Mental Well-being of the Bereaved and Labor Market Outcomes

Atsuko Tanaka* Laurel Beck†

June 24, 2015

First version: May 28, 2014

Abstract

This paper examines how grief caused by the death of an immediate family member affects labor force outcomes through adverse changes to mental health for elderly Americans. To deal with measurement issues, we differentiate mental health conditions from personality by exploiting a panel data. We also apply factor analysis to create a synthetic indicator for mental well-being. We find that, whichever mental well-being measure is used, bereavement of a family causes poor mental health conditions to a significant extent, and associated distraction following bereavement have adverse impacts on labor market outcomes for elderly Americans.

JEL: I10, J22

1 Introduction

Mental health issues afflict millions of people around the world. These conditions can affect many aspects of people's lives, including decisions about whether and how much to work. As of today, little

*Department of Economics, University of Calgary. atanaka@ucalgary.ca (Corresponding author)

†Public Policy Institute of California. beck@ppic.org We are grateful to John Kennan, Chris Reynolds, Chris Taber, Karl Scholz, John Mullahy, Tom DeLeire, and Barbara Wolfe for their feedback. We also thank Herbert Emery, Mingshan Lu, and seminar participants at Labor and Industrial Economics Workshop at Hitsubashi University for helpful comments.

is understood about how mental health problems impact labor force outcomes. This analysis is difficult because we still have much to learn about the ways mental health and working life interact with one another. For instance, people suffering from grief, anxiety, or depression may be less likely to work, or less productive on the job. On the other hand, a bad work-life fit or termination from one's job may cause or exacerbate these mental conditions. Another obstacle to mental health studies is difficulty in measurement. While mental illness is reported to have substantially increased, such a surge could merely be a reflection of increased diagnosis, self-awareness, or willingness to self-identify, given that statistics are based on the numbers reported and/or of people treated for it.

The goal of this paper is to examine how the death of a family member affects mental health and labor market outcomes such as labor force participation, hours worked, and labor income. To do so, we focus on mental well-being after a distinct, personal shock—the death of a respondent's parent or child.[1] Thus, in our paper, the terms depression and mental health are narrowly defined as depressive symptoms following a death in the family.

Our research question is important for three primary reasons. First, the prevalence of mental health issues is very high. According to the National Institute of Mental Health, an estimated 18.1% of Americans suffer from anxiety issues and 6.7% suffer from forms of depression.[2] In this paper, we focus on mental health after a death in the family, an exogenous, negative, personal shock. While this is a narrow segment of the spectrum of mental health disorders, it captures a type of grief that happens to almost everyone at some point. Second, the type of depression we examine can be treated with talk therapy or counseling,[3] but patients often do not realize they have a depressive disorder.[4] Our analysis, which attempts to separate mental status from personality, helps understand how people with depressive symptoms respond to a set of common survey questions. Third, a deeper understanding of how poor mental health impacts labor force outcomes (on both the intensive and extensive margins) may have clear policy implications. For instance, policymakers may consider employer or insurance regulations which focus support toward people with certain characteristics who are more vulnerable to mental health issues.

We use data from the Health and Retirement Study (HRS) to study elderly Americans. We find that, no matter which indicator of mental health is used, the results for elderly Americans largely support that the bereavement has adverse effects on hours worked and labor force participation. These patterns are found throughout our fixed-effect generalized least squares (GLS) regression. Such results are consis-

[1] Throughout the paper, we focus on this type of mood disorder; it is classified in psychiatric literature as "non-endogenous or reactive depression."

[2] http://www.nimh.nih.gov/health/publications

[3] Willner (1985)

[4] Reactive depression is a set of major depressive symptoms that are triggered by some tragic life event such as the death of a family member, while endogenous depression is viewed as a mood disorder and is a reflection of a chemical imbalance in the brain. The distinction can be made regarding whether the symptoms are cured by taking an antidepressant. For a clinical investigation of each type of depression, see, for example, Bodkin et al. (1995).

tent with the literature that shows strong correlations between the death of a family member and social isolation among the elderly (e.g., Bachrach, 1980).

Admittedly, a family member's death may affect labor market outcomes through a channel other than through one's psychological state and the controls. In fact, bereavement affects labor market outcomes through changes in household assets and time to care for family members. Our analysis takes asset changes into account by including the asset variables as controls, but ignores changes in time devoted to caregiving due to lack of data. However, the omitted bias in this case would result in underestimation of how the psychological shocks adversely affect the labor market outcomes since, workers should be able to reduce time to care their family member and allocate more time to work after the bereavement.

To deal with measurement issues often associated with self-reported data, we look at multiple indicators for depressive symptoms. Further, we construct a synthetic indicator for mental health using factor analysis in an attempt to better utilize the richness of the data on reported symptoms. We also run fixed-effect regressions in order to distinguish underlying personality traits from specific episodes of depression. By utilizing panel data sets that have observations over many time periods, we can look at the differences in individuals over time and thus control for individual fixed effects.

Although grief is not technically a disease, numerous authors studying the bereaved have claimed that grief that causes intense distress can lead to physical illnesses, as well as adverse somatic and psychological changes. Among these are depression and anxiety, which can become clinically important. Many studies report an increase in depressive symptoms in the bereaved (Lindemann, 1944; Raphael, 1977; Parkes, 1996). In severe cases, the incidence of the loss of life is reported to trigger post-traumatic stress disorder (Kaltman and Bonanno, 2003). Psychiatric morbidity is also said to increase after losing a loved one (Surtees, 1995). Worse yet, bereavement is reported to be associated with an increase in mortality risk (Clayton et al., 1972, Engel, 1961, Stroebe et al., 2007).

The rest of this paper proceeds as follows. Section 2 reviews the related literature. Section 3 introduces the data sets and constructs an indicator for mental health using factor analysis. Section 4 conducts regression analysis to examine the effect of mental health on labor market outcomes. Section 5 concludes.

2 Background

In this section, we discuss the preceding papers and potential mechanisms for mental well-being affecting labor market outcomes. Depression or mood disorder can be defined as several symptoms that reduce an individual's ability to maintain a psychological balance. Among the major symptoms are feeling less intimacy, enjoyment, and perceived influence in daily social interactions (e.g. Nezlek et al., 2000); feeling sad, lonely, or down; loss of self-esteem; feeling tired or exhausted; insomnia, or wanting to sleep

too much; eating disorders; disinterest in everything and everyone; irritability; concentration problems; decreases in social interaction; highly agitated behavior (in an agitated depression) and exaggerated excitement.

2.1 Related Literature

The papers that explore the relationship between mental well-being and labor force outcomes can be broadly divided into three categories. The studies that are most closely related to this paper consider the causal effect of having good mental health on employment. Hamilton et al. (1997) find that there are beneficial effects of having good mental health on employability. Gresenz and Sturm (2004) look at mental health and transitions into and out of the labor force for men and women. They find that anxiety and depression are associated with greater churning into and out of the labor force for women, but find little evidence that mental health affects the labor force participation of men. Chatterji et al. (2007) investigate people of Latino and Asian descent in the U.S. and find adverse effects on employment for Latinos and mixed evidence for Asians. Similarly, Chatterji et al. (2009) find that anxiety and affective disorders lead to a reduction in the likelihood of employment for men, with a larger effect on minorities relative to non-Latino, white males. They find that affective disorders decrease employment for all women and that there are large negative effects of anxiety disorders on employment for Latino women. Kessler et al. (1999) study the joint effects of mental disorder and physical disorder on the number of days of work.

Cornwell et al. (2009) find that mental illness has a large negative effect on labor force participation for Australian workers, as well as negative effects on employment and occupational skill levels. Lu et al. (2009), using data from China, find that a decrease in average self-reported mental health at the population level leads to a reduction in the employment rate and annual income of both men and women. Uppal (2009) finds that poor mental health leads to a lower likelihood of being employed among Canadian workers and that mental health problems are associated with fewer working hours for women. Nelson and Kim (2011) find that individuals with mental illness have an increased risk of employment termination, voluntary job loss and involuntary job loss. Overall, this literature suggests that depression and affective disorders have negative effects on various labor force outcomes for both men and women across many countries, with larger effects for women in some cases.

A second set of papers investigates the causal effect of employment on mental health. Bjorklund (1985) finds that the unemployed have overall worse levels of mental health than those who are working, but does not find clear evidence that the differences are due to a negative causal effect of unemployment. In addition to the results mentioned above, Hamilton et al. (1997) find that employment has beneficial effects on mental health. Llena-Nozal et al. (2004) use data from the United Kingdom to consider whether occupation is important in understanding the effects of working on mental health. They find

that mental health generally depreciates with age, but that the rate of depreciation is lower for those who work. They also find that occupation is important for women, but not men, while employment status is important for men, but not women. Llena-Nozal (2009) uses longitudinal data from Australia, Canada, Switzerland, and the UK and finds that non-employment is generally worse for mental health than working, but that the magnitude of the effects appears to vary with the type of employment contract and working conditions. However, Tuttle and Garr (2009) find little difference in the effect of working on mental health between self-employed and organizationally-employed women. Beutell (2007) explores the relationship between physical and mental health, family well-being and satisfaction outcomes for self-employed individuals. Mandal et al. (2008) find that involuntary job loss has a negative effect on mental health for older American workers, but that the effect can be undone with re-employment. Strazdins (2011) finds that income and time-constrained families may face compounding barriers to good health. Taken together, both of these strands of literature imply that employment variables and mental health do influence one another, and that estimating the causal effect in one direction requires a creative estimation strategy.

Finally, previous work has examined the impact of the policy environment on mental health and employment. Cseh (2008) investigates whether state mental health parity mandates have effects on labor and insurance markets, finding no evidence that mandates decrease employer provision of or contributions to employee health insurance. There is also no suggestion in Cseh's study that mandates impact labor composition or wages. Chandler (2011) examines employment and treatment outcomes for individuals whose Los Angeles County welfare mental health services ended. Tefft (2011) uses Google Insights for Search data and finds that the state-level unemployment rate is positively correlated with searches related to anxiety and depression, while those searches are negatively related to initial unemployment insurance claims. However, extended periods of high levels of continued unemployment insurance claims are associated with higher levels of depression-related searches. Rote and Quadagno (2011) find that, since welfare reform in the 1990s, a gap in depressive and alcohol-dependence symptoms has emerged between welfare recipients and other poor women, suggesting that unusually symptomatic women were left on the welfare rolls. They suggest that mental health services for welfare recipients would help them to successfully enter the labor force.

2.2 Potential Mechanism: The Effect of Mental Health on Labor Market Outcomes

Severe mood disorders or major depression can affect labor force outcomes through various channels. In this subsection, we discuss the potential mechanisms of mental health-related effects on labor market outcomes.

Suicidal Thoughts

Among the worst possible consequences for people suffering from mood disorders are suicide attempts. Major depression, considered the strongest risk factor for suicide, increases the likelihood of acting on suicidal ideation. While most suicide attempts are survived, nonfatal suicide attempts can result in serious injury or physical disability. A considerable number of people are permanently disabled as a result of self-injury.

Physiological Effects

Mental and physical health are closely linked in multiple ways. poor physical health increases the risk of depression, as do the social and relationship problems that are common among chronically ill patients. The causality can also work in the other direction . For example, depressive illness can precede a physical disease. It has been linked to coronary heart disease, stroke, colorectal cancer, back pain, irritable bowel syndrome, multiple sclerosis, and possibly type 2 diabetes (Collingwood, 2010).

Dysfunctional Social Behavior

Another serious effect of poor mental health is isolation from society. People with greater depressive symptoms report more frequent negative social interactions and show more negative reactions to them (for socio-evolutionary models of depression, see Allen and Badcock, 2003). The experience of depression is often reported to cause social isolation, which typically worsens the feelings of loneliness and generally harms overall mental well-being. Serious effects of social isolation on mental well-being are especially concerning for the elderly. Bachrach (1980) studies the relationship between the number of one's living children and social isolation in old age and finds that childlessness is strongly correlated with the probability of isolation.

3 Data

To understand the impact of mental health on worker productivity, this section provides descriptive statistics of mental health. We begin by documenting summary statistics of our variables of interest for the data set used for estimation. We then construct an additional indicator to measure mental well-being by using factor analysis.

The University of Michigan Health and Retirement Study (HRS) is a longitudinal panel study that interviews a representative sample of Americans over the age of 50 every two years. The HRS is designed to explore the changes in labor force participation and health transitions of elderly individuals.

The survey includes data from five different age cohorts (defined by their year of birth), resulting in a final sample of people born before 1953 and their spouses. The RAND Corporation has produced a consolidated version of the HRS with consistent definitions of variables across waves, which includes all five cohorts. This paper's estimates are based on the RAND-HRS data. The study provides information about income, work, assets, pension plans, health insurance, disability, physical health and functioning, cognitive functioning, and health care expenditures. The survey is currently available from 1992 to 2008. The response rate is similar across all ten mental health questions included in the RAND-HRS, with over 150,000 responses (including multiple observations of the same individuals).

In analyzing mental well-being in the context of labor force participation, a major concern is that we capture the impact of early retirement on mental health. In the U.S, the observed job exit rates spike at ages 62 and 65, when workers are first eligible for the public Social Security system and/or private pensions. In fact, a sharp decline in labor force participation rates starts at age 55 (French, 2005). The decline is also confirmed in our data and presented in Table 13 in the Appendix. To avoid this issue, we allow different treatment effects for individuals younger than 55. While the HRS contains information about the respondent's spouse, we only look at the answers from the respondents themselves, considering the sensitivity of self-reported data. This reduces the size of the universe to 163,914 observations, among which 30,188 are younger than age 55.[5] In our estimation, taking early retirement into account, we divide the group into two—those who are older than age 55 and the rest—and allow them to have different impacts of mental health on their labor market outcomes.

We focus primarily on three mental health measures: *psych*, *depre*, and *cesd*. The summary statistics of these measures are presented in Table 13 in the Appendix. The *psych* variable indicates whether a doctor has ever informed the respondent that they suffer from a psychiatric problem. Of the person-year responses, 14.5% indicate that they have been diagnosed with a psychiatric disorder. In addition to asking about formal diagnoses, the survey also asks respondents about their mental health in the week prior to the interview. The survey includes both positive and negative mental health symptoms. The negative measures include whether respondents experienced the following sentiments all or most of the time: that everything is an effort, that their sleep is restless, feeling alone, feeling sad, and that they could not get going. The positive indicators measure whether the respondent felt happy and enjoyed life, all or most of the time.

Using the original HRS data, the RAND Corporation derived one mental health index, *cesd*, using a score on the Center for Epidemiologic Studies Depression (CESD) scale. The CESD score is the sum of six "negative" indicators minus two "positive" indicators (the value ranges 0–8). A higher CESD score is associated with worse mental health. Table 1 indicates that all eight measures of emotion are commonly reported, although the positive ones are by far the most prevalent. The average CESD score across all responses is 1.53.

[5]There are 22,000 to 35,000 unique individuals observed in each year.

While about 90% of respondents answer that they feel happy and enjoy life, 17% have a diagnosed mental disorder. Such statistics imply that some people are mentally ill, yet report good mental well-being. Thus, we need to be careful when defining mental disorder and mental well-being.

4 Estimating the Effect of Mental Health on Labor Market Outcomes

We estimate the average treatment effect of depressive symptoms on various labor force outcomes using fixed-effect regression approach in order to address the reverse causality issue. In the rest of this section, we present our baseline model and construct measurement for mental well-being.

4.1 Measuring Mental Health

A major challenge for the study of mental health is how to measure a mental disorder. Since mental health has multiple facets, a single trait hardly captures depression in a comprehensive manner. In addition, the definition of mental illness or self-awareness varies across time and culture, which complicates mental health studies that rely on self-reported measures of mental health. While some researchers regard self-reported health as a good predictor of objective measures (e.g. Idler and Benyamini, 1997), it is not, itself, an objective measure, so it is subject to bias due to measurement error.

To address the issue of measuring mental well-being or mental health, we measure mental health using factor analysis in an attempt to better utilize the richness of the data on reported symptoms. Factor analysis allows us to construct a composite variable (factor), comprised of a linear combination of the multiple reported symptoms, as a representative measure of mental health. The main purpose of using the factor structure model is to collapse several pieces of information into fewer latent components.

The basic idea of factor analysis is that we think of mental health as being generated by some unobservable process and think of the responses to the survey questions as imperfect measures of some underlying true state of mental health. We do not have any prior beliefs about the relative importance of each question or how they interact with one another.

In our data set, we observe binary responses to seven kinds of questions regarding depression. Let T_{ij} denote the jth measure of mental disorder for person i ($j = \{1, ..., 7\}$). The data T_{ij} is assumed to be generated by an r dimensional linear process ($r \ll 7$). Factors for individual i are represented in a vector f_i, $i = 1, ..., I$, where I is the number of individuals. The vector has r components, so $f_i = (f_{i1}, ..., f_{ir})$.

Based on these assumptions, the mental disorder j for person i can be expressed as

$$T_{ij} = \mu_j + \lambda_j f_i + \varepsilon_{ij},\ i = 1,...,I,\ j = 1,...,J \tag{1}$$

where μ_j is the mean of jth disorder, λ_j is an $r \times 1$ vector of factor loadings, f_i is an $r \times 1$ vector of factor scores and ε is independent of f. Both f and ε are assumed to be mean-zero. Thus, μ_j is interpreted as externally-manipulated levels of mental illness j and λ is the magnitude of latent factor f on the measurement T_j. We estimate the μ and λ that come closest to representing the original data set.

We conduct this factor analysis using the HRS data and find that there is one latent factor underlying depression symptoms for elderly Americans. Table 2 displays the estimates for the HRS data if we reduce nine measures of depression or bad mental health into one variable, or factor. The numbers under the "Factor 1" column represent the estimated λ for each of the depression indicators, while the "Uniqueness" column displays the extent to which Factor 1 does not capture the variance of the depression indicator. This "uniqueness" measure falls between 0 and 1. The variables with higher uniqueness measures carry less weight in the resulting Factor 1.

Table 2 presents the major result shown. The top table shows that variables such as *psych* and *sleep* have a high level of uniqueness that is not accounted for with Factor 1. This indicates that these two measurements of mental health do not easily reduce to a single measure. Factor 1 is most closely related to the $depre$ variable, which has the highest factor loading and lowest residual uniqueness. Factor 1 can explain 53% of the variance of $depre$. Factor 1 is negatively correlated with variables that indicate the extent of happiness ($whapp$) and delightfulness ($enlif$), which makes sense when we interpret Factor 1 as a representative of adverse mental conditions. The row labeled "% of total variance" simply states that all nine of our dependent variables have sufficient factor loads to be included in the construction of Factor 1.

Finally, the eigenvalue of Factor 1 is equal to 2.74, the total variance across all variables that Factor 1 accounts for. As a general rule, factors with an eigenvalue greater than or equal to 1 should be retained for estimation. The rule is considered reasonable given that the main goal of factor analysis is to reduce the dimension of information into fewer latent components. If some factors have an eigenvalue greater than 1, this means that those factors explain more variation than the original pieces of information. In contrast, factors that have an eigenvalue smaller than 1 account for less variation than the original indicators. Therefore, dropping those variables with less explanatory power achieves the objective of reducing dimensionality.

The bottom table presents our results as we move away from a one-dimensional representation of mental health to a model with two factors. These additional factors are constructed to be orthogonal to the preceding ones, so the correlation between Factor 1 and Factor 2 (and any subsequent factors) is equal to zero. Since the eigenvalue of the additional factor is 0.47, less than 1, we proceed under the

assumption that there is only a single latent factor underlying the self-reported measure of mental health. The eigenvalues and percent of total variance for factors remain largely unchanged when we add three or more additional factors to the analysis.

Going forward, we restrict our analysis to a single factor.

4.2 Correlation between the Event of Death and Mental Health

In the regression presented below, we predict various indicators of the respondent's mental well-being by explanatory variables, including a dummy for the incidence of a family member's death since the last survey.

Table 3 shows the regression of bereavement and other characteristics on mental well-being using the HRS data. The results in the first three rows of the table show data for the death of a respondent's mother, father, and a child respectively since the last interview (i.e. for the past two years). Columns (1) through (4) present the results of OLS, and Columns (5) through (8) present those of fixed-effects generalized least squares (GLS) regression, which allows individual-specific components that are unexplained by observables. In addition to the variables presented in the table, we include marital status and dummies for life events such as divorce among the covariates.[6]

The results using the HRS show that respondents report significant increases in all measures of mental health problems in the wake of a family member's death. The first four columns show that for people whose mother has died within the past two years, there is a two percentage-point increase in diagnosed depression, a 2 percentage-point increase in the probability of indicating major depressive disorder (*depre*) and psychiatric problems (*psych*), a 0.13-point increase on the 8-point CESD scale, and a 0.08-point increase on factor1, the latent factor estimated from the factor analysis, respectively. The effects on major depressive disorder and psychiatric disorders are insignificant after the death of one's father, although the other two mental health scores rise to a similar extent to the death of one's mother. The death of a child shows the strongest impact on all mental health indicators.

We find that individuals tend to have higher chances of having poor mental well-being if they are less educated or/and less wealthy. For example, individuals with 12 years of education are more likely to feel depressed or report psychiatric problems by 8 percentage-points than those with 16 years of education.[7] Regarding religious and secular categories, those who identify as Jewish are most prone

[6]Among the control variables are dummies for partnered, separated, divorced, widowed, never married, the number of marriages, and the spouse being absent. To account for social isolation, we also include a dummy variable of living in a nursing home and found significantly positive correlation, but do not report it here. To control physical disability, a dummy indicator for receiving home care is included as well.

[7]The numbers are calculated using the point estimates as (-0.02*12+0.0004*12)-(-0.02*12+0.0004*12)=0.078 and (-0.02*12+0.0008*12)-(-0.02*12+0.0008*12)=0.077 for depressive disorders and psychiatric problems, respectively. Similarly, the difference in CESD scores between those with 12-year and 16-year education is calculated as 0.4 points.

to poor mental health, followed by non-religious individuals. Among demographic characteristics, the results are somewhat mixed. While black and other non-white races show higher probabilities of having psychiatric problems (*psych*), CESD and $factor1$ points compared to whites, the chances that black and other non-white races report psychiatric problems are lower by 7 percentage-points and 4 percentage-points, respectively. Females are more likely to report poor mental well-being than males. Veterans are the only group that reports psychiatric problems but has better mental health, which may imply that they are under effective treatment or medication.

The last four columns in Table 3 show the results with individual-specific fixed components controlled. Both the significance and the extent of positive correlation between bereavement and mental health indicators are found to be similar to the previous results without individual fixed-effects. These results suggest that, for the HRS sample, the death of a mother or a child is correlated with worse mental health regardless of the measurement of the mental well-being. Our results are consistent with Rostila and Saarela (2011), which find an increase in mortality risk among Swedish adults following the death of a parent, with a stronger effect following the death of the mother than that of the father.

5 Main Results

This section uses both the fixed-effect GLS method and the IV method to estimate the average treatment effect of depressive symptoms on various labor force outcomes. Tables 4 to 6 show the fixed-effect GLS analysis on the HRS data. Each table presents the estimated impacts of mental health indicators *depre*, *psych*, *CESD*, and *Factor*1 on different labor market outcomes. The dependent variable shown in Table 4 is a binary variable of work status (the extensive margin of paid employment); the dependent variable in Table 5 is the number of hours worked per year (the intensive margin), and that in Table 6 is monthly wages for workers (the intensive margin). The effects are separately estimated for those who are older than age 55 and the rest because we may end up catching early retirement for the group of people near normal retirement age. Thus, for the older group, who are prone to early retirement, we need to be careful in interpreting the coefficients of mental well-being.

We find a consistently negative impact of poor mental well-being on the extensive margin of labor supply as shown in Table 4. The dependent variable takes one if an individual provides non-zero hours of market work, and zero otherwise. The fixed-effect GLS results exhibit significant coefficients, regardless of the measurement for mental well-being. This result was robust when we use different model specification, such as a logit model, and when we include dummies for five-year age cohorts instead of age quadratic terms.

In contrast, we find a statistically significant impact on hours worked, the intensive margin of labor supply. The fixed-effect results presented in Table 5 show that poor mental health indicators among

people younger than or equal to age 55 are negatively associated with their hours worked. The effect of poor mental health measured by latent factor ($factor1$) turns out insignificant, which may be due to measurement errors.

Finally, our results show that the effects on weekly wage are significantly negative while those on hourly wage are insignificant throughout the regression analysis. Seemingly incongruent results between weekly wage and hourly wage may be attributed to the fact that mentally ill workers who are paid a fixed amount of salary reduce working hours, which results in higher pay per hour. The results might be different if we limit the sample to those who are paid hourly or on commission, but we cannot investigate this finding further since we could not find such information in the HRS.

The results from the HRS data largely support the hypothesis that poor mental health results in fewer hours worked, lower weekly earnings, and less labor force participation, but show that impact on productivity is insignificant, and thus indeterminate.

We acknowledge that interpretation of these results requires caution since bereavement could affect labor market outcomes directly. As discussed earlier, there are several channels that could affect labor market outcomes. The incidence of death could actually increase subsequent hours worked or market productivity if the person who died required care prior to the death, or a parent's death may results in reduction of labor supply of the bereaved in order to take care of the remaining parent. Thus, what we find here does not merely reflect the effect of mental well-being.

5.1 Robustness and Sensitivity Checks

In this section, we examine the long-term effect of poor mental well-being associated with bereavement. A tragic life event, such as the death of a close friend or family member, can trigger a mental disorder such as depression or bipolar disorder. Once a bad shock hits one's mental health, the adverse effect may be persistent. Many studies have found that adults grieving a parent's death suffer both psychological and physical symptoms for months or years afterward (Douglas, 1990). In our main results, we found that survey respondent's who had recently suffered the death of a parent or child were more likely to report poor mental health, which was associated with negative labor market outcomes. To test the validity of our results, we conducted various specifications, and found that the sign and significance of coefficients on our variable of interest were consistent. We also found the differences between the OLS results to be in the expected direction.[8]

[8]While causality is unclear, the existing literature consistently finds that the mortality rate of the bereaved increases in the early duration of bereavement (e.g., Engel, 1961, Clayton et al., 1972). Incidence of death could have prolonged effects on life of the bereaved. In fact, some studies have found that risks persist for longer than six months after bereavement (Stroebe et al., 2007).

Kreicbergs and Valdimarsdottir (2004) find that bereaved parents are more likely to suffer from anxiety and depression compared with non-bereaved parents, with larger effects 4–6 years after the death than 7–9 years later. Physical effects of

In this subsection, we conduct several analyses to study the persistence of depression. First, we present Table 7 to illustrate the frequency of depression symptoms. Second, we track individuals' mental well-being in different time spans, as shown in Table 8. We find persistency of six years of time-dependency: that is, if someone reports a depressive symptom six years ago, the probability that this person reports a symptom is higher than for the person who did not report the depressive symptom. Such time dependence disappears after eight years of time interval. Last, based on this finding, we include a lagged death term up to three survey periods in regression equations to capture the influence of pre-death on labor market outcomes.

Table 7 reports the frequency of the depressive symptoms observed over nine waves of data collection in the HRS data. There are 1,765 individuals under age 55 who answered the question in at least four waves (5,137 men and 7,457 women answered the questions at least once when they were younger than 55). Among those, 73% never reported being mentally ill while 15.9% continuously reported being so. Most of depression symptoms, except sleeping problems, do not seem chronic for the majority of the HRS sample.

We can visualize persistence using transition matrices, which track self-reported mental health in different time spans as presented in Table 8. The transition matrices consist of transition probabilities, showing how many women stick with their original answer to a question and how many change their answer about whether they suffer from the depression symptom, given their answers in previous surveys.

The transition matrices in Tables 8-A to 8-F are calculated using the HRS data. Table 8-A shows changes in a two-year span, Table 8-B in a four-year span, Table 8-C in a six-year span, and so on.

We find that feelings of depression (dep) at time t depends on the history of depression, and the extent of time dependence is weakened over an eight-year time interval. The results in Table 8 show that approximately 90% of HRS respondents who report no depression symptoms in one period will continue to report no symptoms for up to 12 years. The results also show that at least 60% of those who report symptoms at some point will report them going away within the next 2 years (the numbers in bold print in each panel). This fraction increases to just under 70% after 8 years. Of those who report depression in a given period, approximately 30% will continue to report it after 12 years.

5.2 Policy Implications

Given that grief-driven mental conditions appear to be distinct from other mental disorders, Prigerson et al. (1995) studies spousal bereavement and attempts to separate a set of symptoms interpreted as complicated grief from bereavement-related depression. Additionally, the best attempt to estimate the

grief can include headaches, dizziness, indigestion, chest pain, high rates of disability and illness, and drug use Stroebe et al., 2007).

causal effects in this paper only leads to the highest estimates of the impact of mental distress associated with bereavement, and thus we need to be careful in interpreting our main results using the instruments.

That said, our analysis presents a series of important findings that are worth policymakers' attention. For instance, our descriptive results shown in Table 3 imply that less-educated individuals, ethnic minorities, and females are more prone to depressive symptoms or poor mental well-being. Having individual-specific components controlled, the results from fixed-effects analysis show that bereavement affects elderly Americans to a great extent as well as reduction in household assets and divorce.

These results suggest that policymakers may consider employer or insurance regulations which focus support toward people with certain characteristics making them more vulnerable to mental health issues. For example, social awareness of depressive symptoms maybe important among ethnic minorities given that non-white races, including black people, tend to report feeling of depression (indicator "*depre*" in the analysis in Table 3) and the symptoms of major depressive disorders (e.g. CESD scores), but have a lower probability of being diagnosed with mental illness (measured by the indicator "*psych*").

6 Conclusion

In this paper, we have looked at the significance of poor mental health on workers' productivity and labor force participation decisions. Being aware of the nature of self-reported data, we investigated various measures of mental well-being, including a synthetic indicator created by collapsing several depression symptoms using factor analysis. Applying factor analysis, we find that there is a single, underlying factor of mental well-being for both demographic groups. While the existing literature does not identify a difference between poor mental health and personality, this paper distinguishes between the two by utilizing panel data sets that have multiple observations of the same respondents over several years.

Our main results indicate that, regardless of what mental health measure is used, grief has long-term impacts on labor supply for elderly Americans. Our results are consistent with the literature in psychology and sociology that shows strong correlations between the death of a family member and social isolation among the elderly. In contrast, that depressive symptoms have no significant effect on wages for the both demographic groups. This may be because many workers are paid at a fixed level of salary. The results might be different if we limit the sample to those who are paid hourly or on commission.

This paper addresses several identification issues. To investigate the direction of causality, we use bereavement as an exogenous shock to mental well-being. Applying the fixed-effect model, we find that poor mental well-being decreases in hours worked and labor force participation, and no significant effect on earnings for elderly Americans. The results are robust across different measures of mental well-being, including the synthetic measure created by factor analysis.

To see how bereavement directly interacts with labor market outcomes, we conduct a separate analysis by controlling for lifetime events that could follow bereavement, including changes in household income due to bequest, change in marital status, and time to care in our analysis to address this possibility. We confirm that bereavement affects labor market outcomes through changes in household assets and time to care for family members.

Throughout the analysis, we look only at symptoms of depression or grief that are triggered by the death of others, thereby ignoring different types of mental health shocks and other forms of depression that could result from the work environment or from personal factors. Our paper does not address chronic depression. Therefore, our results are not useful in discussing the causality between depression, in a general sense, and workers' labor market outcomes—if the cause of a mental disorder is different, complications from and persistence of the disorder could vary.

Tables

Table 1: Summary Statistics of Depression Symptoms for Individuals

Variable	Did you/your spouse...	Respondent	Total		Male		Female
		% Yes	# Obs.	% Yes	# Obs.	% Yes	# Obs.
psych	Have mental disorder	16.8	29,668	11.4	10,191	19.6	19,477
depre	Feel depressed	19.6	28,844	16.7	9,472	21.0	19,372
effor	Everything is an effort	28.2	28,836	28.5	9,470	28.1	19,366
sleep	Sleep is restless	36.4	28,848	32.7	9,474	38.2	19,374
whapp	Feel happy	87.5	28,827	89.0	9,468	86.7	19,359
flone	Feel alone	16.8	28,846	14.8	9,475	17.8	19,371
fsad	Feel sad	23.7	28,839	18.9	9,472	26.0	19,367
going	Cannot get going	24.3	28,832	21.5	9,472	25.6	19,360
enlif	Enjoy life	91.9	28,832	93.3	9,472	91.2	19,360
cesd	Mean score	1.53	22,297	1.34	6,967	1.62	15,330
	Standard deviation	(2.07)		(1.91)		(2.13)	

Source: the 1992–2008 HRS data.

Notes: The CESD score is the sum of six “negative” indicators minus two “positive” indicators (the value ranges 0–8).

Table 2: Factor Analysis

Variable	Do you...	Factor 1	Uniqueness
Factor loadings			
psych	have mental disorder	0.26	0.93
depre	feel depressed	0.75	0.44
effor	everything is an effort	0.56	0.69
sleep	sleep is restless	0.47	0.78
whapp	feel happy	-0.57	0.68
flone	feel alone	0.60	0.63
fsad	feel sad	0.70	0.51
going	could not get going	0.52	0.73
enlif	enjoyed life	-0.51	0.74
Eigenvalues		2.83	
% total variance		2.83	
No. test measures		9	

Variable	Do you...	Factor 1	Factor 2	Uniqueness
Factor loadings				
psych	have mental disorder	0.16	-0.13	0.93
depre	feel depressed	0.66	-0.14	0.44
effor	everything is an effort	0.60	–	0.65
sleep	sleep is restless	0.50	–	0.76
whapp	feel happy	–	0.83	0.33
flone	feel alone	0.52	-0.13	0.64
fsad	feel sad	0.62	-0.13	0.51
going	could not get going	0.60	–	0.68
enlif	enjoyed life	–	0.67	0.53
Eigenvalues		2.87	0.39	
total variance		2.47	2.16	
No. test measures		9	5	

Notes: Blanks "–" represent the absolute value of loading smaller than 0.1. The top table shows the results from factor analysis with the number of underlying latent factors specified as one. The bottom table shows the results from factor analysis that assumes there are two latent factors instead of one. The number of observations is 28,282.

Table 3: OLS/Fixed-Effects regression with various mental well-being indicators

Outcome	depre	psych	cesd	factor1	depre	psych	cesd	factor1
Specification	OLS (1)	OLS (2)	OLS (3)	OLS (4)	FE (5)	FE (6)	FE (7)	FE (8)
Mother died	0.02***	0.02**	0.13***	0.08***	0.02***	0.01*	0.14***	0.09***
	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.03)	(0.01)
Father died	0.01	0.01	0.10**	0.06**	0.004	-0.0002	0.10***	0.06***
	(0.01)	(0.01)	(0.04)	(0.02)	(0.01)	(0.01)	(0.04)	(0.02)
Child died	0.05***	0.05***	0.23***	0.15***	0.04***	0.02**	0.17***	0.12***
	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.03)	(0.02)
Age	-0.01***	0.003	-0.10***	-0.05***	-0.01*	0.01**	-0.06***	-0.03***
	(0.001)	(0.002)	(0.005)	(0.003)	(0.004)	(0.01)	(0.02)	(0.01)
Age^2	6.9e-05***	-4.7e-05***	0.0006***	0.0003***	8.1e-05***	-0.0001***	0.0007***	0.0004***
	(7.8e-06)	(1.2e-05)	(4.1e-05)	(2.2e-05)	(1.3e-05)	(1.9e-05)	(6.3e-05)	(3.5e-05)
log(HH asset)	-0.02***	-0.01***	-0.12***	-0.07***	-0.004**	0.0002	-0.02*	-0.01*
	(0.001)	(0.002)	(0.006)	(0.004)	(0.002)	(0.003)	(0.01)	(0.01)
Divorced	0.04***	0.06***	0.38***	0.22***	0.02*	0.06***	0.28***	0.18***
	(0.007)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.05)	(0.03)
Widowed	0.06***	0.03***	0.49***	0.31***	0.06***	0.05***	0.61***	0.39***
	(0.003)	(0.003)	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)
Education	-0.02***	-0.02***	-0.11***	-0.06***	–	–	–	–
	(0.002)	(0.002)	(0.01)	(0.005)				
$Education^2$	0.0004***	0.001***	0.001***	0.001***	–	–	–	–
	(6.7e-05)	(9.8e-05)	(0.0003)	(0.0002)				
Catholic	0.01***	-0.01	0.06***	0.04***	–	–	–	–
	(0.003)	(0.004)	(0.01)	(0.01)				
Jewish	0.06***	0.02**	0.42***	0.24***	–	–	–	–
	(0.01)	(0.01)	(0.04)	(0.02)				
No religion	0.02***	0.04***	0.22***	0.12***	–	–	–	–
	(0.00)	(0.01)	(0.02)	(0.01)				
Other religion	0.02	0.07***	0.13**	0.08***	–	–	–	–
	(0.01)	(0.02)	(0.05)	(0.03)				
Black	0.04***	-0.07***	0.12***	0.07***	–	–	–	–
	(0.003)	(0.01)	(0.02)	(0.01)				
Other race	0.02***	-0.04***	0.10***	0.06***	–	–	–	–
	(0.01)	(0.01)	(0.03)	(0.02)				
Female	0.03***	0.10***	0.17***	0.11***	–	–	–	–
	(0.003)	(0.003)	(0.01)	(0.01)				
Veteran	-0.01***	0.01***	-0.10***	-0.06***	–	–	–	–
	(0.003)	(0.003)	(0.02)	(0.01)				
No. Obs.	114,624	122,684	104,554	114,119	114,895	122,965	104,796	114,388
R-squared	0.08	0.04	0.13	0.14	0.022	0.011	0.030	0.049
No. of ID					24,904	25,691	23,645	24,876

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Included but not reported are time trend, marital status, the number of marriages, physical health indicators (high blood pressure, diabetes, cancer, lung disease, heart problems, stroke, arthritis), a dummy variable of living in a nursing home and a dummy of receiving home care.

Table 4: Fixed-Effects regression

VARIABLES	Dependent Variable: Labor Force Participation			
	GLS	GLS	GLS	GLS
Depre (Feeling)	-0.002			
	(0.004)			
Depre×age≤55	-0.05***			
	(0.01)			
Psych		-0.02***		
		(0.00)		
Psych×age≤55		-0.04***		
		(0.01)		
CESD			-0.002**	
			(0.001)	
CESD×age≤55			-0.01***	
			(0.002)	
Factor1				-0.003**
				(0.001)
Factor1×age≤55				-0.009***
				(0.003)
Age	-0.05***	-0.08***	-0.07***	-0.04***
	(0.004)	(0.00)	(0.00)	(0.004)
Age Squared	0.0005***	0.0005***	0.0005***	0.0004***
	(1.3e-5)	(9.3e-6)	(1.4e-5)	(1.3e-5)
log(HH asset)	0.003	0.02***	0.002	0.003
	(0.002)	(0.001)	(0.002)	(0.002)
Cancer	-0.04***	-0.03***	-0.02***	-0.04***
	(0.01)	(0.00)	(0.01)	(0.006)
Lung disease	-0.01**	-0.05***	-0.01**	-0.01**
	(0.01)	(0.00)	(0.01)	(0.006)
Heart problems	-0.03***	-0.03***	-0.02***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.004)
Stroke	-0.03***	-0.05***	-0.02***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.007)
Arthritis	-0.02***	-0.06***	-0.01***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.003)
No. Obs.	115,095	123,201	104,996	114,587
No. of ID	24,961	25,754	23,702	24,932
R-squared	0.20	0.20	0.16	0.20

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Included but not reported are time trend, marital status, physical health indicators (high blood pressure, diabetes), and a dummy variable of living in a nursing home.

Table 5: Fixed-Effects regression

VARIABLES	Dependent Variable: Hours Worked			
	GLS	GLS	GLS	GLS
Depre (Feeling)	0.78***			
	(0.24)			
Depre×age≤55	-1.10***			
	(0.36)			
Psych		-0.40		
		(0.34)		
Psych×age≤55		-0.84**		
		(0.43)		
CESD			0.23***	
			(0.05)	
CESD×age≤55			-0.29***	
			(0.08)	
Factor1				0.22**
				(0.09)
Factor1×age≤55				-0.10
				(0.12)
Age	2.14***	2.14***	1.53***	2.22***
	(0.20)	(0.20)	(0.23)	(0.20)
Age Squared	-0.02***	-0.02***	-0.01***	-0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
log(HH asset)	-0.08	-0.04	0.19	-0.09
	(0.12)	(0.12)	(0.13)	(0.12)
Cancer	-1.24***	-1.08***	-1.11***	-1.23***
	(0.37)	(0.36)	(0.40)	(0.37)
Lung disease	-0.39	-0.37	-0.66	-0.36
	(0.41)	(0.39)	(0.45)	(0.41)
Heart problems	-1.09***	-1.03***	-1.11***	-1.10***
	(0.28)	(0.27)	(0.31)	(0.28)
Stroke	-2.05***	-2.10***	-2.09***	-2.10***
	(0.65)	(0.62)	(0.69)	(0.65)
Arthritis	-0.42**	-0.34*	-0.29	-0.43**
	(0.20)	(0.19)	(0.22)	(0.20)
No. Obs.	47,809	50,693	40,924	47,700
No. ID	14,214	14,545	12,433	14,202
R-squared	0.12	0.11	0.09	0.12

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Included but not reported are time trend, marital status, physical health indicators (high blood pressure, diabetes), and a dummy variable of living in a nursing home.

Table 6: Fixed-Effects regression

VARIABLES	Dependent Variable: Log Weekly Wage			
	GLS	GLS	GLS	GLS
Depre (Feeling)	0.04**			
	(0.02)			
Depre×age≤55	-0.07***			
	(0.02)			
Psych		-0.04*		
		(0.02)		
Psych×age≤55		-0.01		
		(0.03)		
CESD			0.01***	
			(0.00)	
CESD×age≤55			-0.02***	
			(0.01)	
Factor1				0.01
				(0.01)
Factor1×age≤55				-0.01
				(0.01)
Age	0.18***	0.18***	0.15***	0.18***
	(0.01)	(0.01)	(0.02)	(0.01)
Age Squared	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
log(HH asset)	0.02*	0.02**	0.02*	0.01*
	(0.01)	(0.01)	(0.01)	(0.01)
Cancer	-0.04*	-0.03	-0.04	-0.04
	(0.02)	(0.02)	(0.03)	(0.02)
Lung disease	0.02	0.02	0.03	0.03
	(0.03)	(0.03)	(0.03)	(0.03)
Heart problems	-0.04*	-0.03*	-0.04*	-0.03*
	(0.02)	(0.02)	(0.02)	(0.02)
Stroke	-0.07*	-0.08*	-0.04	-0.07*
	(0.04)	(0.04)	(0.05)	(0.04)
Arthritis	-0.04***	-0.05***	-0.05***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
No. Obs.	42,342	44,354	36,028	42,255
No. ID	13,475	13,805	11,734	13,465
R-squared	0.02	0.02	0.01	0.02

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1
The sample only includes those who reported non-zero weekly labor earnings. Included but not reported are time trend, marital status, physical health indicators (high blood pressure, diabetes), and a dummy variable of living in a nursing home.

Table 7: Frequency of the Depression Symptoms

Freq	#Obs.	psych %	depre %	effort %	sleep %	whapp %	flone %	fsad %	going %	enlif %
0		73.0	50.7	46.1	29.0	1.5	58.4	41.8	42.3	1.2
1		3.2	24.1	20.2	24.4	4.0	22.2	27.7	27.6	3.3
2		2.7	12.9	13.3	17.2	5.8	10.1	13.9	14.1	5.0
3		5.2	6.0	8.0	13.2	13.8	4.9	9.1	7.7	9.0
4+		15.9	6.3	12.4	75.0	6.3	9.4	7.5	16.0	81.5
Total	1765	100%	100%	100%	100%	100%	100%	100%	100%	100%

Table 8: Transition Matrix

Table A	dep in t		
t-2	0	1	Total
0	89.97%	10.03	100
1	**60.39**	39.61	100
Total	84.69	15.31	100
No. Obs.	43,404	7,845	51,249

Table B			
t-4	0	1	Total
0	88.81%	11.19	100
1	**62.71**	37.29	100
Total	83.35	16.65	100
No. Obs.	19,436	3,882	23,318

Table C			
t-6	0	1	Total
0	90.91%	9.09	100
1	**67.32**	32.68	100
Total	85.96	14.04	100
No. Obs.	17,689	2,889	20,578

Table D	dep in t		
t-8	0	1	Total
0	89.73%	10.27	100
1	**69.25**	30.75	100
Total	83.9	16.1	100
No. Obs.	7,042	1,351	8,393

Table E			
t-10	0	1	Total
0	90.64%	9.36	100
1	**69.73**	30.27	100
Total	84.63	15.37	100
No. Obs.	6,862	1,246	8,108

Table F			
t-12	0	1	Total
0	90.75%	9.25	100
1	**69.54**	30.46	100
Total	84.74	15.26	100
No. Obs.	6,634	1,195	7,829

Appendix: Data Variables

A HRS Data

The HRS data have four kinds of health indices: several function limitation indices, one depression index, one health problem index, and one body mass index.

A.1 Raw Response to the Question

Table 9: The Number of Observation for Health Condition Variables

wave	1	2	3	4	5	6	7	8	9
year	1992/3	1994/5	1996	1998	2000	2002	2004	2006	2008
variable									
psych	22,552	30,762	29,889	35,341	32,297	29,794	33,051	30,172	27,836
cesd		30,007	27,149	31,895	28,827	26,407	30,025	28,136	26,064

Notes: This table shows the total number of respondents for two mental health survey questions, psych and cesd.

Table 10: Statistics of Demographics

Variable	Obs	Mean	Std.	Min	Max
Age	165,228	66.12	11.26	22	109

	Obs	Percent	Min	Max
Male	119,295	43.4%	0	1
Female	155,637	56.6%	0	1
	274,932	100.0%		

Race	Obs	Percent	Min	Max
Caucasian	220,716	80.3%	0	1
Black	41,301	15.0	0	1
Other Race	12,753	4.6	0	1
	250,650	100.0%		
Non-Hispanic	250,668	91.3%	0	1
Hispanic	23,012	8.7%	0	1
	274,680	100.0%		

Religion	Obs	Percent	Min	Max
Protestant	172,503	63.0	0	1
Catholic	74,016	27.0	0	1
Jewish	6,606	2.4	0	1
None or no preference	17,253	6.3	0	1
Other religion	3,546	1.3	0	1
	273,924	100.0%		

Source: the 1992-2008 HRS data.

Table 11: Summary Statistics of Other Variables

Variable	Obs	Mean	Std.	Min	Max
Mother died in the last period	274,932	0.02	0.13	0	1
Father died in the last period	274,932	0.01	0.09	0	1
Child died in the last period	274,932	0.09	0.29	0	1
Years of education	273,906	11.91	3.46	0	17
Log of household asset	130,957	11.56	0.98	0	18.20
Number of marriages	164,705	1.34	0.71	0	13
Veteran	274,527	0.23	0.42	0	1
Lives in nursing home	165,186	0.03	0.18	0	1
Receives home care	163,268	0.07	0.25	0	1
High blood pressure	160,809	0.50	0.50	0	1
Diabetes	163,917	0.16	0.37	0	1
Cancer	164,547	0.12	0.32	0	1
Lung disease	164,260	0.10	0.30	0	1
Heart problems	164,606	0.23	0.42	0	1
Stroke	164,834	0.07	0.26	0	1
Arthritis	160,835	0.53	0.50	0	1
Factor1	150,736	-0.24	1.15	-1.11	3.48

Source: the 1992-2008 HRS data.

Table 12: OLS/Fixed-Effects regression with various mental well-being indicators

Outcome	depre	psych	cesd	factor1	depre	psych	cesd	factor1
Specification	OLS (1)	OLS (2)	OLS (3)	OLS (4)	FE (5)	FE (6)	FE (7)	FE (8)
Mother died	0.02***	0.02***	0.14***	0.09***	0.02***	0.01***	0.12***	0.08***
$<$ 2 years ago	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	(0.00)	(0.03)	(0.02)
Mother died	-0.01	0.01	-0.07**	-0.04**	-0.01	0.004	-0.06**	-0.04**
$<$ 4 years ago	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	(0.001)	(0.03)	(0.02)
Mother died	0.002	0.004	-0.0007	-0.001	0.002	-0.001	-0.01	-0.008
$<$ 6 years ago	(0.01)	(0.01)	(0.04)	(0.02)	(0.01)	(0.004)	(0.03)	(0.02)
Father died	0.01	0.005	0.11**	0.06**	0.01	-0.004	0.14***	0.08***
$<$ 2 years ago	(0.01)	(0.01)	(0.04)	(0.03)	(0.01)	(0.01)	(0.04)	(0.02)
Father died	0.01	0.01	0.07	0.04	0.01	-0.003	0.10***	0.05**
$<$ 4 years ago	(0.01)	(0.01)	(0.04)	(0.03)	(0.01)	(0.01)	(0.04)	(0.02)
Father died	-0.02*	0.02*	-0.05	-0.03	-0.02**	0.004	0.005	-0.004
$<$ 6 years ago	(0.01)	(0.01)	(0.05)	(0.03)	(0.01)	(0.01)	(0.04)	(0.02)
Child died	0.05***	0.03***	0.26***	0.16***	0.04***	0.01***	0.19***	0.12***
$<$ 2 years ago	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	(0.00)	(0.03)	(0.02)
Child died	0.01	0.03***	0.03	0.02	-0.004	0.01***	0.01	0.01
$<$ 4 years ago	(0.01)	(0.01)	(0.04)	(0.02)	(0.01)	(0.004)	(0.03)	(0.02)
Child died	0.006	0.01	0.004	0.01	-0.005	0.004	0.01	0.01
$<$ 6 years ago	(0.01)	(0.01)	(0.04)	(0.02)	(0.01)	(0.01)	(0.04)	(0.02)
Age	-0.01***	-0.01***	-0.11***	-0.06***	-0.004	0.01***	-0.06***	-0.03***
	(0.001)	(0.001)	(0.01)	(0.003)	(0.004)	(0.002)	(0.02)	(0.01)
Age^2	6.7e-5***	9.3e-6	0.0007***	0.0004***	5.9e-5***	-6.5e-5***	0.0008***	0.0004***
	(8.4e-6)	(7.9e-6)	(4.3e-5)	(2.5e-5)	(1.6e-5)	(9.6e-6)	(7.1e-5)	(4.2e-5)
Edu	-0.02***	-0.02***	-0.10***	-0.06***	–	–	–	–
	(0.00)	(0.00)	(0.01)	(0.01)				
Edu^2	0.0005***	0.0006***	0.001***	0.0008***	–	–	–	–
	(7.2e-5)	(6.6e-5)	(0.0004)	(0.0002)				
log(HH asset)	-0.02***	-0.01***	-0.12***	-0.07***	-0.01**	-0.001	-0.02*	-0.01**
	(0.001)	(0.001)	(0.01)	(0.005)	(0.002)	(0.001)	(0.01)	(0.01)
Divorced	0.04***	0.05***	0.39***	0.23***	0.03**	0.03***	0.30***	0.19***
	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)	(0.01)	(0.05)	(0.03)
Widowed	0.04***	0.05***	0.39***	0.23***	0.07***	0.04***	0.62***	0.39***
	(0.00)	(0.00)	(0.02)	(0.01)	(0.01)	(0.00)	(0.03)	(0.02)
No. Obs.	95,725	103,233	95,771	95,290	95,949	103,469	95,995	95,512
R-squared	0.07	0.07	0.13	0.13	0.01	0.01	0.03	0.03
No. of ID					22,485	23,540	22,488	22,460

Notes: Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1 Included but not reported are time trend, marital status, the number of marriages, physical health indicators (disability, high blood pressure, diabetes, cancer, lung disease, heart problems, stroke, arthritis), a dummy variable of living in a nursing home and a dummy of receiving home care. For OLS regression, we also include dummy variables of gender, veteran status, race and religion.

Table 13: Labor Force Participation Rates by Age

lbrf	men				women			
age	50-	60-	70-	80-	50-	60-	70-	80-
fulltime	70.6%	32.2	6.5	1.8	45.6	17.6	2.5	0.3
parttime	4.9	3.3	3.0	1.2	14.6	7.7	2.9	0.6
unemployed	2.4	0.7	0.1	0	2.0	0.5	0.1	0
partly retired	4.4	14.1	12.3	4.9	4.0	9.9	6.3	1.9
retired	12.3	46.4	76.7	90.6	13.1	44.5	67.7	68.8
disabled	4.2	2.9	1.0	0.9	4.4	3.4	1.5	2.6
not in the LF	1.3	0.5	0.4	0.7	16.4	16.4	19.1	25.8
Total	100%	100%	100%	100%	100%	100%	100%	100%

Notes: This table presents summary statistics of employment status by age. The employment rate decreases over age. More than half of men and more than 85% of women are out of the labor force by age 70. Age has strong correlation with labor force participation rates for the HRS data sample. To avoid dealing with early retirement, we allow different treatment effect for individuals older than age 55 in our regression analysis.

Table 14: The Number of Death Incidence

The respondent's	total
Father	4441
Mother	2369
child	4927

Data: HRS 1992–2008

Notes: Among 549,864 observations, 7695 lost his/her mother during the survey and 4178 lost his/her father. The following table shows summary statistics of loved one's death.

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