare the results. As discussed above, I assume that business closure is exogenous to health change, while being laid off, quitting, and leaving for health reasons might be endogenous. I find that being laid off, which could be for any reason, has no significant effect on health change. People who quit their job subsequently experience improving health. This finding could be explained if these respondents qut for example because they started a better job with a new employer. However, people who leave their job for health reasons experience a very strong negative change in their health. As shown in table 1, leaving a job for health reasons is also quite common in this age group. In summary, these results suggest that the subsequent change of health varies substantially for different reasons of job termination. This implies that reverse causality can bias estimation results if the reason for unemployment is not exogenous.

Table 5 presents the effect of job loss for several measures of health change. Measures of health change in table 5 include the change in limitations of activities in daily living, the change in longevity expectations, the change in the CESD score for mental health, and first incidence of doctor diagnosed mental health conditions. For all of these measures, I find no significant effect of job loss on health change. This adds credibility to the hypothesis that job loss does not cause ill health.

[Table 5 about here]

D. The effect of job loss on health by subgroups

Columns 1 and 2 of Table 6 show how the effect of job loss on health varies with prior expectations about job loss. Column 1 includes a binary indicator for respondents who stated that their risk of involuntary job loss was zero. The table shows the effect of this variable both for laid-off respondents, and for the entire sample. Respondents who did not expect to lose their job faced improving health. The interaction term of zero job loss expectations and business-closed is also associated with improving health, but is not statistically significant. Column 2 includes an interaction term of the probability of involuntary job loss and business closed. The coefficient for this interaction term is zero, indicating that the effect of job loss on health does not depend on previous job loss expectations.

[Table 6 about here]

Columns 3 and 4 of Table 6 examine the role of unemployment in the relationship between job loss and ill health. As shown in Table 1, most respondents affected by job loss are not unemployed at the time of the second interview. Many laid-off employees find new employment, although typically at substantially lower wages (see discussion in section 4). Column 3 includes a binary indicator for respondents who are unemployed at the time of the second interview and an interaction term between unemployment at the time of the second interview and business-closed. Unemployment at the time of the second interview is not exogenous to health change if persons with deteriorating health are more likely to become or stay unemployed. The estimation results indicate that unemployment is associated with strongly declining health. However, the interaction term of business-closed and unemployment point to improving health, but is not significantly different from zero. Column 4 includes a binary indicator for respondents who did not work at the time of the second interview and an interaction term between this variable and business-closed. As for unemployment, work status at the time of the second interview is not exogenous to health change if respondents with deteriorating health are more likely to stop working. The estimation results show that persons who do not work at the time of the second interview face strongly deteriorating health. However, the interaction term of not working at the second interview and business closed is close to zero and not statistically significant. Columns 3 and 4 of Table 6 imply that persons with deteriorating health are more likely to become unemployed or leave the labor force, but there is no significant relationship between health change and unemployment or work status at the second interview for laid-off respondents.

[Table 7 about here]

The estimation results shown in Column1 of Table 7 include interaction terms of business-closed with gender and marital status, black race, education level, and previous job characteristics. The omitted reference group would be unmarried white females without high school degree. The results suggest that married, black, and more educated respondents might be less affected by the negative health consequences of job loss, while respondents with low wages and with jobs that involve a high degree of stress or physical effort are more affected by job loss. However, these interaction terms are not statistically significant.

Column 2 of table 7 shows the effect of lagged job loss on self-reported health change. It includes a binary indicator which is set to one for respondents who lost their job due to business closure in the two year period prior to the first interview. This specification examines effect of job loss on health for a period of two to four years after the layoff. The estimation results show no evidence for a longer lasting effect of business closure on subsequent changes in health. Column 3 of Table 7 reports the effects of a spousal job loss on health. The estimation results provide no evidence for an effect of spousal layoffs on the health of respondents.

6. Conclusion

In summary, I find no evidence of any significant effects of job loss on health within a period of up to four years after job loss. This result is robust across specifications. It holds for various measures of physical and mental health, for the average effect of job loss on health for all laid off persons, as well as for the effect of job loss on specific groups defined by previous job loss expectations as well as by gender, marital status, race, education, and previous working conditions. There is also no effect of the job loss of a spouse.

These results contradict much of the previous literature that finds strong negative health consequences of unemployment. However, many previous studies do not account for the cause of unemployment which might be related to ill health, and studies which do account for this possible source of endogeneity – for example by examining the effect of mass-layoffs on health - might not sufficiently account for differences in the characteristics of individuals who are laid-off and individuals who are not laid off. This raises the possibility that results of previous studies might not reflect the causal effect of unemployment on health.

In contrast to many previous studies, this study focuses on people who have lost their job for an exogenous reason – the closure of their previous employer's business. This study also accounts for a detailed list of individual characteristics including the ex-ante subjective probability of involuntary job loss in order to control for differences between laid-off employees and employees who are not laid-off. Thus, the identification strategy of this study is well suited to identify the causal effect of job loss on health.

The results of my study also make it plausible that the inferior health of the unemployed compared to the employed could be explained by reverse causality. Specifically, I find that leaving a job for health reasons is both quite common in this age group, and associated with a rapid deterioration in health (Table 5), and that persons with deteriorating health are more likely to become unemployed or leave the labor force (Table 6). This leads me to the cautious conclusion that the absence of any significant effect of job loss on health in this study might indeed unveil that job loss does not cause ill health.

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Table 1: Sample Statistics

	Entire Sample		Business Closed	
	Mean	Std. Dev.	Mean	Std. Dev.
Health Measures				
Health Change	3.038	0.706	3.043	0.657
ADL Change	0.038	0.424	0.016	0.416
Life Exp. Change	-0.011	0.381	-0.016	0.408
CESD Change	0.086	1.944	0.175	2.243
Psych Diagnosis	0.019	0.136	0.032	0.177
Health	2.353	0.971	2.363	0.963

	Number Affected
Reasons for Job termination	
Business Closed	369
Laid Off	720
Quit	544
Left for Health	507
Spouse Business Closed	209

	Entire Sample		Business Closed	
	Mean	Std. Dev.	Mean	Std. Dev.
Prob. Of Job Loss	15.359	25.005	31	34.817
Zero prob. of job loss	0.540	0 .498	0.371	0.483
Spouse Prob. of Job Loss	14.872	24.692	20.335	29.583
Demographics				
Age	55.481	4.958	54.880	5.203
Female	0.599	0.489	0.615	0.487
Black	0.146	0.353	0.111	0.314
Married	0.741	0.437	0.764	0.425
Social Status				
High School	0.560	0.496	0.604	0.489
College	0.233	0.422	0.113	0.318
Log(income)	9.477	0.900	9.372	0.846
Wealth (in $100,000)	0.651	1.720	0.497	0.739
Part time work	0.146	0.353	0.176	0.381
Health Behaviors				
Smoking	0.224	0.417	0.300	0.459
High BMI	0.263	0.440	0.292	0.455
Health Insurance	0.927	0.259	0.880	0.324
Number of Observation in Baseline	15,218		369	

	Entire Sample		Business Closed	
	Mean	Std. Dev.	Mean	Std. Dev.
Endogenous Variables				
Unemployed at 2nd interview	0.016	0.1281	0.108	0.311
Not working at 2nd interview	0.195	0.396	0.392	0.489
Income change	0.003	0.7229	-0.129	0.808
Health Insurance at 2nd Interview	0.924	0.2644	0.810	0.392
Job Characteristics				
Job stressful	2.204	0.806	2.296	0.799
Job physical effort	2.801	1.110	2.736	1.100
Low Wage	0.186	0.389	0 .272	0.446
Firm size 5-14 employees	0.025	0.156	0.040	0.197
Firm size 15-24 employees	0.017	0.129	0.037	0.191
Firm size 25-99 employees	0.064	0.244	0.081	0.273
Firm size 100-499 employees	0.120	0.325	0.100	0.300
Firm size > 500 employees	0.461	0.498	0.368	0.483
Industry: mining and construction	0.038	0.191	0.054	0.226
Industry: manufacturing nondurables	0.077	0.267	0.127	0.333
Industry: manufacturing durables	0.112	0.316	0.195	0.396
Industry: transportation	0.067	0.250	0.070	0.256
Industry: wholesale	0.036	0.188	0.056	0.231
Industry: retail	0.100	0.300	0.184	0.388
Industry: finance / insurance	0.063	0.244	0.043	0.203
Industry: business services	0.049	0.216	0.054	0.226
Industry: personal services	0.031	0.175	0.040	0.197
Industry: entertainment	0.012	0.111	0.010	0.103
Industry: professional services	0.333	0.471	0.130	0.336
Industry: Public administration	0.061	0.240	0.010	0.103
Number of observations in baseline	15218		369	

Table 2: Cross- Section Regression of Health on Unemployment

	Health
Unemployed	0.212***
	(0.050)
Age	0.016***
	(0.002)
Female	-0.054**
	(0.022)
Black	0.192***
	(0.030)
Married	-0.01
	(0.025)
High School	-0.318***
	(0.027)
College	-0.556***
	(0.034)
Income	-0.165***
	(0.011)
Wealth (in $100,000)	-0.001
	(0.003)
Part time work	0.068***
	(0.026)
Smoking	0.214***
	(0.024)
High BMI	0.381***
	(0.022)
Health Insurance	-0.054*
	(0.033)
Observations	20,776
Pseudo R-Squared	0.05

Robust standard errors clustered for individuals in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Coefficients for binary wave variables not shown
Ordered probit estimation
Higher values for health represent worse health

Table 3: The causal Effect of Job Loss on Health

	Health Change (1)	Health Change (2)	Health Change (3)	Health Change (4)
Business Closed	-0.005	-0.002	-0.049	-0.068
	(0.059)	(0.060)	(0.060)	(0.060)
Age		0.010***	0.010***	0.010***
		(0.002)	(0.002)	(0.002)
Black		-0.059*	-0.114***	-0.116***
		(0.031)	(0.032)	(0.032)
Female		0.014	0.017	0.016
		(0.022)	(0.026)	(0.026)
Married			0.021	0.023
			(0.026)	(0.026)
High School			-0.100***	-0.100***
			(0.030)	(0.030)
College			-0.154***	-0.151***
			(0.038)	(0.038)
Income			-0.040***	-0.039***
			(0.014)	(0.014)
Wealth (in $100,000)			-0.011**	-0.011**
			(0.005)	(0.005)
Part Time Work			0.027	0.024
			(0.030)	(0.030)
Smoking			0.134***	0.133***
			(0.026)	(0.026)
High BMI			0.112***	0.110***
			(0.025)	(0.025)
Health Insurance			-0.024	-0.02
			(0.045)	(0.045)
Prob. of Job Loss				0.001***
				(0.000)
Observations	15,218	15,218	15,218	15,218
Pseudo R- Squared	0.000	0.001	0.008	0.008

Robust standard errors clustered for individuals in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Coefficients for binary wave variables not shown; Columns (3) and (4) also include binary variables for six firm size categories and thirteen industry codes, which are not shown
All columns show ordered probit Estimations
Higher values for health change represent worsening health

Table 4: Endogenous Causes of Job Termination

	Health Change (1)	Health Change (2)	Health Change (3)
Laid Off	-0.018		
	(0.049)		
Quit		-0.098*	
		(0.052)	
Left for Health			1.159***
			(0.068)
Prob. of Job Loss	0.001***	0.001***	0.001**
	(0.000)	(0.000)	(0.000)
Age	0.010***	0.010***	0.009***
	(0.002)	(0.002)	(0.002)
Female	0.015	0.015	0.012
	(0.026)	(0.026)	(0.026)
Black	-0.116***	-0.117***	-0.123***
	(0.032)	(0.032)	(0.032)
Married	0.022	0.022	0.024
	(0.026)	(0.026)	(0.026)
High School	-0.100***	-0.100***	-0.071**
	(0.030)	(0.030)	(0.029)
College	-0.151***	-0.150***	-0.112***
	(0.038)	(0.038)	(0.038)
Income	-0.039***	-0.040***	-0.033**
	(0.014)	(0.014)	(0.014)
Wealth (in $100,000)	-0.011**	-0.011**	-0.011**
	(0.005)	(0.005)	(0.005)
Part time work	0.024	0.025	0.007
	(0.030)	(0.030)	(0.030)
Smoking	0.133***	0.134***	0.118***
	(0.026)	(0.026)	(0.026)
High BMI	0.110***	0.109***	0.091***
	(0.025)	(0.025)	(0.025)
Health Insurance	-0.021	-0.021	-0.024
	(0.045)	(0.045)	(0.045)
Observations	15,218	15,218	15,218
Pseudo R- Squared	0.008	0.008	0.027

Robust standard errors clustered for individuals in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Coefficients of wave indicators, six firm size categories and thirteen industry codes not shown
All columns are ordered probit estimations
Higher values for health change represent worsening health

Table 5: Alternative Measures of Health

	ADL Change (1)	Life Exp. Change (2)	CESD Change (3)	First Psych. Diagnosis (4)
Business Closed	-0.072	-0.003	0.064	0.008
	(0.089)	(0.023)	(0.114)	(0.010)
Prob. of Job Loss	0.001	0.000	0.000	0.000***
	(0.001)	(0.000)	(0.001)	(0.000)
Age	-0.002	0.000	-0.001	-0.001***
	(0.002)	(0.001)	(0.003)	(0.000)
Female	0.010	0.023***	0.059**	0.010***
	(0.025)	(0.006)	(0.027)	(0.003)
Black	0.016	0.007	0.017	-0.012***
	(0.035)	(0.009)	(0.035)	(0.003)
Married	-0.063**	0.013**	0.059*	-0.002
	(0.027)	(0.006)	(0.031)	(0.003)
High School	-0.052	-0.002	0.013	-0.009**
	(0.032)	(0.008)	(0.036)	(0.004)
College	-0.110***	0.005	0.017	-0.011**
	(0.038)	(0.009)	(0.043)	(0.004)
Income	-0.015	0.002	-0.005	0.000
	(0.017)	(0.004)	(0.020)	(0.002)
Wealth (in $100,000)	-0.001	0.000	-0.009	-0.001*
	(0.003)	(0.001)	(0.006)	(0.000)
Part time work	-0.062	-0.009	-0.024	-0.002
	(0.040)	(0.008)	(0.045)	(0.004)
Smoking	0.051*	0.000	0.091***	0.009***
	(0.029)	(0.007)	(0.032)	(0.003)
High BMI	0.058**	-0.005	0.034	0.007**
	(0.028)	(0.006)	(0.030)	(0.003)
Health Insurance	0.007	-0.013	0.112	0.002
	(0.059)	(0.014)	(0.070)	(0.005)
Observations	15,216	13,775	14,910	14,004
(Pseudo) R-squared	0.009	0.003	0.01	0.01

Robust standard errors clustered for individuals in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Coefficients of wave indicators, six firm size categories and thirteen industry codes not shown
Column (1) is ordered probit regression
Columns (2) to (4) are least square regressions

Table 6: Interactions of job loss with job loss expectations and with employment status at 2nd interview

	Health Change (1)	Health Change (2)	Health Change (3)	Health Change (4)
Business Closed	-0.02	-0.082	-0.063	-0.111
	(0.078)	(0.076)	(0.064)	(0.069)
Zero prob. of job loss	-0.102			
× Business Closed	(0.114)			
Zero prob. of job loss	-0.051**			
	(0.021)			
Prob. of Job Loss		0.000		
× Business Closed		(0.002)		
Prob. of job loss		0.001***		
		(0.000)		
Unemployed at 2nd interview			-0.170	
× Business Closed			(0.193)	
Unemployed at 2nd interview			0.150*	
			(0.085)	
Work at 2nd interview				0.010
× Business Closed				(0.123)
Work at 2nd interview				0.217***
				(0.028)
Observations	15,218	15,218	15,218	15,218
Pseudo R- Squared	0.000	0.001	0.008	0.011

Robust standard errors clustered for individuals in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Estimation includes all variables in Column 4 of Table 3; these coefficients are not shown
All columns show ordered probit Estimations
Higher values for health change represent worsening health

Table 7: Effects of Job Loss interacted with socioeconomic and job characteristics, longer term effects of job loss, and spousal Job Loss

	Health Change	Health Change	Health Change
Business Closed	-0.29		
	(0.196)		
Married Male	-0.116		
× Business Closed	(0.153)		
Married Female	-0.155		
× Business Closed	(0.278)		
Not Married Male	0.061		
× Business Closed	(0.184)		
Black × Business Closed	-0.151		
	(0.195)		
High School	-0.112		
× Business Closed	(0.147)		
College	-0.205		
× Business Closed	(0.224)		
Job Stressful	0.054		
× Business Closed	(0.069)		
Job Physical Effort	0.066		
× Business Closed	(0.056)		
Low Wage	0.231		
× Business Closed	(0.140)		
Business closed in		0.098	
previous wave		(0.069)	
Spouse Business Closed			0.118
			(0.077)
Spouse Prob. of Job Loss			-0.001
			(0.001)
Observations	14,174	18,233	7,915
Pseudo R- Squared	0.01	0.008	0.005

Robust standard errors clustered for individuals in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
Estimation in column 1 includes all variables in Column 4 of Table 3 and additional variables for stressful job, job requires physical effort and low wage; columns 2 and 3 include variables for demographics, socioeconomic characteristics and health behaviors
All columns are Ordered Probit estimations