Life Insurance Holdings and Well-Being of Surviving Spouses

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Premature death of a breadwinner can have devastating financial consequences on surviving dependents. This study investigates the role of life insurance in mitigating the long-run financial consequences of spousal mortality. Using the Health and Retirement Study, we examine individuals whose spouses died during or soon after his or her peak earnings years. Using an instrumental variables approach, we find that lump-sum life insurance payouts do not significantly influence spousal well-being. JEL: D31, G22, I31, J32, J33, J38

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Death of a breadwinner can have catastrophic financial consequences for surviving dependents. In the United States, there are high rates of widow poverty with one in five widows being below the federal poverty line (FPL) and evidence of increased labor force participation by surviving dependents (Sevak, Weir and Willis, 2004; Elliott et al., 2011; Fadlon and Nielsen, 2015). Consequences from premature death like higher poverty or increased labor supply, precautionary savings, remarriage rates, or reliance on relatives can be mitigated by holding life insurance. To what extent does life insurance fulfill the classic "consumption smoothing" role, in turn reducing other distortions? Although several studies have speculated that increased life insurance coverage would reduce the incidence of poverty for surviving spouses (Auerbach and Kotlikoff, 1991; Bernheim et al., 2003), there has been, to date, no direct evidence.

Our study provides such evidence on how life insurance payouts influence surviving spouses, by using 20 years of data from the Health and Retirement Study (HRS). We analyze the well-being of individuals whose spouses died during or soon after his or her peak earnings years, and examine the elderly individual's financial status three years following

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the spouse's death. The HRS contains detailed financial information including payouts from life insurance policies and accurate information on the precise date of death.

In this sample of premature deaths, the correlation between the surviving spouse's financial well-being and life insurance holdings is positive, yet interpreting such a relationship as causal is problematic due to omitted variables bias. In particular, households with more competent financial planning would likely have both greater levels of life insurance coverage and better outcomes for surviving spouses. Therefore, we adopt an instrumental variables (IV) approach. We exploit the fact that employer-sponsored life insurance is a non-trivial portion of total life insurance payouts, and that such payouts vary systematically by industry, after controlling for other sources of heterogeneity like job quality. Additionally, these payouts vary by age-at-death and work status (often ratcheting down dramatically at age 65, and only paying out for recent workers). Thus, the nearly as-good-as-random variation that arises from precise age at death among the sample of premature deaths provides additional identifying variation.

With OLS, we find significant effects of lump-sum life insurance payouts on the well-being of surviving spouses without controlling for socio-economic factors. Once we control for such factors and instrument for life insurance payouts, there is no significant effect on reducing poverty of surviving spouses. These IV findings are consistent with the idea that life insurance payouts are simply a proxy for financial savviness, but do not cause higher long-run financial well-being. One possible explanation for this result is that surviving spouses spend the large financial windfall from life insurance very quickly, mitigating its effect in the medium- or long-run. Our findings suggest that lump-sum life insurance payouts may be less effective than an annuitized payout.

In addition to the policy importance, our findings contribute to a literature where commonly assumed causal relationships are either diminished or eliminated with the inclusion of additional covariates, balanced samples, or IV techniques. Examples include the consequences of subsidized housing (Currie and Yelowitz, 2000), military service (Angrist, 1990), arrests (Grogger, 1995), substance use (Rees, Argys and Averett, 2001), teen pregnancy (Hotz, McElroy and Sanders, 2005), and depression (Cseh, 2008).

The remainder of the paper is organized as follows. Section I provides an overview of life insurance markets. Section II describes the data. Section III provides the empirical specification. Section IV presents and discusses our results. Section V concludes.

I. Life Insurance Markets

Institutional features of the life insurance markets are important for understanding life insurance's influence on the well-being of surviving spouses and explaining the instrumental variables approach described hereafter. Individuals generally pay an annual premium, and their heirs receive a payment if the insured individual dies while covered by life insurance. Life insurance is separated into individual and group markets. Consumers purchase individual market coverage directly through the insurer commonly in the form of term or whole life coverage policies.[1] In contrast, group coverage generally originates through an employer and is known as employer-sponsored life insurance (ESLI). ESLI typically has an automatic portion provided by the employer and an option to purchase additional coverage through payroll deductions. Overall, ESLI constitutes a significant portion of all life insurance, representing 37 percent of the face value (amount payable at death) for all life insurance holdings. The standard form of payment for group life insurance is a lump-sum distribution (Grossman, 1992). For employed adults, 53 percent have some ESLI coverage and 24 percent exclusively have ESLI coverage.[2] Although ESLI and individual market coverage are close substitutes, there appears to be minimal crowd-out between individual and ESLI coverage (Harris and Yelowitz, 2015*a*). Consequently, increased ESLI generally translates into increased total life insurance coverage.

Employer-sponsored life insurance (ESLI) varies systematically by industry even for workers in similar occupations.[3] Table 1 shows the proportion of individuals in each industry that have life insurance coverage at all, as well as those exceeding face values of $10,000, $20,000 and $50,000.[4,5] The table shows significant variation by industry with a 37 percentage point difference in having any coverage between the most and least generous industries.

[1]Term life insurance provides coverage for a specified period of time (typically ranging from 10 to 30 years) and pays the face value of the policy upon death of the policyholder. Whole life insurance provides coverage for life and has an investment portion that accumulates a cash value over time.

[2]Percents calculated from tabulations of the 1990, 1991, 1992, and 1993 panels of the Survey of Income and Program Participation using individual weights.

[3]Other fringe benefits also vary systematically by industry, even for the same occupation. See Ahn and Yelowitz (2016) for an analysis of paid sick leave.

[4]We use the 1990-1993 SIPP for these calculations; it contains individual level information on life insurance coverage, large sample sizes, and industry codes. Additionally, SIPP data has been used in recent studies on life insurance (Harris and Yelowitz, 2014, 2015*b*; Hedengren and Stratmann, 2016).

[5]We use SIPP data from 1990 to 1993 to match the industry conditions when we first observe individuals in the HRS.

The second panel gives an example of within-occupation variation coming from industry classification. The table shows that secretaries—where duties/quality of the job is thought to be fairly homogeneous—have at least $20,000 in face value coverage 30 percentage points more often in the most generous industry relative to the least generous industry. The third panel shows that this variation persists for low earners with relatively little education that are the most likely to be near the poverty line.[6] In short, for workers with the same skill set, the likelihood of being offered ESLI, and the generosity of such insurance, varies with industry draw.[7]

In addition to industry variation for ESLI, there is also a large discontinuity in the face value of ESLI coverage at age 65 for several reasons. First, due to cost considerations, firms commonly reduce the face value of automatic ESLI for employees at age 65 (Miller, 1985).[8] In 1988, 56 percent of ESLI plans for full-time workers imposed benefit reductions for older workers, most commonly occurring at age 65 (Bellet, 1989).[9] These reductions occur most frequently for firms offering coverage in larger face values relative to firms that offer smaller face values (Hyland, 1991). If plans have multiple age based reductions, generally these occur at age 65 and 70. For example, coverage might be reduced to 65 percent of the full benefit amount at age 65 and then further reduced to 50 percent at age 70 (Bellet, 1989; Grossman, 1992). Second, supplemental ESLI policies are commonly priced based on 5-year age bins with increasingly large supplemental premium hikes as employees age. For example, at a large public university studied in Harris and Yelowitz (2015*a*), premiums increase 84 percent upon turning age 65. This increased cost may deter the purchase of supplemental coverage as employees age. Third, ESLI is employment-contingent, meaning that if an individual dies while employed they will receive the ESLI payout whereas individuals that die even shortly after leaving the firm will not receive a payout.[10] This mechanically decreases life insurance coverage when employees retire, which

[6] Appendix Table A1 shows significant industry variation using a regression framework controlling for earnings, education and occupational codes.

[7] Both Poterba, Venti and Wise (1995) and Chetty et al. (2014) exploit firm-level variation in pension offerings in examining the effects on savings behavior.

[8] The Age Discrimination in Employment Act (ADEA) prevents employer from discriminating against older workers in benefits. However, if employers spend equal amounts to buy life insurance coverage for old and young employees, they do not violate the ADEA even though this translates into more coverage for the young. For a review of the ADEA see Neumark (2003).

[9] Given that our instrumental variables strategy uses work behavior for HRS participants when initially observed (most often 1992), the findings on ESLI structure from this period are highly relevant.

[10] Some ESLI policies have a "portability" clause where individuals can continue with the same coverage after leaving the firm. However, insurance companies generally price these policies based on the adversely selected pool of individuals that choose to continue coverage. Therefore, the portable insurance represents a significant cost to former

often occurs at 65.

Figure 1(a) illustrates that there was a 30.7 percent decline in employees with ESLI coverage at age 65 relative to age 64.[11] Selection bias—where only workers with jobs that are less likely to have coverage continue to be employed after age 65—could be driving this distinct drop. From the SIPP, employees that completed at least 12 years of education have ESLI coverage twice as much as those that did not. Additionally, the proportion of employees with less than 12 years of education increases with age as they have a tendency to retire later. In Figure 1(b) we exclude employees who have less than 12 years of education who are both more likely to continue employment after 65 and less likely to have ESLI in an attempt to lessen the selection bias. That is, the sample of workers and jobs is likely to be more balanced. As shown, the drop is nearly identical, with a 32.1 percent reduction at age 65 with the restricted sample. This provides empirical support that the institutional features described above drive the discontinuous drop in coverage at age 65, and the drop does not appear to be coming from more negatively selected jobs, but rather institutional design.

II. Data

We use longitudinal data from the HRS from 1992 to 2012 to analyze the effect of life insurance on the well-being of surviving spouses. For consistency across survey years, we use the RAND HRS data file (version O) supplemented by the original HRS data files.[12] The HRS uses both exit interviews completed by surviving relatives and merged information from the National Death Index (NDI) to ascertain accurate mortality information.

There are 37,317 unique individuals surveyed from 1992 to 2012. We restrict the sample to individuals that reported being married during the sample years (N=26,037). In addition, we restrict the sample to widows or widowers whose spouses died during or soon after the peak earning years (between age 55 and 68) who we observe three years following their spouse's death (439 surviving spouses).[13]

employees that wish to continue coverage.

[11] These figures would suggest a fuzzy regression discontinuity design, where the running variable is age. See Imbens and Lemieux (2008). Unfortunately, our HRS sample sizes for age at death around this discontinuity are too small for such an approach.

[12] The RAND version imputes income and assets based on unfolding bracket questions that are used in this study. For full documentation see http://hrsonline.isr.umich.edu/modules/meta/rand/randhrso/randhrs_O.pdf.

[13] Given the biennial nature of the HRS, we technically look at the financial status of individuals two to three years following their spouse's death. For brevity, in the text we simply refer to this as three years.

The HRS sample started in 1992 with individuals aged 51-61. At that time, average life expectancy, conditional on living to age 51, was 77 for men and 82 for women.[14] Of the individuals who died between age 55 and 68, nearly 60 percent reported having better than a 50 percent chance of living to 75. Therefore, our sample consists of widows and widowers whose spouses had premature deaths, the majority of which were unexpected.

Table 2 shows the summary statistics for individuals as measured three years following their spouse's death. The sample is predominately white and approximately three-quarters have at least a high school education. A little over half of the sample received life insurance payouts. However, many of these policies were relatively small and only 30 percent received payouts greater than $20,000.[15] Conditional on receiving a life insurance settlement, the mean payout was $50,031 with a median payout of $26,348. Figure (2) shows that distribution of payouts conditional on receiving one. Approximately half off all individuals that were awarded a settlement received less than $25,000.

III. Empirical Methods

State and federal assistance programs such as Medicaid, Supplemental Nutrition Assistance Program (SNAP), and Supplemental Security Income (SSI) are designed to help low-income individuals, including those that are at or near poverty. To capture life insurance's influence on reducing reliance on government assistance programs, we use the threshold of 1.5x the Federal Poverty Line (FPL) as our primary measure of well-being.[16] Given the somewhat arbitrary nature of this cutoff, we include alternative specifications in the appendix, which include being below 1.0x the FPL, receiving food stamps, and being on Medicaid. The results from these specifications are consistent with the findings presented in the main text.

We use the following regression framework to estimate the influence of life insurance on

[14] Life expectancy estimates come from the Social Security Administration Period Life Table, 1994. See https://web.archive.org/web/19970617031009/http://www.ssa.gov/OACT/STATS/table4c6.html.

[15] All dollar amounts are converted to constant 2012 dollars using the Consumer Price Index.

[16] We use the RAND measure of total household income less food stamp income for income used in the poverty status calculations. A more accurate measure would add income from all non-core household residents to the measure of total household income. However, for earlier years in the sample, income from non-core household residents is not available. Consequently, we use official poverty thresholds for the relevant years from the Bureau of Labor Statistics (BLS) and assume that the household contains only the individual after the death of the spouse. In addition, the thresholds given by the BLS have discontinuities at age 65, which could confound our analysis. We therefore use the threshold for those under 65 regardless of age.

the financial status of surviving spouses:

$$(1) \qquad Under1.5xFPL_i = \beta_0 + \beta_1 Total\ Payout_i + \beta_2 X_i + \beta_3 X_j + \beta_4 X_h + \varepsilon_i$$

where $Under1.5xFPL_i$ equals one for surviving spouse i if income is less than 1.5x the federal poverty line three years following the spouse's death. $Total\ Payout_i$ is an indicator for individual i receiving a payout greater than a given threshold. X_i is a vector of controls for the spouse's education, race/ethnicity, and employment status measured at the first observation of the husband/wife pair (generally 1992). X_j is a vector of characteristics for deceased spouse that includes educational level and occupation code from the current job or if not working from a previous job. Both of these covariates attempt to control for financial astuteness and job quality.[17] X_h is a vector of controls for income and net worth for household h measured once again at the initial interview for the couple. The key coefficient is β_1; the hypothesis is that higher life insurance payouts reduce poverty, so that $\hat{\beta}_1 < 0$.

The above regression imperfectly controls for financial planning. Households that are adept at financial planning will likely have more life insurance coverage and are more likely to have financial means during retirement.[18] Consequently, our results will be biased toward finding a larger effect (more negative) of receiving a life insurance payout on being below the 1.5x FPL.

To address these concerns, we use an instrumental variables approach that uses payout differences by industry, and age of death. As outlined above, there is substantial industry variation in ESLI coverage, which constitutes a significant portion of total life insurance coverage. Industry choice is arguably orthogonal to financial planning capabilities including life insurance preferences after controlling for occupation and socio-economic variables. Additionally, if the spouse died prior to retirement, then the individual would receive an ESLI payout whereas if the spouse died following retirement a ESLI payout would not likely

[17]Our approach of controlling for job quality with occupation, and relying on the across-industry variation in ESLI generosity for identification, is similar in spirit to other work. Einav, Finkelstein and Cullen (2010) note that in the company they examine, "employees doing the same job in the same location may face different prices for their health insurance benefits due to their business unit affiliations."

[18]Gandolfi and Miners (1996) find that education increases life insurance holdings and Browne and Kim (1993) postulate that a higher education level raises life insurance holdings through increased risk aversion and awareness of the necessity of insurance.

be received. However, actual retirement age is correlated with financial planning and health and therefore endogenous as well.

Given the institutional features of decreased coverage at age 65 in addition to age 65 being a focal point for retirement, we construct our instrument, Z_i, to be zero if the deceased spouse dies after age 65 and assign the industry average based on their earliest observation (when the worker was typically 51-61) if they die prior to age 65.[19] For example, from the first panel of Table 1, the instrument for receiving any life insurance ($Payout > \$0$) for someone who died at age 63, who was employed in the public administration industry in the initial survey, would be 0.89. However, if the individual died at age 66, the instrument would be coded zero. Similarly, when we instrument for receiving a payout greater than \$50,000, we use the proportion of employees in a given industry who have life insurance coverage greater than \$50,000. For example, from the last column and first panel of Table 1, individuals who initially reported working in retail who died at age 58 would be coded as 0.33 for the instrument of receiving a payout greater than \$50,000. In addition, we code Z_i to be zero if the deceased spouse was unemployed or self-employed in the initial survey. After controlling for other covariates—like occupation—the interaction of the deceased spouse's age-at-death (conditional on early death), initial employment status, and initial industry strongly predict ESLI holdings and is highly correlated with total holdings, yet is likely uncorrelated with the subsequent well-being of the surviving spouse, except insofar as it predicts life insurance holdings. Therefore, Z_i should be correlated with the endogenous regressor, $Total\ Payout_i$, and uncorrelated with ε_i.

The first-stage IV estimation equation directly tests our assumption that our instrument is significantly correlated with life insurance payouts.

$$Total\ Payout_i = \gamma_0 + \gamma_1 Z_i + \gamma_2 X_i + \gamma_3 X_j + \gamma_4 X_h + u_i \tag{2}$$

where u_i is the error term and all other variables are defined the same way as in equation (1). The second stage is the same as the regression presented in equation (1) except we use the estimated $Total\ Payout_i$ from the first stage. The second stage estimation will recover the local average treatment effect (LATE) for receiving a life insurance payout. The

[19]As shown in Appendix Table A3, the only major difference between individuals that die just prior to age 65 relative to those that die shortly thereafter is employment status and spouses age (mechanical).

2SLS estimator will explain the influence of the life insurance payout on the well-being of the surviving spouse for those who have or do not have life insurance coverage based on industry assignment and as-good-as-random time of death. The estimate will not capture the effect on those that would have had life insurance coverage regardless of ESLI (Imbens and Angrist, 1994).

IV. Results

To give a baseline comparison, we first regress having income below 1.5x FLP on payouts without controls. For ease of interpretation, all results use linear models, even though the outcome is binary.[20] The first columns of Table 3 show a significant correlation between receiving a payout (at various thresholds) and being above the 1.5x FPL. The latter columns of Table 3 show that after the inclusion of controls, the effect is drastically reduced or disappears altogether. For example, the coefficient on receiving a payout greater than $20,000, the point estimate changed from a 15.4 percentage point decrease in the probability of being under 1.5x FPL without controls to essentially zero with controls from a base of 27.3 percent. The only coefficient that remains statistically significant after controls is for receiving any life insurance payout, although the magnitude has been significantly reduced. A priori, one might expect small payouts to not significantly influence well-being and larger payouts, such as $50,000, to have a significant influence. This finding highlights that receiving any payout might be indicative of financial planning—which is imperfectly controlled for in the specification—rather than a consumption smoothing influence of a significant payout. An alternative explanation could be that small payouts are significant enough to help those on the margin avoid high interest debt that reduces long-run well-being, but that there are rapidly diminishing returns to large payouts. As expected, for the surviving spouse, more education and being employed during the initial survey significantly decreases the likelihood of being under the near poverty line. In addition, surviving spouses of households with higher net worth in the initial interview are less likely to be in poverty three years following their spouse's death.

To understand which covariates cause the change in magnitude from the regression without controls to the full specification with controls we use a decomposition method described

[20] Results from a probit model are similar. For a discussion of the use of linear probability models in two state least squares estimation see Angrist and Krueger (2001) and Kelejian (1971).

in Gelbach (2016). Essentially, the traditional method of sequentially adding covariates to see changes in the coefficient of interest produces ambiguous results based on the order in which covariates are added. Gelbach (2016) proposes calculating the omitted variable bias of excluding each covariate separately from the full model to ascertain the contribution of each covariate to the total change. Table 4 illustrates the influence of different groups of controls in explaining the percentage point change in the coefficient for $Total\ Payout_i$. For example, isolating the regressions that use receiving any payout as the independent variable of interest (columns 1 and 5 of Table 3) we see that the total change in the coefficient from adding controls was 0.089. From Table 4 we can see that 38.9 percent of the change in the coefficient on receiving a payout comes from controlling for household net worth. As well, the addition of household income accounts for 19.1 percent of the overall coefficient change from adding covariates. From this table we can also see that deceased spouse's education becomes increasingly important as the payout threshold increases in explaining the decrease in influence of life insurance payouts. This reflects not only the correlation of net worth, income and deceased spouse's education with the well-being of the surviving spouse, but also the correlation between these factors and receiving a payout. These findings illustrate that a majority of the effect of life insurance may be due to financial sophistication as captured by net worth, income and the deceased spouse's education.

We next instrument for life insurance payouts using industry averages from the SIPP interacted with spouse's age of death. Each threshold is instrumented for by using the corresponding proportion of individuals in a given industry that have face value coverage greater than the given threshold. For example, the instrument for receiving a payout greater than \$20,000 is the proportion of individuals with life insurance coverage greater than \$20,000 in the same industry as the observation, conditional on being employed and dying before age 65.

The first stage is reported in Table 5 and indicates statistically significant correlation between life insurance payouts and industry averages for face values greater than \$10,000, \$20,000 or \$50,000. The F-statistics for the excluded instruments in the final three columns vary between 9.3 and 18.2 all above the 15 percent maximal bias threshold (8.96) in Stock and Yogo (2005). This indicates strong instruments for payouts greater than \$10,000,

$20,000 or $50,000.[21] We present the second stage regression results in Table 6. After taking into account the endogenous nature of life insurance payouts, we do not find an effect of life insurance in reducing the propensity to be below 1.5x FPL three years after death. Given that we do not find an effect three years following the spouse's death, it is very unlikely that we would find a significant effect looking at a longer time horizon.[22]

Life insurance payouts have the potential to decrease other, arguably less-efficient, ways of smoothing consumption such as increased labor force participation and re-marriage. Table 7 shows that receiving a life insurance payout greater than $50,000 does not reduce labor supply or remarriage and does not increase annuitization. Additionally, in Table 8 we show that the effect of life insurance payouts is the same for widows and widowers.

Lusardi, Michaud and Mitchell (2016) show that 30-40 percent of retirement wealth inequality comes from differences in financial knowledge. As is shown from the significant reduction in the influence of life insurance by adding basic socioeconomic variables, life insurance appears to be more of a marker for financial knowledge rather than a factor in improving the well-being of surviving spouses. Nonetheless, one would expect that receiving $50,000 could have a measurable influence on financial well-being. One possible explanation for the lack of a significant effect of life insurance on the well-being of surviving spouses is that individuals spend the money soon after receipt rather than using it to replace lost future income.

There is ample evidence supporting this argument. A similar type of lump sum distribution occurs when individuals with defined contribution (DC) plans change employment. When employees switch jobs, they generally have the option to leave their DC pension plans with their former employer, rollover the amount into their new employers' DC plan, or receive a preretirement lump sum distribution. Poterba and Venti (1998) find that lump sum distributions are common and most distributions are not rolled over into qualified retirement saving accounts. In order to encourage rollover of lump sum distributions into qualified savings accounts—rather than increase spending from the distribution—the federal government implemented excise taxes and withholding taxes to discourage such behavior. Chang (1996) finds that such tax penalties in general encourage rollover into qualified sav-

[21]In a similar fashion, Saiz (2010) cites evidence of a strong instrument given an F-statistic above the 20 percent maximal bias threshold.

[22]Due to sample limitations, we do not look at longer time horizons than three years.

ings accounts but are insignificant at deterring the use of funds for current consumption by lower-income recipients. In addition, Johnson, Parker and Souleles (2006) in a study on tax rebate spending find that individuals with the lowest income and the least liquid assets—those that are most likely to be near the poverty line—spent significantly more of the rebate relative to higher income individuals. This persistent tendency to quickly spend lump sum transfers, especially for those that are close to the poverty line, certainly could be the reason that medium- or long-run outcomes are unaffected.

One possible alternative to lump sum distributions of life insurance payouts is annuitization. As shown in the last section of Table 7, there is no evidence that surviving spouses—on their own accord—increase use of annuities upon receiving life insurance payouts. It is likely that sophisticated financial planning, like annuitization, is a low priority given the circumstances surrounding a premature or unexpected death. In the context of lump sum payments from DC plans, Brown (2009) argues for automatic annuitization to provide a guaranteed income stream for life to hedge against the risk of outliving one's income. Furthermore, Bütler and Teppa (2007) show using Swiss data that an initial default of annuitization is effective at increasing overall annuitization.

The literature on behavioral economics potentially sheds light on policy options to make lump sum payments from life insurance more effective. Individuals tend to display time inconsistent preferences thus necessitating the need for commitment mechanisms (Laibson, 1997). Research has shown that individuals display relatively high discount rates in the short run, but lower discount rates in the long run known as hyperbolic discounting (Ainslie, 1992). Therefore, individuals would be more likely to sign on to annuitization of life insurance payouts at the time they purchase life insurance coverage. An initial default from ESLI of annuitization (with the possibility of opting into a lump sum payment) might circumvent the issue of increased consumption following a payout.

However, there is one possible concern with automatic annuitization of life insurance payouts. Due to correlated socioeconomic status and bereavement effects, life expectancy between a husband and wife is highly correlated (Espinosa and Evans, 2008). The value of a life annuity is directly related to the owner's longevity and longer-lived individuals have more to gain from an annuity relative to shorter-lived individuals. Consequently, annuities would be a relatively worse deal for surviving spouses who have a higher mortality rate than the typical annuitant. Nonetheless, if insurance companies used pooled life insurance payout recipients in the determination of annuity payments then bundling the two products could be advantageous.

V. Conclusion

Premature death of a breadwinner can have devastating financial consequences on the surviving spouse. Increased longevity and years spent in retirement for the surviving spouse only exacerbates these negative consequences. Additionally, the aging population in the United States is straining the Social Security System including Survivor's Benefits, which provided an average monthly benefit of $1,309 to 3.8 million widows and widowers in 2010 (Shelton and Nuschler, 2012). These features highlight the importance of private life insurance in mitigating the negative financial consequences of premature death on elderly surviving spouses. Not only could life insurance reduce these negative financial consequences, but it also has the potential of reducing dependence on other government assistance programs such as SNAP, Medicaid, and SSI for elderly surviving spouses.

Using the HRS, we analyzed the effect of life insurance coverage and subsequent payouts on the well-being of surviving spouses. We find that after controlling for financial and educational factors and using instrumental variables to address endogeneity, the influence of life insurance disappears. These findings indicate that life insurance is more of a marker for financial planning rather than a driver at improving the well-being of surviving spouses and decreasing the incidence of government assistance. The HRS is the only panel dataset of which we are aware that allows us to follow a reasonably sized sample of widows and widowers before and after the death of their spouse and also observe life insurance payouts. Nevertheless, our sample sizes are fairly small and we are unable to fully exploit the regression discontinuity that arises from the institutional design of ESLI, which typically ratchets down payout at 65.

A natural question that remains, given that well-being is unaffected, is how are large lump-sum life insurance payouts actually utilized? Evidence from other studies suggests different lump sum payments translate into immediate, increased consumption but no parallel evidence exists for life insurance payouts. Assuming that behavior from life insurance payouts is in fact similar, a potential way to increase the effectiveness of life insurance is through a restructuring of policies for ESLI. Employers in conjunction with insurance companies could structure policies such that annuitization was the default method of receiving payout rather than a lump sum transfer. Given the extensive literature on inertia in the workplace, it is likely that relatively few employees would opt out of default annuitizaiton of life insurance payouts for their dependents, thereby potentially increasing well-being of surviving spouses (Madrian and Shea, 2001; Chetty et al., 2014; Harris and Yelowitz, 2015*a*).

Another question that arises from these findings is how large would life insurance payouts need to be to significantly influence well-being of surviving spouses. From our analysis, we know that even $50,000 dollars in payouts does not significantly change the well-being of surviving spouses. This implies that payouts would need to be larger, but how large it would need to be is uncertain, and without annuitization, it is unclear whether larger payouts would significantly influence well-being.

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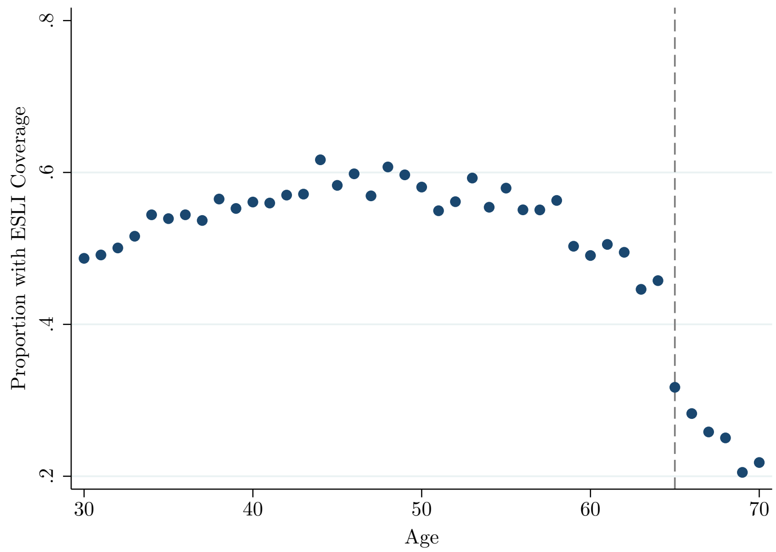
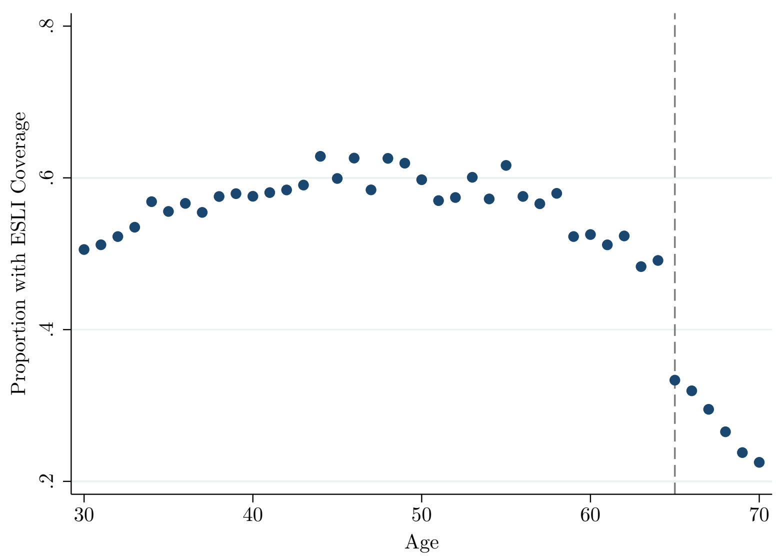


(a) Employed Individuals



(b) Employed with at least 12 years of Education

FIGURE 1. PROPORTION WITH ESLI COVERAGE BY AGE

Note: The sample comes from the 1990, 1991, 1992, and 1993 panels of the SIPP and includes employed individuals and employees with at least 12 years of education. Person level weights were applied.

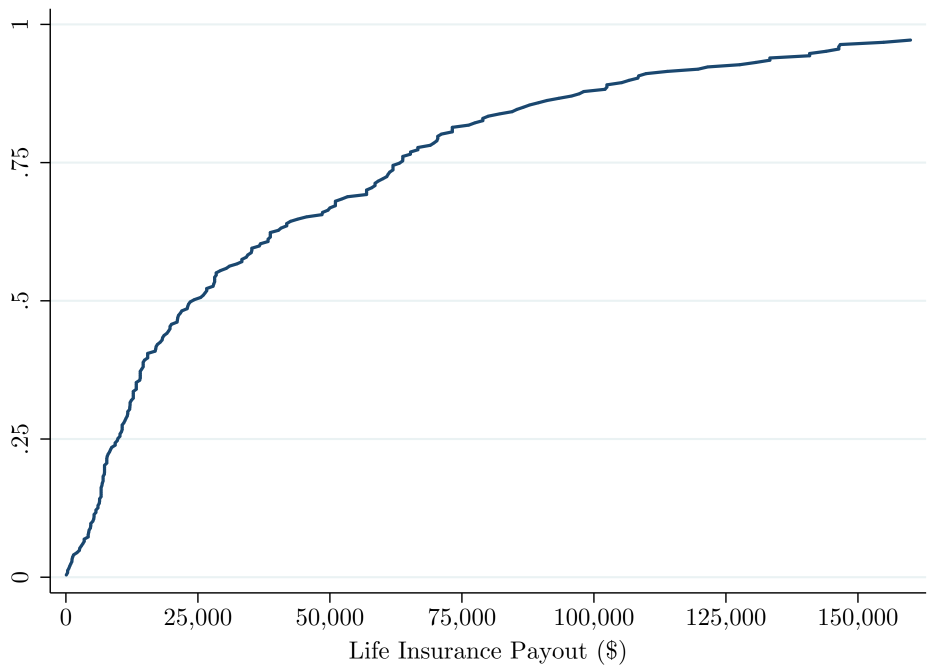


Figure 2. CDF: Life Insurance Payouts

Note: The CDF of payouts is conditional on receiving a payout. The sample consists of individuals whose spouses died between the ages of 55 and 68 from the HRS.

Table 1—Life Insurance Proportions by Industry- SIPP

Face Value:	>$0k	>$10k	>$20k	>$50k
Personal Services	0.52	0.42	0.33	0.23
Agriculture/Forestry/Fishing	0.53	0.47	0.40	0.29
Entertainment/Recreation	0.60	0.53	0.41	0.34
Retail	0.62	0.54	0.44	0.33
Business/Repair Services	0.65	0.59	0.51	0.41
Mining and Construction	0.68	0.63	0.54	0.43
Professional/Related Services	0.77	0.70	0.59	0.45
Wholesale	0.78	0.74	0.65	0.52
Manufacturing Non-durable	0.79	0.72	0.61	0.48
Finance/Insurance/Real Estate	0.82	0.75	0.67	0.55
Manufacturing Durable	0.82	0.76	0.66	0.53
Transportation	0.83	0.78	0.69	0.57
Public Administration	0.89	0.83	0.75	0.62
Secretaries				
Entertainment/Recreation	0.60	0.60	0.60	0.40
Personal Services	0.63	0.50	0.50	0.33
Business/Repair Services	0.65	0.56	0.46	0.34
Retail	0.69	0.63	0.51	0.37
Mining and Construction	0.75	0.67	0.49	0.31
Agriculture/Forestry/Fishing	0.75	0.67	0.42	0.25
Manufacturing Non-durable	0.78	0.72	0.60	0.47
Professional/Related Services	0.80	0.68	0.54	0.36
Finance/Insurance/Real Estate	0.81	0.71	0.65	0.45
Wholesale	0.81	0.74	0.64	0.43
Manufacturing Durable	0.83	0.73	0.58	0.43
Transportation	0.86	0.77	0.72	0.58
Public Administration	0.87	0.80	0.67	0.47
No High School Diploma & Earnings <$20,000				
Agriculture/Forestry/Fishing	0.26	0.16	0.12	0.05
Wholesale	0.35	0.29	0.18	0.09
Personal Services	0.36	0.24	0.13	0.07
Entertainment/Recreation	0.36	0.21	0.07	0.07
Business/Repair Services	0.36	0.28	0.23	0.16
Retail	0.37	0.27	0.18	0.12
Mining and Construction	0.38	0.31	0.22	0.10
Finance/Insurance/Real Estate	0.45	0.40	0.31	0.15
Manufacturing Durable	0.48	0.35	0.20	0.12
Transportation	0.49	0.44	0.27	0.16
Manufacturing Non-durable	0.49	0.35	0.22	0.10
Public Administration	0.51	0.34	0.26	0.14
Professional/Related Services	0.54	0.35	0.21	0.11

Note: Means are derived from the 1990, 1991, 1992, and 1993 SIPP panels consisting of 62,137 full and part time workers from ages 24 to 64. In the second and third panels, means were derived from 2,251 and 2,563 individuals respectively. Earnings used in the third panel are measured in 2012 dollars and roughly capture the lowest earnings quartile.

Table 2—Summary Statistics for Surviving Spouse

	(1)
Demographics (3 years after spouse's death)	
Age (Years)	65.29
White	0.83
Black	0.09
Hispanic	0.07
Other race/ethnicity	0.01
Education (3 years after spouse's death)	
Less than High School	0.25
High School Grad.	0.65
College Grad.	0.11
Poverty (3 years after spouse's death)	
Poverty Ratio	3.62
Under Poverty Line	0.11
Under 1.5x Poverty Line (Near Poverty)	0.26
Finances (at Initial Survey)	
Household Income ($1k)	42.29
Household Net Worth ($100k)	3.84
Life Insurance (at spouse's death)	
Received Payout	0.55
Received Payout > $5k	0.49
Received Payout > $10k	0.41
Received Payout > $20k	0.30
Received Payout > $50k	0.19
Received Payout > $100k	0.07
Payout ($1k)	27.46
Payout if >0 ($1k)	50.03
Observations	439

Note: The sample consists of surviving spouses from the HRS whose spouses died between the ages of 55 and 68. Respondent level weights were used to calculate means. Payouts, income, and net worth are reported in 2012 dollars.

Table 3—OLS, Dependent Variable: Below 1.5x poverty line (Near Poverty) 3 Years After Spouse's Death

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Surviving Spouse (at spouse's death)								
Life Ins. Payout > $0	−0.170***				−0.080**			
	(0.039)				(0.037)			
Life Ins. Payout > $10k		−0.141**				−0.015		
		(0.050)				(0.045)		
Life Ins. Payout > $20k			−0.154**				−0.011	
			(0.065)				(0.049)	
Life Ins. Payout > $50k				−0.161**				−0.045
				(0.064)				(0.048)
Surviving Spouse (at initial survey)								
High School Grad.					−0.111*	−0.115**	−0.115**	−0.115**
					(0.052)	(0.052)	(0.052)	(0.051)
College Grad.					−0.049	−0.055	−0.055	−0.051
					(0.061)	(0.062)	(0.061)	(0.060)
Black					−0.037	−0.038	−0.038	−0.041
					(0.043)	(0.042)	(0.042)	(0.042)
Hispanic					0.194*	0.205**	0.207**	0.206**
					(0.091)	(0.092)	(0.093)	(0.095)
Other race/ethnicity					−0.014	−0.002	−0.002	−0.012
					(0.097)	(0.097)	(0.097)	(0.098)
Employed Full-time					−0.096***	−0.092***	−0.092***	−0.095***
					(0.020)	(0.020)	(0.020)	(0.020)
Deceased Spouse (at initial survey)								
High School Grad.					−0.102***	−0.103***	−0.102***	−0.103***
					(0.032)	(0.030)	(0.030)	(0.030)
College Grad.					−0.131**	−0.127**	−0.127**	−0.123**
					(0.047)	(0.047)	(0.047)	(0.047)
Household (at initial survey)								
Net Worth 2nd Quartile					−0.156**	−0.164**	−0.166**	−0.165**
					(0.058)	(0.060)	(0.059)	(0.058)
Net Worth 3rd Quartile					−0.223***	−0.239***	−0.241***	−0.241***
					(0.069)	(0.070)	(0.068)	(0.067)
Net Worth 4th Quartile					−0.227***	−0.233***	−0.234***	−0.234***
					(0.073)	(0.073)	(0.073)	(0.073)
Income $25k-50k					−0.032	−0.035	−0.035	−0.034
					(0.042)	(0.040)	(0.040)	(0.041)
Income $50k-100k					−0.142***	−0.152***	−0.153***	−0.150***
					(0.034)	(0.034)	(0.036)	(0.037)
Income >$100k					−0.123**	−0.126**	−0.126*	−0.122*
					(0.053)	(0.058)	(0.060)	(0.059)

Note: The sample consists of 439 surviving spouses from the HRS whose spouses died between the ages of 55 and 68. Initial occupation code of the deceased spouse is included but not reported. Of the sample, 27.3 percent are under the near poverty line. Standard errors are clustered at the industry level and shown in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 4—Gelbach Decomposition: Explaining the Coefficient Change on Payout Due to Adding Controls

	Payout>$0		Payout>$10k		Payout>$20k		Payout>$50k	
	contribution	% of gap	contribution	% of gap	contribution	% of gap	contribution	% of gap
Household Net Worth	0.035**	38.9%	0.043***	34.3%	0.042**	28.6%	0.044**	38.0%
	(0.014)		(0.015)		(0.018)		(0.018)	
Household Income	0.017***	19.1%	0.026***	20.6%	0.032***	21.6%	0.028***	24.0%
	(0.006)		(0.007)		(0.008)		(0.010)	
Deceased Spouse's Education	0.009*	10.5%	0.016**	12.4%	0.023***	15.6%	0.023***	19.9%
	(0.005)		(0.006)		(0.006)		(0.007)	
Surviving Spouse's Education	0.012	13.0%	0.013	10.6%	0.015	10.6%	0.010	8.7%
	(0.007)		(0.009)		(0.010)		(0.010)	
Surviving Spouse's Race/ethnicity	0.015	17.4%	0.019*	14.9%	0.018	12.0%	0.010	8.5%
	(0.010)		(0.010)		(0.011)		(0.011)	
Surviving Spouse's Employment	0.002	2.8%	0.006	4.6%	0.008	5.3%	0.005	4.5%
	(0.003)		(0.005)		(0.007)		(0.006)	
Deceased Spouse's Occupation	0.001	1.7%	0.003	2.5%	0.009	6.3%	0.006	5.3%
	(0.007)		(0.007)		(0.009)		(0.021)	
Total Change	0.089***		0.125***		0.146***		0.114***	
	(0.016)		(0.019)		(0.032)		(0.037)	

Note: Numbers reported reflect the influence of each covariate in the change of the Payout coefficient from the bivariate to the full controls specification. The sum of an individual column will fully describe the Payout coefficient change from the bivariate case (first columns of Table 3) to the specification with full controls (latter columns of Table 3). Standard errors are shown in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5—First Stage: HRS

Dependent Variable: payout	>\$0	>\$10k	>\$20k	>\$50k
Deceased Spouse (at initial survey)				
Industry proportion with life insurance face value >\$0	0.078			
	(0.059)			
Industry proportion with life insurance face value >\$10k		0.263***		
		(0.071)		
Industry proportion with life insurance face value >\$20k			0.283***	
			(0.066)	
Industry proportion with life insurance face value >\$50k				0.305***
				(0.100)
Surviving Spouse (at initial survey)				
High School Grad.	0.059	0.054	0.065	0.020
	(0.037)	(0.057)	(0.053)	(0.040)
College Grad.	0.088	0.041	0.106	0.106
	(0.105)	(0.089)	(0.070)	(0.076)
Black	0.011	−0.021	−0.026	−0.074*
	(0.050)	(0.053)	(0.048)	(0.035)
Hispanic	−0.175**	−0.187**	−0.130***	−0.061
	(0.059)	(0.070)	(0.040)	(0.049)
Other race/ethnicity	−0.177	−0.173	−0.227	−0.282**
	(0.181)	(0.293)	(0.199)	(0.116)
Employed Full-time	−0.062	−0.042	−0.055	−0.065*
	(0.043)	(0.049)	(0.044)	(0.034)
Deceased Spouse (at initial survey)				
High School Grad.	0.008	0.010	0.058	−0.009
	(0.088)	(0.063)	(0.047)	(0.031)
College Grad.	−0.028	0.091	0.108	0.112
	(0.158)	(0.097)	(0.082)	(0.072)
Household (at initial survey)				
Net Worth 2nd Quartile	0.141**	0.198***	0.109*	0.044
	(0.049)	(0.046)	(0.058)	(0.037)
Net Worth 3rd Quartile	0.230***	0.187***	0.081	0.021
	(0.070)	(0.050)	(0.049)	(0.045)
Net Worth 4th Quartile	0.111*	0.157*	0.115	0.035
	(0.062)	(0.077)	(0.072)	(0.069)
Income \$25k-50k	0.049	0.049	0.061	0.022
	(0.083)	(0.068)	(0.043)	(0.034)
Income \$50k-100k	0.149	0.157**	0.172***	0.081
	(0.092)	(0.068)	(0.054)	(0.049)
Income >\$100k	0.064	0.128	0.162*	0.117
	(0.104)	(0.104)	(0.084)	(0.068)
Partial R^2 (excluded instrument)	0.002	0.024	0.025	0.026
F-stat (excluded instrument)	1.735	13.894	18.196	9.285

Note: The sample consists of 439 surviving spouses from the HRS whose spouses died between the ages of 55 and 68. Initial occupation code of the deceased spouse is included but not reported. Standard errors are clustered at the industry level and shown in parentheses *** p<0.01, ** p<0.05, * p<0.1. The F-statistic is calculated using standard errors clustered at the industry level.

TABLE 6—INSTRUMENTAL VARIABLES REGRESSION, DEPENDENT VARIABLE: BELOW 1.5X POVERTY LINE (NEAR POVERTY) 3 YEARS AFTER SPOUSE'S DEATH

	(1)	(2)	(3)	(4)
Surviving Spouse (at spouse's death)				
Received Life Ins. Payout	0.894			
	(1.081)			
Received Life Ins. Payout > $10k		0.289		
		(0.300)		
Received Life Ins. Payout > $20k			0.303	
			(0.316)	
Received Life Ins. Payout > $50k				0.355
				(0.367)
Surviving Spouse (at initial survey)				
High School Grad.	−0.163**	−0.126**	−0.130**	−0.118**
	(0.067)	(0.054)	(0.055)	(0.055)
College Grad.	−0.131	−0.064	−0.085	−0.090
	(0.152)	(0.075)	(0.082)	(0.090)
Black	−0.047	−0.031	−0.029	−0.011
	(0.056)	(0.042)	(0.041)	(0.049)
Hispanic	0.364	0.262***	0.248***	0.231***
	(0.231)	(0.086)	(0.080)	(0.082)
Other race/ethnicity	0.158	0.049	0.068	0.099
	(0.318)	(0.148)	(0.157)	(0.179)
Employed Full-time	−0.034	−0.076***	−0.072***	−0.065**
	(0.067)	(0.020)	(0.025)	(0.032)
Deceased Spouse (at initial survey)				
High School Grad.	−0.119*	−0.114***	−0.129***	−0.108***
	(0.065)	(0.040)	(0.049)	(0.032)
College Grad.	−0.105	−0.156**	−0.162**	−0.169**
	(0.144)	(0.065)	(0.074)	(0.076)
Household (at initial survey)				
Net Worth 2nd Quartile	−0.287*	−0.218***	−0.194***	−0.177***
	(0.174)	(0.082)	(0.072)	(0.058)
Net Worth 3rd Quartile	−0.446*	−0.294***	−0.265***	−0.248***
	(0.248)	(0.079)	(0.065)	(0.061)
Net Worth 4th Quartile	−0.324**	−0.270***	−0.260***	−0.237***
	(0.130)	(0.075)	(0.070)	(0.075)
Income $25k-50k	−0.083	−0.053	−0.057	−0.046
	(0.121)	(0.047)	(0.046)	(0.037)
Income $50k-100k	−0.298	−0.210**	−0.217***	−0.193***
	(0.241)	(0.082)	(0.081)	(0.061)
Income >$100k	−0.195	−0.175*	−0.186*	−0.179*
	(0.170)	(0.094)	(0.102)	(0.096)

Note: The sample consists of 439 surviving spouses from the HRS whose spouses died between the ages of 55 and 68. Initial occupation code of the deceased spouse is included but not reported. Of the sample, 27.3 percent are under the near poverty line. Standard errors are clustered at the industry level and shown in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 7—Alternative Metrics for Well-Being of Surviving Spouse 3 Years After Spouse's Death

Dependent Variable:	Work 3 Years After Death			Married 3 Years After Death			Annuity 3 Years After Death		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Received Life Ins. Payout > $50k	0.016	0.073	0.280	−0.044*	−0.040	0.334	0.018	−0.011	−0.133**
	(0.049)	(0.044)	(0.419)	(0.024)	(0.025)	(0.274)	(0.027)	(0.037)	(0.060)
Controls:	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
IV:	No	No	Yes	No	No	Yes	No	No	Yes

Note: The sample consists of 439 surviving spouses from the HRS whose spouses died between the ages of 55 and 68. Controls include education, race/ethnicity and education of the surviving spouse, education and initial occupation code of the deceased spouse, and initial net worth and income of the household. Standard errors are clustered at the industry level and shown in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 8—Does Gender Matter? OLS, Dependent Variable: Below 1.5x poverty line (Near Poverty) 3 Years After Spouse's Death

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Surviving Spouse (at spouse's death)								
Received Life Ins. Payout	−0.156**	−0.044						
	(0.064)	(0.054)						
Received Life Ins. Payout * Male	−0.039	−0.097						
	(0.095)	(0.092)						
Received Life Ins. Payout > $10k			−0.178*	−0.039				
			(0.088)	(0.077)				
Received Life Ins. Payout > $10k * Male			0.087	0.059				
			(0.114)	(0.105)				
Received Life Ins. Payout > $20k					−0.195**	−0.039		
					(0.079)	(0.068)		
Received Life Ins. Payout > $20k * Male					0.084	0.072		
					(0.084)	(0.077)		
Received Life Ins. Payout > $50k							−0.204**	−0.076
							(0.068)	(0.055)
Received Life Ins. Payout > $50k * Male							0.117	0.104
							(0.106)	(0.079)
Male	−0.042	0.006	−0.109*	−0.073	−0.111**	−0.068*	−0.101**	−0.069**
	(0.071)	(0.062)	(0.058)	(0.047)	(0.043)	(0.032)	(0.037)	(0.024)
Additional Controls:	No	Yes	No	Yes	No	Yes	No	Yes

Note: The sample consists of 439 surviving spouses from the HRS whose spouses died between the ages of 55 and 68. Additional controls include education, race/ethnicity and education of the surviving spouse, education and initial occupation code of the deceased spouse, and initial net worth and income of the household. Of the sample, 27.3 percent are under the near poverty line. Standard errors are clustered at the industry level and shown in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Table A1—Industry Variation with Occupational and Educational Controls: SIPP

Dependent Variable: Total Coverage	>$0	>$10k	>$20k	>$50k
Industry				
Mining and Construction	0.035	0.013	−0.002	0.017
	(0.023)	(0.024)	(0.026)	(0.026)
Manufacturing Non-durable	0.107***	0.073***	0.039	0.054**
	(0.022)	(0.024)	(0.025)	(0.025)
Manufacturing Durable	0.123***	0.102***	0.075***	0.083***
	(0.022)	(0.023)	(0.024)	(0.025)
Transportation	0.116***	0.099***	0.080***	0.101***
	(0.022)	(0.023)	(0.025)	(0.025)
Wholesale	0.078***	0.067***	0.051**	0.049*
	(0.023)	(0.024)	(0.025)	(0.026)
Retail	−0.021	−0.058**	−0.086***	−0.076***
	(0.022)	(0.023)	(0.025)	(0.025)
Finance/Insurance/Real Estate	0.088***	0.053**	0.039	0.052**
	(0.022)	(0.023)	(0.025)	(0.025)
Business/Repair Services	−0.040*	−0.066***	−0.083***	−0.054**
	(0.022)	(0.024)	(0.025)	(0.025)
Personal Services	−0.067***	−0.109***	−0.131***	−0.104***
	(0.024)	(0.025)	(0.027)	(0.027)
Entertainment/Recreation	−0.071**	−0.108***	−0.168***	−0.123***
	(0.028)	(0.030)	(0.032)	(0.032)
Professional/Related Services	0.074***	0.021	−0.027	−0.047*
	(0.021)	(0.023)	(0.024)	(0.024)
Public Administration	0.146***	0.119***	0.090***	0.089***
	(0.022)	(0.024)	(0.025)	(0.025)
Income and Education				
Log Earned Income	0.054***	0.062***	0.067***	0.065***
	(0.001)	(0.001)	(0.002)	(0.002)
High School Grad	0.114***	0.134***	0.143***	0.146***
	(0.006)	(0.006)	(0.007)	(0.007)
College Grad	0.123***	0.164***	0.209***	0.247***
	(0.007)	(0.007)	(0.008)	(0.008)

Note: The sample consists of 61,716 workers from the SIPP from panels 1990, 1991, 1992, 1993 between the ages of 24 and 64. Occupation code is included but not reported. The ommitted industry code is for Agriculture/Forestry/Fishing. Standard errors are shown in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A2—Alternative Metrics for Well-Being of Surviving Spouse 3 Years After Spouse's Death

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent: Under 1x FPL												
Surviving Spouse (at spouse's death)												
Received Life Ins. Payout	−0.111**				−0.047*				0.978			
	(0.037)				(0.026)				(0.813)			
Received Life Ins. Payout > $10k		−0.089**				0.003				0.316*		
		(0.040)				(0.027)				(0.189)		
Received Life Ins. Payout > $20k			−0.092*				0.011				0.334*	
			(0.045)				(0.026)				(0.185)	
Received Life Ins. Payout > $50k				−0.077				−0.008				0.398*
				(0.053)				(0.041)				(0.241)
Dependent: Received Food Stamps												
Surviving Spouse (at spouse's death)												
Received Life Ins. Payout	−0.048**				−0.009				−0.008			
	(0.020)				(0.013)				(0.407)			
Received Life Ins. Payout > $10k		−0.042*				0.003				−0.000		
		(0.023)				(0.010)				(0.131)		
Received Life Ins. Payout > $20k			−0.045*				0.001				0.003	
			(0.025)				(0.012)				(0.141)	
Received Life Ins. Payout > $50k				−0.043*				−0.011				0.007
				(0.023)				(0.017)				(0.164)
Dependent: On Medicaid												
Surviving Spouse (at spouse's death)												
Received Life Ins. Payout	−0.069***				−0.029*				0.383			
	(0.019)				(0.014)				(0.537)			
Received Life Ins. Payout > $10k		−0.055**				−0.007				0.114		
		(0.020)				(0.014)				(0.143)		
Received Life Ins. Payout > $20k			−0.054**				0.009				0.117	
			(0.021)				(0.019)				(0.151)	
Received Life Ins. Payout > $50k				−0.059**				−0.002				0.115
				(0.021)				(0.016)				(0.166)
Controls:	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV:	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes

Note: The sample consists of 439 surviving spouses from the HRS whose spouses died between the ages of 55 and 68. Controls include education, race/ethnicity and education of the surviving spouse, education and initial occupation code of the deceased spouse, and initial net worth and income of the household. Of the sample, 12.8 percent are under the poverty line, 4.8 percent received Food Stamps, and 6.2 percent were on Medicaid. Standard errors are clustered at the industry level and shown in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table A3—Deceased Spouse Mean Comparison at Last Interview

Death Age:	62-64	65-68
Work Full-time	0.26	0.15*
Spouse's Age	59.19	63.07***
Self-reported Probability of Living to 75	0.56	0.58
White	0.82	0.73
Black	0.11	0.18
Hispanic	0.07	0.09
Other race/ethnicity	0.00	0.00
Has a Child	0.96	0.98
Less than High School	0.20	0.23
High School Grad.	0.72	0.63
College Grad.	0.08	0.15
Earned Income ($1k)	14.72	19.52
Household Net Worth ($100k)	2.74	3.83
Observations	100	200

Note: Sample consists of individuals who died between the age 62 and 68 measured in the last interview prior to death from the HRS. Income and net worth are reported in 2012 dollars. Indicators for statistical difference between means are given by *** $p<0.01$, ** $p<0.05$, * $p<0.1$