Chaire de recherche Industrielle Alliance
sur les enjeux économiques
des changements démographiques
CEDIA.ca

17-02

# WHISTLE WHILE YOU WORK: JOB INSECURITY AND OLDER WORKERS' MENTAL HEALTH IN THE UNITED STATES

CAHIER DE RECHERCHE
WORKING PAPER

Italo A. Gutierrez and Pierre-Carl Michaud

Octobre / October 2017

UNIVERSITÉ LAVAL
Faculté des sciences sociales
HEC MONTRÉAL
ESG UQÀM

La Chaire de recherche Industrielle Alliance sur les enjeux économiques des changements démographiques est une chaire multi-institutionnelle qui s'appuie sur un partenariat avec les organisations suivantes :

**- Centre interuniversitaire de recherche en analyse des organisations (CIRANO)**
**- iA Groupe financier**
**- Retraite Québec**





Dépôt légal : Bibliothèque et Archives nationales du Québec et Bibliothèque et Archives Canada, 2017.
ISSN 2368-7207

# Whistle While You Work: Job Insecurity and Older Workers' Mental Health in the United States*

Italo A. Gutierrez† & Pierre-Carl Michaud‡

October, 2017

**ABSTRACT**

We estimate the effects of job insecurity on older workers' health outcomes using an instrumental variables approach which exploits downsizing and state-industry level changes in employment. We provide evidence that job insecurity, as measured by the self-reported probability of job loss, increases stress at work, the risk of clinical depression and lowers self-reported health status. IV estimates are much larger than OLS estimates which we interpret as evidence that job insecurity which is outside the control of workers may have much larger effects on mental health. These findings suggest that employers ought to consider actions to offset the detrimental health effects of reducing personnel on their remaining (older) workers and pay attention at the stress that industry level changes in economic conditions may have on workers.

**JEL Codes:** I12, M51

**Keywords:** older workers, job insecurity, employer downsizing, health outcomes

* This research was supported by the National Institute on Aging, under grant R01AG040176. We thank Nancy Campbell, Orla Hayden, Prodyumna Goutam and Nelly Mejia for excellent research assistance. Errors are our own.
† RAND Corporation, italo@rand.org
‡ HEC Montréal, IZA and NBER, pierre-carl.michaud@hec.ca

## 1. INTRODUCTION

Previous research has found that job loss can adversely affect health, especially for older workers. Job loss has been linked to increased risk of heart problems and stroke (Gallo et al., 2004, Gallo et al., 2006); of depression and mental illness (Browning and Heinesen, 2012, Burgard, Brand and House, 2007, Gallo et al., 2000) ; hospitalizations due to drinking, car accidents, and suicide attempts (Browning and Heinesen, 2012, Eliason and Storrie, 2009); of worse health in terms of biomarkers (Michaud, Crimmins and Hurd, 2016); and overall mortality (Browning and Heinesen, 2012, Eliason and Storrie, 2009, Sullivan and Von Wachter, 2009).

The fear of job loss can also have important health effects (Burgard, Brand and House, 2009, Hellgren and Sverke, 2003). Many exogenous factors that can lead to heightened levels of job insecurity are far more common than actually experiencing an unemployment spell. For example, in this paper, we look at the role of employer downsizings in increasing workers fear of job loss and psychological stress. Data from the Health and Retirement Study (HRS) indicates that in 2010, in the aftermath of the Great Recession, about 6% of workers who were 50 to 55 years old in 2008 reported to be unemployed, whereas as astounding rate of 44% reported that they continued to be employed but with employers that had permanently downsized their workforce since 2008. In years prior to the Great Recession, still about 25% of older workers reported their employers have permanently cut jobs. These numbers suggest that we should pursue a better understanding of the effects that job insecurity, due to circumstances outside the control of workers, can have on the health of workers.

This paper makes two important contributions to the existing literature on how job insecurity or the fear of job loss might affect workers' mental health. While there are many papers that explore this issue, potential endogeneity is an important concern. For instance, a worker expectation of job loss may come from the possibility that he or she is physically unable to perform the tasks his job requires. This potential reverse causality makes it difficult to disentangle the causal effect of job insecurity on workers' health. Our first contribution to the literature is using instrumental variables to identify the causal effect of job insecurity on workers' mental health. We pay particular attention to selection due to survival at the firm (only those who did not lose their job stay with the same employer). In particular, we use information on employers' downsizing episodes, distinguishing by whether employers have cut jobs similar to the workers' or different types of jobs. We discuss that this distinction is important because it allows to test for unobserved selectivity in terms of survival on the job. We also use information on employment growth in the employers' industries in the states when they are located. This is a novel instrument that we are able to use because of geo-coded information in HRS. We find that IV estimates are larger than OLS. Our analysis indicate that job loss expectations are more predictive of future separations from employers if we use the predictive power of the instruments. This suggests that workers who are afraid of job loss because of exogenous factors are more likely to actually experience a job separation, and therefore also more likely to experience higher levels of depression and stress.

Our second contribution to the literature is using data that is representative of older workers in the United States (U.S.). With a few exceptions (e.g., Lee et al., 2004), previous work has mostly focused on data from a single employer or industry (e.g. Ferrie et al., 2002) to study

how job insecurity affects health. Results from studies using data from single employers or industries might not generalize to a larger population. Also in contrast with previous work, we focus our study on older workers (50 years and older), for whom worsened or uncertain employment conditions may have a higher toll on their health (Michaud, Crimmins and Hurd, 2016). No prior work has analyzed specifically this subpopulation despite being the focus of considerable policy interest given the potential of longer working lives to alleviate pressures from population aging.

Our work proceeds as follows. In Section 2 we review the relevant literature for this study. In Section 3 we present the data and discuss the empirical strategy. In section 4 we present the estimation methods, discuss the differences between the OLS and IV results and conduct additional robustness checks. We summarize our work in Section 5.

## 2. LITERATURE REVIEW

Several studies in psychology, organizational behavior, and economics have analyzed the adverse effects of job loss and job insecurity on health. Identifying the causal impact of job loss and job insecurity on health is complicated by reverse causality (e.g., workers with lower health status might be more likely to lose their jobs) and by unobserved characteristics that may correlate with job status and health (e.g., anxiety-prone workers might be more likely to report higher levels of job insecurity as well as lower levels of health or psychological well-being). Studies on job loss have circumvented this issue by identifying exogenous sources of variation in job status such as plant closures (e.g., Browning and Heinesen, 2012, Kuhn, Lalive and Zweimüller, 2009, Schmitz, 2011) or mass layoffs (e.g., Sullivan and Von Wachter, 2009). Generally, these studies

have found job loss negatively affected health and increased mortality risk (e.g, Browning and Heinesen, 2012, Sullivan and Von Wachter, 2009).[4] Michaud, Crimmins and Hurd (2016) use the panel dimension of the HRS and matching estimators. They report effects consistent with those reported in earlier studies.

Estimates of causal effects of job insecurity on health are harder to find. A number of studies have examined cross-sectional associations between employment insecurity and health. Cheng et al. (2005), using data from Taiwan, find that perceived job insecurity has detrimental effects on self-rated health, mental health, and vitality. László et al. (2010), in a study pooling data on individuals across 16 European countries, similarly find that job insecurity negatively affects self-rated health. Recognizing the limitations of cross-sectional analysis, most such studies have used longitudinal data (e.g., Burgard, Brand and House, 2009, Ferrie et al., 2002, Hellgren and Sverke, 2003). The general consensus from these studies is that job insecurity adversely affects self-rated health and depressive symptoms (Burgard, Brand and House, 2009) and mental health (Hellgren and Sverke, 2003). Perhaps most relevant to our study, Ferrie et al. (2002), in considering physiological measures in addition to self-rated health, self-reported morbidity, and psychiatric morbidity, find perceived job insecurity negatively affects mental health and leads to a lower body-mass index and higher blood pressure for women.

While longitudinal studies present a significant improvement over cross-sectional studies for ascertaining causality, a potential problem with this identification strategy is that changes in health status can also affect job insecurity. A small number of studies have examined sources of

[4] In contrast, Schmitz (2011) finds no impact of job loss on health.

exogenous variation in job insecurity to identify the causal impact of insecurity on health. Ferrie et al. (1998) using the privatization of some government departments in the United Kingdom as an indicator of job insecurity, and finds it adversely affected health. Caroli and Godard (2014), using a sample of male workers from 22 European countries, find job insecurity, as indicated by the levels of employment protection in each country, to have a significant negative impact on headaches, eyestrain and skin problems.

The work most closely related to our study is Reichert and Tauchmann (2011). They use data from Germany and instrument perceived job insecurity through a measure of employer downsizing and find a negative impact of job insecurity on mental health.[5] Our work is informative for many reasons. First, older workers in Germany are more protected against dismissals, and in the event of job loss, they can receive unemployment benefits for a much larger period than in the US (up to three years). Thus, a priori, there are no reasons to believe that the results would be similar in the U.S. In particular, one may expect them to be even larger. Second, the authors do not focus specifically on older workers. These workers may have worse re-employment prospects following job loss and may have to retire under less advantageous circumstances. Third, our work distinguishes the effect by whether the employer downsizing has affected similar jobs or other types of jobs, since this distinction is important to test for potential downsizing survival selectivity and thus the validity of the instruments. Furthermore, we further

[5] Other studies have also analyzed the effects of downsizing on health either directly or indirectly (e.g., Dekker and Schaufeli, 1995, Hellgren and Sverke, 2003, Hellgren, Sverke and Isaksson, 1999, Kivimäki et al., 2000, Parker, Chmiel and Wall, 1997, Vahtera, Kivimaki and Pentti, 1997). However, most use data from a single employer and focus only on mental health. As noted earlier, we analyze a nationally representative sample of U.S. workers who are 50+ years old and therefore their health might be more susceptible to adverse working conditions.

use as an additional instrument the rate of employment growth at the industry-state level. Hence, we focus specifically in job loss risk outside the control of workers. We find that all instruments deliver similar results, but with varying levels of statistical precision. Finally, both the measures of job insecurity and mental health are different in our study and in Reichert and Tauchmann (2011). We measure job insecurity with a subjective probability of job loss, which is a continuous measure from 0 to 100. Reichert and Tauchmann (2011) use a categorical variable that records whether workers are very, somewhat or not concerned at all about their job security. In our study we use an shortened version of the well-known Center for Epidemiological Studies-Depression Scale (CES-D) as the main outcome, whereas Reichert and Tauchmann (2011) combines information from twelve questions than in addition to psychological well-being, also measures physical problems and vitality. Hence, we are able to look specifically at the risk of being diagnosed with clinical depression in addition to other health outcomes.

## 3. DATA AND EMPIRICAL STRATEGY

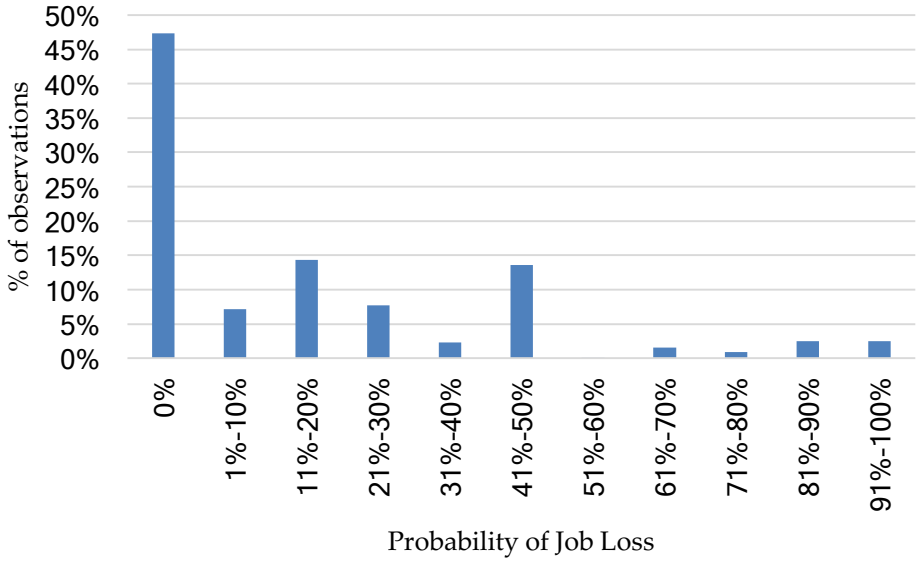
We use data from the Health and Retirement Study (HRS).[6] The HRS is a biennial longitudinal survey of the U.S. population over the age of 50. The HRS collects information on work status, earnings, job characteristics, and health conditions, among other variables. We restrict our analysis to respondents who are working for pay and are not self-employed. We pool data from waves 1996 to 2006 and 2010 to 2012. Wave 2008 is excluded from our analysis because the job insecurity question (discussed below) was not asked in that year. Hence, we measure job insecurity prior and after the great recession. Although it might have been interesting to look at the year in which the great recession occurs, our analysis will exploit specifically regional variation in economic conditions at the industry level. As we will show, plenty of variation is occurring because of long-run changes in the industrial structure of the economy at the state-level. Second, waves prior to 1996 are excluded because they do not have information on employer downsizing status, which we use in our analysis as an instrument for job insecurity. The final sample, after excluding additional observations with missing information in the outcomes variables, includes approximately 9,500 individuals and 28,000 individual-wave observations (the exact number varies with the specific outcome).

We measure job insecurity using workers' responses to the following question in the HRS: *"Sometimes people are permanently laid off from jobs that they want to keep. On the (same) scale from 0 to 100 where 0 equals absolutely no chance and 100 equals absolutely certain, what are the chances that you*

[6] We combine information from the HRS raw files, with information from the RAND HRS Data file (RAND). The RAND HRS Data file is an easy-to-use longitudinal data set based on the HRS raw data. We also use restricted-access HRS data containing state-of-residency information.

*will lose your job during the next year?"* The average response is 16% (see Table A1 in the Appendix). Figure 1 below shows the distribution of the responses, aggregated in bins of 10 percentage points. About 47% of workers responded zero and more than two thirds of workers gave a probability equal or smaller than 20%, which indicates that most older workers feel relatively safe in their jobs (see Figure 1).[7]

**Figure 1: Distribution of the Subjective Probability of Job Loss**



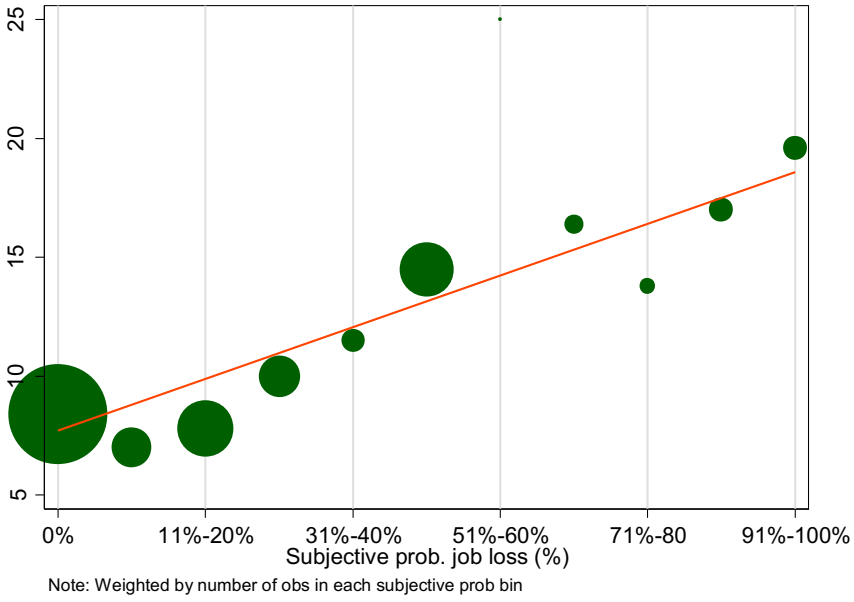

Source: HRS, 1996-2006, and 2010-2012.

Our main outcome to measure mental health is a shortened version of the 20-item Center for Epidemiologic Studies Depression (CES-D) Scale used to identify individuals at risk of clinical depression, available in the HRS. These items record whether a respondent experienced a series of negative or positive sentiments during the *last week*. Negative items measure whether the

[7] There are important bunching of responses at 0%, 10% and 50%, and to a lesser extent around 90%, which is indicative that responses might be rounded around some focal points (Kleinjans and van Soest, 2010, Manski and Molinari, 2010).

respondent experienced all or most of the time the following sentiments: depression, "everything is an effort," sleep is restless, felt alone, felt sad, and "could not get going." Positive items measure whether the respondent all or most of the time felt happy and enjoyed life. A mental-health index can be constructed by adding the affirmative answers to the five negative indicators and the negative answers to the two positive indicators. In addition, we follow the recommendations from the HRS Health Working Group (Steffick and others, 2000) and flagged individuals scoring 4 or higher on this shortened 8-items index, as these are individuals who have symptoms of potential clinical depression (similar to scoring 16+ on the full CESD index). About 10% of our sample are above this threshold (Table A1 in the Appendix). A cross-tabulation indicates a positive correlation between the subjective probability of job loss and the probability of scoring above 4 or higher in the shortened CESD index indicates, as shown in Figure 2.

**Figure 2: Subjective Probability of Job Loss and Probability of scoring 4 or higher in the CESD Index**



Besides the CESD index, we also look at other health outcomes. First, we examine the effect of job insecurity on self-reported health. HRS asks respondents to rate their health on a five-point scale (1=Excellent, 2=Very Good, 3=Good, 4=Fair, 5=Poor). We construct a subjective indicator, equal to one if the respondents report his or her health as fair or poor, and equal to zero otherwise. Second, we examine the effect of job insecurity on the level of stress at work. HRS ask individuals about their agreement with the statement *"My job involves a lot of stress."*, and we construct a variable of high level of stress if that takes the value of 1 if the person agrees or strongly agrees, and takes the value of 0 if the person disagrees, strongly disagrees or it doesn't apply. Finally, we investigate if job insecurity is related to higher rates of regularly use of prescription to alleviate anxiety or depression and to help sleep. Information on regularly use of prescription drugs for specific health problems is only available since 2006.

To examine the effects of job insecurity on older workers' health, we estimate the ordinary least-squares (OLS) specification in equation (1). We estimate separate models, one for each outcome of interest. We denote the outcome of interest for individual in $i$, in year $t$, living in state $s$, and employed in industry $k$, as $Y_{itsk}$. The independent variable $p_{it}$ is our measure of job insecurity, i.e. the subjective probability of job loss in the next year. The main coefficient of interest is $\beta_p$. In the analysis, we also control for several worker and employer characteristics in vector $\boldsymbol{X}_{it}$. They include age, gender, marital status, race, Hispanic ethnicity, education level, whether the person works full or part time, tenure in the job, whether the employer provides health insurance and pension plans, employer size, and type of occupation (white, blue or pink collar). We also control for the unemployment rate in the state they reside in, $UR_{st}$. Finally, we include fixed effects for year ($\phi_t$), state of residency ($\phi_s$), and industry of employment ($\phi_k$). Standard

errors are clustered at the individual level. In robustness analysis, we also estimate the same models with individual level fixed effects.

$$Y_{itsk} = \alpha + \beta_p p_{it} + \beta_X \boldsymbol{X}_{it} + \beta_{UR} UR_{st} + \phi_t + \phi_s + \phi_k + \epsilon_{itsk} \quad (1)$$

*Instrumental variables estimation*

The estimation of $\beta_p$ might be biased because of omitted variables that affect the subjective probability of job loss and mental health (or some of the other related health outcomes studied here). For example, workers with some limiting disability might have both higher levels of perceived job insecurity and also be more likely to be depressed. Another threat to the validity of the estimates of $\beta_p$ is reverse causality. Mental health problems can lead to poor work performance and, thus, to higher levels of job insecurity.

We use instrumental variables to address these potential sources of bias in the estimation of $\beta_p$. We use two sources of variation, that are not determined by workers' unobserved characteristics as instrumental variables. The first type of instrumental variables is whether the workers' employers have downsized since the last interview or since they started working if they were hired between waves. The question is worded as follows in the HRS: *"Has your employer experienced a permanent reduction in employment since [last interview month and year/ month and year respondent started job/ 2 years ago]?"*, with interviewers coding references to downsizing and permanent layoffs as "yes" and those to temporary layoffs as "no". On average 23% of workers in our sample report their employer have downsized (Table A1 in the Appendix). This number is consistent with the available information from studies that use firms' administrative employment

records. Table A2 in the Appendix shows that, at least in the late 1990s and early 2000s, the fraction of firms that destroyed employment but did not close (i.e. downsizing firms) was around 25%.[8] Furthermore, if a worker reports a downsizing, HRS follows up with the following question *"Has this downsizing affected workers whose jobs are similar to yours?"*. About 62% of workers who report a downsizing, also report it has affected workers in similar jobs.

Downsizing is expected to increase expectations of job loss for reasons that are exogenous to the workers (Gutierrez, 2016). Therefore, using the two downsizing-related questions in the HRS, we generate two dummy variables that we use as instrumental variables for the subjective probability of job loss: i) whether there was a downsizing that affected workers in similar jobs (14.2% of all observations); and ii) whether there was a downsizing but it did not affect workers in similar jobs (8.9% of all observations). Each of these two variables has its advantages and disadvantages. On one hand, the former instrumental variable, downsizing that affected similar jobs, should deliver more precise estimates since the complier population (those who increase their job loss expectations following a change in the instrument) is expected to be larger. In other words, workers' subjective probability of job loss is more likely to have been affected by downsizings that have permanently cut similar jobs than by downsizings that have affected other types of jobs (we come back to this issue later). On the other hand, this variable might not be independent of worker unobserved characteristics, as workers who report their employer have cut similar jobs might be selected on unobserved characteristics. Put differently, the "downsizing survivors" can be different than the workers who were let go by the employer. To bias our

[8] A better benchmark would be the share of employment in downsizing employers, but this figure is not readily available from the literature.

estimates, "downsizing survivors" should be different regarding their mental health (or regarding factors that affect their mental health) than workers that left.[9] The second instrumental variable, downsizing that has not affected similar jobs, is likely to deliver more imprecise estimates because, as discussed above, the complier population is expected to be smaller. However, on the other hand, there are less concerns about survival selection when job cuts have affected other types of jobs.

Given that we have two potential instruments and one endogenous regressor, we use Sargan (1958) overidentifying restrictions test to examine the validity of the instruments. Implicitly, this yields an indirect test of selection. In all cases, we cannot reject the null hypothesis that the instruments are valid and uncorrelated with the residuals (see Table A3 in the Appendix). As an additional check, we test directly for selectivity at downsizing employers by investigating if workers with potential mental health problems leave their jobs at different rate when employers are downsizing than when they are not. We present this analysis in Appendix B. Our findings indicate that workers are more likely to separate from downsizing employers, especially if employers have cut similar jobs in the past. We also find that, although workers with potential depression (i.e. scoring high on the CESD index) leave their jobs at a higher rate, this rate is not statistically different in downsizing and non-downsizing employers. Taken together, the overidentifying restriction test and the test of selectivity at downsizing employers indicate that

[9] For example, one may think management who want to reduce their workforce are more likely to fire less healthy workers (because they are less productive) and retain the healthier ones. Similarly, less healthy workers might be less likely to manage the increased levels of uncertainty associated with downsizing and thus more likely to quit. Conversely, one may think that healthier workers are likely to leave firms that are downsizing because they are more attractive to other employers.

there is not significant selection of workers (at least in aspects related to mental health) in downsizing employers, even in cases where similar jobs has been cut.

In addition to information about downsizing, we use the employment growth rate in the industry of employment in the state of residency as a second type of instrumental variable for the subjective probability of job loss. We construct the growth rates using yearly averages in quarterly employment statistics from the Quarterly Census of Employment and Wages (QCEW). The employment growth rate for industry $k$ in state $s$ in year $t$, $g_{t,s,k}$, is calculated as shown in equation (2) below, where $E_{t,s,k}$ measures the total employment in levels.

$$g_{t,s,k} = \frac{E_{t,s,k} - E_{t-1,s,k}}{(E_{t,s,k} + E_{t-1,s,k})/2} \quad (2)$$

We expect that workers employed in industries that are growing (in their state of residency) feel on average less insecure in their jobs. The implicit assumption is that performance of other firms (as proxied by net employment growth) is informative about the financial health of one's own firm. Note that in our empirical specification in equation (1) we control for industry, state and year fixed effects. So, the effect of the employment growth rate is net of the main effects for state, industry and year. Note that we also control for the yearly unemployment rate in the state. Thus, the identification is not coming from recessions or weak labor markets (at the state - level), but from differential performances across industries within a state (in terms of employment growth). Adding $g_{t,s,k}$ allows testing for the validity of the downsizing-based instruments. For all outcomes, we cannot reject the null hypothesis that instruments are valid and uncorrelated with the residuals (see Table A3 in the Appendix). We discuss further robustness specifications in Section 4, which in particular adds individual fixed effects to the specifications.

Before presenting our main findings, we show in Table 1 below shows the sample first stage regression, for the outcome of scoring high in the CESD index, our main outcome of interest. The results are similar in the first stage regressions for the other outcomes. Table 1 shows the first stage using each instrumental variable separately, and all three of them together. As expected, workers in downsizing employers have higher expectations of job loss, especially if employers have cut similar jobs. Using the results from the last column in Table 1, we find that workers whose employers have downsized similar jobs have subjective probability of job loss than are on average 11 percentage points higher than for workers whose employers have not downsized. This is a substantial effect considering that the mean value of the subjective probability of job loss in the sample is 15.8%. Workers whose employers have downsized by cutting other types of jobs still have higher job loss expectations on average than workers whose employers have not downsized, but only half as large (5.1 percentage points) as those for workers whose employers have cut similar jobs. Also, as expected, we find that workers employed in industries that are growing in a given state feel less job insecure, although the effects are relatively small in magnitude. For example, an increase of one standard deviation in the employment growth rate at the industry-state level (about 3.1 percentage points, see Table A1 in the Appendix) leads to a decrease in the subjective probability of job loss of only 0.39 percentage points.[10] Table 1 also shows that the instruments related to employer downsizing are strong, with F-statistics that are well above the standard critical value of 10. The instrument related to employment growth is a

[10] This number is obtain using the following calculation= -0.126*0.031*100=0.39

little short of the critical value. However, when we use all instruments together, the joint F-statistic is also well above the critical value.

**Table 1: First Stage Results**

| | Outcome: Subjective probability of job loss | | | |
|---|---|---|---|---|
| | **IV: Downsizing affected similar jobs** | **IV: Downsizing did not affect similar jobs** | **IV: Employment growth at industry-state level** | **IV: All instruments** |
| Downsizing similar jobs | 0.103*** | | | 0.110*** |
| | (0.005) | | | (0.005) |
| Downsizing not similar jobs | | 0.050*** | | 0.051*** |
| | | (0.006) | | (0.006) |
| Employment growth at industry-state level | | | -0.176*** | -0.126** |
| | | | (0.059) | (0.058) |
| Observations | 28,064 | 24,068 | 28,064 | 28,064 |
| F-stat | 400.6 | 80.9 | 9.0 | 161.3 |

Data: HRS, pooled 1992-2012 (data from 2008 missing)
Notes: Other controls included in each regression are age, gender, marital status, race, Hispanic ethnicity, education level, whether the person works full or part time, tenure in the job, whether the employer provides health insurance and pension plans, employer size, type of occupation (white, blue or pink collar), industry dummies, state dummies, wave dummies and the unemployment rate at the state level. Standard errors are clustered at the individual level. *** denotes p-value<0.01; ** denotes p-value<0.05; * denotes p-value<0.1.

## 4. EFFECTS OF JOB INSECURITY ON MENTAL HEALTH AND RELATED OUTCOMES

Table 2 shows the OLS and IV estimation results for the outcomes of interest. We find that higher expectations of job loss are associated with worsened health outcomes. Interestingly, we

also find that the IV results are much larger than the OLS results. We discuss further this issue below.

Regarding the CESD scale, we find that a 25-percentage-points increase in the subjective probability of job loss (about one standard deviation, see Table A1 in the appendix) results in an increase of 0.14 in the CESD index using the OLS estimate, and in an increase of 0.59 using the IV estimate; it also results in an increase of 2 percentage points or 9 percentage points in the probability of scoring high in the CESD index, using the OLS and IV estimates, respectively. These effects sizes are substantial, given that the mean value of the CESD index in the sample is 1.086, and the overall prevalence of high scores is 9.5%. Thus, job insecurity appears to be an important determinant of mental health, as measured by the CESD scale. Table A3 in the Appendix shows the job insecurity affects each of the components of the CESD index and, as in Table 2, the IV estimates are much larger than the OLS estimates.

**Table 2: Effect of Job Insecurity on Mental Health and other Related Outcomes**

| Outcomes | Mean Value | OLS | IV | # Observations |
|---|---|---|---|---|
| **Depression Scale** | | | | |
| CESD Raw Score | 1.09 | 0.562*** | 2.352*** | 28,064 |
| | | (0.049) | (0.320) | |
| CESD High Score (>= 4) | 0.10 | 0.088*** | 0.352*** | 28,064 |
| | | (0.009) | (0.056) | |
| **Other outcomes** | | | | |
| Fair or poor health | 0.13 | 0.071*** | 0.286*** | 28,155 |
| | | (0.010) | (0.061) | |
| High level of stress | 0.56 | 0.107*** | 0.777*** | 28,124 |
| | | (0.013) | (0.087) | |
| Takes drugs for sleeping | 0.07 | 0.018 | 0.024 | 6,285 |
| | | (0.016) | (0.106) | |
| Takes drugs for depression | 0.12 | 0.002 | -0.113 | 6,285 |
| | | (0.020) | (0.131) | |

Data: HRS, pooled 1992-2012 (data from 2008 missing)

Notes: Each cell reports the coefficient of the subjective probability of job loss (measured from 0 to 1) estimated in a separate regression. The instruments in the IV regression includes whether the employer downsized (and whether it affected jobs similar to the respondent) and the employment growth in the individuals' industry in their state of residency. Other controls included in each regression are age, gender, marital status, race, Hispanic ethnicity, education level, whether the person works full or part time, tenure in the job, whether the employer provides health insurance and pension plans, employer size, type of occupation (white, blue or pink collar), industry dummies, state dummies, wave dummies and the unemployment rate at the state level. The outcome high level of stress takes the value of 1 if the person agrees or strongly agrees that his/her current job involves lots of stress, and takes the value of 0 if the person disagrees, strongly disagrees or it doesn't apply. Standard errors are clustered at the individual level. *** denotes p-value<0.01; ** denotes p-value<0.05; * denotes p-value<0.1.

Regarding other outcomes, we find that a 25-percentage points increase in the subjective probability of job loss increases in the probability that workers report rate their health as fair or poor in 2 percentage points in the OLS estimation and in 7 percentage points in the IV estimation. These effects are also important in size given that the overall prevalence of self-reported poor or fair health in the sample is 13%. We also find that increased job insecurity can cause higher levels of stress at work. A 25-percentage points increase in probability of job loss leads to an increase of 3 percentage points (OLS) or 19 percentage points (IV) in the probability of reporting high levels of stress at work. We do not find a statistically significant effect of job insecurity on the probability of taking prescription drugs for sleeping or depression.

*Discussion of IV Results*

The IV estimates in Table 2 are larger than the OLS estimates by an order on magnitude. One potential explanation is that job loss expectations might have a stronger effect on mental health if they are based on reasons that are outside the control of the worker. Because workers cannot manipulate job loss risk when it is outside their control, it would be expected that job loss expectations based on factors outside of the workers' control have a higher correlation with the

actual probability of job loss, and thus are more likely to negatively affect workers' stress and mental wellness. This explanation can help to understand the difference in the size of the effects between the OLS and IV estimates, since the complier population in the IV estimation is composed of workers whose job loss expectations were increased because of external reasons, namely that their employers are downsizing (or recently downsized) or that their industries are underperforming in their state of residency. Hence the local average effect identified by the IV estimates could be larger than the average treatment effect of job loss risk.

One can also rationalize the difference in effect sizes between the OLS and the IV estimates in terms of measurement error. For example, workers might report a relatively high level of expected job loss probability, when there is no reason to fear a potential job loss. For example, this could happen if the person wants to be conservative in responding the subjective probability question, or he or she doesn't understand well the concept of probabilities. In any case, if the worker is not truly worried about job loss, higher reported levels of job insecurity should not correlate with worsened mental health.

Both explanations suggest that the predictive power of job insecurity in terms of job separations should be also different in the OLS and IV frameworks, with a higher predictive power in the latter case. To test this, we estimate a model like equation (1) but the left-hand side dependent variable equals 1 if the workers are separated from his current employer by the next wave, and it equals 0 if the worker is still at the same employer in the next wave. About 29% of workers in the sample are separated from their employers by the next wave (in many cases because of retirement, see Table A1). Table 3 shows the OLS and IV estimates of the coefficient

on the subjective probability of job loss. The difference in the estimates are substantial. We find that a 25-percentage points increase in the subjective probability of job loss translates into an increase in the probability of separating from the employer (by the next wave) of 4 percentage points in the OLS model and of 13 percentage points in the IV model. In other words, the subjective probability of job loss has a higher correlation with the actual probability of job separation in the IV model. Thus, it is perhaps not surprising IV results in higher negative effects on mental health and stress levels.

We regard the IV as our preferred estimates, since we are interested in evaluating the effects of changes in job insecurity for reasons that are not under the control of the worker, for example, situations of economic distress for employers. We are less interested in the effect of job insecurity for reasons that are under control or even endogenous to the worker (like shirking at work).

**Table 3: Subjective probability of job loss separation rate from employer**

| | Outcome: Separation from employer by next wave | | |
|---|---|---|---|
| | **OLS** | **IV** | **# Observations** |
| Subjective probability of job loss (from 0 to 1) | 0.165*** | 0.528*** | 24,356 |
| | (0.013) | (0.078) | |

Data: HRS, pooled 1992-2012 (data from 2008 missing)
Notes: Each cell reports the coefficient of the subjective probability of job loss (measured from 0 to 1) estimated in a separate regression. The instruments in the IV regression includes whether the employer downsized (and whether it affected jobs similar to the respondent) and the employment growth in the individuals' industry in their state of residency. Other controls included in each regression are age, gender, marital status, race, Hispanic ethnicity, education level, whether the person works full or part time, tenure in the job, whether the employer provides health insurance and pension plans, employer size, type of occupation (white, blue or pink collar), industry dummies, state dummies, wave dummies and the unemployment rate at the state level. Standard errors are clustered at the individual level. *** denotes p-value<0.01; ** denotes p-value<0.05; * denotes p-value<0.1.

*Robustness checks*

We tested the robustness of our findings to different specifications. Table 4 reproduces the OLS and IV findings from Table 2 and compares them with other alternative models. First, we present estimation results where we used each instrumental variable separately. We find that in all cases the IV results are much larger than the OLS estimates. Also, we find that the IV estimates are similar in size in most cases (except for the drug taking outcomes, which are all non-significant). This is not surprising, given that all the IV estimations in Table 2 passed the overidentification test, as described earlier.

However, Table 4 also shows that the IV estimates when we use as instruments whether the employer downsized jobs that are different to the workers' and the employment growth in

the same industry and state, have larger standard errors are not statistically significant. The reason for the more imprecise estimates is most likely that the complier population in these two cases are smaller. This should be expected since an employer cutting similar jobs should have a larger effect in increasing workers job insecurity than an employer cutting other types of jobs; and an employer cutting jobs should have a large effect on job insecurity than an industry-average employment trend. Figure A1 in the Appendix presents this argument graphically, by showing the size of the complier population. At each level of the subjective probability of job loss, the size of the complier population is the fraction of workers for whom the instrument raised their subjective probability of job loss from that level or below to a higher level. We can see that at each level of subjective probability of job loss the size of the complier population for downsizings that affected similar jobs is between 2 and 4 four times the size of the complier population for downsizings that did not affected similar jobs. We also observe that the size of the complier population that responds to one-standard-deviation increase in the employment growth is relatively small, which explains why this instrument provides the largest standard errors in the estimates.

We also ran an IV model with individual fixed effects to control for unobserved fixed heterogeneity. This is a good test for omitted variables at the individual level. Table 4 presents the estimation results. The estimated effects are still much larger than in the OLS case, albeit a bit smaller than in the IV model without individual fixed effects. In any case, our findings still indicate that job insecurity can have a large effect in workers' mental health.

## 5. CONCLUSIONS

In this paper, we focus on the effect of job insecurity on mental health. In order to address endogeneity problems, we use an IV strategy which exploits plausibly exogenous changes in job loss expectations following downsizing, in jobs similar and other jobs, as well as changes in industry-state level economic conditions. We make use of the longitudinal measures of health and job loss expectations in the Health and Retirement Study as well as geo-coded information on the state of residence. The instruments are largely predictive and appear valid overall using standard over-identifying test statistics. We find evidence of large effects on mental health, as measured by the CESD scores, as well as general self-reported health. We do not find evidence that job insecurity affects drug consumption for depression and sleeping which may indicate that depression symptoms are undiagnosed. The IV estimates are much larger than OLS estimates. A convincing explanation is that the instruments uncover a local average treatment effect which is much higher than the average treatment effect because induced job insecurity is outside the control of workers and much more predictive of future job loss than residual individual variation. We do not find that those who experience downsizing in similar jobs and those experiencing other downsizing, who subsequently lose their jobs are different in terms of mental health. This may be interpreted as evidence that our larger effects with IV are not the result of differential survival of those in better mental health in firms which downsize.

Although a large literature has looked at the effects of job loss on health, few studies have investigated the causal effect of job insecurity on health, in particular on older workers who may have lower re-employment prospects. Given that this population is arguably much larger, our findings that there are substantial effects of job insecurity on health, should be cause for concern. One can see job insecurity as a health spillover from economic conditions, outside the control of

workers. In that sense, if health effects result in productivity losses, higher absenteeism and higher health care costs, job insecurity can have negative economic consequences. This has implications for firms, who should worry about the mental health of workers in periods of downsizing, periods which are crucial for the recovery of firms in financial difficulties and which may depend particularly on the productivity of its workers. More generally, it may imply that economies which higher levels of job insecurity may have worse health, holding other factors constant.

## Table 4: Alternative Specifications

| Outcomes | OLS | IV: Downsizing affected similar jobs | IV: Downsizing did not affect similar jobs | IV: Employment growth at industry-state level | IV: All instruments | IV: All instruments + individual FE | # Observations |
|---|---|---|---|---|---|---|---|
| **Depression Scale** | | | | | | | |
| Raw Score | 0.562*** | 2.401*** | 1.735** | 3.453 | 2.352*** | 1.296*** | 28,064 |
| | (0.049) | (0.348) | (0.719) | (2.614) | (0.320) | (0.422) | |
| High Score (>= 4) | 0.088*** | 0.366*** | 0.225* | 0.345 | 0.352*** | 0.266*** | 28,064 |
| | (0.009) | (0.061) | (0.127) | (0.421) | (0.056) | (0.084) | |
| **Other outcomes** | | | | | | | |
| Fair or poor health | 0.071*** | 0.289*** | 0.233 | 0.668 | 0.286*** | 0.147* | 28,155 |
| | (0.010) | (0.065) | (0.152) | (0.571) | (0.061) | (0.087) | |
| High level of stress | 0.107*** | 0.783*** | 0.729*** | 0.574 | 0.777*** | 0.678*** | 28,124 |
| | (0.013) | (0.093) | (0.226) | (0.653) | (0.087) | (0.130) | |
| Takes drugs for sleeping | 0.018 | 0.029 | -0.135 | 0.040 | 0.024 | 0.044 | 6,285 |
| | (0.016) | (0.115) | (0.391) | (0.341) | (0.106) | (0.166) | |
| Takes drugs for depression | 0.002 | -0.102 | -0.140 | -0.314 | -0.113 | -0.058 | 6,285 |
| | (0.020) | (0.139) | (0.523) | (0.461) | (0.131) | (0.169) | |

Data: HRS, pooled 1992-2012 (data from 2008 missing)

Notes: Each cell reports the coefficient of the subjective probability of job loss (measured from 0 to 1) estimated in a separate regression. Other controls included in each regression are age, gender, marital status, race, Hispanic ethnicity, education level, whether the person works full or part time, tenure in the job, whether the employer provides health insurance and pension plans, employer size, type of occupation (white, blue or pink collar), industry dummies, state dummies, wave dummies and the unemployment rate at the state level. The outcome high level of stress takes the value of 1 if the person agrees or strongly agrees that his/her current job involves lots of stress, and takes the value of 0 if the person disagrees, strongly disagrees or it doesn't apply. Standard errors are clustered at the individual level. *** denotes p-value<0.01; ** denotes p-value<0.05; * denotes p-value<0.1.

References


Bose, Lakshmi and Philip Bohle. 2002. "Health and Social Effects of Downsizing: A Review." *The Economic and Labour Relations Review*, 13(2), 270-87.

Browning, Martin and Eskil Heinesen. 2012. "Effect of Job Loss Due to Plant Closure on Mortality and Hospitalization." *Journal of Health Economics*, 31(4), 599-616.

Burgard, Sarah A; Jennie E Brand and James S House. 2009. "Perceived Job Insecurity and Worker Health in the United States." *Social Science & Medicine*, 69(5), 777-85.

____. 2007. "Toward a Better Estimation of the Effect of Job Loss on Health." *Journal of Health and Social Behavior*, 48(4), 369-84.

Caroli, Eve and Mathilde Godard. 2014. "Does Job Insecurity Deteriorate Health? A Causal Approach for Europe," IZA,

Cheng, Yawen; Chun-Wan Chen; Chiou-Jong Chen and Tung-Liang Chiang. 2005. "Job Insecurity and Its Association with Health among Employees in the Taiwanese General Population." *Social science & medicine*, 61(1), 41-52.

Clayton, Richard L. and James R. Spletzer**.** 2009. "Business Employment Dynamics," *Producer Dynamics: New Evidence from Micro Data.* University of Chicago Press, 125-47.

Dekker, Sidney WA and Wilmar B Schaufeli. 1995. "The Effects of Job Insecurity on Psychological Health and Withdrawal: A Longitudinal Study." *Australian psychologist*, 30(1), 57-63.

Eliason, Marcus and Donald Storrie. 2009. "Does Job Loss Shorten Life?" *Journal of Human Resources*, 44(2), 277-302.

Ferrie, Jane E; Martin J Shipley; Michael G Marmot; Stephen Stansfeld and George Davey Smith. 1998. "The Health Effects of Major Organisational Change and Job Insecurity." *Social science & medicine*, 46(2), 243-54.

Ferrie, Jane Elizabeth; Martin John Shipley; Stephen Alfred Stansfeld and Michael Gideon Marmot. 2002. "Effects of Chronic Job Insecurity and Change in Job Security on Self Reported Health, Minor Psychiatric Morbidity, Physiological Measures, and Health Related Behaviours in British Civil Servants: The Whitehall Ii Study." *Journal of epidemiology and community health*, 56(6), 450-54.

Gallo, William T; Elizabeth H Bradley; Michele Siegel and Stanislav V Kasl. 2000. "Health Effects of Involuntary Job Loss among Older Workers Findings from the Health and Retirement Survey." *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 55(3), S131-S40.

Gallo, William T.; Elizabeth H. Bradley; Tracy A. Falba; Joel A. Dubin; Laura D. Cramer; Sidney T. Bogardus and Stanislav V. Kasl. 2004. "Involuntary Job Loss as a Risk Factor for Subsequent Myocardial Infarction and Stroke: Findings from the Health and Retirement Survey." *American journal of industrial medicine*, 45(5), 408-16.

Gallo, William T.; Hsun-Mei Teng; Tracy A. Falba; Stanislav V. Kasl; Harlan M. Krumholz and Elizabeth H. Bradley. 2006. "The Impact of Late Career Job Loss on Myocardial Infarction and Stroke: A 10 Year Follow up Using the Health and Retirement Survey." *Occupational and environmental medicine*, 63(10), 683-87.

Gutierrez, Italo A. 2016. "Job Insecurity, Unemployment Insurance and on-the-Job Search. Evidence from Older American Workers." *Labour Economics*, 41(Supplement C), 228-45.

Hellgren, Johnny and Magnus Sverke. 2003. "Does Job Insecurity Lead to Impaired Well-Being or Vice Versa? Estimation of Cross-Lagged Effects Using Latent Variable Modelling." *Journal of Organizational Behavior*, 24(2), 215-36.

Hellgren, Johnny; Magnus Sverke and Kerstin Isaksson. 1999. "A Two-Dimensional Approach to Job Insecurity: Consequences for Employee Attitudes and Well-Being." *European Journal of Work and Organizational Psychology*, 8(2), 179-95.

Kivimäki, Mika; Jussi Vahtera; Jaana Pentti and Jane E Ferrie. 2000. "Factors Underlying the Effect of Organisational Downsizing on Health of Employees: Longitudinal Cohort Study." *Bmj*, 320(7240), 971-75.

Kleinjans, Kristin J. and Arthur van Soest. 2010. "Nonresponse and Focal Point Answers to Subjective Probability Questions." *IZA Discussion Paper No. 5272*.

Kuhn, Andreas; Rafael Lalive and Josef Zweimüller. 2009. "The Public Health Costs of Job Loss." *Journal of Health Economics*, 28(6), 1099-115.

László, Krisztina D; Hynek Pikhart; Mária S Kopp; Martin Bobak; Andrzej Pajak; Sofia Malyutina; Gyöngyvér Salavecz and Michael Marmot. 2010. "Job Insecurity and Health: A Study of 16 European Countries." *Social science & medicine*, 70(6), 867-74.

Lee, Sunmin; Graham A Colditz; Lisa F Berkman and Ichiro Kawachi. 2004. "Prospective Study of Job Insecurity and Coronary Heart Disease in Us Women." *Annals of epidemiology*, 14(1), 24-30.

Manski, Charles F. and Francesca Molinari. 2010. "Rounding Probabilistic Expectations in Surveys." *Journal of Business and Economics Statistics*, 28, 219-31.

Michaud, Pierre-Carl; Eileen M. Crimmins and Michael D. Hurd. 2016. "The Effect of Job Loss on Health: Evidence from Biomarkers." *Labour Economics*, 41, 194-203.

Parker, Sharon K; Nik Chmiel and Toby D Wall. 1997. "Work Characteristics and Employee Well-Being within a Context of Strategic Downsizing." *Journal of occupational health psychology*, 2(4), 289.

Pinkston, Joshua C. and James R. Spletzer. 2004. "Annual Measures of Gross Job Gains and Gross Job Losses." *Monthly Lab. Rev.*, 127, 3-3.

____. 2002. "Annual Measures of Job Creation and Job Destruction Created from Quarterly Es-202 Microdata." *Bureau of Labor Statistics, Washington*.

Pivetz, Timothy R.; Michael A. Searson and James R. Spletzer. 2001. "Measuring Job and Establishment Flows with Bls Longitudinal Microdata." *Monthly Lab. Rev.*, 124, 13-13.

RAND. "Rand Hrs Data, Version O. Produced by the Rand Center for the Study of Aging, with Funding from the National Institute on Aging and the Social Security Administration. Santa Monica, Ca (October 2015)."

Reichert, Arndt and Harald Tauchmann. 2011. *The Causal Impact of Fear of Unemployment on Psychological Health*. Ruhr Economic Papers.

Sargan, John D. 1958. "The Estimation of Economic Relationships Using Instrumental Variables." *Econometrica: Journal of the Econometric Society*, 393-415.

Schmitz, Hendrik. 2011. "Why Are the Unemployed in Worse Health? The Causal Effect of Unemployment on Health." *Labour Economics*, 18(1), 71-78.

Spletzer, James R. 2000. "The Contribution of Establishment Births and Deaths to Employment Growth." *Journal of Business & Economic Statistics*, 18(1), 113-26.

Steffick, Diane E. and others. 2000. "Documentation of Affective Functioning Measures in the Health and Retirement Study." *Ann Arbor, MI: HRS Health Working Group*.

Sullivan, Daniel and Till Von Wachter. 2009. "Job Displacement and Mortality: An Analysis Using Administrative Data." *The Quarterly Journal of Economics*, 124(3), 1265-306.

Vahtera, Jussi; Mika Kivimaki and Jaana Pentti. 1997. "Effect of Organisational Downsizing on Health of Employees." *The Lancet*, 350(9085), 1124-28.

## APPENDIX A: ADDITIONAL TABLES AND FIGURES

**Table A1: Sample Statistics of outcome and control variables**

| Variables | Mean | Std. Dev. |
|---|---|---|
| Subjective probability of job loss | 0.16 | 0.25 |
| Employer downsized jobs | 0.23 | 0.42 |
| Employer downsized similar jobs | 0.14 | 0.35 |
| Employer downsized different jobs | 0.09 | 0.28 |
| State Unemployment Rate | 5.30 | 1.76 |
| Employment growth at state-industry level | 0.01 | 0.03 |
| Separated from employer by next wave | 0.29 | 0.45 |
| Depression Scale | | |
| Felt depressed | 0.11 | 0.31 |
| Everything was an effort | 0.17 | 0.38 |
| Sleep was restless | 0.25 | 0.44 |
| Felt happy | 0.89 | 0.31 |
| Felt Lonely | 0.11 | 0.31 |
| Felt Sad | 0.15 | 0.35 |
| Could not get going | 0.13 | 0.34 |
| Enjoyed life | 0.94 | 0.23 |
| CESD Raw Score | 1.09 | 1.65 |
| CESD High Score (>= 4) | 0.10 | 0.29 |
| Poor or fair health | 0.13 | 0.34 |
| High level of stress | 0.56 | 0.50 |
| Takes drugs for sleeping | 0.07 | 0.26 |
| Takes drugs for depression | 0.12 | 0.32 |

Data: HRS, pooled 1992-2012 (data from 2008 missing)

Notes: The outcome high level of stress takes the value of 1 if the person agrees or strongly agrees that his/her current job involves lots of stress, and takes the value of 0 if the person disagrees, strongly disagrees or it doesn't apply.

**Table A1: Sample Statistics of outcome and control variables (continued)**

| Variables | Mean | Std. Dev. |
|---|---|---|
| Age | 59.91 | 6.27 |
| Female | 0.57 | 0.50 |
| Married | 0.70 | 0.46 |
| Black | 0.14 | 0.35 |
| Hispanic | 0.07 | 0.26 |
| Tenure | 13.00 | 11.25 |
| Education | | |
| Less than high school | 0.13 | 0.34 |
| High school | 0.60 | 0.49 |
| College or more | 0.26 | 0.44 |
| Employment status | | |
| Works FT | 0.71 | 0.45 |
| Works PT | 0.13 | 0.33 |
| Partly Retired | 0.16 | 0.37 |
| Occupation | | |
| White collar | 0.53 | 0.50 |
| Pink collar | 0.24 | 0.43 |
| Blue collar | 0.22 | 0.41 |
| Armed Forces | 0.00 | 0.02 |

Data: HRS, pooled 1992-2012 (data from 2008 missing)

**Table A1: Sample Statistics of outcome and control variables (continued)**

| Variables | Mean | Std. Dev. |
|---|---|---|
| Employer size | | |
| Missing | 0.14 | 0.35 |
| < 5 workers | 0.10 | 0.30 |
| 5-14 workers | 0.15 | 0.36 |
| 15-24 workers | 0.07 | 0.26 |
| 25-99 workers | 0.21 | 0.41 |
| 100-499 workers | 0.19 | 0.40 |
| 500+ workers | 0.13 | 0.34 |
| Fringe Benefits | | |
| Employer-provided health Insurance | 0.67 | 0.47 |
| Employer provided pensions | 0.61 | 0.49 |
| Industry | | |
| Agric/forest/fish | 0.01 | 0.12 |
| Mining and construction | 0.04 | 0.19 |
| Manufacturing | 0.15 | 0.36 |
| Transportation | 0.06 | 0.25 |
| Wholesale | 0.04 | 0.20 |
| Retail | 0.11 | 0.32 |
| Finance/insurance /real estate | 0.06 | 0.25 |
| Business, repair and personal services | 0.09 | 0.28 |
| Entertainment /recreation | 0.02 | 0.14 |
| Professional and related services | 0.35 | 0.48 |
| Public administration | 0.06 | 0.24 |

Data: HRS, pooled 1992-2012 (data from 2008 missing)

**Table A2: Employer downsizing incidence**

| Study | Geographic coverage | Frequency & period | % Firms that destroyed jobs in each quarter/year | | % Firms that gained jobs in each quarter/year | |
|---|---|---|---|---|---|---|
| | | | Continuing firms | Closures | Expanding firms | Openings |
| (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Spletzer (2000) | West Virginia | Quarterly: 1990Q4-1994Q2 | 24.0 | 3.2 | 24.7 | 3.5 |
| | | Annual: 1990Q4-1994Q2 | 25.7 | 10.7 | 27.9 | 12.2 |
| | | Biennial: 1990Q4-1994Q2 | 24.9 | 18.1 | 28.2 | 21.0 |
| | | Triennial: 1990Q4-1994Q2 | 23.6 | 24.5 | 27.0 | 27.9 |
| Pivetz, Searson and Spletzer (2001) | US | Quarterly: 1999Q4 | 22.8 | 5.0 | 24.9 | 6.1 |
| Pinkston and Spletzer (2002) | California | Annual: March 1999-March 2000 | 25.4 | 13.0 | 30.1 | 15.0 |
| Pinkston and Spletzer (2004) | US | Quarterly: 1998Q1-2001Q4 | 23.7 | 5.3 | 24.1 | 5.6 |
| | | Annual: 1998-2002 | 26.3 | 12.0 | 28.1 | 13.0 |
| Clayton and Spletzer (2009) | US | Quarterly: 2005Q1 | 21.8 | 5.0 | 21.8 | 5.0 |

*Source: Cited articles*

**Table A3: Tests of Overidentifying Restrictions**

| Outcomes | Sargan F-Statistic | P-value |
|---|---|---|
| **Depression Scale** | | |
| CESD Raw Score | 0.56 | 0.76 |
| CESD High Score (>= 4) | 0.54 | 0.77 |
| | | |
| **Other outcomes** | | |
| Fair or poor health | 0.80 | 0.67 |
| High level of stress | 0.10 | 0.95 |
| Takes drugs for sleeping | 0.06 | 0.97 |
| Takes drugs for depression | 0.18 | 0.92 |

Data: HRS, pooled 1992-2012 (data from 2008 missing)

Notes: The instruments in the IV regression includes whether the employer downsized (and whether it affected jobs similar to the respondent) and the employment growth in the individuals' industry in their state of residency. Other controls included in each regression are age, gender, marital status, race, Hispanic ethnicity, education level, whether the person works full or part time, tenure in the job, whether the employer provides health insurance and pension plans, employer size, type of occupation (white, blue or pink collar), industry dummies, state dummies, wave dummies and the unemployment rate at the state level. The outcome high level of stress takes the value of 1 if the person agrees or strongly agrees that his/her current job involves lots of stress, and takes the value of 0 if the person disagrees, strongly disagrees or it doesn't apply. Standard errors are clustered at the individual level. *** denotes p-value<0.01; ** denotes p-value<0.05; * denotes p-value<0.1.

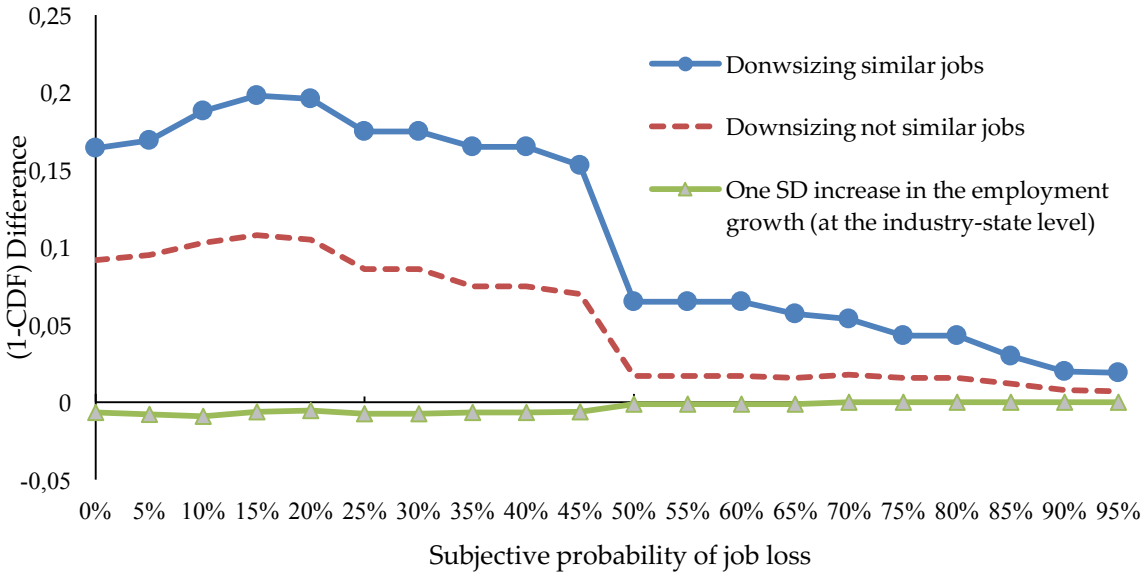
**Table A4: Effect of Job Insecurity on each component of the CESD Index**

| "Much of the time during the past week ..." | Mean Value | OLS | IV | # Observations |
|---|---|---|---|---|
| Felt depressed | 0.11 | 0.083*** | 0.306*** | 28,138 |
| | | (0.009) | (0.056) | |
| Everything was an effort | 0.17 | 0.061*** | 0.309*** | 28,132 |
| | | (0.011) | (0.067) | |
| Sleep was restless | 0.25 | 0.084*** | 0.404*** | 28,139 |
| | | (0.012) | (0.077) | |
| Felt happy | 0.89 | -0.076*** | -0.265*** | 28,108 |
| | | (0.009) | (0.056) | |
| Felt Lonely | 0.11 | 0.052*** | 0.214*** | 28,135 |
| | | (0.009) | (0.055) | |
| Felt Sad | 0.15 | 0.081*** | 0.370*** | 28,126 |
| | | (0.010) | (0.064) | |
| Could not get going | 0.13 | 0.074*** | 0.323*** | 28,133 |
| | | (0.010) | (0.061) | |
| Enjoyed life | 0.94 | -0.050*** | -0.190*** | 28,131 |
| | | (0.007) | (0.043) | |
| CESD Raw Score | 1.09 | 0.562*** | 2.352*** | 28,064 |
| | | (0.049) | (0.320) | |
| CESD High Score (>= 4) | 0.10 | 0.088*** | 0.352*** | 28,064 |
| | | (0.009) | (0.056) | |

Data: HRS, pooled 1992-2012 (data from 2008 missing)

Notes: Each cell reports the coefficient of the subjective probability of job loss (measured from 0 to 1) estimated in a separate regression. The instruments in the IV regression includes wheter the employer downsized (and whether it affected jobs similar to the respondent) and the employment growth in the individuals' industry in their state of residency. Other controls included in each regression are age, gender, marital status, race, Hispanic ethnicity, education level, whether the person works full or part time, tenure in the job, whether the employer provides health insurance and pension plans, employer size, type of occupation (white, blue or pink collar), industry dummies, state dummies, wave dummies and the unemployment rate at the state level. Standard errors are clustered at the individual level. *** denotes p-value<0.01; ** denotes p-value<0.05; * denotes p-value<0.1.

**Figure A1: Size of the complier population**




Note: Each point represents the effect of the instrument in increasing the fraction of workers who have a subjective probability of job loss equal or below the level in the x-axis to a level above that. In other words, represents the size of complier population evaluated at that level of the subjective probability of job loss. The excluded category is having a subjective probability of job loss equal to zero.

## APPENDIX B: ANALYSIS OF JOB SEPARATIONS

We investigate if workers with potential mental health problems leave their jobs at different rate when employers are downsizing than when they are not. We estimate the following model:

$$S_{i,t+1,s,k} = \alpha + \theta_1 DSASJ_{it} + \theta_2 DSNASJ_{it} + \theta_3 CESD\_High_{it} + \theta_4 (DSASJ_{it} \times CESD\_High_{it}) + \theta_5 (DSNASJ_{it} \times CESD\_High_{it}) + \beta_X \boldsymbol{X}_{it} + \beta_{UR} UR_{st} + \phi_t + \phi_s + \phi_k + \epsilon_{itsk} \quad \text{(B1)}$$

Here, we define the outcomes $S_{i,t+1,s,k}$ as a dichotomous variable that takes the value of 1 if the workers separated from their employers by the next wave, and takes the value of 0 if they continue their employment. The right-hand side variable $DSASJ_{it}$ takes the value of 1 if the employer downsized similar jobs and takes the value of zero otherwise; the variable $DSNASJ_{it}$ takes the value of 1 if the employer downsized different types of similar jobs and takes the value of zero otherwise; and the variable $CESD\_High_{it}$ takes the value of one if the worker scored high in the CESD index in the current wave, and zero otherwise. All of the other variables in the right-hand side are defined as in equation (1).

We are interested in coefficients $\theta_1$ to $\theta_5$. Coefficient $\theta_1$ and $\theta_2$ measures whether workers who report their employer have recently downsize are more likely to separate by the next wave. Coefficient $\theta_3$ measures whether workers who score high in the CESD index (i.e. presents symptoms of potential depression) are more likely to separate by the next wave. Finally, coefficients $\theta_4$ and $\theta_5$ report if the rate of separation for workers to score high in the CESD index is different in downsizing versus non-downsizing employers. The estimation results of coefficients $\theta_1$ to $\theta_5$ are shown in Table B1 below. We find that that workers are more likely to

separate from downsizing employers, especially if employers have cut similar jobs in the past (i.e., $\theta_1 > \theta_2 > 0$). We also find that workers scoring high on the CESD index leave their jobs at a higher rate (i.e., $\theta_3$>0). However, this rate is not statistically different in downsizing employers (both those that have cut similar jobs and different type of jobs) than in non-downsizing employers (i.e., $\theta_4$ and $\theta_5$.are not statistically different from zero).

**Table A5: Employer downsizing, mental health, and probability of job separation**

| | Outcome: Separation from employer by next wave (OLS) |
|---|---|
| High CESD score (>=4) | 0.045*** |
| | (0.012) |
| Downsizing similar jobs | 0.056*** |
| | (0.009) |
| Downsizing not similar jobs | 0.021* |
| | (0.011) |
| (High CESD score) X (Downsizing similar jobs) | 0.010 |
| | (0.027) |
| (High CESD score) X (Downsizing not similar jobs) | 0.046 |
| | (0.037) |

Data: HRS, pooled 1992-2012 (data from 2008 missing)

Notes: Other controls included in each regression are age, gender, marital status, race, Hispanic ethnicity, education level, whether the person works full or part time, tenure in the job, whether the employer provides health insurance and pension plans, employer size, type of occupation (white, blue or pink collar), industry dummies, state dummies, wave dummies and the unemployment rate at the state level. Standard errors are clustered at the individual level. *** denotes p-value<0.01; ** denotes p-value<0.05; * denotes p-value<0.1.