Marriage Protection or Marriage Selection?

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Abstract

Researchers from a variety of fields have noted a sharp rise in mortality for widows soon after the death of their spouse. Because of assortative mating, married couples tend to share many of the same characteristics, so this result may reflect an omitted variable bias rather than a causal relationship. The heart of this paper is the notion that some causes of death reveal more information about the surviving spouse than others. In the extreme, if a cause of death was randomly assigned, then these types of deaths could be used to identify the marriage protection effect. In practice, we cannot specify what causes of death are randomly assigned, but instead, we can identify those that are uncorrelated with observed characteristics. Specifically, we use data from the National Longitudinal Mortality Survey and the National Health Interview Survey Multiple Cause of Death supplement to create longitudinal datasets of married couples, aged 50 to 70. We initially use this sample to identify those causes of death that are predicted by socio-economic status (income and education) and those that are not. We refer to these two types of deaths as informative and uninformative causes of death, respectively. If the heightened mortality of surviving spouses is subject to an omitted variables bias, in single-equation models, we should find a stronger marital protection effect for informative deaths than for uninformative causes of death. In Cox proportional hazard models, we find the death of a spouse from an uninformative cause has a smaller impact on mortality than a death from an informative cause. We also find that for husbands the death of a spouse from an uninformative cause generates a statistically significant increase in mortality.

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I. Introduction

Research from a variety of disciplines documents the social and economic outcomes of the married and their families are better along many dimensions than singles and their families. Married people, for example, have higher wages, lower levels of unemployment, accumulate more wealth, have higher rates of health insurance coverage, report higher levels of happiness, and are less likely to be involved in violent crimes, compared to singles. Researchers have also documented a potential health benefit of marriage -- married people have a longer life expectancy than the non-married. Scholars have titled this relationship 'marriage protection'. Some of the most convincing evidence consistent with the marriage protection hypothesis demonstrates a heightened mortality rate for widows and widowers in the years just after the death of their spouse.

There is however an alternative hypothesis called marriage selection that may explain the longer lifespans of married couples. In a marriage market where potential husbands and wives find one another, there is a selection process that underlies the matching of two people. Much of the empirical works about marriage markets demonstrate positive assortative mating, which is the occurrence of mating between similar individuals at higher than random frequencies. Given the importance health habits have on life expectancy and mortality (McGinnis and Foege, 1993) and the similarity in health choices by spouses, we would expect to see life expectancy patterns among the married to converge as well.

This investigation estimates the impact of spousal death on the surviving spouse's mortality. The heart of this paper is the notion that some causes of death reveal more information about the surviving spouse than others. In the extreme, if a cause of death was randomly assigned, then these types of deaths could be used to identify the marriage protection effect. In practice, we cannot specify what causes of death are random, but instead, we can identify those that are uncorrelated with observed characteristics. We use both the National Longitudinal Mortality Survey (NLMS) and the National Health Interview Survey (NHIS) data merged with the Multiple Cause of Death (MCOD) supplement to create longitudinal datasets of married couples, aged 50 to 70. We initially use this sample to identify those causes of death that are predicted by socio-economic status (income end education) and those that are not. We refer to these two types of deaths as informative and uninformative causes of death, respectively. If the heightened mortality of surviving spouses is subject to an omitted variables bias, in single-equation models, we should find a stronger marital protection effect for informative deaths than for uninformative causes of death. In contrast, if marital protection explains all of the heightened mortality of a recent widow, then the impacts of informative and uninformative deaths should be similar.

In the next section of the paper, we discuss some of the previous literature that documents the longer lifespans of married couples and the heightened mortality of the recently widowed. In section III, we use the NLMS and NHIS/MCOD datasets to recreate some of the stylized facts from the literature. In section IV, we use the same data to select a sample of informative and uninformative deaths for our empirical strategy to deal with an omitted variable bias. In Section V, we re-estimate the Cox proportional hazard models from section III but include indicators for death from informative and uninformative causes. In these models, we find the death of a spouse from an uninformative cause has a smaller impact on the surviving spouse's mortality than a death from a correlated cause, which is evidence that the traditional models are subject to an omitted variables bias. In addition, we find that deaths of wives from uninformative causes generate statistically significant increases in mortality for the surviving husband, a result consistent with the theory of marital protection.

II. Marital Status and Mortality

The antecedents for the current study flow from two different but related strands of literature. The first group of papers document lower mortality rates among the married. Empirical investigations of the differences in mortality rates between married and unmarried individuals go back as far as Farr (1858) and Durkheim (1897). The negative association between marriage and mortality has been documented in the US with by a number of authors including Gove (1973), Kobrin and Hendershot (1977), Smith and Waitzman (1994), Mergenhagen, Lee, Gove (1985), Rogers (1995), Kisker and Goldman (1987), Lillard and Waite (1995), Johnson et al (2000). This relationship has been established for other countries including 16 developed countries (Hu and Goldman, 1990), England (Gardner and Oswald, 2002), Canada (Trovoto, 1991), Israel (Manor et al. 2000), and Bangladesh (Rahman, 1993).

There are a variety of reasons that mortality rates may be lower among the married. Marriage may increase the financial standing of the partners by increasing family income or providing insurance when bad health and/or financial shocks occur (Lillard and Waite, 1995). Marriage may also provide important psychological benefits such as reducing stress, improving one's disposition or integrating a person into a community.[1] Finally, marriage may discourage risky behavior such as smoking (Duncan, Wilkerson and England, 2003) or criminal activity (Laub, Nagin and Sampson, 1998) or encourage healthy behavior such as visiting the doctor.

In a related line of work, researchers have also documented heightened mortality of the recently widowed, a relationship referred to by some as the "bereavement effect". This basic

[1] Gove (1973) notes that much of the mortality benefits of marriage stem from reductions in causes of death that are associated with social fractures such as suicide, murder, and accidental deaths. In recent years a growing literature has demonstrated a link between social networks and mortality with those less connected to their community, friends, relatives or coworkers experiencing a higher mortality rate Berkman and Syme, 1979; Blazer, 1982; House et al, 1982; Berkman 1995 and 2000; Cohen et. al. 1997; Zuckerman et. al. 1984; Putnam 2000). Seeman et al (1987) and Blazer (1982) looked at the elderly in particular and found that higher mortality rates in those with fewer social ties.

statistical relationship between widowhood and mortality has been documented by a number of authors including Cox and Ford (1964), Parkes, Benjamin and Fitzgerald (1999), Hesling and Szklo (1981), Hesling, Szklo and Hi (1981), Kaprio, Koskenvou and Rita (1987), Mendes de Leon et al. (1993), Mineau, Smith, and Bean (2002), Korenman, Goldman and Fu (1997), and Lillard and Waite (1995), just to name a few. Excess mortality among the recently widowed has been demonstrated to exist in a wide variety of age groups, socioeconomic levels, countries and cultures. The impact of a spouse's death is qualitatively large. After controlling for a variety of factors, Schaefer, Quesenberry and Wi, (1995) and Kaprio, Koskenvou and Rita (1987), for example, find mortality rates double for the surviving spouse in the first year after the death of their spouse. Estimates also suggest that the bereavement effect is strongest in the period right after the death of a spouse (Lichtenstein, Gatz, and Berg 1998; Manor and Eisebach, 2003).

All of the studies mentioned above demonstrate excess mortality for surviving males, but the results for surviving females are less definitive. Helsing and Szklo (1981) find no excess mortality for widows, and Mineaeu, Smith and Bean (2002) find smaller effects for widows compared to widowers but the results for women vary considerably across birth cohorts. Lillard and Waite (1995) find some excess mortality for women but the results are sensitive to model specification. Data on couples from Northern California (Schaefer, Quesenberry and Wi, 1995), Finland (Kaprio, Koskenvou and Rita, 1987), and Israel (Manor and Eisenbach, 2003), show similar bereavement effects on mortality for males and females.

There are several pathways through which widowhood can become an immediate health risk. Some suggest that excess mortality is generated by the emotional stress of the death of a loved one (Martikainen and Valkonen, 1996; Louma and Pearson, 2002) or the emotional and physical stress of caring or a dying loved one (Christakis and Iwashyna, 2003). Recent research by Wittstein et al. (2005) suggests that emotional stress can cause the over production of particular hormones that can cause sudden life-threatening heart spasm in otherwise healthy people. Rosenbloom and Whittington (1993) find elderly widowed people suffer from poor nutrition right after the death of their spouse. Finally, Iwashyna and Christakis (2003) find evidence suggesting that widowhood compromises the quality of medical care sought by the surviving spouse.

The accumulated empirical evidence is convincing that mortality rates of the bereft are higher than their married counterparts. It is, however, not clear whether we can interpret these events as causal relationships. These results are potentially explained by an alternative hypothesis called marriage selection, which has no causal interpretation. In a marriage market where potential husbands and wives find one another, there is a selection process that underlies the matching of two people (Becker, 1973 and 1974). Much of the empirical work about marriage markets demonstrate positive assortative mating, which is the occurrence of mating between similar individuals at higher than random frequencies. There are strong positive correlations between many characteristics of married couples including ages, years of education, IQ, height, waist circumference, and even earlobe length (Vandenberg, 1972; Harrison, Gibson and Hiorns, 1976; Mascie-Taylor, Gibson, 1979; Johnson, 2002; Caspi and Herbener, 1994; Murray, 2000). Not surprisingly, there are also strong correlations in the investments that husbands and wives make concerning their health. Many married couples share a love of exercise, food, wine, cigarettes, or a sedentary lifestyle. Given the strong correlation between health and mortality (McGinnis and Foege, 1993) and the similarity in health choices by spouses, we would expect to see life expectancy patterns among the married to converge as well.

The similarity in the characteristics of spouses is also matched by a similarity in life events. Married couples that last past middle-age live through the same inter-temporal events, shocks, income patterns, consumption patterns. Such a convergence of lives can explain why there is evidence that widowed spouses die soon after the loss of their spouse: simply put, they started leading the same lives (Smith and Zick, 1994).

To demonstrate the strong correlation in health and health habits among older married couples, we use a sample of older married couples from the 1987-1990 National Health Interview Survey (NHIS). We introduce the data set in more detail in the next section, but we note here that the samples include information on white, married men aged 50-70 and a similar sample of women. First, we consider whether knowing information about a husband's health habits conveys any information about the wife's behavior. We look at four discrete outcomes: whether the person is obese (has body mass index > 30), whether they self-report fair or poor health, whether they had any bed rest days in the past 12 months, and whether they had a short term hospital stay in the past 12 months. We calculate the conditional probability that a wife answers yes to each of these questions (X_w=1) given that their husband answers yes or no (X_w =1 or 0).

The results from this exercise are reported in the top half of Table 1. Equality of the conditional probabilities means that the behaviors and outcomes for wives and husbands are independent. In the married women sample, for each of the four variables, the differences in the conditional probabilities are large and we easily reject the null hypothesis that the conditional probabilities are equal. Wives with obese husbands are twice as likely to report they are obese. Wives with husbands in fair or poor health are 4.5 times as likely to report they are in poor health compared to when their husband are not in fair or poor health.

In the lower half of the table, we repeat the exercise for white married males, aged 50-70. In each of these cases, we can reject the null of equality in the conditional means and the relative differences and absolute differences in probabilities are similar to the married women sample.

The NHIS survey that we use in this analysis does not ask respondents whether they smoked. Supplemental surveys to the NHIS do ask about smoking habits but these surveys are typically only administered to one person in the household. Therefore, we cannot conduct this same analysis with this key health behavior. In the last row of each panel in Table 1, we generate estimates of probabilities for whether a married respondent currently smoked based on whether their spouse smokes from the September 1992, January 1993 and May 1993 Tobacco Use Supplements from the Current Population Survey.[2] Both married women and married men are about three times as likely to report they smoke when their spouse smokes, compared to when their spouse does not smoke.

To date, there have been few attempts, other than efforts to control for more observed characteristics, to isolate whether the bereavement effect is a statistical correlation or a causal effect. Lichtenstein, Gatz and Berg (1998) use a large sample of twins from the Sweden to control for unobserved genetic and environmental factors in surviving spouses. In this study, the authors find that a recently-bereaved males and females have substantially higher mortality after the death of their spouse compared to their twin counterpart who still has a living spouse. Using a large sample from Finnish mortality records, Martikainen and Valkonen (1996) find that widows/widowers who die after the death of their spouse, as a group, have excess mortality in causes of death associated with behaviour such as motor vehicle accidents, heart disease, suicide, and alcohol-related causes.

[2] The CPS is a monthly survey of households in the US and respondents are in the survey for the same four months in a to-year period. Therefore, one-quarter of the sample rotates out of the sample, either temporarily or permanently each month.. The TUS we use are administrated in September 1992, January 1993 and May 1993 and since they are all five months apart, each survey has a completely different sample. These surveys are designed to be pooled together.

III. Data, Descriptive Statistics, and Cox proportional hazard model

The data we use in our analysis come from two different sources: the National Longitudinal Mortality Study (NLMS) and the NHIS Multiple Cause of Death Sample. Both datasets are similar in their construction, for they begin with an initial cross-section of individuals and include a mortality follow-up with cause of death information, which makes our empirical study possible. Mortality for most observations is censored by the endpoints of the follow-up periods; so, we use Cox proportional hazard models to compare mortality risks between different marital states.

Data

The NLMS (Sorlie, Backlund and Keller, 1995; Rogot, Sorlie, Johnson and Schmitt, 1992) is a project that has linked data from a number of Current Population Surveys and the 1980 census to the National Death Index (NDI) . We use a public-use version of the NLMS that contains data from five monthly CPS samples from 1979 through 1981. The CPS data provides information on household income, labor force status, individual education and other demographic variables; however, it does not provide any information on health status. The endpoint to the mortality follow-up is fixed to nine years from entry into the CPS; so, we observe mortality for those who die in our observation period. The NLMS measures days of follow-up from the original survey. Data from the NDI includes information on the cause of death, which is recorded using the ICD-9 coding system.[3] The NLMS contains CPS and NDI information for 637,162 individuals.

[3] The World Health Organization's International Classification of Disease, Ninth Revision, which is used to classify mortality data from death certificates.

NHIS and Multiple Cause of Death (MCOD) supplement file are data sets maintained by the National Center for Health Statistics (NCHS). The NHIS is a cross-sectional household interview survey the NCHS conducts continually throughout the year. For the interview years our data span, 1987-1990, between 36,000 and 47,000 households were surveyed providing data records for 92,000 to 125,000 individuals (NCHS, 2005). The household information includes type of living quarters, size of family, region, and other household identifiers. Personal information includes demographic variables (i.e. race, sex, age, etc.), marital status, veteran status, family income, employment information, and detailed health information such as self-reported health status, bed days, work-loss days, and restricted-activity days.

In similar fashion to the NLMS, the NHIS data can be merged to the Multiple Cause of Death (MCOD) supplement that matches individuals 18 years and older at the time of interview for NHIS to the NDI. Using the MCOD, we are able to observe deaths of respondents to the month and year through December 31, 1995. MCOD also provides cause of death information using ICD-9 codes. Merging mortality data to the NLMS and NHIS generates longitudinal characteristics of otherwise cross-sectional data sets, enabling us to investigate how marital status impacts mortality for married men and women.

Analysis Sample

We focus our attention to married, white, non-Hispanic people between the ages of 50 and 70. Using household identification numbers and variables in the NLMS and NHIS that identify a respondent's relationship to the head of household, we match the records of husbands and wives. Although spouses of 50-70 year olds are primarily within this age range, some are not, so there are different sized samples for "married men" and "married women".

Table 2 provides the means for several of the variables of interest in our study of marriage and mortality from the two data sources. Among the NLMS data, a smaller proportion of women die within nine years of being surveyed than do married men, 9 percent for women compared to 18 percent for men. Likewise, 8 percent of married men become widowers after their initial interview, and 22 percent of married women lose their spouse. The NHIS produces mortality statistics slightly lower than the NLMS. As a different exercise, we calculate mortality rates over a shorter period of time after the initial interview. In Table 2, we report the proportion of married men and married women that died within five years of entering the survey and the proportion that were widowed over the same period. These mortality rates for both men and women are much lower compared to the rates we compute when we do not restrict the follow-up period. Tables A and B of the appendix provide means and standard deviations for income, education and age variables, as well as mortality, for the NLMS and NHIS.

Cox Proportional Hazard Models

In our data, an observation consists of a married couple that enters the NLMS between 1979 and 1981 or the NHIS at some point between January 1, 1987 and December 31, 1990. Our observation period begins with this entry point and extends nine years (NLMS), until December 31, 1995 (NHIS), or until death, which ever comes first. Our data is therefore considered right-censored, because we do observe events (i.e. widowhood and death) after the end of the mortality follow-up period. While there are several modeling techniques for the analysis of survival data, we follow previous work by employing a Cox proportional hazard model, which is a maximum partial likelihood estimation method (Cox, 1972; Allison, 1995). The Cox model begins with the assumption that hazard for individual i can be written as

(1) $h_i(t) = \lambda_o(t)\exp(X_i\beta)$,

where, for simplicity, we assume X_i is a vector of time invariant characteristics. The model assumes that the hazard at time t for individual i is a function of the baseline hazard $\lambda_o(t)$, plus a function of observed characteristics. The baseline hazard is left unspecified but it is assumed to be constant across people, meaning that the proportional hazard for person i relative to person j for fixed time t is only a function of observed characteristics $h_i(t)/h_j(t) = \exp(X_i\beta)/\exp(X_j\beta)$. To get around specifying the baseline hazard, the Cox model specifies a partial likelihood, which can be described as follows. If we order the data from the shortest to longest spell $t_1, t_2, \ldots t_n$, the conditional probability that person 1 dies at time period t_1, given that anyone could have died at that time, is

(2) $\lambda_o(t_1)\exp(X_1\beta)/ \Sigma_i \lambda_o(t)\exp(X_i\beta) = \exp(X_1\beta)/ \Sigma_i \exp(X_i\beta)$.

By definition, the baseline hazard drops out and term at the right in equation (2) represents the partial likelihood for person 1. The model is partial likelihood because the estimation does not exploit all the information in the data, namely, the baseline hazard $\lambda_o(t)$. As a result, the estimates for β are consistent but not efficient. However, the benefit of the procedure is that the researcher does not have to specify the form for the baseline hazard $\lambda_o(t)$. The Cox model outlined in (1) and (2) is easily adapted to include incomplete spells and time-varying covariates. In our study, we are primarily interested in a set of time-variant variables that indicate the respondent's spouse has died.

In Table 3, we report results from Cox proportional hazard models for married women and married men. In these specifications, the time-invariant variables are income, education, and age at initial survey, which are all measured at the first interview. The only time-variant variable is one that takes a value of 1 in the day or month (depending on NLMS or NHIS) an individual becomes a widow, and all subsequent days or months, and it equals zero otherwise. There are two panels to the table--in the top panel are the Cox regression results for married men and in the bottom panel are the results for married women. In each panel, the left column shows results using NLMS data, and the right column displays NHIS results. Since all of the covariates are dummy variables, for each model, we report both the parameter estimate and the hazard ratio, which measures the ratio of the hazard when the particular covariate equals 1 divided by the hazard when the same covariate is zero. The two NLMS samples consist of 37,775 married men and 34,465 married women. The two NHIS samples have 20,290 observations of married women and their spouses and 22,164 observations of married men and their spouses.

The important point to take away from Table 3 is that we find both widowed men and women have greater than 20 percent excess mortality rates than married men and women, except for widowed women in the NLMS data who have 19% excess mortality. The NLMS results suggest that married men have a much higher risk of dying after the death of a spouse (hazard ratio = 1.34) than do married women (h.r. = 1.19). On the other hand, the NHIS data produce widowhood effects that are nearly the same for both married men (h.r. = 1.19) and married women (h.r. 1.21).

These results are similar to findings in previous literature, and they will serve as base results for comparison purposes in section V. Also, these results, like their predecessors, are shadowed by the concern over selection mechanisms at work in the marriage market (i.e.

assortative mating) that cannot be observed and included in the model specification. The possibility of such an omitted variable bias can cast doubt over the interpretation of a model's results.

IV. Informative and Uninformative Causes of Death

In order to reduce the omitted variable bias possibly present in previous analyses, we exploit the exogeneity that some causes of spousal death exhibit in their affliction (e.g., leukemia, brain hemorrhage). In these special cases, the death of a spouse reveals less information regarding the health of the surviving spouse. Therefore, if there is heightened mortality after the death of a spouse from a disease that conveys less information about the health of the surviving spouse, we are less concerned that the results are driven by an omitted variables bias. In what follows, we provide evidence that certain causes of death (COD) are uncorrelated with socio-economic status (SES) indicators like income and education; therefore, the COD cannot be explained by assortative mating.

We use income and education as our measures of socioeconomic status because the bulk of research that has examined the SES/mortality gradient for all-cause and cause-specific mortality has predominantly used these two variables as the primary covariates of interest. The genesis for much of the work in social sciences is the research of Kitagawa and Hauser (1973) who matched survey data from the 1960 Census long form, conducted in April of 1960, to death records from the May - October 1960 period. The stylized facts from their work are that mortality rates decline with income and education but at a decreasing rate. This relationship is present for all age groups but Kitagawa and Hauser find less variation in mortality across socioeconomic groups for the elderly. [4] These basic results have been replicated for more recent data sets in numerous papers for all cause mortality and the basic stylized facts are present in a number of cause-specific death categories.

Causes of Death

From the NLMS data described previously, we use detailed 3-digit ICD-9 cause of death information to construct a series of dummy variables to indicate whether a person died in the nine-year follow-up from a particular cause.[5] For example, a dichotomous variable for the cause of death "ischemic heart disease" takes on the value of 1 for an individual who dies of ischemic heart disease. For both married men and women, we then run a series of logistic regressions that identify whether the death from a particular cause is predicted by the income and education of the respondent—our SES measures, controlling for a cubic term in age.[6] For each regression, we conduct three -2 loglikelihood tests: whether the income dummies are jointly zero, whether the education dummies are jointly zero, and whether both the income and education dummies are jointly zero. If we can reject all three null hypotheses, then we consider the cause to be an informative-COD group (ICOD). Likewise, if we cannot reject the three hypothesis tests, we consider the cause of death to be uninformative (UCOD).[7]

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[4] The more egalitarian nature of mortality among the elderly has also been recently documented by Hurd, McFadden and Merrill (1999), Deaton and Paxson (1998), and Snyder and Evans (2002).

[5] NLMS data is solely used to develop the UCOD grouping because of the greater number of observations providing a greater variance in cause of death. However, when we conduct a similar analysis using the NHIS data, we obtain nearly identical groupings of UCOD and ICODs.

[6] In these initial models, we use a cubic in age rather than a set of age dummy variables because some single-year age groups have zero deaths.

[7] Because the UCOD category is small relative to ICOD, the penalty of including an invalid cause in the UCOD category is relatively high. Subsequently, we use a cutoff p-value of 0.25 to selected informative and uninformative causes of death.

We note that we are careful to not disaggregate death causes into too small of cells so that we have a high Type II error rate for the -2 log likelihood tests.[8] For example, there are very few incidents of infectious disease deaths; therefore, we aggregate to a more general COD, in this case the residual category. We find 9 percent of deaths for men married to women aged 50-70 and 26 percent of deaths for women married to men aged 50-70 falls into causes that are uncorrelated with observed characteristics. A full list of the causes in the UCOD group for both men and women is listed in Table 4. The list includes the number of deaths attributed to each cause, as well as each cause's proportion of UCOD deaths, using NLMS data only. Some other authors have demonstrated in the past that these causes of death are uncorrelated or, at best, weakly correlated with SES. Steenland, Henley and Thun (2002) use data from 2.2 million respondents to two American Cancer Society cohort studies and find less educated women have higher death rates for almost all cause specific groups they consider except external causes (e.g. accidents) and breast cancer. They also show a weak relationship between education and stroke mortality with the only statistically significant relationship being the two lowest education groups. The same study finds for men a weak relationship between education and prostate cancer death risk, a cause in our UCOD group. They found this was true for household income and education, for men. In our group of UCOD, we do not include motor-vehicle accidents among men because of the strong correlation between SES indicators and these accidents, but we do include other types of accidents like poisonings and accidental falls. Eng, et al. (2002) find similar evidence, however, they do not make the distinction between motor vehicle and

[8] To minimize the Type II error rate, we use the following procedure. For males and females, we first run a series of logistic regression models where the outcome of interest is a five-year cause specific mortality rate for each of the 272 CODs in our sample. The covariates include cubics in age plus a set of dummy variables for income and education. Next, we find the smallest mean for the COD where we cannot reject the null hypotheses that (1) all the education estimates are jointly zero, (2) all the income estimates are jointly zero, and 3) all the income and education estimates are jointly zero. For CODs with five year mortality rates below this mean, we aggregate deaths from similar causes until the grouped mean death rate falls above the minimum threshold.

other types of accident. We should note however that our results are not directly comparable to most studies because we restrict our attention to married white respondents in a particular age range, whereas most other data sets have no sample restrictions based on marital status and race.

Verification

We verify the validity of the UCOD group as a proxy for a randomly-assigned group of deaths using two analysis samples—women married to men aged 50-70 and men married to women aged 50-70, extracted from both the NLMS and NHIS.[9] For each sex/data set pair, we run two specifications. In one specification, the dependent variable is the probability the individual dies of an UCOD with the sample time frame, and for the other specification, the dependent variable is the probability of dying of an ICOD under the same condition. The other explanatory variables consist of income, education and age groups. The full results of these regressions are listed in Tables E and F of the appendix, and we find an inverse, monotonic relationship between mortality and the SES variables for income and education when we model the probability of dying from an ICOD. This is not the case for the group of UCOD. The marginal effects we find are very small, and in every case, we cannot reject the null hypothesis that the individual coefficient estimates are equal to zero.

The results of our joint hypothesis tests are listed in Table 5. In the top half of the table, we report results for the NLMS and in the lower half, results from the NHIS. For both men and women, and for both the NLMS and NHIS samples, we easily reject the null that the ICODs are not correlated with income and education. All p-values for this outcome are <0.0001 except for

[9] Recall, we are interested in understanding how widowhood affects women (men); so, we separate the causes of death of their husbands (wives) into correlated and uncorrelated groups. The women (men) we study are between 50 and 70, and their husbands (wives) can be of any age.

the education coefficients for women on the NHIS sample where the p-value is 0.0004. In contrast to the results for ICODs, the results for UCODs support our assertion that income and education are uninformative about the probability of dying from these causes. In the NLMS results, the p-values associated with the hypothesis that all education variables are jointly zero are greater than or equal to 0.362. However, the p-values for the hypothesis that all the income coefficients are jointly zero are low, 0.022 for men and 0.107 for women. While we may not be able to reject the null hypothesis, the point estimates and marginal effects of the income variables are very small and close to negligible in comparison to the magnitudes of the point estimates and marginal effects under the ICOD specification (see appendix). The NHIS results also support the conjecture that these deaths are uniformative; however, we focus on the NLMS data because of the greater number of observations.

V. Cox Proportional Hazard Model Results

In this section, we examine whether mortality of the surviving spouse is a function of the type of death experienced by their spouse. In the Cox model results outlined in table 3, we included a single covariate that indicated the periods after their spouse died. In this section, we estimate models where we replace the time-variant widowhood variable with two time-variant variables that measure whether their spouse has died in this or current periods of a UCOD and ICOD. UCOD has a value of 1 for the day, and each subsequent day, an individual becomes a widow by a UCOD. ICOD has a value of one when the spouse dies of a ICOD. Other covariates in the model include the same set of covariates used in table 3.

The Cox regression results for married men and women using the two different methods of accounting for widowhood (i.e. (1) a single widowhood variable, (2) UCOD and ICOD widowhood variables) are presented in Table 6. In the first column of results, we present estimates for men from NLMS and NHIS respectively. In the next column, we report the models for women. We report the hazard ratio ands its associated standard error for the various covariates that measure widow/widower status.

With the NLMS data, we find widowed men have a 1.34 hazard ratio (34% greater risk of death than still-married men), and widowed women have a 1.187 hazard ratio (19%). With the NHIS data, we find the hazard ratios are 1.19 and 1.21, respectively. The second columns in each group of results list the Cox proportional hazard model results when we split the widowhood variable into UCOD and ICOD. Using data from the NLMS, we find that men have a 24% greater likelihood of dying if widowed by a UCOD, while ICOD widowers experience a 37% greater risk of death. The lower hazard ratio associated with UCOD widows suggests that the married men results in column 1 and for ICOD are biased upwards by an omitted variable bias. These results show a clear causal relationship between widowhood and mortality for men.

For women in the NLMS, however, we find a different story. After breaking up the time-dependent variable by cause of death, we find that widows of UCOD spouses experience an impact to their mortality that is not statistically significant; in fact, the parameter estimate is negative and the hazard ratio is less than 1.[10] The hazard ratio associated with ICOD, though, is almost exactly the same as that of the general widowhood variable: 1.21 compared to 1.19. The large difference in the coefficients between UCOD and ICOD variables in the Cox model for women suggests that the mortality effects of losing a spouse are subject to an omitted variables bias. We should stress however that the large standard errors on the estimate of UCOD for women in the NLMS mean that we cannot reject the null hypothesis that these two coefficients

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[10] Although not listed in the tables of results, we found very similar results for the income and education variables for all specifications of our survival analysis. Mortality monotonically decreases for higher levels of education and family income.

are the same. These results do suggest that the theory of marital protection does not explain the lower mortality rates of married women as it does for married men.

The bottom half of Table 6 displays the results from the two specifications of the Cox proportional hazard models for men and women using the NHIS data. The results are qualitatively very similar to the results from the NLMS data set. The husband has a slightly lower probability of death when a wife dies from an UCOD compared to a ICOD. We do however begin to see the capacity limitations of the NHIS data. The standard errors for the proportional hazard estimates are extremely large giving very imprecise measurements of the impact of widowhood on the surviving spouse. The NHIS data does not provide much leverage in this final analysis.

Discussion

Researchers from a variety of disciplines have demonstrated a heightened mortality rate for widows and widowers in the years just after the death of their spouse. Because married couples tend to share life experiences and health habits, there is some question whether these results represent a causal relationship, or an omitted variables bias. Using data from two large cross-sections of older married men and women, we find that deaths by a spouse convey a great deal of information about socioeconomic status, and hence, more information about their spouse, tend to have larger impacts on morality than deaths that are more randomly generated. This result is consistent with a hypothesis that informative causes of death overstate the bereavement effect of a spouse's death due to an omitted variables bias. In the case of men, our results provide strong evidence of that losing a spouse has serious consequences on the mortalities of men. This result is less susceptible to an omitted variables bias since this estimate is generated for causes of death that convey little information about the surviving spouse. In contrast, we cannot find any compelling evidence that the death of a husband from uninformative cause of death has any negative impact on mortality for surviving wives.

There are however a number of caveats to our work. The analysis only considers two marital states--married and widowed. Since death is our only longitudinal variable, we do not observe whether couples divorce and, more importantly, whether widows remarry. These different marital states could affect our analysis. For example, it could very well be that widows aged 50-70 remarry at greater rates than widowers. Thus, we do not find a mortality effect among women because the widows of these UCOD spouses are remarrying instead of dying from some bereavement effect.

Although both the marriage protection and marriage selection hypotheses explain the observed patterns in the data, only the former purports a causal relationship between marriage and mortality. Deciphering which story is correct can have important policy implications. Standard cost-effectiveness studies produce an estimate of the cost of treatment per quality adjusted life year saved. The denominator in this value is exclusively the patient being treated. However, if widows die at much higher rates in the first year after the death of the husband and this event can be attributed to marriage protection, some standard cost-effectiveness estimates may understate the benefits of certain treatments (Christakis, 2003).

REFERENCES

Allison PD. 1995. *Survival Analysis Using the SAS®: A Practical Guide* North Carolina: SAS Institute.

Anson O. 1989. Marital status and women's health revisited: the importance of a proximate adult. *Journal of Marriage and the Family* 51: 185-194.

Bassuk SS, Berkman LF, and Amick BC. 2002. Socioeconomic Status and Mortality among the Elderly: Findings from Four US Communities. *Ameican Journal of Epidemiology* 155: 520-533

Becker GS. 1973. A theory of marriage: part I. *Journal of Political Economy* 81(4): 813-846.

Becker GS. 1974. A theory of marriage: part II. *Journal of Political Economy* 82(2.2): S11-S26.

Berkman LF. 1995. The role of social relations in health promotion. *Psychosocial Medicine* 57(3): 245-254.

Berkman LF. 2000. Social support, social networks, social cohesion and health. *Soc Work Health Care* 31(2): 3-14.

Berkman LF. 2000. Which influences cognitive function: living alone or being alone? *Lancet* 355: 1291-1292.

Berkman LF, Glass T, Brissette I, and Seeman TE. 2000. From social integration to health: Durkheim in the new millennium. *Social Science and Medicine* 51(6): 843-857.

Berkman LF and Syme SL. 1979. Social networks, host resistance, and mortality: a nine-year follow-up study of Alameda County residents. *American Journal of Epidemiology* 109(2): 186-204.

Blazer DG. 1982. Social support and mortality in an elderly community population. *American Journal of Epidemiology* 115(5): 684-694.

Caspi A and Herbener ES. 1993. Marital assortment and phenotypic convergence---longitudinal evidence. *Social Biology*, 40(1-2): 48-60.

Christakis NA. 2004. Social networks and collateral health effects have been ignored in medical care and clinical trials, but need to be studied. B*ritish Medical Journal* 329: 184-185.

Christakis NA and Iwashyna TJ. 2003. The health impact of health care on families: a matched cohort study of hospice use by decedents and mortality outcomes in surviving, widowed spouses. *Social Science and Medicine* 57: 465-75.

Cohen, Sheldon, et al. 1997. Social ties and susceptibility to the common cold. *Journal of the American Medical Association* 277(24): 1940-44.

Cox PR and Ford JR. 1964. The mortality of widows shortly after widowhood. *Lancet*. 46: 163-164.

Cox R. 1972. Value of objective examinations. *Nature*. 237(5357): 489-492.

Deaton AS and Paxson CH. 1998. Aging and Inequality in Income and Health. *American Economic Review* 88: 248-53.

Duncan GJ, Wilkerson B, and England P. 2003. Cleaning Up Their Act: The Impact of Marriage and Cohabitation on Licit and Illicit Drug Use. *Northwestern Working Paper* WP-03-02

Durkheim E. 1951 (1897). *Suicide: A Study in Sociology*, translated by Spaulding JA and Simpson G. New York: The Free Press of Glenco.

Farr W. 1858. The influence of marriage on the mortality of the French people. In: *Transactions of the National Association for the Promotion of Social Sciences*, edited by Hastings GW. London: Parker and Son, p. 504-513.

Gardner J and Oswald A. 2002. How is mortality affected by money, marriage, and stress? *Journal of Health Economics* 23(6): 1181-1207.

Ginther DK and Pollak RA. 2004. Family structure and children's educational outcomes: blended families, stylized facts, and descriptive regressions *Demography* 41(4): 671-696.
Goldman N. 1994. Social factors and health: the causation-selection issue revisited. *Proceedings of the National Academy of Sciences USA* 91(4), 1251-1255.
Goldman N. 1993. Marriage selection and mortality patterns: inferences and fallacies. *Demography* 30(2): 189-208.
Gove WR. 1973. Sex, marital status and mortality. *American Journal of Sociology* 79: 45-67.
Gove WR, Hughes MM, and Style CB. 1983. Does marriage have positive effects on the psychological well-being of the individual? *Journal of Health and Social Behavior* 24: 122-131.
Harrison GA, Gibson JB, and Hiorns RW. 1976. Assortative marriage for psychometric, personality and anthropometric variation in a group of Oxfordshire villages. *Journal of Biosocial Science* 8(2): 145-153.
Helsing K, Szklo M, and Comstock G. 1981. Factors associated with mortality after widowhood. *American Journal of Public Health* 71: 802-809.
Herbener CA. 1993. Marital assortment and phenotypic convergence---longitudinal evidence. *Social Biology* 40(1-2): 48-60.
House JS, Robbins C, and Metzner HL. 1982. The association of social relationships and activities with mortality: prospective evidence from the Tecumseh Community Health Study. *American Journal of Epidemiology* 116(1): 123-140.
Hu Y and Goldman N. 1990. Mortality differentials by marital status: an international comparison. *Demography* 27(2): 233-250.
Hurd M, McFadden D, and Merrill A. 1999. Predictors of Mortality Among the Elderly. *NBER Working Papers* 7440.
Iwashyna TJ and Christakis NA. 2003. Marriage, widowhood, and health-care use. *Social Science and Medicine* 57(11): 2137-2147.
Johnson RC, DeFries JC, Wilson JR, McClearn GE, Vandenberg SG, Ashton GC, Mi MP, and Rashad MN. 1976. Assortative Marriage for Specific Cognitive Abilities in Two Ethnic Groups. *Human Biology* 48: 343-352.
Kalbfleisch J and Prentice R. 1980. *The Statistical Analysis of Failure Time Data* New York: Wiley.
Kaprio J, Koskenvuo M, and Rita H. 1987. Mortality after bereavement: a prospective study of 95,647 widowed persons. *American Journal of Public Health* 77(3): 283-287.
Kisker EE and Goldman N. 1987. Perils of single life and benefits of marriage. *Social Biology* 34(3-4): 135-152.
Kitagawa EM and Hauser PM. 1973. *Differential mortality in the United States: A study in socioeconomic epidemiology*. Cambridge: Harvard University Press.
Kobrin, Francis E, and Hendershot G. 1977. Do family ties reduce mortality? Evidence from the United States, 1966-68. *Journal of Marriage and the Family* 39: 737-745.
Korenman S, Goldman N, Fu H. 1997. Misclassification bias in estimates of bereavement effects. *American Journal of Epidemiology* 145: 11(1997), 995-1002.
Korenman S and Neumark D. 1991. Does marriage really make men more productive? *Journal of Human Resources* 26 (2): 282-307.
Kremer M. 1997. How much does sorting increase inequality? *Quarterly Journal of Economics* 112(1): 115-139.
Laub JH, Nagin DS, and Sampson RJ. 1998. Trajectories of change in criminal offending: good marriages and the desistance process. *American Sociological Review* 63(2): 225-238.

Lichtenstein P, Gatz M, and Berg S. 1998. A twin study of mortality after spousal bereavement. *Psychological Medicine* 28: 635-643.

Lillard LA and Panis CWA. 1996. Marital status and mortality: the role of health. *Demography* 33(3): 313-327.

Lillard L and Waite L. 1995. Til' death do us part: marital disruption and mortality. *American Journal of Sociology* 100(5): 1131-1156.

Luoma JB, Pearson JL. 2002. Suicide and marital status in the United States, 1991-1996: is widowhood a risk factor? *American Journal of Public Health* 92(9): 1518-1522.

Manor O and Eisenbach Z. 2003. Mortality after spousal loss: are there socio-demographic differences? *Social Science and Medicine* 56(2): 405-413.

Manor O, Eisenbach Z, Israeli A, and Friedlander Y. 2000. Mortality differentials among women: the Israel longitudinal mortality study. *Social Science and Medicine* 51(8): 1175-1188.

Martikainen P and Valkonen T. 1996. Mortality after the death of a spouse: rates and causes of death in a large Finnish cohort. *American Journal of Public Health* 86: 1087-1093.

Mascie-Taylor CG and Gibson JB. 1979. A biological survey of a Cambridge suburb: assortative marriage for IQ and personality traits. *Annals of Human Biology* 6(1):1-16.

McGinnis JM and Foege WH. 1993. Actual causes of death in the United States. *JAMA* 270(18): 2207-2212.

Mendes de Leon CF, Kasl SV, and Jacobs S. 1993. Widowhood and mortality risk in a community sample of the elderly---a prospective-study. *Journal of Clinical Epidemiology* 46(6): 519-527.

Mergenhagen PM, Lee BA, and Gove WR. 1985. Till death do us part: recent changes in the relationship between marital status and mortality. *Sociology and Social Research* 70: 53-56.

Mineau GP, Smith KR, and Bean LL. 2002. Historical trends of survival among widows and widowers. *Social Science and Medicine* 54: 245-254.

Montoya RM and Horton RS. 2004. On the importance of cognitive evaluation as a determinant of interpersonal attraction. *Journal of Personality and Social Psychology* 86(5): 696-712.

Murray JE. 2000. Marital protection and marital selection: evidence from a historical-prospective sample of American men. *Demography* 37(4): 511-521.

National Center for Health Statistics. 2005. http://www.cdc.gov/nchs/. *US Department of Health and Human Services.*

Painter G and Levine DI. 2000. Family structure and youths' outcomes---which correlations are causal? *Journal of Human Resources* 35(3): 524-549.

Parkes CM, Benjamin B, and Fitzgerald RG. 1969. Broken heart: a statistical study of increased mortality among widowers. *Br Med J* 1(646): 740-743.

Phelan JC, Link BG, Diez-Roux A, Kawachi I, and Levin B. 2004. "Fundamental causes" of social inequalities in mortality: a test of the theory. *Journal of Health and Social Behavior* 45(3): 265-285.

Putnam RD. 2000. *Bowling alone: the collapse and revival of American community.* New York: Simon & Schuster.

Rahman O. 1993. Excess mortality for the unmarried in rural Bangladesh. *International Journal Epidemiology* 22(3): 445-456.

Riessman CK and Gerstel N. 1985. Marital dissolutiona and health: do males or females have greater risk? *Social Science and Medicine* 20: 627-635.

Rogers RG. 1995. Marriage, sex and mortality. *Journal of Marriage and the Family*. 57(2): 515-526.

Rogot E, Sorlie PD, Johnson NJ, and Schmitt C. 1992. *A mortality study of 1.3 million persons by demographic, social, and economic factors: 1979-1985 Followup.*Bethesda, MD: National Institutes of Health.

Ross CD, Mirowsky J, and Goldsteen K. 1990. The impact of the family on health: decade in review. *Journal of Marriage and the Family* 52: 1059-1078.

Rosenbloom CA and Whittington FJ. 1993. The effects of bereavement on eating behaviors and nutrient intakes in elderly widowed persons. *Journal of Gerontology: Social Sciences* 48(4): S223-S229.

Schaefer C, Quesenberry CP Jr, and Wi S. 1995. Mortality following conjugal bereavement and the effects of a shared environment. *American Journal of Epidemiology* 141(12): 1142-1152.

Schoeni RF. 1995.Marital status and earnings in developed countries. *Journal of Population Economics* 8(4): 351-359.

Seeman TE, Kaplan GA, Knudsen L, Cohen R, and Guralnik J. 1987. Social network ties and mortality among the elderly in the Alameda County Study. *American Journal of Epidemiology* 126(4): 714-723.

Smith KR and Waitzman NJ. 1994. Double jeopardy: interaction effects of marital and poverty status on the risk of mortality. *Demography* 31: 487-507.

Smith KR and Zick CD. 1994. Linked lives, dependent demise? Survival analysis of husbands and wives. *Demography* 31: 81-89.

Sorlie PD, Backland E, and Keller JB. 1995. U.S. Mortality by economic, demographic and social characteristics: The National Longitudinal Mortality Study. *American Journal of Public Health.* 85:949-56.

Spuhler JN. 1968. Assortative mating with respect to physical characteristics. *Eugenics Quarterly* 15 (2): 128-140.

Stack S and Eshleman JR. 1998. Marital status and happiness: a 17-nation study. *Journal of Marriage and the Family* 60(2): 527-536.

Steenland K, Henley J, and Thun M. 2002. All-cause and cause-specific death rates by educational status for two million people in two American Cancer Society cohorts, 1959-1996. *American Journal of Epidemiology* 156: 11-21.

Tcheng-Laroche F and Prince R. 1983. Separated and divorced women compared with married controls: selected life satisfaction, stress, and health indices from a community survey. *Social Science and Medicine* 17: 95-105.

Trovato F. 1991. Sex, marital status, and suicide in Canada: 1951-1981. *Sociological Perspectives* 34(4): 427-445.

Vandenburg SG. 1972. Assortive mating, or who marries whom? *Behavior Genetics* 2(2-3): 127-157.

Waite LJ and Gallagher M. 2000. *The Case for Marriage: Why Married People Are Happier, Healthier, and Better Off Financially.* New York: Broadway Books, 2000.

Wittstein IS, et al. 2005. Neorohumoral features of myocardial studding due to sudden emotional stress. *New England Journal of Medicine* 352(6):539-548.

Zuckerman DM, Kasl SV, and Ostfeld AM. 1984. Psychosocial predictors of mortality among the elderly poor. The role of religion, well-being, and social contacts. *American Journal of Epidemiology* 119(3): 410-423.

Table 1
Estimate of Probability (Standard Error) [Observation]
Married Male and Female Samples,

		Married Women		
Variable	Data Set	$Pr(X_w=1\|X_h=1)$	$Pr(X_w=1\|X_h=0)$	Difference
Obese?	NHIS	0.233 (0.008) [2,870]	0.124 (0.002) [17,426]	0.109 (0.007)
Fair or poor health at survey?	NHIS	0.450 (0.008) [3,998]	0.097 (0.002) [16,298]	0.353 (0.006)
Bed days in past 12 months?	NHIS	0.500 (0.006) [6,724]	0.275 (0.004) [13,572]	0.225 (0.007)
Short term hospital stay past 12 months?	NHIS	0.118 (0.006) [2,618]	0.091 (0.002) [17,678]	0.027 (0.006)
Current Smoker?	CPS Tobacco Use Supplements	0.401 (0.008) [3,509]	0.123 (0.003) [15,316]	0.277 (0.007)
		Married Men		
		$Pr(X_h=1\|X_w=1)$	$Pr(X_h=1\|X_w=0)$	Difference
Obese?	NHIS	0.258 (0.008) [3,077]	0.133 (0.003) [19,094]	0.125 (0.007)
Fair or poor health at survey?	NHIS	0.507 (0.009) [3,281]	0.117 (0.002) [18,890]	0.390 (0.007)
Bed days in past 12 months?	NHIS	0.482 (0.006) [8,093]	0.255 (0.004) [14,078]	0.227 (0.006)
Short term hospital stay past 12 months?	NHIS	0.143 (0.008) [1,975]	0.114 (0.002) [20,196]	0.029 (0.008)
Current Smoker?	CPS Tobacco Use Supplements	0.459 (0.008) [4,085]	0.147 (0.003) [17,433]	0.312 (0.007)

Table 2
Characteristics of the
Married Male and Female Samples,
NLMS & NHIS

	Married Males	Married Females
	NLMS	
Variable	Mean	Mean
Dead within 9 years of survey	0.178	0.093
Died within 5 years of survey	0.091	0.044
Widow or widower	0.077	0.220
Widow or widower (5 years)	0.035	0.116
Individuals	37,775	34,465
	NHIS	
Dead before 01/01/1996	0.124	0.070
Died within 5 years of survey	0.079	0.045
Widow or widower	0.059	0.160
Widow or widower (5 years)	0.038	0.104
Individuals	22,164	20,290

Table 3
Maximum Likelihood Estimates, Cox Proportional Hazard Models
Married Male and Female Samples,
NLMS & NHIS

	NLMS (days)		NHIS (months)	
	Parameter	Hazard ratio	Parameter	Hazard ratio
	Married Males			
Widow or widower	0.290 (0.054)	1.337 (0.072)	0.170 (0.091)	1.185 (0.108)
Individuals	37,775		22,164	
Censored	31,065		19,410	
Events	6,710		2.54	
% deaths	17.8		12.43	
-2 log likelihood	130,233.66		39,243.62	
	Married Females			
Widow or widower	0.171 (0.049)	1.187 (0.092)	0.192 (0.082)	1.212 (0.099)
Individuals	34,465		20,290	
Censored	31,252		18,862	
Events	3,213		1,428	
% deaths	9.32		7.04	
-2 log likelihood	63,879.33		21,978.07	

Standard errors in parenthesis. Other covariates include dummy variables for education groups, income levels and age in years at the time of the initial survey.

Table 4
Uninformative Causes of Death (UCOD)
NLMS

Men			
ICD9 (first 3 digits)	Cause of Death	Number	Proportion of UCOD
157	pancreatic cancer	107	16%
188-189	urinary tract cancer	116	18%
204-208	leukemia	87	13%
431-432	brain hemorrhage	65	10%
434	cerebral thrombosis	66	10%
480-487	pneumonia	149	22%
950-959; 960-978	murder/suicide	73	11%

Women			
ICD9 Code	Cause of Death	Number	Proportion of UCOD
140-239 (various)[+]	residual cancer*	256	34%
174	breast cancer	216	28%
179-189 (not 183)	genitourinary cancer	82	11%
183	ovarian cancer	67	9%
431,432,434	brain hemorrhage or cerbral thrombosis	61	8%
800-999	accidents	79	10%

[+]ICD 9 codes included are: 140-152;154-156; 157-161;163-173;175-178; 190-199
*residual cancer does not include the following types of cancer: colon, pancreatic, trachael, bronchal, lung, breast, genitourinary, ovarian or lymphatic tissue cancers.

Table 5
Maximum Likelihood Estimates of Logistic Regression,
Die from Informative or Uninformative Causes,
NLMS/NHIS

Marginal Effects and (Standard Errors)

	NLMS: Males married to women aged 50-70		NLMS: Females married to men aged 50-70	
Hypothesis Tests:	Informative death	Uninformative death	Informative death	Uninformative death
	P-values on -2 log likelihood test statistics			
Education coefs. are all zero	< 0.0001	0.362	< 0.0001	0.979
Income coefs. are all zero	< 0.0001	0.022	< 0.0001	0.107
Educ. and income coefs. are all zero	<0.0001	0.012	< 0.0001	0.317
Mean of outcome	0.200	0.019	0.057	0.020
-2 log likelihood	15,829.32	6279.30	15,228.64	7,304.94

	NHIS: Males married to women aged 50-70		NHIS: Females married to men aged 50-70	
Hypothesis Tests:	Informative death	Uninformative death	Informative death	Uninformative death
	P-values on -2 log likelihood test statistics			
Education coefs. are all zero	< 0.0001	0.488	0.0004	0.508
Income coefs. are all zero	< 0.0001	0.332	< 0.0001	0.670
Educ. and income coefs. are all zero	<0.0001	0.136	< 0.0001	0.715
Mean of outcome	0.145	0.015	0.042	0.017
-2 log likelihood	15,292.88	2,943.96	7,078.44	3,667.18

The reference person is a 60 year old with a high school degree/and or some college, and $40K or more in family income. Other covariates include dummy variables for ages 50-72 and over 72 years of age.

Table 6
Maximum Likelihood Estimates, Cox Proportional Hazard Models
Married Male and Female Samples,
NLMS and NHIS Samples

Hazard Ratios and (Standard Errors)

	NLMS: Married males, aged 50-70 (n=37,775)		NLMS: Married females, aged 50-70, (n=34,465)	
	Model (1)	Model (2)	Model (1)	Model (2)
Widower	1.337 (0.072)		1.187 (0.092)	
Widower due to uninformative COD		1.237 (0.130)		0.905 (0.153)
Widower due to informative COD		1.373 (0.084)		1.213 (0.062)
-2 log likelihood	130,233.66	130,232.89	63,879.33	63,876.18

	NHIS: Married males, aged 50-70 (n=22,164)		NHIS: Married females, aged 50-70, (n=20,290)	
	Model (1)	Model (2)	Model (1)	Model (2)
Widower	1.185 (0.108)		1.212 (0.099)	
Widower due to uninformative COD		1.120 (0.197)		0.707 (0.225)
Widower due to informative COD		1.195 (0.123)		1.263 (0.106)
-2 log likelihood	39,243.62	39,243.43	21,978.07	21,974.27

Other covariates include dummy variables for education groups, income levels and age in years at the time of the initial survey.

Table A
Characteristics of the
Married Male and Female Samples,
NLMS

	Married Males		Married Females	
Variable	Mean	Standard Deviation	Mean	Standard Deviation
Dead before	0.18	0.38	0.09	0.29
Died within 5 years of survey	0.09	0.29	0.04	0.20
Widow or widower	0.08	0.27	0.22	0.41
Widow or widower (5 years)	0.04	0.19	0.12	0.32
Age: 50-59	0.54	0.50	0.57	0.49
Age: 60-70	0.46	0.50	0.43	0.49
Income < $5K	0.04	0.20	0.05	0.22
$5K <= Income < $10K	0.13	0.34	0.17	0.37
$10K <= Income < $15K	0.17	0.37	0.18	0.39
$15K <= Income < $20K	0.14	0.35	0.14	0.34
$20K <= Income < $25K	0.15	0.36	0.14	0.35
$25K <= Income < $50K	0.29	0.45	0.25	0.43
$50K <= Income	0.08	0.27	0.07	0.25
No high school	0.21	0.40	0.16	0.36
Some high School	0.16	0.37	0.16	0.37
High school graduate	0.34	0.47	0.46	0.50
Some college	0.12	0.33	0.13	0.33
College graduate	0.17	0.37	0.09	0.29
Individuals	37,775		34,465	

Standard errors in parenthesis. Other covariates include a complete set of dummy variables for age in years at the time of the initial survey.

Table B
Characteristics of the
Married Male and Female Samples,
NHIS/MCOD 1987-1990

	Married Males		Married Females	
Variable	Mean	Standard Deviation	Mean	Standard Deviation
Dead before by 01/01/1996	0.12	0.33	0.07	0.26
Died within 5 years of survey	0.08	0.27	0.05	0.21
Widow or widower	0.06	0.24	0.16	0.37
Widow or widower (5 years)	0.04	0.19	0.10	0.31
Age: 50-59	0.50	0.50	0.52	0.50
Age: 60-70	0.50	0.50	0.48	0.50
Income < $10K	0.05	0.21	0.06	0.23
Income $10K - $20K	0.18	0.39	0.22	0.41
Income $20K - $30K	0.20	0.40	0.21	0.41
Income $30K - $40K	0.17	0.37	0.16	0.36
Income > $40K	0.40	0.49	0.35	0.48
No High School	0.13	0.33	0.09	0.28
< High school	0.13	0.34	0.13	0.34
High school graduate	0.51	0.50	0.65	0.48
College graduate	0.23	0.42	0.13	0.34
Individuals	22,164		20,290	

Standard errors in parenthesis. Other covariates include a complete set of dummy variables for age in years at the time of the initial survey.

Table C
Maximum Likelihood Estimates, Cox Proportional Hazard Models
NLMS

	Married Men (n=37,775)		Married Women (n=34,465)	
Covariate	Parameter Estimate	Hazard Ratio	Parameter Estimate	Hazard Ratio
Widow/Widower	0.290	1.337	0.171	1.187
	(0.054)	(0.072)	(0.049)	(0.058)
Income < $5K	0.818	2.266	0.370	1.448
	(0.081)	(0.184)	(0.111)	(0.161)
$5K <= Income < $10K	0.692	1.997	0.332	1.394
	(0.072)	(0.144)	(0.098)	(0.137)
$10K <= Income < $15K	0.538	1.713	0.199	1.221
	(0.071)	(0.121)	(0.097)	(0.118)
$15K <= Income < $20K	0.412	1.509	0.066	1.068
	(0.072)	(0.109)	(0.102)	(0.109)
$20K <= Income < $25K	0.340	1.405	0.057	1.058
	(0.072)	(0.102)	(0.102)	(0.108)
$25K <= Income < $50K	0.230	1.259	0.008	1.008
	(0.069)	(0.086)	(0.096)	(0.097)
No high school	0.274	1.315	0.363	1.438
	(0.048)	(0.063)	(0.082)	(0.118)
Some high School	0.314	1.369	0.289	1.335
	(0.049)	(0.067)	(0.083)	(0.111)
High school graduate	0.151	1.163	0.170	1.185
	(0.045)	(0.052)	(0.075)	(0.089)
Some college	0.205	1.228	0.075	1.078
	(0.053)	(0.065)	(0.088)	(0.094)
-2 log likelihood	130,233.66		63,879.33	

Other covariates include a complete set of dummy variables for education groups, income levels and age in years at the time of the initial survey.

Table D
Maximum Likelihood Estimates, Cox Proportional Hazard Models
NHIS

	Married Men (n=22,164)		Married Women (n=20,290)	
Covariate	Parameter Estimate	Hazard Ratio	Paramter Estimate	Hazard Ratio
Widow/Widower	0.170 (0.091)	1.185 (0.108)	0.192 (0.082)	1.212 (0.099)
Income < $10K	0.811 (0.081)	2.250 (0.182)	0.516 (0.111)	1.676 (0.186)
$10K <= Income < $20K	0.555 (0.061)	1.742 (0.106)	0.367 (0.082)	1.444 (0.118)
$20K <= Income < $30K	0.390 (0.060)	1.477 (0.089)	0.235 (0.082)	1.265 (0.104)
$30K <= Income < $40K	0.147 (0.068)	1.159 (0.079)	0.026 (0.096)	1.026 (0.098)
No high school	0.408 (0.073)	1.504 (0.110)	0.362 (0.125)	1.437 (0.180)
Some high school	0.387 (0.073)	1.473 (0.107)	0.264 (0.119)	1.303 (0.155)
High school graduate	0.201 (0.060)	1.223 (0.073)	0.166 (0.100)	1.180 (0.118)
-2 log likelihood	39,243.62		21,978.07	

Other covariates include a complete set of dummy variables for education groups, income levels and age in years at the time of the initial survey.

Table E
Maximum Likelihood Estimates of Logistic Regression,
Die from Informative or Uninformative Causes, NLMS

Marginal Effects and (Standard Errors)

Covariates	Males Observations		Females Observations	
	Die by the end of the follow-up from an:		Die by the end of the follow-up from an:	
	Informative death	Uninformative death	Informative death	Uninformative death
Income < $5K	0.148 (0.020)	0.009 (0.006)	0.023 (0.009)	-0.004 (0.004)
$5K <= Income < $10K	0.122 (0.016)	0.004 (0.004)	0.020 (0.007)	0.003 (0.004)
$10K <= Income < $15K	0.091 (0.014)	0.001 (0.004)	0.013 (0.006)	0.004 (0.004)
$15K <= Income < $20K	0.066 (0.014)	< 0.001 (0.003)	0.008 (0.006)	-0.002 (0.003)
$20K <= Income < $25K	0.063 (0.014)	-0.001 (0.003)	0.006 (0.006)	-0.0001 (0.003)
$25K <= Income < $50K	0.031 (0.012)	-0.001 (0.003)	0.001 (0.005)	-0.014 (0.003)
No high school	0.049 (0.009)	0.002 (0.002)	0.024 (0.006)	0.001 (0.003)
Some high School	0.049 (0.009)	0.003 (0.003)	0.019 (0.006)	< 0.001 (0.003)
High school graduate	0.027 (0.008)	< 0.001 (0.002)	0.010 (0.004)	-0.0003 (0.002)
Some college	0.029 (0.010)	0.004 (0.003)	0.007 (0.005)	< 0.001 (0.003)
Mean of outcome	0.200	0.019	0.057	0.020
-2 log likelihood	15,829.32	6279.30	15,228.64	7,304.94
P-values on -2 log likelihood test statistics				
Education coefs. are all zero	< 0.0001	0.362	< 0.0001	0.979
Income coefs. are all zero	< 0.0001	0.022	< 0.0001	0.107
Educ. and income coefs. are all zero	<0.0001	0.012	< 0.0001	0.317

The reference person is a 60 year old with a high school degree/and or some college, and $40K or more in family income. Other covariates include dummy variables for ages 50-72 and over 72 years of age.

Table F
Maximum Likelihood Estimates of Logistic Regression,
Die from Informative or Uninformative Causes,
50-70 Year old Married White Males and Females,
1987-1990 NHIS/MCOD

Marginal Effects and (Standard Errors)

	Male Observations		Female Observations	
	Die by the end of the follow-up from an:		Die by the end of the follow-up from an:	
Covariates	Informative death	Uninformative death	Informative death	Uninformative death
No High School	0.049 (0.010)	0.003 (0.003)	0.024 (0.008)	-0.003 (0.003)
Some high school	0.058 (0.011)	0.003 (0.003)	0.019 (0.007)	-0.002 (0.003)
High school graduate	0.016 (0.007)	0.003 (0.002)	0.010 (0.004)	-0.003 (0.002)
<$10K family income	0.132 (0.016)	0.005 (0.004)	0.051 (0.010)	0.001 (0.004)
≥$10K, <$20K family income	0.070 (0.009)	0.003 (0.002)	0.025 (0.005)	-0.001 (0.002)
≥$20K, <$30K family income	0.047 (0.008)	0.003 (0.002)	0.016 (0.004)	0.002 (0.002)
≥$30K, <$40K family income	0.024 (0.009)	-0.0002 (0.002)	0.007 (0.004)	0.003 (0.003)
Mean of outcome	0.145	0.015	0.042	0.017
-2 log likelihood	15,292.88	2,943.96	7,078.44	3,667.18
Education coefs. are all zero	< 0.0001	0.488	0.0004	0.508
Income coefs. are all zero	< 0.0001	0.332	< 0.0001	0.670
Educ. and income coefs. are all zero	<0.0001	0.136	< 0.0001	0.715

The reference person is a 60 year old with a high school degree/and or some college, and $40K or more in family income. Other covariates include dummy variables for ages 50-72 and over 72 years of age

Table G
Maximum Likelihood Estimates, Cox Proportional Hazard Models
Married Male and Female Samples,
NLMS

Covariates	Married Males (n=37,775) Parameter Estimate	Married Males (n=37,775) Hazard Ratio	Married Females (n=34,465) Parameter	Married Females (n=34,465) Hazard
Widower due to uninformative COD	0.212 (0.105)	1.237 (0.130)	-0.100 (0.169)	0.905 (0.153)
Widower due to informative COD	0.317 (0.061)	1.373 (0.084)	0.193 (0.051)	1.213 (0.234)
Income < $5K	0.817 (0.081)	2.265 (0.183)	0.370 (0.111)	1.448 (0.161)
$5K <= Income < $10K	0.691 (0.072)	1.996 (0.144)	0.331 (0.098)	1.393 (0.461)
$10K <= Income < $15K	0.538 (0.071)	1.713 (0.122)	0.198 (0.097)	1.219 (0.118)
$15K <= Income < $20K	0.412 (0.072)	1.509 (0.109)	0.064 (0.101)	1.067 (0.108)
$20K <= Income < $25K	0.340 (0.072)	1.405 (0.101)	0.056 (0.102)	1.057 (0.108)
$25K <= Income < $50K	0.230 (0.069)	1.259 (0.087)	0.007 (0.096)	1.007 (0.097)
Education1	0.274 (0.048)	1.315 (0.360)	0.364 (0.082)	1.439 (0.118)
Education2	0.313 (0.049)	1.368 (0.067)	0.289 (0.083)	1.335 (0.111)
Education3	0.151 (0.045)	1.163 (0.052)	0.169 (0.075)	1.185 (0.089)
Education4	0.205 (0.053)	1.227 (0.065)	0.074 (0.088)	1.077 (0.095)
-2 log Likelihood	130,232.89		63,876.18	

Other covariates include a complete set of dummy variables for education groups, income levels and age in years at the time of the initial survey.

Table H
Maximum Likelihood Estimates, Cox Proportional Hazard Models
Married Male and Female Samples,
NHIS

	Married Males (n=22,164)		Married Females (n=20,290)	
	Parameter Estimate	Hazard Ratio	Parameter	Hazard
Widow due to uninformative COD	0.104 (0.179)	1.110 (0.199)	-0.347 (0.319)	0.707 (0.226)
Widow due to informative COD	0.192 (0.104)	1.212 (0.126)	0.233 (0.084)	1.263 (0.106)
Income < $10K	0.810 (0.081)	2.247 (0.182)	0.515 (0.111)	1.674 (0.186)
$10K <= Income < $20K	0.554 (0.061)	1.741 (0.106)	0.366 (0.082)	1.442 (0.118)
$20K <= Income < $30K	0.389 (0.060)	1.476 (0.089)	0.235 (0.082)	1.265 (0.104)
$30K <= Income < $40K	0.147 (0.068)	1.158 (0.079)	0.025 (0.096)	1.025 (0.098)
No high school	0.408 (0.073)	1.504 (0.110)	0.363 (0.125)	1.438 (0.180)
Some high school	0.387 (0.073)	1.473 (0.108)	0.264 (0.119)	1.303 (0.155)
High school graduate	0.201 (0.060)	1.223 (0.073)	0.166 (0.100)	1.181 (0.118)
-2 log Likelihood	39,243.43		21,974.27	

Other covariates include a complete set of dummy variables for education groups, income levels and age in years at the time of the initial survey.