

The Life Insurance Market: Adverse Selection Revisited

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Abstract

This paper finds evidence for the presence of adverse selection in the life insurance market, a conclusion contrasting with the existing literature. In particular, we find a significant and positive correlation between the decision to purchase life insurance and subsequent mortality, conditional on risk classification. Individuals who died within a 12-year time window after a base year were 19 percent more likely to have taken up life insurance in that base year than were those who survived the time window. Moreover, we find that individuals are most likely to obtain life insurance four to six years before death. Methodologically, we address sample-selection and omitted-variables issues overlooked in the previous literature.

Keywords: adverse selection, private information, life insurance, sample selection, differential mortality, new buyers, health status, pricing factors, risk classification.

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I. Introduction

Empirical testing of contract theory comprises a burgeoning area of economic research (see Chiappori and Salanie 2003 for a review). Especially important have been inquiries into whether asymmetric information prevails in particular markets and, if so, how to disentangle adverse selection from moral hazard. In insurance markets, much of the literature has adopted the “conditional correlation” approach illustrated in Chiappori et al. (2006), in which the presence of information asymmetry implies that, conditional on risk classification, the risk outcome is positively correlated with insurance coverage. Evidence has been mixed.²

In an important contribution, Cawley and Philipson (1999) use Health and Retirement Study (HRS) data to examine cross-sections of life insurance contracts and find a negative or neutral correlation between mortality risk and coverage. A potential explanation for their findings is that, given risk classification, the insured may have no informational advantage over the insurer. This negative-or-neutral-correlation result, together with their evidence for bulk discounts, has been widely cited as evidence that adverse selection is non-prevalent in life insurance markets.³

We find, in contrast, evidence of adverse selection in these very markets. With the same HRS dataset, we recover a significant positive correlation between mortality outcome and the decision to purchase life insurance, conditional on risk classification. In particular, individuals with higher risk (those dying within a 12-year time window after a base year) were 19% more likely to have purchased life insurance in that base year than were individuals with lower risk (those who survived beyond the window). Indeed, decomposing mortality outcome into time-until-death categories, we find that the earlier an individual died, the more likely she was to have initially taken up insurance. Such monotonicity further suggests the prevalence of adverse selection.

Differences between our and earlier findings can be explained in several ways. First, we focus on potential new life-insurance buyers rather than on the entire cross-sectional

² For example, see Chiappori and Salanie (2000) and Cohen (2005) for the auto insurance market; Finkelstein and Poterba (2004) for the annuity market; Cardon and Hendel (2001) for the employer-provided health insurance market; and Fang et al. (2006) for the Medigap market.

³ For example, see Chiappori and Salanie (2000), de Meza and Webb (2001), Hendel and Lizzerri (2003), Fang et al. (2006), Chiappori and Salanie (2008), and Cutler et al. (2008).

sample. Potential new buyers are the subset of the total sample who did not own life insurance at the beginning of the sample period. We argue they are a more informative group for adverse selection tests than is the entire sample because, not being subject to a sample-selection problem discussed below, they best provide information about mortality differences between those with and without coverage. Suppose that individuals do have private information about their mortality risk. Those for whom the information is unfavorable, and who decide to buy life insurance on the basis of that information, then are more likely to die early and thus less likely to be found in a cross-sectional sample than are those for whom the information was favorable. High-risk individuals with coverage therefore are under-represented in cross-sectional samples. Sample selection induced by potential mortality differences between the covered and uncovered may bias estimates of the conditional correlation between insurance coverage and mortality risk.⁴

To illustrate, consider the following thought experiment. Four individuals with the same appearance of good health are alive at time $t - 5$, five years before a sample is collected. Individuals 1 and 2 choose at $t - 5$ not to obtain coverage because they know they are in good health. Individuals 3 and 4 do choose to buy insurance at $t - 5$ because they know they are in poor health despite their healthy appearance. Four years later, at time $t - 1$, individual 4 dies. The remaining three are randomly drawn into the sample at time t , which records information from year t to $t + 5$. All three survive that additional five years. A researcher examining this sample will conclude that adverse selection is absent: observed mortality in the t through $t + 5$ window does not differ between the two individuals without insurance and the one with insurance, inasmuch as all three survived the five-year sample period. The real story, however, is that half of the covered, and neither of the uncovered, died within the full ten-year horizon.

The second distinction between our and earlier approaches is that, unlike the earlier literature, we control for individuals' health status and medical and family history, factors which weigh heavily on life insurers' determination of an applicant's insurability and premium. Because those health-related factors are likely to be correlated with both mortality

⁴ In survival analysis, "left truncation" is used to describe the situation in which the existence of an individual is unknown to the researcher if she dies before the beginning of the observation period. In our case, left truncation cannot be ignored because the mortality risk of those observed in the sample may not be representative of the population of interest. See Kalbfleisch and Prentice (2002), p13 -14.

and a life-insurance purchase event, failing to control for them potentially biases the estimate of the conditional correlation between mortality risk and coverage. The a priori direction of the bias from omitting health-related variables is unclear. On the one hand, insurers may subject those with worse observable health status, and consequently higher expected mortality, to a higher premium or declare them uninsurable altogether. Because in either event fewer of them will obtain coverage, this *supply* effect will induce a spurious negative correlation between mortality risk and coverage, biasing downward the estimate of the conditional correlation between the two variables. On the other hand, those in worse observable health likely have greater *demand* for coverage, producing a spurious positive correlation between coverage and mortality and biasing upward the conditional correlation between them. We address this omitted-variables problem by including detailed controls for health status, medical records, and family history, which life-insurance underwriters commonly consider.

Finally, thanks to the long data panel now available, we are able to directly and precisely observe the actual mortality outcome of every sample individual within a 12-year time window. The literature, in contrast, heretofore has relied on self-perceived and estimated actual mortality risk, both of which likely contain substantial noise as measures of true subjective risk.⁵

The remainder of the paper is organized as follows. Section II provides background information on the life insurance market and a brief review of the literature. Section III describes the dataset. Section IV discusses the empirical strategy. Section V presents the results. Section VI concludes.

II. Life Insurance Markets and Previous Literature

The life insurance market is of particular interest for adverse selection tests. First, it is an important market on account of size alone. In 2004, 77% of American households held life insurance, total protection reaching \$19.1 trillion in 2006. The industry had overall assets of \$4.5 trillion and it invested \$4 trillion in the economy, making it one of the most

⁵ Individuals may have difficulty understanding and answering probabilistic questions, so that they report probabilities that do not truly represent their privately held perception of their own mortality risk. See Hurd and McGarry (1995) and Gan et al. (2005).

important sources of investment capital in the United States (NAIC 2007; ACLI2007). Second, moral hazard can be largely ignored in this market because possessing life insurance is unlikely to be an incentive for an individual to die sooner than she otherwise would.⁶ Life insurance therefore is a clean market to study in the sense that researchers can avoid the difficult task of disentangling adverse selection from moral hazard. Third, life insurance contracts are relatively explicit and simple. The only risk outcome is the death of the policyholder, an event in principle easy to verify and measure.⁷

A. *Life Insurance Markets and Underwriting*

Two basic types of life insurance are available: term and cash-value. Term life insurance pays a pre-specified award to the beneficiaries upon the death of the insured within the contract term, while cash-value insurance combines functions of saving and insurance, paying out when the insured dies or even before death if the insured chooses that option. A term policy can be either an individual or group policy. In the present paper, we focus on individual term life insurance.⁸

The life insurance industry's underwriting procedure is quite uniform across states. Basic pricing factors include age, gender, personal habits (e.g., tobacco, alcohol, or drug use), health status and medical history, family history, and some vocations and hobbies. Other factors may include driving records, aviation activities, residence, and frequency and destination of foreign travel.⁹ Premiums are higher for the elderly, males, those with a history of smoking, drinking, or drug abuse, those with unfavorable health status and/or an unfavorable medical or family history, those in hazardous vocations, and those with high-risk hobbies.

A life insurance agent typically interviews the applicant after the application is received. Standard questions about health status and medical history are whether one has

⁶ Tseng (2004) finds that suicide exclusion clauses (in which suicide is a coverable risk only after a certain period) in individual life insurance policies affect the timing and method of committing suicide. This however is hardly evidence of moral hazard. One explanation, as the author points out, is that "ex ante some of the insureds have sustainable suicide intentions, and they choose to commit suicide after it becomes a covered risk."

⁷ See Chiappori (2000) for complications in other insurance markets. For example, in the auto insurance market, accidents and claims can differ from one another and the decision to file a claim after an accident likely is endogenous to the contractual form.

⁸ Fifty-three percent of the face amount of all life insurance in force in the U.S. in 2006, or 76% of the premiums, was for individual coverage, making individual policies the most widely used form of life insurance. Among new individual insurance purchased, 71% of face value was issued for term insurance. See ACLI (2007b).

⁹ See McGill's Life Insurance (2000), Cummins et al., (1983) and records of the author's phone conversations with state insurance departments.

been diagnosed with high blood pressure, stroke, cancer, diabetes, high cholesterol, or a series of other conditions. The common question about family history is whether one or both parents have died before 60 or 70 of cardiovascular disease or cancer.¹⁰ The insurer typically also requires a medical examination of the applicant and her permission to release medical records. During the medical examination, a paramedic usually collects blood and urine samples, measures blood pressure, height, and weight, and records the applicant's medical history. The higher the face value of the insurance policy, the more detailed is the information required.

After gathering the applicant's information, the insurer adds to or deducts from a common base score points for favorable or unfavorable information. Based on the final score, the insurer classifies an applicant into a risk category such as "preferred plus," "preferred," "standard plus," or "standard." Sub-categories often are available within these categories.¹¹ The premium is largely similar for applicants in the same risk category given the same age, gender, and smoking status. The insurer usually would decline as uninsurable individuals with five times the base score (McGill's Life Insurance 2000).

Appendix A illustrates the underwriting guidelines for individual term life insurance provided by QuickQuote.com, an online quoting system. It shows how applicants with alternative pricing characteristics would be generally grouped into alternative risk categories. The first table includes most pricing factors except medical history; the second includes medical history.¹² In both tables, column (1) lists the requirements an applicant needs in order to qualify for the best risk category, "preferred plus." Columns (2), (3), and (4) refer respectively to "preferred," "standard plus," and "standard." For example, an applicant usually will not qualify for "preferred plus" if she has ever received high blood pressure treatments or her blood pressure readings have ever exceeded 140/85 (see column 1, "blood pressure" row, Appendix A, first table). This individual may, however, still qualify for "preferred" if her blood pressure is now under control and her readings have not exceeded 145/88 in the past two years (column 2, "blood pressure" row, same table).

B. *Related Literature*

¹⁰ The weight placed on family history has, except for cardiovascular-renal diseases, been declining in recent years on account of the difficulty of verifying the information. See McGill's Life Insurance (2000), p 520-521.

¹¹ Some companies have three categories: preferred, standard, and substandard. Category names can vary.

¹² Age, gender, and factors like height, weight, and BMI are not listed here, as they are self-explanatory.

A testable implication of standard asymmetric information models pioneered by Akerlof (1970) and Rothschild and Stiglitz (1976) is that, conditional on the observables that insurance companies use in pricing, risk outcome and insurance coverage should be positively correlated with each other (Chiappori et al., 2006). Empirical evidence of this prediction has been mixed.¹³ Chiappori and Salanie (2000), for example, find no evidence of asymmetric information in the auto insurance market, while Cohen (2005) finds that individuals who choose lower deductibles have more accidents. Cardon and Hendel (2001) dismiss the role of adverse selection in health insurance markets. Finkelstein and Poterba (2004) uncover evidence of adverse selection in certain dimensions of annuity markets but not in others.

On the basis of several data sources, Cawley and Philipson (1999) provide evidence against information asymmetry in the life insurance industry. Using in particular the HRS data, they show that both self-reported and estimated actual mortality are negatively or neutrally correlated with coverage once age, gender, smoking status, marital status, income and wealth, and bequest motives are controlled for. Their results suggest higher-risk individuals are less or at least not more likely to carry life insurance coverage than are lower-risk individuals. This may hold if, after underwriting, individuals do not have residual private information about their mortality risk. Finally, Hendel and Lizzeri (2003) use data from life insurance markets to study properties of long-term contracts to which buyers cannot commit. They show that in their sample every type of life insurance contract involves front-loading (prepayment) of premiums and argue that adverse selection is not a plausible explanation for this fact.¹⁴

III. Data

We use the Health and Retirement Study (HRS) dataset. HRS is a nationally representative longitudinal survey of the elderly and near-elderly in the United States. It contains rich information on health status, insurance coverage, financial measures,

¹³ Given the mixed evidence of adverse selection, a more recent literature has brought up the opposite possibility of advantageous selection. See de Meza and Webb (2001), Wambach (1997), and Fang et al. (2006).

¹⁴ Front-loaded contracts may attract individuals with private information about their deteriorating health because these individuals may be seeking a low cap on their future premiums. Hendel and Lizzeri however argue against this possibility because if it were true, more front-loaded contracts would be more costly, contrary to one of their findings that more front-loaded contracts have a lower present value of premiums.

demographics, and family structure as well as some data on individuals' expectations. Our analysis uses the HRS cohort, which consists of individuals born between 1931 and 1941. This cohort has been interviewed biennially since 1992. Our sample ends in 2004.

We obtain data on life insurance coverage from two early waves, 1992 and 1994, in order to simplify comparison with the previous literature. The 1992 and 1994 waves also are the only ones in which the HRS survey explicitly asked whether a respondent held individual term life insurance. Moreover, following sample individuals from early waves allows us to observe actual mortality outcome in a sufficiently long time window.

Tracker 2004 provides the mortality data. HRS divides a respondent's vital status in each wave into one of five categories: alive in current wave, presumed alive in current wave, death reported in current wave, death reported in a prior wave, and vital status unknown.¹⁵ We code a respondent as alive in 2004 if she falls into category 1 or 2 – and dead if she falls into category 3 or 4 – in wave 2004. We treat those in category 5 as missing observations.¹⁶ In this way, we observe actual mortality outcome during a 12-year time window.

Each HRS wave contains demographics, health status, and medical history information, and some data on family history. This information is important for testing for adverse selection in life insurance markets because insurers use it to determine an applicant's insurability and subsequent premium. Whenever possible, we obtain variables from the RAND version of HRS.

Respondents also reported a self-perceived probability to live to age 75. That probability, however, is a controversial measure of their private information about mortality risk because many people have difficulty understanding and answering probabilistic questions (Hurd and McGarry 1995, Gan et al. 2005). For example, the histogram of self-reported mortality probabilities in the HRS sample, shown in Figure 1, indicates that self-reported probabilities tend to anchor at appealing numbers known as “focal points.” Nearly

¹⁵ For the precise coding criteria, see HRS Tracker 2004, Version 2, January 2007.

¹⁶ As a robustness check, we also code a mortality upper bound and a mortality lower bound variable, as in Cawley and Philipson (1999), treating those in category 5 as dead and alive, respectively. All the Section V results remain qualitatively the same.

half the respondents reported either 50% or 100% as the chance they would live to age 75, an unlikely representation of “true” subjective mortality probabilities.¹⁷

HRS also uses a sequence of gambling questions to solicit information about individuals’ risk preferences (see Appendix B for the survey design). Kimball et al. (2007) impute risk aversion data for the HRS cohort partly in order to correct for measurement errors arising from employing the raw data to measure individuals’ risk attitudes.

Table 1 provides summary statistics of the relevant variables in our sample, based mainly on information from the 1992 wave. Twenty-four percent of the HRS cohort owned individual term life insurance in 1992 and 27% owned it in 1994. Nineteen percent of potential new buyers obtained individual term life insurance between 1992 and 1994. By 2004, about 15% of the cohort had died. The sample was largely balanced in gender, and nearly three-quarters of the respondents were married. High blood pressure, arthritis, and back pain were the most commonly reported medical conditions. About a tenth of the sample had had a hospital stay in the past year, and roughly the same portion had been diagnosed with heart disease. Less than 10% of the sample was diagnosed with diabetes, cancer, lung disease, stroke, or asthma. Nearly a third of the sample had healthy weight, 44% were overweight, and 22% were obese.

VI. Empirical Strategy

An ideal sample would satisfy the following requirements for testing the presence of adverse selection in life insurance markets. First, it should constitute a random sample of the population below a certain age threshold such that no individual in the population younger than that age would consider purchasing life insurance. For example, age 20 can be such a threshold if, given the absence of dependents, no individual younger than 20 demands life insurance. Second, the sample should follow every individual until the last one dies. At the end of the sample period, a researcher could then observe the coverage status, mortality outcome, and complete set of pricing factors of every sample individual who is a potential customer in the life insurance market. In such a sample, differential mortality would not

¹⁷ Suppose individuals make purchase decisions on the basis of “true” subjective mortality probabilities but report numbers different than those probabilities, measurement errors would arise from using self-reported probabilities to measure subjective mortality risk.

create a selection problem. A positive correlation, conditional on the pricing factors, between the decision to purchase insurance and a proper measure of mortality risk would provide evidence of adverse selection.

A. *Potential New Buyers*

Such an ideal sample does not, of course, exist. The HRS sample likely suffers from the selection bias arising from potential mortality differences between those with coverage and those without. HRS respondents were between 51 and 61 years old at time of first interview, an age by which many of them probably had owned life insurance for many years.¹⁸ This cohort may consist disproportionately of individuals with a relatively low mortality risk since higher-risk individuals with coverage were more likely to have died before the survey started and thus are less likely to be found in the sample. The conditional correlation between mortality risk and coverage therefore would be biased downward. Such selection bias may be partly responsible for the negative or neutral conditional correlations found in the earlier literature.

One of our contributions is to address this selection bias induced through differential mortality. We define *potential new buyers* as those who did not own individual term life insurance in the 1992 wave. By the time of the 1994 wave, some individuals (“new buyers”) in this group had purchased coverage, while the rest (“non-owners”) remained uncovered. Distinguishing between potential new buyers and the entire cross-sectional sample is key to our approach. With potential new buyers – those who potentially were customers at the beginning of the sample period – a researcher does not face the differential-mortality pitfall, since she can completely track mortalities within the permitted time window.

B. *Pricing Factors*

We also address the omitted-variables problem in the earlier literature by controlling as exhaustively as possible for the factors influencing insurers’ willingness-to-insure, namely the “pricing factors.” In particular we include detailed control variables for recorded health

¹⁸ Other ways in which the HRS sample might fall short are: (a) most respondents were still alive by 2004, the end of our sample period; and (b) we may not observe every pricing factor a typical life insurer might consider. These two limitations are, however, not very serious. Regarding (a), we define mortality risk in terms of whether an individual had died during the observed sample period. Below, we show that the period during which buyers are most likely to take advantage of private information is four to six years before death. Regarding (b), HRS already is one of the most comprehensive datasets available and we believe, therefore, we have controlled for the majority of the pricing factors that underwriters consider.

status, medical history, and family history, factors which underwriters can observe and which they consider important in addition to the age, gender, and smoking status employed in the previous literature. Because these health-related variables likely are correlated with both mortality and coverage, omitting them could induce a correlation between risk and coverage that is independent of any asymmetric information. If an observable health condition reduces the insurer's willingness to supply coverage, so that the premium rises or insurance is denied, then omitting observable health information biases the mortality-coverage correlation *downward* because the insurer's reduced supply will incorrectly be interpreted as a decline in the individual's privately harbored demand. If the observable health condition instead increases the individual's insurance demand, then omitting this observable information biases the mortality-coverage correlation *upward* because the increase in the buyer's demand induced by this publicly observable information will be interpreted as an increase in her privately harbored demand. Rigorous tests for adverse selection require that only underwriters' supply or pricing factors be used as controls. Irrelevant are such purely demand factors as income, wealth, marital status, and bequest motives, since insurers cannot price on them even if observable. Controlling for purely demand factors does, however, provide useful robustness checks.

We record, for every individual in the potential-new-buyer group, the pricing factors observable to the insurer when underwriting took place at the beginning of the sample period. Recording the observable underwriting-time data is important because this is the information relevant to an adverse selection test given that health status and medical history can change substantially after underwriting, and given that HRS data do not allow one to retrieve signing-time characteristics for contracts which had been in force before the sample began. Unfortunately for studies based on entire cross-sectional samples, entire-cross-sectional data introduce considerable measurement error into pricing control variables. Table 2 shows changes in pricing factors' sample means and standard deviations across the 1992, 1998, and 2004 waves. Almost all health indicators changed considerably over those time intervals. For example, while only 5% of the sample was diagnosed with cancer in 1992, 9% were diagnosed with it in 1998, and 15% were diagnosed with it in 2004, a two- to threefold increase. Actual health changes likely were more dramatic than this because those suffering

the greatest health deterioration probably died disproportionately early and dropped out of the sample.

C. Estimation Model

With these considerations in mind, we estimate the following linear probability model:

$$\text{[redacted]} \quad (1)$$

where α and β are scalar parameters and γ is a parameter vector conformable to [redacted] ¹⁹ Binary dependent variable [redacted] is unity if an individual reported holding individual term life insurance in 1994 but not in 1992 (a new buyer), and 0 if she reported having individual term life insurance in neither 1994 nor 1992 (a non-owner). [redacted] indicates whether an individual had died by wave 2004, our measure of mortality risk. Vector \mathbf{X} represents the pricing controls observed in 1992, including: (a) the respondent's age, gender, and smoking and drinking status (whether an individual has ever smoked, whether she smokes now, and whether she drinks alcohol now); (b) health status and medical history (whether she has been diagnosed with diabetes, high blood pressure, cancer, heart disease, arthritis, lung disease, stroke, asthma, kidney disease, ulcer, high cholesterol, or back pain; whether she has had a hospital stay in the previous 12 months; and whether her BMI indicates she has healthy weight, is overweight, or obese);²⁰ and (c) family history (whether her father or mother had died before age 60).²¹ Coefficient β is our parameter of interest, measuring the correlation between mortality risk and coverage conditional on the pricing factors. A positive estimate of β suggests the presence of adverse selection.²²

V. Results

¹⁹ The Probit version of model (1) produces almost identical estimates.

²⁰ In the BMI, healthyweight lies between 18.5 and 24.5 and overweight between 24.5 and 30. A BMI above 30 is obese.

²¹ HRS records whether the respondent's mother and father are alive and if so what their age is; and if they are not, the age when they died. We code a parent who died before 60 as an indicator for unfavorable family history. We thus have two indicator variables for family history, one being whether the father had died before 60 and the other whether the mother had died before 60. These are crude measures. HRS data do not, however, provide information about parents' cause of death.

²² Ideally, we would like to examine the conditional correlation between the amount of individual term insurance purchased and subsequent mortality. HRS did not, however, ask a respondent for the amount of *individual* term insurance she held, although it asked her to report the amount of term insurance. Since term insurance can be either individual or group, and group-market underwriting procedures are different from individual-market procedures, we cannot investigate the conditional correlation on the intensive margin.

Table 3 presents our model (1) estimates. For the sake of comparison, we first report in column (1) the results one obtains using Cawley and Philipson's (1999) primarily demand-side controls in conjunction with the entire cross-sectional 1992 sample.²³ In contrast to β_1 in equation (1), the dependent variable in the column (1) regression is β_2 , a binary indicator for whether the respondent held individual term life insurance in the 1992 wave. The point estimate of β_2 is negative and statistically insignificant, consistent with the previous literature. Column (2) adds the health-related control variables omitted in the previous literature. The β_2 estimate remains negative and insignificant, likely because of the selection problem arising from differential mortality and because of the aforementioned measurement errors in the health-related control variables. Each problem is typical of cross-sectional samples.

A. *Adverse Selection in Individual Term Life Insurance Markets*

The remainder of Table 3 presents the model (1) results themselves and, for robustness checks, a number of variants on them. Column (3) employs the same controls as in column (1), namely primarily demand rather than supply-side variables. The estimate of β_2 becomes positive at 0.035 although it is not significant at conventional levels. The contrasts between columns (3) and (1) suggest the importance of addressing the sample selection problem induced by potential differential mortality. Column (4) adds the controls for health status, medical history, and family history omitted in the previous literature. The β_2 estimate jumps to 0.045 and now is significant at the 10% level. Comparing columns (3) and (4) shows that omitting the health-related pricing controls leads to a downward bias in the estimate of the conditional correlation between mortality risk and coverage. Controlling for observable health conditions, in other words, increases β_2 's point estimate by about one-third and renders it statistically significant.

In column (5) we instead include only the controls relevant for an adverse selection test, namely the pricing control set \mathbf{X} which the insurer observes at underwriting time. The point

²³ Cawley and Philipson (1999) control for age, gender, marital status, smoking status, income, wealth, and the following proxies for bequest motives: number of grandchildren, number of children, age of the youngest child, average age of children, number of siblings, and age of spouse. In columns (1) and (2), we use age dummies and income and wealth quartiles rather than linear age, income, and wealth. Results are almost identical to those with linear age, income, and wealth.

estimate of the conditional correlation between mortality risk and life insurance coverage is 0.034, significant at the 5% level.²⁴ Because lower-risk individuals' take-up rate in our sample is 0.18, the 0.034 says that higher-risk individuals have a 19 percent $[(0.034/0.18)100]$ greater take-up rate than do lower-risk ones. That is, once risk classification is properly accounted for, those with higher mortality risk are substantially more likely to buy life insurance than are those with lower risk, implying that, even in the presence of stringent underwriting practices, individuals hold a substantial amount of private information about their risk. And although the column (5) estimate remains our acid test for adverse selection, it remains qualitatively the same after – for robustness checks – we add controls for marital status in column (6), income and wealth quartiles in column (7), and group term insurance possession in column (8).^{25,26}

The column (5) estimate of the *male* effect is small and insignificant. Being a male increases demand for life insurance because males are more likely to be a household's main income source and thus to have a stronger bequest motive than do females. At the same time, males are associated with higher mortality risk and likely engage in riskier behavior than do females and thus face a higher price.²⁷ In equilibrium, these demand and supply effects may simply cancel one another out, rendering an insignificant estimate. Such supply-demand countervailences may, indeed, explain why most pricing factors, which in the insurance industry are on both the supply and demand side, remain insignificant in column (5).²⁸ Including these pricing variables in the conditional correlation specification is, nonetheless, both necessary and sufficient for an adverse selection test. Marital status, on the other hand, is a purely demand-side factor and is significant in robustness-check columns

²⁴ To allow for possible nonlinearity among pricing factors, we also estimate model (1) with a complete set of two-way interaction terms among these factors. Estimates of α_1 are similar to those in models not containing interaction terms.

²⁵ An individual's access to close substitutes such as group life insurance may be correlated with both her demand for life insurance and her mortality risk if better jobs are more likely to offer group insurance and individuals with better jobs live longer.

²⁶ In separate results (available upon request), we replace actual mortality outcome in model (1) with dummy indicators for self-perceived mortality probabilities, as in Cawley and Philipson (1999). Few coefficient estimates are significant and we cannot detect any sign patterns. We de-emphasize these results because of the difficulties, discussed above in connection with Figure 1, that many people have in assessing mortality probability. The conditional correlation estimates may thus suffer from attenuation bias due to measurement errors in self-perceived mortality risk.

²⁷ For example, a 56 year old, non-smoking male qualifying for "preferred plus" generally pays 40-50% more, and in some cases 70%, than a comparable female. This is on the order of \$1500 for a 10-year term contract with \$750,000 face value, according to a popular individual term insurance quoting website (www.term4sale.com) which provides quotes for 125 – including most major – life insurance companies.

²⁸ Measurement errors in self-reported variables could be another factor contributing to the insignificance.

(6)-(8), implying that being married increases life insurance take-up rate by about three percentage points.

Because the empirical contract theory literature has emphasized that risk aversion is an important determinant of insurance demand and yet likely is correlated with risk occurrences, we also add, in column (9), control variables for risk aversion in addition to the pricing factors.²⁹ Variables *ra2*, *ra3*, and *ra4* in column (9) are dummies representing risk aversion levels inferred from the HRS survey's gambling questions, *ra4* indicating the most risk averse and omitted category *ra0* the least risk averse (see Appendix B for survey design). Interestingly, the estimate of the conditional correlation remains quantitatively the same as in column (5), suggesting that selection on risk preference probably is not a significant issue in life insurance markets.³⁰

B. Testing for Back-Door Bias

We have focused on potential new buyers in order to avoid downward selection bias in the estimate of the conditional correlation between risk and coverage, and to measure more precisely the impacts of observed health conditions on the take-up event. However, restricting analysis to potential new buyers may create another sample selection problem: that of excluding those who already owned individual term insurance in 1992, the beginning of our sample window. Conditional on mortality risk and pricing factors, these excluded individuals may have experienced a positive shock at the point of an earlier purchase decision, represented by a positive disturbance in a model characterizing the pre-1992 decision. The potential new buyers in our analysis might instead have experienced a negative shock at the same point. If these purchase-decision shocks are correlated over time, excluding part of the sample based on the magnitudes of past shocks effectively produces a selection on the dependent variable. As is well known, selection on the dependent variable can bias coefficient estimates.

Using a Heckman two-step procedure, we provide evidence that this potential sample selection does not threaten our empirical strategy. The key to performing a Heckman sample

²⁹ See, for example, Chiappori and Salanie (2008), Culter et al. (2008), Chiappori et al. (2006), Finkelstein and McGarry (2006), de Meza and Web (2001), and Wambach (1997).

³⁰ Coincidentally, Fang et al. (2006) also find that risk attitude does not seem to play a role in the Medigap market. Besides using the raw risk aversion data, we tried Kimball et al's (2007) imputed risk aversion measure and found results to be almost identical. Cutler et al. (2008), however, emphasize the role of risk attitude in life insurance markets, finding that risky behavior is negatively associated with term life coverage and positively associated with mortality risk.

selection test rests in finding an exclusion restriction variable which predicts the outcome in the selection equation but does not enter the equation of interest. The HRS cohort reported detailed information on individual marital history, including current marital status, starting year of current marriage if married, and starting and ending years of most recent marriage if currently unmarried. Respondents also reported the starting and ending years of up to three of their earliest marriages. Since more than 99% of respondents reported four or fewer marriages, we are able to construct a complete marital history profile for almost the entire sample. In particular, we create a set of dummy variables indicating whether the respondent was married now (i.e., in wave 1992), five years ago, ten years ago, and so on up to 30 years ago. Among these variables, marital status five years ago is a significant predictor of individual term life insurance coverage in wave 1992. This variable should not, however, influence whether an individual chose to obtain coverage or instead remain uninsured between the 1992 and 1994 waves, once we control for her marital status in 1992. It therefore serves well as an exclusion restriction variable and we employ it to test whether excluding part of the cross-sectional sample induces bias in the conditional correlation estimates.³¹

Formally, we implement the following Heckman two-step procedure:

$$\boxed{\times} \quad (2)$$

$$\boxed{\times} \quad (3)$$

where equation (2) is the first-stage selection equation and equation (3) is the second-stage equation of interest. $\boxed{\times}$ is a binary indicator taking unity if an individual did not own individual term insurance in 1992, and zero if she did. Those with $\boxed{\times}$ are the potential new buyers and are included in our main analysis to recover the conditional correlation between coverage and risk. $\boxed{\times}$ and pricing control set \mathbf{X} are defined as before. $\boxed{\times}$ is a dummy variable indicating whether the individual was married in 1992, and $\boxed{\times}$ whether she was married five years before that. $\boxed{\times}$ is the inverse Mills ratio estimated from the selection equation. Selection on $\boxed{\times}$ in the main equation can induce bias in

³¹ The exclusion restriction variable ideally would be continuous rather than discrete, but no such variable is available. A continuous variable which we attempted but which had no predictive power in the selection equation was earnings from past employment.

its coefficient estimates if error ϵ_{1i} is correlated with error ϵ_{2i} in the selection equation. A simple t -test of the estimate of the inverse Mills ratio $\lambda(\cdot)$ is a valid test for sample-selection bias.

Table 4 presents the Heckman test results, in which we have specified the selection equation as a Probit and the main equation as a linear probability model.³² Column (1) reports the first-stage and column (2) the second-stage results. As shown in column (1), an individual's marital status five years ago is a significant predictor of whether she is selected in the first stage. Column (2) reports a statistically insignificant estimate of the inverse Mills ratio coefficient (p-value 0.637), relieving concern that our estimates of the parameter of interest could be biased by excluding part of the cross-sectional sample. The conditional correlation between risk and mortality in Table 4 (column 2) is similar to what we obtained in the main result in Table 3 (column 5).

C. Purchase Timing

The binary indicator we have employed for recording death during a given time window is a coarse measure of mortality risk, as it assigns the same risk to one who died, for example in 2004 (more than ten years from the 1992 baseline), as it does to one who died in 1994 (soon after 1992). In the present section, we break this risk measure into indicators of mortality outcomes between given pairs of consecutive waves. We estimate the following linear probability model:

$$\text{newbuyer}_i = \alpha + \beta_1 \text{mort}_{t-1} + \beta_2 \text{mort}_t + \gamma \mathbf{X}_i + \epsilon_i \quad (4)$$

where *newbuyer* and control set \mathbf{X} are defined as in model (1).³³ Dummy variable *mort_t* indicates whether a respondent died between waves $t - 2$ and t , with t taking values 1994, 1996, 1998, 2000, 2002, and 2004 corresponding to the respective interview waves. The later the wave in which a person died, the lower her mortality risk. The β 's are the parameters of interest, measuring how mortality risk affects the take-up decision. They should be

³² We specify equation (3) as a linear probability rather than as a Probit model in order to circumvent the difficulty of programming the complicated double integral in binary response models with sample selection (Wooldridge 2002, p. 570). Given that all the linear probability estimates in the present analysis are similar to the Probit estimates, we expect a Probit version of equation (3) to be similar to a linear probability one as well.

³³ Probit versions of model (4) again produce results very similar to the linear probability versions.

monotonically decreasing as t grows because, if potential buyers hold residual private information about their mortality risk and incorporate such information into their life insurance purchase decision, they rationally should try to effect that purchase shortly before death.

Table 5 presents the model (4) results. Each column corresponds to that in Table 3. Columns (1) and (2) provide results based on the entire cross-sectional sample. None of the mortality dummies are statistically significant, nor is monotonicity observed. Columns (3) to (9) focus instead on potential new buyers. In column (5), which for adverse selection testing purposes correctly controls only for pricing factors \mathbf{X} , the monotonically decreasing estimates of 0.131, 0.086, and 0.067 suggest that those who died respectively two, four, and six years after the 1992 baseline exhibited take-up rates 73%, 48%, and 37% higher than those who survived more than 12 years after 1992 (the latter with a 0.18 take-up rate). The first two estimates are significant at the 5% level and the last, with p-value 0.11, is marginally significant. Coefficients of *mort_2000*, *mort_2002*, and *mort_2004* are insignificant. The remainder of the Table 5 specifications similarly reveals monotonically decreasing dummy coefficient estimates, a robustness to specification strongly suggesting that individuals have private information about their mortality risk and use it in an effort to buy life insurance shortly before death.

The above discrete measure of mortality risk provides a useful diagnosis of how those with residual private information time their purchase decisions. Column (5) of Table 5 implies that buyers are most likely to take up individual term life insurance four to six years before death.³⁴ If so, one alternatively may measure mortality risk with an indicator signifying whether a potential new buyer had died by wave 1998.³⁵ Table 6 presents the model (1) estimates under this possibly more refined risk measure. Columns again correspond to those in Tables 3 and 5. In the total cross-sectional sample, the mortality parameter is still insignificant. And in the potential-new-buyer sample, we estimate, as expected, a much larger coverage-risk conditional correlation than we do using the 12-year-window mortality risk measure. In the column (5) specification, which most correctly includes only pricing controls,

³⁴ This may explain the fact that 5-year Level Term insurance accounts for the highest market share of all individual term life insurance (34.8%) (LIMRA, 1997).

³⁵ The 12-year time-window length in the main analysis (Table 3) is somewhat arbitrary in the sense that it is determined by sample period length.

mortality's 0.086 point estimate (significant at 1%) implies that individuals who died four to six years after a baseline year had a 48% higher take-up rate in that base year than did those who survived beyond year six (the latter with a 0.18 mean take-up rate). This estimate remains robust after controlling for marital status, income and wealth quartiles, access to group coverage, and risk aversion.

VI. Conclusions

We find, contrary to the earlier literature, evidence for adverse selection in the life insurance market. After supply or pricing factors are carefully taken into account, individuals with higher mortality risk are 19% to 48% more likely to buy individual term life insurance than are those with lower risk, depending on the length of the time window in which mortality risk is defined. Moreover, buyers appear to employ this informational advantage by seeking to take up insurance four to six years before death. These results provide an alternative view of the informational content of life insurance markets, calling into question the widely held notion that life insurance is free of adverse selection. Furthermore, the failure of the life insurance industry's comparatively stringent underwriting practices to eliminate strategic purchasing suggests that informational asymmetry might be even more prevalent in other insurance markets.

The methodological contributions of the present analysis are twofold. First, with the assistance of data on potential new buyers, we address the sample selection bias induced by potential differential mortality between those with and those without coverage. Analysis based on entire cross-sectional data would produce downward-biased estimates of the coverage-risk correlation if individuals do hold private information. Second, we include a detailed set of controls for health status, medical history, and family history, information underwriters have at their disposal when setting insurability and premiums and without which adverse selection tests are invalid. Such information is more accurately obtainable among potential new buyers than it is among the entire sample. Earlier literature has excluded these important supply variables, focusing in a less illuminating way on primarily demand factors.

One might ask whether we have created another sample selection problem in that, by basing on potential new buyers only, we have excluded the part of the total cross-sectional sample that had coverage at the beginning of the sample period. Reassuringly, our application

of the Heckman test has relieved this concern. Because, however, only a discrete rather than a continuous exclusion restriction variable could be employed in that test, further analysis of back-door bias is warranted.

References

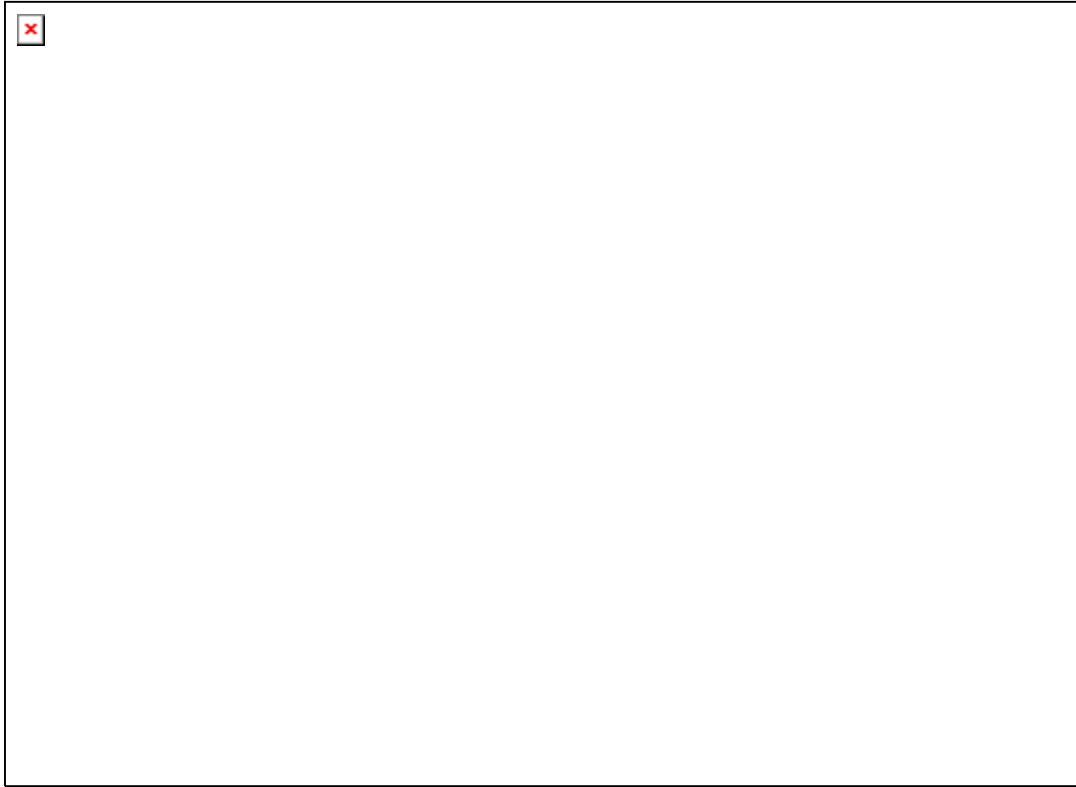
- Akerlof, G., 1970. The market for “lemons”: quality uncertainty and the market mechanism. *Quarterly Journal of Economics* 84, 488-500.
- American Council of Life insurers (ACLI), 2007a. Protectors and Investors: America’s Life Insurers. Available at http://www.acli.com/NR/rdonlyres/F40056AC-871D-4E1A-B0E0-EDA1DEA1AB92/10868/ProtectorsInvestors_Jan2007.pdf
- American Council of Life insurers (ACLI), 2007b. Life Insurers Fact Book 2007. Available at http://www.acli.com/NR/rdonlyres/A85A882F-F871-431D-976E-3316884C63EB/15016/FB_07_AllChapters2_w_insert.pdf
- Cawley, J., Philipson T., 1999. An empirical examination of information barriers to trade in insurance. *American Economic Review* 89, 827-846.
- Cardon, J., Hendel, I., 2001. Asymmetric information in health insurance: evidence from the national medical expenditure survey. *Rand Journal of Economics* 32, 408-427.
- Chiappori, P., Salanie, B., 2008. Modeling competition and market equilibrium under asymmetric information: empirical issues. 2008 AEA Annual Meeting, session titled “Empirical Work on Asymmetric Information in Insurance Markets.”
- Chiappori, P., Salanié, B., 2003. Testing contract theory: a survey of some recent work. In: Dewatripont, M., Hansen, L., Turnovsky, P. (Eds.). *Advances in Economics and Econometrics - Theory and Applications, Eighth World Congress, Econometric Society Monographs*. Cambridge: Cambridge University Press, 115-149.
- Chiappori, P., Salanié B., 2000. Testing for asymmetric information in insurance markets. *Journal of Political Economy* 108, 56-78.
- Chiappori, P., 2000. Econometric models of insurance under asymmetric information. In: Dionne, G., (Eds.). *Handbook of Insurance*, Boston: Kluwer, 365-94.
- Chiappori, P., Jullien, B., Salanié, B., Salanié, F., 2006. Asymmetric information in insurance: general testable implications. *Rand Journal of Economics* 37, 783-798.
- Cohen, A., 2005. Asymmetric information and learning: evidence from the automobile insurance market. *Review of Economics and Statistics* 87, 197-207.
- Cummins, J. D., Smith, B.D., Smith, R.N., Vanderhei, J.L., 1983. *Risk classification in life insurance*. Kluwer-Nijhoff Publishing.

- Cutler, D., Finkelstein A., McGarry, K., 2008. Preference heterogeneity in insurance markets: explaining a puzzle. *American Economic Review Papers and Proceedings* 98, 157-162.
- de Maza, D., Webb, D., 2001. Advantageous selection in insurance markets. *Rand Journal of Economics* 32, 249-262.
- Fang, H., Keane, M., Silverman, D., 2006. Sources of advantageous selection: evidence from the Medigap insurance market. Working paper.
- Finkelstein, A., McGarry, K., Sufi A., 2005. Dynamic inefficiencies in insurance markets: evidence from long-term care insurance. *American Economic Review Papers and Proceedings* 95, 224-228.
- Finkelstein, A., Poterba, J., 2004. Adverse selection in insurance markets: policyholder evidence from the U.K. annuity market. *Journal of Political Economy* 112, 183-208.
- Finkelstein, A., McGarry, K., 2006. Multiple dimensions of private information: evidence from the long-term care insurance market. *American Economic Review* 93, 938-958.
- Gan, L., Hurd, M., McFadden, D., 2005. Individual subjective survival curves. In: Wise, D. (Eds.). *Analyses in Economics of Aging*. University of Chicago Press: 377-411.
- Hendel, I., Lizzeri, A., 2003. The role of commitment in dynamic contracts: evidence from life insurance. *Quarterly Journal of Economics* 118, 299-327.
- Hurd, M., McGarry, K., 1995. Evaluation of the subjective probabilities of survival in the Health and Retirement Study. *Journal of Human Resources (Special Issue on the Health and Retirement Study: Data Quality and Early Results)* 30: S268-S292.
- Kalbfleisch, J., Prentice, R., 2002. *The Statistical Analysis of Failure Time Data*, 2nd Edition. John Wiley & Sons, Inc.
- Kimball, M. S., Saham, C. R., Shapiro, M. D., 2007a. Imputing risk tolerance from survey responses. *Journal of the American Statistic Association: Applications*, forthcoming.
- Kimball, M. S., Saham, C. R., Shapiro, M. D., 2007b. User's guide for risk preference parameters. Available at http://www-personal.umich.edu/~shapiro/data/risk_preference/ImputationUsersGuideJASA.pdf
- LIMRA, 1997. Buyer's Study. Connecticut.

Lizzeri, A., Hendel, I., 2008. Who commits to long-term contracts? How much does it cost? The case of life insurance. 2008 AEA Annual Meeting, session titled “Empirical Work on Asymmetric Information in Insurance Markets.”

Wooldridge, J.M., 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press.

Figure 1: Histogram of Self-Reported Probability to Live to Age 75



Note: Histogram is based on HRS 1992 sample individuals' response to the following question: "What do you think are the chances that you will live to be 75 or more?" The answers are on a 0-10 scale, with 0 being "absolute no chance" and 10 being "absolutely certain."

Table 1 Sample Summary Statistics

variable	definition	mean	std. dev
individual_term	whether owning individual term life insurance	0.24	0.43
term	whether owning term life insurance	0.51	0.50
life	whether owning life insurance	0.72	0.45
newbuyer	=1 if owning individual term life insurance in 1994, but not in 1992; =0 if owning in neither years.	0.19	0.39
mortality (entire 1992 sample, 2004)	whether dead by wave 2004	0.15	0.35
mortality (potential new buyers, 2004)	whether dead by wave 2004	0.15	0.35
mortality (entire 1992 sample, 1998)	Whether dead by wave 1998	0.06	0.23
mortality (potential new buyers, 1998)	Whether dead by wave 1998	0.06	0.23
newbuyer (higher risk, 2004)	Whether being a new buyer among those who died before 2004.	0.21	0.41
newbuyer (lower risk, 2004)	Whether being a new buyer among those who survived beyond 2004	0.18	0.39
newbuyer (higher risk, 1998)	Whether being a new buyer among those who died before 1998.	0.26	0.39
newbuyer (lower risk, 1998)	Whether being a new buyer among those who survived beyond 1998.	0.18	0.44
age	age	55.56	3.25
gender	=1 if male, =0 if female	0.48	0.50
smoke_ever	whether smoke now	0.64	0.48
smoke_now	whether smoke ever	0.27	0.44
drink	whether drink now	0.63	0.49
diabetes	whether diagnosed with diabetes	0.08	0.28
HBP	whether diagnosed with HBP	0.33	0.47
cancer	whether diagnosed with cancer	0.05	0.21
heart	whether diagnosed with heart disease	0.10	0.31
arthritis	whether diagnosed with arthritis	0.34	0.47
lunge	whether diagnosed with lung disease	0.06	0.23
stroke	whether diagnosed with stroke	0.02	0.15
asthma	whether diagnosed with asthma	0.06	0.24
kidney	whether diagnosed with kidney disease	0.10	0.30
ulcer	whether diagnosed with ulcer	0.09	0.28
cholesterol	whether diagnosed with high cholesterol	0.25	0.43
back_pain	whether suffering from back pain	0.35	0.48
hospital_stay	whether had a hospital stay in the previous 12 months	0.11	0.31

BMI	Body mass index	26.98	5.00
underweight	whether BMI<=18.5	0.01	0.11
healthyweight	whether BMI<=24.5 and BMI>18.5	0.32	0.47
overweight	whether BMI<=30 and BMI>24.5	0.44	0.50
obese	whether BMI>30	0.22	0.41
history_father	whether father died before 60	0.20	0.40
history_mother	whether mother died before 60	0.12	0.33
income	household income	49,717	54,349
wealth	household wealth	235,626	485,259
ra1	least risk averse	0.13	0.33
ra2	more risk averse	0.12	0.32
ra3	even more risk averse	0.11	0.31
ra4	most risk averse	0.65	0.48
num_grandkid	number of grandchildren	2.28	3.97
num_kid	number of children	3.18	2.05
min_age_kid	age of the youngest child	24.46	7.09
mean_age_kid	average age of children	28.58	6.61
num_sibling	number of siblings	2.85	2.40
age_spouse	spouse age	55.12	6.92
married	whether married	0.74	0.44

Note: Summary statistics are, unless otherwise noted, based on HRS 1992 and weighted by 1992 individual sampling weights.

Table 2 Changes in Pricing Factors over Time

variable	1992			1998			2004		
	# of obs	mean	st.dev	# of obs	mean	st.dev	# of obs	mean	st.dev
age	12542	55.18	5.58	10584	60.59	5.81	9362	66.13	6.01
gender	12543	0.46	0.50	10584	0.45	0.50	9362	0.43	0.50
smoke_ever	12543	0.63	0.48	10474	0.63	0.48	5697	0.99	0.09
smoke_now	12543	0.27	0.45	10582	0.21	0.40	5697	0.26	0.44
drink	12543	0.61	0.49	10580	0.49	0.50	9361	0.47	0.50
diabetes	12543	0.09	0.29	10572	0.13	0.34	9338	0.21	0.40
HBP	12543	0.34	0.47	10574	0.42	0.49	9349	0.57	0.50
cancer	12543	0.05	0.21	10566	0.09	0.28	9334	0.14	0.35
heart	12543	0.11	0.31	10575	0.16	0.37	9344	0.24	0.43
arthritis	12543	0.34	0.47	10574	0.49	0.50	9339	0.63	0.48
BMI	12543	27.10	5.18	10456	27.50	5.25	9212	27.94	5.59
height	12543	1.70	0.10	10579	1.69	0.10	9353	1.69	0.10
weight	12543	78.21	16.77	10460	79.17	17.15	9221	80.23	17.98
lunge	12543	0.06	0.23	10578	0.08	0.27	9347	0.11	0.32
stroke	12543	0.03	0.16	10579	0.05	0.21	9354	0.08	0.26
asthma*	12543	0.06	0.24	0			0		
back_pain*	12543	0.34	0.47	193	0.43	0.50	9351	0.36	0.48
kidney*	12543	0.11	0.31	0			0		
ulcer*	12543	0.09	0.29	0			0		
cholesterol*	12543	0.23	0.42	0			0		
hospital_stay	12531	0.11	0.32	10573	0.22	0.41	9344	0.25	0.43
history_father	12543	0.19	0.39	10584	0.19	0.39	9362	0.19	0.39
history_mother	12543	0.13	0.34	10584	0.13	0.33	9362	0.12	0.33

* Questions related to these diagnoses were not asked or were asked only to a small subgroup of the sample in the latter waves.

Table 3 Take-up Decisions: Mortality Outcome Measured within a 12-Year Time Window

VARIABLES	Cross section		The group of potential new buyers						
	(1) CP	(2) CP+ health	(3) CP	(4) CP+ health	(5) pricing	(6) pricing+ marital	(7) pricing+ wealth+ marital	(8) pricing+ wealth+ marital+ group	(9) pricing+ risk aversion
mortality	-0.008 (0.019)	-0.012 (0.020)	0.035 (0.023)	0.045* (0.023)	0.034** (0.017)	0.037** (0.017)	0.037** (0.017)	0.037** (0.017)	0.039** (0.018)
male	0.100*** (0.017)	0.101*** (0.017)	0.013 (0.019)	0.012 (0.020)	0.004 (0.011)	0.001 (0.011)	-0.000 (0.012)	0.001 (0.012)	0.004 (0.012)
smoke_ever	-0.040*** (0.014)	-0.041*** (0.014)	-0.010 (0.016)	-0.010 (0.016)	-0.007 (0.013)	-0.007 (0.013)	-0.007 (0.013)	-0.007 (0.013)	-0.009 (0.014)
smoke_now	0.019 (0.015)	0.022 (0.016)	0.003 (0.017)	0.002 (0.018)	-0.006 (0.014)	-0.001 (0.014)	0.001 (0.014)	0.001 (0.014)	0.000 (0.014)
drink		-0.003 (0.013)		0.001 (0.014)	-0.002 (0.011)	-0.002 (0.011)	-0.003 (0.012)	-0.003 (0.012)	0.001 (0.012)
diabetes		-0.025 (0.022)		0.002 (0.025)	0.006 (0.020)	0.006 (0.020)	0.007 (0.020)	0.007 (0.020)	0.001 (0.020)
HBP		0.023* (0.013)		-0.009 (0.015)	-0.005 (0.012)	-0.004 (0.012)	-0.004 (0.012)	-0.003 (0.012)	-0.004 (0.012)
cancer		0.006 (0.028)		-0.029 (0.029)	-0.030 (0.024)	-0.031 (0.024)	-0.031 (0.024)	-0.031 (0.024)	-0.036 (0.024)
heart		0.005 (0.021)		-0.005 (0.022)	0.012 (0.019)	0.011 (0.019)	0.012 (0.019)	0.012 (0.019)	0.018 (0.019)
arthritis		0.017 (0.013)		0.024 (0.015)	0.025** (0.012)	0.026** (0.012)	0.026** (0.012)	0.026** (0.012)	0.026** (0.013)
lung		-0.007 (0.028)		-0.005 (0.032)	0.001 (0.025)	0.001 (0.025)	0.001 (0.025)	0.001 (0.025)	0.002 (0.026)
stroke		0.046 (0.046)		-0.049 (0.041)	-0.049 (0.032)	-0.049 (0.032)	-0.048 (0.032)	-0.049 (0.032)	-0.054 (0.033)
asthma		-0.028 (0.026)		-0.010 (0.029)	-0.016 (0.022)	-0.014 (0.022)	-0.012 (0.023)	-0.012 (0.023)	-0.014 (0.023)
kidney		-0.012 (0.020)		-0.021 (0.022)	-0.026 (0.017)	-0.024 (0.017)	-0.024 (0.017)	-0.024 (0.017)	-0.022 (0.018)
ulcer		-0.015 (0.021)		-0.036* (0.022)	-0.011 (0.018)	-0.010 (0.018)	-0.011 (0.018)	-0.011 (0.018)	-0.005 (0.019)
cholesterol		-0.009 (0.014)		-0.010 (0.015)	-0.001 (0.013)	-0.001 (0.013)	-0.002 (0.013)	-0.002 (0.013)	0.004 (0.013)
back_pain		0.015 (0.013)		-0.002 (0.014)	-0.008 (0.012)	-0.007 (0.012)	-0.006 (0.012)	-0.006 (0.012)	-0.003 (0.012)
hospital_stay		0.017 (0.021)		-0.029 (0.021)	-0.022 (0.017)	-0.021 (0.017)	-0.020 (0.017)	-0.021 (0.017)	-0.029* (0.018)
healthyweight		-0.062 (0.064)		0.007 (0.065)	0.043 (0.038)	0.038 (0.038)	0.036 (0.038)	0.037 (0.038)	0.040 (0.040)
overweight		-0.066 (0.064)		0.010 (0.065)	0.053 (0.038)	0.048 (0.038)	0.045 (0.038)	0.046 (0.038)	0.052 (0.040)
obese		-0.066 (0.065)		0.010 (0.066)	0.067* (0.039)	0.063 (0.039)	0.060 (0.040)	0.061 (0.039)	0.064 (0.041)
history_father		-0.001 (0.015)		0.004 (0.017)	0.013 (0.014)	0.014 (0.014)	0.014 (0.014)	0.013 (0.014)	0.015 (0.014)
history_mother		0.003 (0.018)		-0.010 (0.020)	-0.008 (0.016)	-0.007 (0.016)	-0.007 (0.016)	-0.008 (0.016)	-0.007 (0.017)
married	0.060* (0.033)	0.066** (0.033)	0.024 (0.034)	0.026 (0.034)		0.036*** (0.012)	0.029** (0.013)	0.028** (0.013)	
num_grandkid	0.005** (0.002)	0.005** (0.002)	0.001 (0.003)	0.001 (0.003)					
num_kid	-0.004 (0.004)	-0.003 (0.004)	-0.005 (0.005)	-0.005 (0.005)					

min_age_kid	0.002 (0.002)	0.002 (0.002)	-0.000 (0.002)	-0.000 (0.002)					
mean_age_kid	-0.005 (0.003)	-0.005* (0.003)	-0.003 (0.003)	-0.003 (0.003)					
num_sibling	0.000 (0.002)	0.000 (0.002)	0.006** (0.003)	0.006** (0.003)					
age_spouse	0.000 (0.001)	0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)					
income_qrt1	0.001 (0.021)	-0.003 (0.021)	-0.024 (0.023)	-0.020 (0.023)	-0.016 (0.019)		-0.022 (0.019)		
income_qrt2	-0.006 (0.017)	-0.010 (0.017)	-0.018 (0.019)	-0.018 (0.019)	-0.023 (0.017)		-0.026 (0.017)		
income_qrt3	-0.025 (0.015)	-0.027* (0.015)	-0.010 (0.017)	-0.010 (0.017)	-0.010 (0.016)		-0.011 (0.016)		
wealth_qrt1	0.006 (0.021)	0.004 (0.021)	0.007 (0.023)	0.011 (0.024)	0.005 (0.018)		0.006 (0.018)		
wealth_qrt2	0.047*** (0.017)	0.046*** (0.017)	0.023 (0.019)	0.025 (0.020)	0.029* (0.017)		0.032* (0.017)		
wealth_qrt3	0.058*** (0.015)	0.058*** (0.016)	0.033* (0.017)	0.035* (0.018)	0.026 (0.016)		0.027* (0.016)		
group_life_ins								-0.015 (0.012)	
ra2									0.018 (0.023)
ra3									0.040* (0.022)
ra4									0.026 (0.017)
Observations	6191	6188	4336	4335	6124	6124	6124	6124	5759
R-squared	0.022	0.025	0.011	0.014	0.009	0.011	0.012	0.012	0.011

Note: The dependent variable in columns (1)-(2) is *individual_term*, indicating whether an individual owned individual term life insurance in the 1992 wave; the dependent variable in columns (3)-(9) is *newbuyer*, indicating whether an individual is a new buyer or a non-owner as defined in the text. Age dummies are included in all regressions and coefficient estimates are suppressed. All regressions are weighted by HRS 1992 individual sampling weights. Robust standard errors are reported in parentheses. ***, **, and * indicates significance level at 1%, 5% , and 10% respectively.

Table 4 Heckman Selection Test

VARIABLES	(1) first stage selection equation	(2) second stage equation of interest
mortality	0.001 (0.015)	0.039** (0.018)
male	-0.058*** (0.011)	-0.013 (0.035)
smoke_ever	0.024* (0.012)	0.001 (0.019)
smoke_now	-0.003 (0.013)	-0.001 (0.014)
drink	0.011 (0.011)	0.001 (0.013)
diabetes	0.030* (0.017)	0.018 (0.027)
HBP	-0.022* (0.011)	-0.012 (0.017)
cancer	0.001 (0.023)	-0.027 (0.024)
heart	0.003 (0.017)	0.007 (0.019)
arthritis	-0.008 (0.011)	0.025* (0.013)
lung	-0.010 (0.024)	-0.002 (0.027)
stroke	-0.038 (0.037)	-0.074* (0.039)
asthma	0.023 (0.021)	-0.013 (0.027)
kidney	0.026 (0.016)	-0.016 (0.024)
ulcer	-0.003 (0.017)	-0.013 (0.019)
cholesterol	0.009 (0.012)	0.001 (0.014)
back_pain	-0.007 (0.011)	-0.010 (0.013)
hospital_stay	-0.003 (0.017)	-0.020 (0.018)
healthyweight	0.016 (0.044)	0.056 (0.039)
overweight	0.010 (0.045)	0.062 (0.039)
obese	0.003 (0.045)	0.076* (0.040)
history_father	0.002 (0.013)	0.017 (0.014)
history_mother	-0.004 (0.015)	-0.009 (0.017)
married	0.008 (0.021)	0.027 (0.017)
inverse mills ratio		0.183 (0.387)
married 5 years ago	-0.036* (0.021)	
Constant		-0.334 (0.423)
Observations	8461	5899
Pseudo R2	0.009	.
R-squared	.	0.010

Note: The dependent variable in column (1) is *selection*, indicating whether an individual is a potential new buyer, i.e., someone who did not own individual term insurance in 1992; the dependent variable in column (2) is *newbuyer*, indicating whether an individual is a new buyer or a non-owner as defined in the text. Age dummies are included in all regressions and coefficient estimates are suppressed. All regressions are weighted by HRS 1992 individual sampling weights. Robust standard errors are reported in parentheses. ***, **, and * indicates significance level at 1%, 5% , and 10% respectively.

Table 5 Take-up Decisions: Mortality Outcome Measured by Dummy Indicators between Given Pairs of Consecutive Waves

VARIABLES	Cross section		The group of potential new buyers						
	(1) CP	(2) CP+ health	(3) CP	(4) CP+ health	(5) pricing	(6) pricing+ marital	(7) pricing+ wealth+ marital	(8) pricing+ wealth+ marital+ group	(9) pricing+ risk aversion
mort_94	-0.039 (0.066)	-0.054 (0.064)	0.094 (0.097)	0.115 (0.098)	0.131** (0.058)	0.132** (0.058)	0.138** (0.058)	0.136** (0.058)	0.144** (0.060)
mort_96	-0.004 (0.053)	-0.047 (0.062)	0.216** (0.090)	0.226** (0.090)	0.086** (0.043)	0.089** (0.043)	0.090** (0.043)	0.090** (0.043)	0.088** (0.044)
mort_98	0.024 (0.033)	-0.036 (0.040)	0.090* (0.053)	0.094* (0.053)	0.067 (0.043)	0.066 (0.043)	0.067 (0.043)	0.067 (0.043)	0.079* (0.045)
mort_00	-0.044* (0.026)	-0.026 (0.038)	-0.055 (0.035)	-0.038 (0.036)	-0.015 (0.030)	-0.012 (0.030)	-0.011 (0.030)	-0.012 (0.030)	-0.003 (0.032)
mort_02	0.055** (0.027)	0.037 (0.037)	0.009 (0.041)	0.016 (0.041)	0.007 (0.031)	0.010 (0.031)	0.011 (0.031)	0.010 (0.031)	0.004 (0.032)
mort_04	-0.005 (0.030)	-0.013 (0.040)	0.041 (0.048)	0.046 (0.048)	0.019 (0.036)	0.022 (0.036)	0.022 (0.036)	0.022 (0.036)	0.017 (0.039)
male	0.081*** (0.012)	0.103*** (0.017)	0.011 (0.019)	0.010 (0.020)	0.002 (0.011)	-0.001 (0.011)	-0.002 (0.012)	-0.000 (0.012)	0.002 (0.012)
smoke_ever	-0.037*** (0.010)	-0.041*** (0.014)	-0.009 (0.016)	-0.009 (0.016)	-0.007 (0.013)	-0.007 (0.013)	-0.008 (0.013)	-0.008 (0.013)	-0.009 (0.014)
smoke_now	0.019* (0.011)	0.023 (0.016)	0.002 (0.017)	0.002 (0.018)	-0.005 (0.014)	-0.000 (0.014)	0.001 (0.014)	0.001 (0.014)	0.001 (0.014)
drink		-0.003 (0.013)		0.000 (0.014)	-0.001 (0.011)	-0.002 (0.011)	-0.003 (0.012)	-0.002 (0.012)	0.001 (0.012)
diabetes		-0.022 (0.023)		0.002 (0.025)	0.003 (0.020)	0.004 (0.020)	0.004 (0.020)	0.004 (0.020)	-0.002 (0.021)
HBP		0.025* (0.013)		-0.008 (0.015)	-0.004 (0.012)	-0.003 (0.012)	-0.002 (0.012)	-0.002 (0.012)	-0.003 (0.012)
cancer		0.009 (0.029)		-0.032 (0.029)	-0.034 (0.023)	-0.035 (0.023)	-0.035 (0.023)	-0.035 (0.023)	-0.040* (0.023)
heart		0.005 (0.021)		-0.006 (0.023)	0.010 (0.019)	0.009 (0.019)	0.010 (0.019)	0.010 (0.019)	0.016 (0.019)
arthritis		0.018 (0.013)		0.024 (0.015)	0.025** (0.012)	0.026** (0.012)	0.025** (0.012)	0.026** (0.012)	0.025** (0.013)
lung		-0.006 (0.028)		-0.000 (0.031)	-0.001 (0.025)	-0.002 (0.025)	-0.001 (0.025)	-0.002 (0.025)	-0.002 (0.026)
stroke		0.048 (0.046)		-0.038 (0.040)	-0.047 (0.032)	-0.048 (0.032)	-0.047 (0.032)	-0.047 (0.032)	-0.049 (0.033)
asthma		-0.029 (0.026)		-0.011 (0.029)	-0.016 (0.023)	-0.013 (0.023)	-0.012 (0.023)	-0.011 (0.023)	-0.013 (0.024)
kidney		-0.012 (0.020)		-0.020 (0.022)	-0.028 (0.017)	-0.026 (0.017)	-0.026 (0.017)	-0.026 (0.017)	-0.024 (0.018)
ulcer		-0.013 (0.021)		-0.035 (0.022)	-0.008 (0.018)	-0.008 (0.018)	-0.008 (0.018)	-0.008 (0.018)	-0.003 (0.019)
cholesterol		-0.009 (0.014)		-0.009 (0.015)	-0.000 (0.013)	-0.001 (0.013)	-0.002 (0.013)	-0.001 (0.013)	0.005 (0.013)
back_pain		0.013 (0.013)		-0.002 (0.014)	-0.008 (0.012)	-0.008 (0.012)	-0.006 (0.012)	-0.007 (0.012)	-0.004 (0.012)
hospital_stay		0.016 (0.021)		-0.030 (0.021)	-0.023 (0.017)	-0.022 (0.017)	-0.021 (0.017)	-0.021 (0.017)	-0.031* (0.018)
healthyweight		-0.062 (0.063)		0.016 (0.063)	0.047 (0.038)	0.044 (0.038)	0.041 (0.039)	0.042 (0.039)	0.044 (0.040)
overweight		-0.067 (0.063)		0.020 (0.063)	0.060 (0.039)	0.054 (0.039)	0.052 (0.039)	0.053 (0.039)	0.056 (0.041)
obese		-0.066 (0.066)		0.021 (0.066)	0.074* (0.074)	0.070* (0.074)	0.067* (0.074)	0.068* (0.074)	0.068 (0.074)

		(0.064)		(0.064)	(0.040)	(0.040)	(0.040)	(0.040)	(0.042)
history_father		-0.001		0.006	0.015	0.016	0.016	0.016	0.016
		(0.015)		(0.017)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
history_mother		0.002		-0.008	-0.009	-0.008	-0.009	-0.009	-0.008
		(0.018)		(0.020)	(0.016)	(0.016)	(0.016)	(0.016)	(0.017)
married	0.049**	0.065*	0.019	0.022		0.036***	0.029**	0.028**	
	(0.024)	(0.033)	(0.034)	(0.034)		(0.012)	(0.013)	(0.013)	
num_grandkid	0.003**	0.005**	0.001	0.001					
	(0.001)	(0.002)	(0.003)	(0.003)					
num_kid	-0.005	-0.003	-0.005	-0.005					
	(0.003)	(0.004)	(0.005)	(0.005)					
min_age_kid	0.002	0.002	-0.000	-0.000					
	(0.002)	(0.002)	(0.002)	(0.002)					
mean_age_kid	-0.005***	-0.005*	-0.003	-0.003					
	(0.002)	(0.003)	(0.003)	(0.003)					
num_sibling	0.004**	0.001	0.006**	0.006*					
	(0.002)	(0.002)	(0.003)	(0.003)					
age_spouse	0.001	0.000	0.000	-0.000					
	(0.001)	(0.001)	(0.001)	(0.001)					
income_qrt1	-0.024	-0.002	-0.021	-0.018			-0.018	-0.024	
	(0.020)	(0.021)	(0.023)	(0.023)			(0.019)	(0.020)	
income_qrt2	-0.034**	-0.010	-0.017	-0.017			-0.024	-0.027	
	(0.016)	(0.017)	(0.019)	(0.019)			(0.017)	(0.017)	
income_qrt3	-0.051***	-0.026*	-0.011	-0.010			-0.010	-0.012	
	(0.014)	(0.015)	(0.017)	(0.017)			(0.016)	(0.016)	
wealth_qrt1	-0.014	0.003	0.009	0.012			0.006	0.007	
	(0.020)	(0.021)	(0.023)	(0.024)			(0.018)	(0.018)	
wealth_qrt2	0.023	0.046***	0.023	0.025			0.030*	0.032*	
	(0.016)	(0.017)	(0.019)	(0.020)			(0.017)	(0.017)	
wealth_qrt3	0.031**	0.057***	0.034**	0.035**			0.027*	0.028*	
	(0.014)	(0.016)	(0.017)	(0.018)			(0.016)	(0.016)	
group_life_ins								-0.015	
								(0.012)	
ra2									0.016
									(0.023)
ra3									0.039*
									(0.022)
ra4									0.025
									(0.017)
Observations	11874	6161	4323	4322	6084	6084	6084	6084	5722
R-squared	0.017	0.025	0.014	0.017	0.011	0.012	0.014	0.014	0.013

Note: The dependent variable in columns (1)-(2) is *individual_term*, indicating whether an individual owned individual term life insurance in the 1992 wave; the dependent variable in columns (3)-(9) is *newbuyer*, indicating whether an individual is a new buyer or a non-owner as defined in the text. Age dummies are included in all regressions and coefficient estimates are suppressed. All regressions are weighted by HRS 1992 individual sampling weights. Robust standard errors are reported in parentheses. ***, **, and * indicates significance level at 1%, 5% , and 10% respectively.

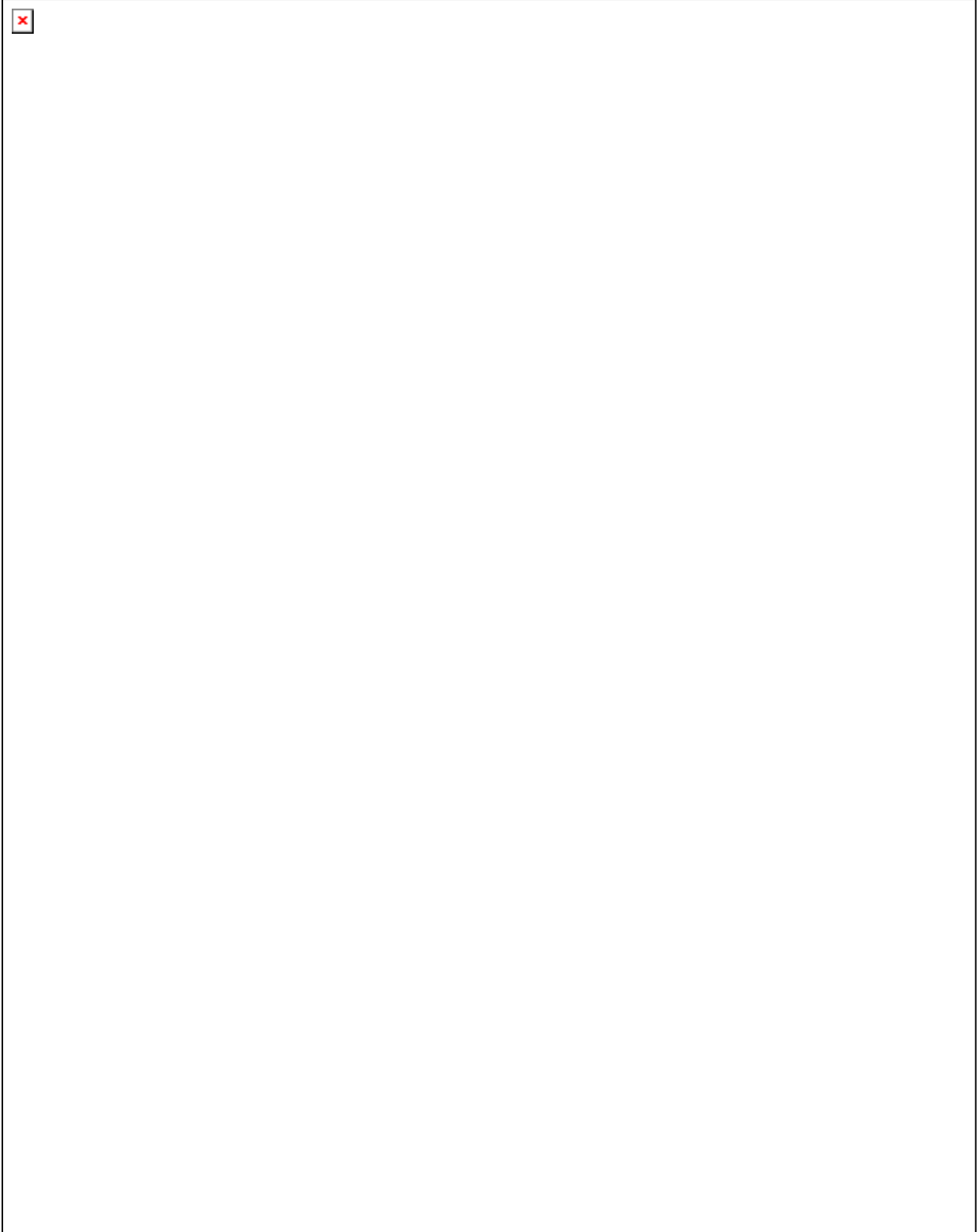
Table 6 Take-up Decisions: Mortality Outcome Measured within a Six-Year Time Window

VARIABLES	Cross section		The group of potential new buyers						
	(1) CP	(2) CP+ health	(3) CP	(4) CP+ health	(5) pricing	(6) pricing+ marital	(7) pricing+ wealth+ marital	(8) pricing+ wealth+ marital+ group	(9) pricing+ risk aversion
mortality	-0.038 (0.030)	-0.046 (0.030)	0.123*** (0.042)	0.130*** (0.043)	0.086*** (0.028)	0.087*** (0.028)	0.089*** (0.028)	0.089*** (0.028)	0.093*** (0.029)
male	0.102*** (0.016)	0.104*** (0.017)	0.011 (0.019)	0.009 (0.019)	0.003 (0.011)	-0.000 (0.011)	-0.002 (0.011)	0.000 (0.011)	0.003 (0.012)
smoke_ever	-0.039*** (0.013)	-0.040*** (0.013)	-0.011 (0.015)	-0.011 (0.015)	-0.007 (0.013)	-0.007 (0.013)	-0.008 (0.013)	-0.007 (0.013)	-0.009 (0.013)
smoke_now	0.026* (0.015)	0.028* (0.015)	0.001 (0.017)	0.000 (0.017)	-0.007 (0.014)	-0.001 (0.014)	0.000 (0.014)	-0.000 (0.014)	-0.000 (0.014)
drink		-0.006 (0.013)		0.002 (0.014)	-0.002 (0.011)	-0.002 (0.011)	-0.002 (0.011)	-0.002 (0.011)	0.002 (0.012)
diabetes		-0.020 (0.022)		0.004 (0.025)	0.007 (0.020)	0.008 (0.020)	0.008 (0.020)	0.008 (0.020)	0.002 (0.021)
HBP		0.024* (0.013)		-0.009 (0.014)	-0.005 (0.012)	-0.003 (0.012)	-0.003 (0.012)	-0.002 (0.012)	-0.003 (0.012)
cancer		0.012 (0.028)		-0.021 (0.030)	-0.026 (0.023)	-0.027 (0.023)	-0.028 (0.023)	-0.027 (0.023)	-0.031 (0.024)
heart		0.001 (0.021)		-0.008 (0.022)	0.009 (0.018)	0.008 (0.018)	0.009 (0.018)	0.010 (0.018)	0.014 (0.019)
arthritis		0.021 (0.013)		0.024 (0.015)	0.025** (0.012)	0.026** (0.012)	0.025** (0.012)	0.026** (0.012)	0.025** (0.012)
lung		-0.005 (0.028)		0.008 (0.032)	0.006 (0.025)	0.005 (0.025)	0.006 (0.025)	0.006 (0.025)	0.006 (0.026)
stroke		0.062 (0.045)		-0.028 (0.042)	-0.039 (0.032)	-0.038 (0.032)	-0.037 (0.032)	-0.037 (0.032)	-0.040 (0.033)
asthma		-0.029 (0.026)		-0.019 (0.029)	-0.021 (0.022)	-0.019 (0.022)	-0.017 (0.022)	-0.017 (0.022)	-0.019 (0.023)
kidney		-0.011 (0.020)		-0.026 (0.021)	-0.032* (0.017)	-0.030* (0.017)	-0.029* (0.017)	-0.030* (0.017)	-0.028 (0.017)
ulcer		-0.011 (0.021)		-0.026 (0.022)	-0.005 (0.018)	-0.004 (0.018)	-0.004 (0.018)	-0.004 (0.018)	0.000 (0.019)
cholesterol		-0.005 (0.014)		-0.008 (0.015)	-0.001 (0.012)	-0.002 (0.012)	-0.003 (0.012)	-0.002 (0.012)	0.003 (0.013)
back_pain		0.015 (0.013)		-0.003 (0.014)	-0.007 (0.012)	-0.007 (0.012)	-0.005 (0.012)	-0.005 (0.012)	-0.003 (0.012)
hospital_stay		0.016 (0.021)		-0.032 (0.021)	-0.023 (0.017)	-0.022 (0.017)	-0.021 (0.017)	-0.022 (0.017)	-0.030* (0.017)
healthyweight		-0.052 (0.060)		0.028 (0.059)	0.055 (0.036)	0.051 (0.036)	0.049 (0.036)	0.050 (0.036)	0.051 (0.038)
overweight		-0.055 (0.060)		0.035 (0.060)	0.068* (0.036)	0.062* (0.036)	0.060* (0.036)	0.061* (0.036)	0.064* (0.038)
obese		-0.058 (0.060)		0.036 (0.060)	0.082** (0.037)	0.078** (0.037)	0.075** (0.037)	0.077** (0.037)	0.077* (0.039)
history_father		-0.002 (0.015)		0.003 (0.016)	0.011 (0.014)	0.011 (0.014)	0.011 (0.014)	0.011 (0.014)	0.013 (0.014)
history_mother		0.011 (0.018)		-0.007 (0.020)	-0.008 (0.016)	-0.007 (0.016)	-0.008 (0.016)	-0.008 (0.016)	-0.007 (0.017)
married	0.068** (0.032)	0.073** (0.032)	0.022 (0.034)	0.024 (0.034)		0.039*** (0.012)	0.032** (0.013)	0.031** (0.013)	
num_grandkid	0.005*** (0.002)	0.005** (0.002)	0.000 (0.003)	0.000 (0.003)					
num_kid	-0.005 (0.004)	-0.005 (0.004)	-0.004 (0.005)	-0.004 (0.005)					
min_age_kid	0.001	0.001	-0.000	-0.000					

	(0.002)	(0.002)	(0.002)	(0.002)					
mean_age_kid	-0.003	-0.003	-0.003	-0.003					
	(0.003)	(0.003)	(0.003)	(0.003)					
num_sibling	0.001	0.001	0.006**	0.006**					
	(0.002)	(0.002)	(0.003)	(0.003)					
age_spouse	0.000	0.000	0.000	-0.000					
	(0.001)	(0.001)	(0.001)	(0.001)					
income_qrt1	0.002	-0.004	-0.023	-0.020		-0.019	-0.026		
	(0.021)	(0.021)	(0.023)	(0.023)		(0.019)	(0.019)		
income_qrt2	-0.013	-0.016	-0.012	-0.012		-0.018	-0.022		
	(0.017)	(0.017)	(0.019)	(0.019)		(0.017)	(0.017)		
income_qrt3	-0.025*	-0.027*	-0.008	-0.008		-0.007	-0.009		
	(0.015)	(0.015)	(0.017)	(0.017)		(0.016)	(0.016)		
wealth_qrt1	0.015	0.011	0.006	0.009		0.006	0.008		
	(0.021)	(0.021)	(0.023)	(0.023)		(0.018)	(0.018)		
wealth_qrt2	0.051***	0.048***	0.022	0.024		0.028*	0.031*		
	(0.017)	(0.017)	(0.019)	(0.019)		(0.016)	(0.016)		
wealth_qrt3	0.059***	0.058***	0.028	0.029*		0.022	0.023		
	(0.015)	(0.015)	(0.017)	(0.017)		(0.015)	(0.015)		
group_life_ins							-0.017		
							(0.012)		
ra2									0.016
									(0.022)
ra3									0.039*
									(0.022)
ra4									0.025
									(0.017)
Observations	6387	6384	4457	4456	6310	6310	6310	6310	5934
R-squared	0.022	0.025	0.013	0.016	0.011	0.013	0.014	0.014	0.013

Note: The dependent variable in columns (1)-(2) is *individual_term*, indicating whether an individual owned individual term life insurance in the 1992 wave; the dependent variable in columns (3)-(9) is *newbuyer*, indicating whether an individual is a new buyer or a non-owner as defined in the text. Age dummies are included in all regressions and coefficient estimates are suppressed. All regressions are weighted by HRS 1992 individual sampling weights. Robust standard errors are reported in parentheses. ***, **, and * indicates significance level at 1%, 5% , and 10% respectively.

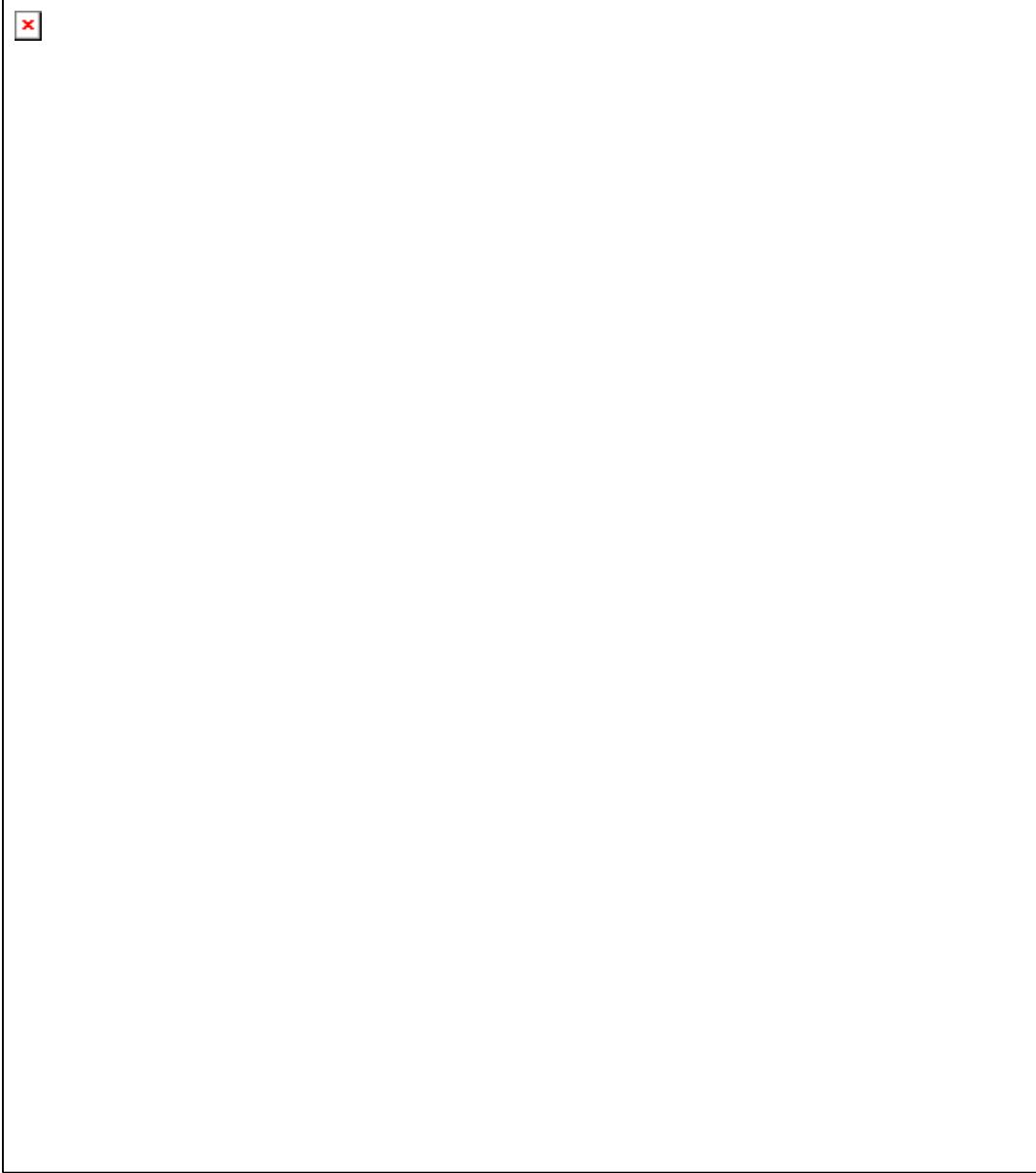
Appendix A: An illustration of the Risk Classification Table*



* The information here is from QuickQuote.com , a popular online life insurance quoting

system and represents a collective sample of underwriting guidelines. The original table is available at <http://www.quickquote.com/uwGuideLines.html>.

** Examples include, but are not limited to, scuba diving, jet, snow, and water skiing, snowboarding, hang gliding, skydiving, paragliding, bungee jumping, mountain climbing, and amateur racing. Rules can vary by company.



*** A substandard rating may be available for these medical conditions, depending on individual circumstances and insurance company guidelines

Appendix B: Survey design for risk preference questions.

In the 1992 wave, the HRS asked a series of gambling questions to solicit information about respondents' risk attitudes. The interviewer first asked the following question:

“Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life. You are given the opportunity to take a new and equally good job, with a 50-50 chance it will double your (family) income and a 50-50 chance that it will cut your (family) income by a third. Would you take the new job?”

If the respondent answered “yes,” the interviewer continues with the following question:

“Suppose the chances were 50-50 that it would double your (family) income, and 50-50 that it would cut it in half. Would you still take the new job?”

If the respondent answered “no,” the interviewer instead continues with the following question:

“Suppose the chances were 50-50 that it would double your (family) income and 50-50 that it would cut it by 20 percent. Would you then take the new job?”

The responses to these questions place respondents into four ordered risk categories: a person with answer (yes, yes) is in category I (most risk loving); a person with answer (yes, no) is in category II (less willing to take risk than those in category I); a person with answer (no, yes) is in category III (less willing to take risk than those in categories I and II.); a person with answers (no, no) is in category IV (most risk averse).