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ABSTRACT

Conventional theory for private information of adverse selection predicts a positive correlation between insurance coverage and ex post risk. This paper shows the opposite in the life insurance market despite the clear evidence of private information on mortality risk. The reason for this contradictory result is the existence of multiple dimensions of private information. The paper discusses how the private information on insurance preference offsets the effect of the private information on mortality risk. A mixture density model is applied to disentangle these two effects.

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I. Introduction

Much literature has argued that adverse selection or moral hazard induced by the private information may lead to an under-provision or lack of trade in insurance, causing a substantial consumer welfare loss. However, this paper shows that people who have lower mortality risk are more likely to have life insurance, despite the clear evidence of private information on mortality risk. The reason for this contradictory result is the existence of multiple dimensions of private information. The paper discusses how the private information on insurance preference offsets the effect of the private information on mortality risk and applies a mixture density model to disentangle these two effects.

As one of the most widely held financial products, by the end of 2009, total life insurance coverage in the United States had achieved $18.1 trillion (American Council of Life Insurance, 2010). In light of its large size, it is important to understand the influence of the private information in this market.

Rothschild and Stiglitz (1976) argue that individuals may still have residual information about their own eventual risk in a competitive market after conditional on all observables to insurers. Those who believe they have higher risk would purchase more insurance than those lower-risk individuals. Therefore, one standard test for detecting asymmetric information used in most literature is to test for a positive correlation between the amount of insurance coverage and *ex post* occurrence of insured risk (Chiappori and Salanié 1997, 2000; Chiappori, Julian, Salanié, and Salanié, 2006).

Existing empirical literature on asymmetric information in life insurance markets, however, is mixed. Cawley and Philipson (1999) found a neutral or even negative relationship between life insurance ownership and subsequent mortality using 1992-1994 Health and Retirement Study (HRS) data. We find similar results using HRS data during the period between 2000 and 2008. In Table 1, 20.6% of people in the sample passed away during the period of 2000 and 2008. However, the mortality rates are quite different by life insurance. Among 69.5% of people who have life insurance in year 2000, 18.4% of them passed away. Meanwhile, 25.6% of people who do not have life insurance died.

Various explanations for this interesting phenomenon are offered in the literature. Pauly *et al* (2003) explain the absence of private information with individuals' sufficiently low risk elasticity. They argue that even if individuals indeed know more than insurers, serious adverse selection will not occur if those individuals are sluggish in their willingness to respond to that information. He (2009), however, attributes the absence to a sample selection problem: Even if high-risk individuals are more likely to purchase life insurance, they are also more likely to die early and thus less likely to be found in a cross-sectional sample.

Recent theoretical research suggests that a positive correlation between insurance purchases and risk occurrence is neither necessary nor sufficient for the presence of asymmetric information about risk type when multiple dimensions of private information, such as risk type or insurance preferences, coexist (Smart, 2000; De Meza and Webb, 2001; Jullien, Salanié, and Salanié , 2007; Chiappori and Salanié, 2013). To illustrate, consider the following thought experiment. There are five individuals each in groups I and II, which are a high-insurance-preference (*h*) group and low-insurance-preference (*l*) group, respectively. The *l* group is more likely to die and has a weaker preferences in insurance; while, the *h* group has a lower probability to experience the risky event but has a stronger preferences for insurance. As shown in Table 2, the probability to die for individuals 1 to 5 in group I is 20, 30, 40, 50, and 60 percent, respectively; and the corresponding amount of insurance purchases for this group is 1, 1, 2, 3, and 4. For individuals A to E in group II, their mortality risks are 10, 20, 30, 40, and 50, respectively; and the amount of insurance purchased by this group is 1, 2, 2, 3, and 4. If we combine these two groups as a whole, a researcher examining this sample may conclude that the asymmetric information is absent: When the probability of mortality is increased from 50 to 60 percent, the amount of insurance purchased, on the contrary, decreases from 7 to 4. However, a positive correlation between individual insurance purchases and the probability of *ex post* risk can be found, conditional on each category of individuals' insurance preferences.

Empirically, Finkelstein and McGarry (2006) demonstrate the existence of these multiple dimensions of private information on risk type and on individual insurance preferences in long-term care insurance markets. They confirm that these two dimensions of private information operate in offsetting directions, leading to a neutral or negative relationship between insurance coverage and the occurrence of risky events, even if the market is known to have asymmetric information on *ex post* risk. However, despite direct evidence of private information on risk type, they still fail to detect it using the “positive correlation” test by controlling proxy variables for individuals’ preferences in insurance.

Intuitively, when a full set of proxy variables for insurance preferences is available, controlling these variables enables us to fully exclude the effect of heterogeneous insurance preferences on the relationship between insurance purchase and subsequent mortality. However, under most circumstances, the accessibility of only a partial set of proxy variables related to insurance preferences would lead to the error term still consisting of these two kinds of private information, resulting in failures of the standard test for private information. (See Gan, Huang, and Mayer (2011) for a more formal discussion on this point.)

This paper makes three contributions to the literature. First, contrary to the conclusions drawn in Cawley and Philipson (1999), this paper provides direct evidence of private information in life insurance markets. In particular, after conditioning on a set of variables used by insurance companies for the determination of risk classifications, individuals’ subjective responses on their own mortality risks that are available in HRS (but not typically available to insurance companies) have additional predictive power to their actual mortality risks. Nevertheless, the traditional positive correlation test fails to detect this asymmetric information.

Second, we find a series of socioeconomic factors, which are correlated with the second type of private information (i.e., heterogeneity in insurance preferences), and show that this type of private information has an opposite effect on insurance purchase and subsequent mortality. Similar results are reported by Finkelstein and McGarry (2006) and Cutler, Finkelstein, and McGarry (2008). Specifically, individuals who have stock, houses, and loans, as well as those who have employment are more likely to buy life insurance but less likely to experience insured event. Similarly pattern applies to individuals who have more years of education, more annual income, lower risk tolerance and stronger bequest motives. However, with the effort of excluding individuals' heterogeneity in insurance preferences through controlling these variables, we still fail to find a positive correlation between life insurance purchases and subsequent mortality.

Third, this paper applies the mixture density model, in which we separate individuals into two unobserved types based on their different preferences in life insurance. Under this framework, we successfully obtain a significant and positive correlation between life insurance purchases and subsequent mortality conditional on each type. It is worth pointing out that, due to the specificity of life insurance markets, a positive correlation between life insurance ownership and subsequent mortality signifies the existence of adverse selection, in light of the small possibility of moral hazard in this market. Our result also implies that, different from long-term care insurance markets shown by Finkelstein and McGarry (2006), such heterogeneity in preferences of life insurance is driven by a variety of socioeconomic factors, not solely the risk attitude.

The remainder of this paper proceeds as followings. In section II, we illustrate the identification strategy used to detect the private information in life insurance market and describe our data. Section III presents the results and specification test. The final section concludes.

II. Empirical Approach

Our empirical strategy proceeds in three steps. First, we demonstrate that individuals have residual private information about their mortality risk; and this residual information is also negatively correlated with insurance coverage. However, the standard positive correlation test does not provide any evidence for the existence of this private information. Second, we empirically identify a set of socioeconomic factors which are related to the second type of private information, (i.e., the heterogeneity in insurance preferences) and show that they can offset the effect of the private information on mortality risk on the correlation between insurance coverage and risk exposure in life insurance markets. In the final step of our analysis, we apply the mixture density model and present that a positive correlation between insurance coverage and insured event can be obtained only if individuals' insurance preferences is conditioned by distinguishing people into two groups based on the series of factors we mentioned above.

A. Econometric Model

We characterize the market for life insurance with the following two equations. The first equation relates the individual characteristics to the probability of mortality. The second relates the same characteristics to the decision to purchase life insurance.

$$\begin{aligned} Die &= 1(c_\beta + X\beta_X + H\beta_H + SS\beta_{SS} + u > 0) \\ LFI &= 1(c_\delta + X\delta_X + H\delta_H + SS\delta_{SS} + v > 0) \end{aligned}, \quad (1)$$

where Die is an indicator variable for whether the individual died during the period 2000-2008. LFI is a binary variable for whether the individual had life insurance in year 2000. We chose year 2000 as the starting period because the 2000 wave is the first year that includes all the variables we need in our analysis. We use X to denote the individual characteristics that are public information– information that is available for both individuals and insurers. SS is individuals' subjective survival probability for the next 10 to 15 years, so that β_{SS} is expected to be less than zero. Also, everything equal, individuals with higher expectation on their longevity are less likely to purchase life insurance, thus δ_{SS} is also expected to be less than zero.

The variable H in (1) represents the unobserved individual preferences for life insurance. Without losing generality, we assume $\delta_H > 0$, i.e., a higher H implies a higher possibility to purchase life insurance. Meanwhile, as shown by De Meza and Webb (2001) and Fang, Keane, and Silverman (2008), a higher H may also be associated with a lower probability of the occurrence of an insured event, i.e., $\beta_H < 0$.

The first step of our analysis is to examine the effect of individuals' subjective survival probabilities (SS) on actual mortality and on life insurance purchase, respectively, after conditioning on risk classifications by the insurance company (X). Previous literature (Hurd and McGarry, 2002; Gan, Hurd, and McFadden, 2005) has shown that this "first-type" private information has additional predictive power but suffers serious focal response error. We estimate the following bivariate probit models. The key interest is on the coefficient of *SS*:

$$\begin{aligned} Die &= 1(c_\beta + X\beta_X + SS\beta_{SS} + u^* > 0) \\ LFI &= 1(c_\delta + X\delta_X + SS\delta_{SS} + v^* > 0) \end{aligned}, \quad (2)$$

where, $u^* = H\beta_H + u$ and $v^* = H\delta_H + v$.

We next implement the positive correlation test for private information in the absence of private subjective survival information. The key interest is in the correlation coefficient of the two error terms. In particular, the model to be estimated is:

$$\begin{aligned} Die &= 1(c_\beta + X\beta_X + u^{**} > 0) \\ LFI &= 1(c_\delta + X\delta_X + v^{**} > 0) \end{aligned}, \quad (3)$$

where, $u^{**} = H\beta_H + Z\beta_Z + u$ and $v^{**} = H\delta_H + Z\delta_Z + v$. Clearly, error terms in equation (3) include not only private information on risk type but also private information on insurance preferences. Thus, the correlation between u^{**} and v^{**} would reflect a combined effect of these two types of private information, resulting in an ambiguous sign of ρ. Note the problem discussed here is the familiar omitted variable problem.

According to Chiappori and Salanié (1997, 2000), a positive correlation can serve as a test for the presence of adverse selection when heterogeneous insurance preference (*H*) is absent. Chiappori *et al.* (2006) as well as Chiappori and Salanié (2013) further show that the test can actually be extended to a more general setup: In the case of competitive markets, the correlation between insurance coverage and insured events can only be positive or zero even in the presence of the private heterogeneous insurance preference, *H*.

However, under the imperfect competition, if insurance preference is public, the positive correlation property still holds; while, the correlation between the insurance coverage and *ex post* risk can take any sign when individuals' insurance preference is private information. Similar analyses are also provided in Jullien, Salanié, and Salanié (2007). Gan, Huang, and Mayer (2011) also show that the positive correlation test may fail to detect the private information on risk when individuals have heterogeneous insurance preferences.

The structure of life insurance markets exhibit more like an imperfect competition instead of an perfect competition. According to American Council of Life Insurers (2010), by total direct life insurance premiums, the first largest life insurer in U.S. is 4.15 times that of the 10^{th} largest one; and 7.88 times that of the 20^{th}. Similar findings are also documented at an industry website http://InvestmentNews.com , which shows that, for 2008, the market share calculated based on direct premiums for the first largest life insurance company is 18.08%; sharply decreases to 2.56% for the 10^{th} largest; and for the 20^{th} largest company, it is only 1.12%. In fact, Chiappori and Salanié (2013) also point out that perfect competition does not well approximate insurance markets due to differentiation on fixed cost, product characteristics and switching cost.

We also apply the other approach, which estimates a probit model of mortality as a function of insurance coverage controlling for risk classification, as proposed by Finkelstein and Poterba (2002):

$$\Pr(Die = 1) = \Phi\,(X\beta_X + \theta\, LFI) \qquad (4)$$

The positive correlation predicts $\theta > 0$. One potential issue with this approach is that the endogeneity of *LFI* due to the omitted private information on the mortality, a biased estimate of θ may be obtained.

In the second step of our analysis, we try to control the effect of individuals' heterogeneous insurance preferences, *H*, on the relationship between insurance purchases and insured events.

Although we cannot observe *H*, a series of proxy variables, *W*, which are related to *H* is able to be obtained. In the classic models about life insurance such as Yaari (1965) and Hakansson (1969), the demand for life insurance is attributed to a person's desire to bequeath funds to dependents and provide income for retirement. Later models such as that of Lewis (1989) extend this framework by incorporating the preferences of the beneficiaries into the model, which shows that the probability of owning life insurance increases with the primary wage earners' death, the present value of the beneficiaries' consumption, and the degree of risk aversion; simultaneously, this probability decreases with the household's net wealth. Walliser and Winter (1998) report that tax advantages and bequest motives indeed are the two important factors determining life insurance demand in Germany. Cutler, Finkelstein, and McGarry (2008) find that individuals who engage in more risky behavior (i.e., smoking, drinking) or less risk reducing behavior (i.e., use preventative care, always wear seatbelt) are systematically less likely to have term life insurance; and not surprisingly, riskier behaviors are associated with higher mortality after controlling individuals' risk classification. Browne and Kim (1993) present evidence on life insurance demand across 45 countries. They find that the main determinants of cross-country variations in the demand for life insurance include the dependency ratio (i.e., the number of dependents per potential life insurance consumer), education and income. In Beck and Webb (2003), economic indicators, religious and institutional indicators are the robust predictors of life insurance.

Following the literature discussed above, we suggest *W* includes: *(i) Bequest motives,* which is represented by 100 or more hours spent (or not) in last two years taking care of grandchildren if they have; and religious preference, if any. *(ii) Risk aversion,* which is represented by decision to practice preventative health activities such as getting a flu shot or blood test for cholesterol. *(iii) Education,* represented by the *number of years of education*—a proxy variable for knowledge about life insurance; *(iv) Employment status* — the individual who has employment usually has a lower transaction cost for obtaining life insurance; more importantly, employed people are more likely to use life insurance, especially the whole life insurance, as an investment for retirement considering they have more uncertainties about future income than those who are already retired; *(v) Financial situation*, including income of the insured – as suggested in the literature, and whether the individual has loan, stock, and house—people with a loan usually prefer term life insurance, which helps meet the responsibility for an ensured repayment in case of any possibility of mortality during an anticipated period, while holding stock or owning a house is a reflection of investment attitudes.

We, therefore, plug these proxy variables into the following bivariate probit model to examine whether they have an opposite effect on *Die* and *LFI*:

$$Die = 1(c_\beta + X\beta_X + W\beta_W + u^{***} > 0)$$
$$LFI = 1(c_\delta + X\delta_X + W\delta_W + v^{***} > 0) \quad (5)$$

Again, if we assume *W* can fully characterize *H* such that *H* can be written as $H = W + \delta$ where δ is the error term that is independent on *W*, u^{***} and v^{***}. Given this, the correlation between the two error terms in equation (5) can be used to test for the presence of private information.

However, more commonly, the set *W* is composed of two subsets, $W = (W_o, W_u)$, where we only observe W_o but not W_u. Further, W_o and W_u are often correlated, i.e., $corr(W_o, W_u) \neq 0$. In this case, the unobserved W_u is omitted from the model. The same omitted variable problem discussed earlier remains. Thus, it is necessary to propose a method that can *fully* exclude the effect of heterogeneity in insurance preferences to uncover the private information on mortality risk.

One method to fully exclude the insurance preferences is to assume that all individuals are to be categorized into one of these *K* types: $H = (H_1, H_2, \ldots\ldots, H_K)$, based on their different life insurance preferences. Without loss of generality, we assume that $H_k < H_{k+1}$. A greater value of *H* indicates a stronger preference on life insurance. For individuals belong to the *k*-th type ($H = H_k$):

$$\begin{aligned}
Die &= 1(c_\beta + X\beta_X + SS\beta_{SS} + H_k\beta_k + u_k > 0) \\
&= 1(c_\beta^k + X\beta_X + SS\beta_{SS} + u_k > 0) \\
&= 1(c_\beta^k + X\beta_X + u_k^* > 0) \\
LFI &= 1(c_\delta + X\delta_X + SS\delta_{SS} + H_k\delta_k + v_k > 0) \\
&= 1(c_\delta^k + X\delta_X + SS\delta_{SS} + v_k > 0) \\
&= 1(c_\delta^k + X\delta_X + v_k^* > 0)
\end{aligned} \quad (6)$$

By assuming *H* to be categorical, the effect of insurance preference is absorbed into the constant terms c_β^k and c_δ^k. The correlations between u_k^* and v_k^*, therefore, only reflect the presence of private information *SS* in *k-th* type. By construction, constant terms are different for different types to reflect the effect of insurance preferences on subsequent mortality and life insurance purchase, respectively.

Implication 1. With everything equal, for any $1 \le m < n \le K$, where K is the total number of types, the n^{th} -type individual would be more likely to buy life insurance but less likely to experience mortality than the m^{th} -type individual, i.e., $c_{\beta}^{n} < c_{\beta}^{m}$ and $c_{\delta}^{n} > c_{\delta}^{m}$.

Based on above analysis, the empirical model we used to estimate is written as follows:

$$Pr(Die = i, LFI = j | X, W) = \sum_{k=1}^{K} Pr(Die = i, LFI = j | X, H = H_k) Pr(H = H_k | W)$$

for i, j = 0, 1; (7)

B. Identification of finite mixture density model

The model in equation (7) is a standard mixture density model, whose identification issue has been well studied in the literature (Hu, 2008; Lewbel, 2007; Chen, Hu, and Lewbel, 2008, 2009; Mahajan, 2006; Gan and Henandez, 2013; Henry, Kitamura and Salanié, 2013). In particular, Henry, Kitamura, and Salanié (2013), *HKS* for short, show that under the following assumptions, the mixture density model with unobserved heterogeneity in equation (7) is non-parametrically identified.

Assumption 1 (Dependency condition). The probability of being a certain type does depend on the value of W. That is, the type variable H must be correlated with W. This assumption holds since W is regarded as proxies for H.

Assumption 2 (Exclusive restriction). The set of variables W no longer affects the outcome once conditional on a certain type. That is,

$$W \perp Die \quad | X, H = H_k \text{ and } W \perp LFI \quad | X, H = H_k, \text{ for any } k \in \{1, 2, \ldots\ldots, K\}. \quad (8)$$

Note that Assumption 2 can be equivalently represented by:

$$Pr(Die = i, LFI = j \mid X, H = H_k) = Pr(Die = i, LFI = j \mid X, H = H_k, W) \quad (8')$$

for i, j = 0, 1. In particular, equation (8) implies:

$$W \perp u_k^* | X, H = H_k \text{ and } W \perp v_k^* | X, H = H_k \text{ for any } k \in \{1, 2, \ldots\ldots, K\} \quad (9)$$

Such property of W in equation (9) is quite similar to the requirement of instrumental variable (IV) in the two-stage least square (2SLS) estimation, in which the instrumental variable is supposed to be correlated with the unobserved H variable but not correlated with the error term.

It is worth noting that Assumption 2 in HKS implies that life insurance preferences can be *fully* controlled by only using a *partial* set of proxy variables W.[2]

HKS also suggests that a violation of Assumption 2 will result in a biased estimate of coefficients *provided that X and W_o* (observed proxy variables) *are correlated*, as shown in Assumption 3.

Assumption 3. $Corr\ (X, W_o) \neq 0.$

This property forms the specification test of this paper. Specifically, we successively drop each one of the five sets of proxy variables and check whether there is a significant difference between estimated coefficients of X using different proxy-variable sets. If so, this indicates that the effect of heterogeneous preferences on life insurance cannot be *fully* excluded through the mixture density model by only using a partial set of proxy variables. Assumption 3 is necessary for the validity of specification test we proposed above; otherwise, the coefficient of X would always be consistently estimated even if the unobserved insurance preference is not fully excluded.

In HKS, a sharp boundary for both the probability of being each type and the probability of the outcome conditional on a certain type can be obtained under Assumption 1 and 2. Moreover, in the two-type case, point identification can be achieved under Assumption 1, 2 as well as an additional restriction. It is suggested that one type dominates in the left tail and the other type dominates in the right tail, which is satisfied, in our case, by the assumption of symmetric distribution of dependent variables with the same variance but different means, as implied in Implication 1.

Under Implication 1, Assumption 1, and Assumption 2, the mixture density model, as shown in equation (7) with only two categories (K=2) is uniquely identified.

In the rest of this part, we will start with the simplest case in which we assume there are only two types of life insurance preferences (*high-type (h)* and *low-type (l)*)

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[2] W is called Instrumental-Like Variables (ILV) in Mahajan (2006) in which studies the non-parametric identification and estimation of regression models with a misclassified binary regressor (H_{mis}) under the mixture density framework. The existence of ILV (W) is one of the key assumptions in his paper. ILV is assumed to be independent of the observed but misclassified (H_{mis}) conditional on covariates X and true type. A direct implication of this conditional independence in his context is that the only channel for the ILV affecting the outcome is through the true type.

and construct the likelihood function with the assumption that the error terms have a standard joint normal distribution to jointly identify the parameter set (c_β^h , c_β^l , c_δ^h , c_δ^l , β_X , δ_X ,). The probability of belonging to each type and the correlations between the error terms for each type can also be estimated simultaneously.

Our objective function for MLE is:

$$\max_\theta \sum_{i=1}^{N} \ln f(Die_i, LFI_i \mid X_i, W_i) \qquad (10)$$

where,

$$f(Die_i, LFI_i) = \Pr(Die_i = 1, LFI_i = 1)^{1(Die_i=1, LFI_i=1)} * \Pr(Die_i = 1, LFI_i = 0)^{1(Die_i=1, LFI_i=0)} * \Pr(Die_i = 0, LFI_i = 1)^{1(Die_i=0, LFI_i=1)} * \Pr(Die_i = 0, LFI_i = 0)^{1(Die_i=0, LFI_i=0)}$$

$$= \prod_{\substack{m=0,1 \\ n=0,1}} [f(Die_i = m, LFI_i = n)]^{1(Die_i=m, LFI_i=n)}$$

$$= \prod_{\substack{m=0,1 \\ n=0,1}} \{\Pr(Die_i = m, LFI_i = n \mid H = H_h) * \Pr(H = H_h) + \Pr(Die_i = m, LFI_i = n \mid H = H_l) * \Pr(H = H_l)\}^{1(Die_i=m, LFI_i=n)}$$

Let $u_h^* = \rho_1 v_h^* + \eta_h$, and $u_l^* = \rho_2 v_l^* + \eta_l$; then $\sigma_{\eta_h}^2 = 1 - \rho_1^2$ and $\sigma_{\eta_l}^2 = 1 - \rho_2^2$ by the assumption that $u_{h(l)}^* \sim N(0,1)$ and $v_{h(l)}^* \sim N(0,1)$. We then write down one of the four cases in our objective function as below:

$$f(Die_i = 1, LFI_i = 1 \mid X_i, W_i) = \Pr(Die_i = 1, LFI_i = 1 \mid H = H_h, X_i) * \Pr(H = H_h \mid W_i) + \Pr(Die_i = 1, LFI_i = 1 \mid H = H_l, X_i) * \Pr(H = H_l \mid W_i)$$

$$= \Pr(c_\beta^h + X_i\beta_X + u_h^* > 0, C_\delta^h + X_i\delta_X + v_h^* > 0 \mid X_i) * \Pr(W_i\gamma^* + \omega > 0) + \Pr(c_\beta^l + X_i\beta_X + u_l^* > 0, c_\delta^l + X_i\delta_X + v_l^* > 0 \mid X_i) * [1 - \Pr(W_i\gamma^* + \omega > 0)]$$

$$= \int_{-c_\delta^h - X_i\delta_X}^{\infty} \Phi\left(\frac{c_\beta^h + X_i\beta_X + \rho_1 v_h^*}{\sqrt{1-\rho_1^2}}\right)\phi(v_h^*)dv_h^* \Phi(W_i\gamma^*) + \int_{-c_\delta^l - X_i\delta_X}^{\infty} \Phi\left(\frac{c_\beta^l + X_i\beta_X + \rho_2 v_l^*}{\sqrt{1-\rho_2^2}}\right)\phi(v_l^*)dv_l^*[1 - \Phi(W_i\gamma^*)] \quad ; \qquad (11)$$

C. Data

The data set to be used here is the HRS cohort of the Health and Retirement Study (HRS) data during the period 2000 to 2008. We restrict our analysis to data from 2000 to 2008, since 2000 is the first year which includes all the variables we apply to distinguish individuals' heterogeneity in preferences of life insurance, and 2008 is the latest data we may access. The average age of our respondents in 2000 is 66, and 70 percent have life insurance (including both term and whole life insurance). Same respondents are followed over time, allowing us to observe actual mortality from 2000 to 2008. During this eight-year time window, 20.6% of our sample die at some point. A different approach to measure the *ex-post* risk is to work on age-sex-race adjusted mortality instead of working on the binary variable of dying. This method calculates each individual's updated survival possibility conditional on if he/she has died, as suggested in Gan, Hurd, and McFadden (2005). For simplicity, this paper employs the binary variable as the record of the occurrence of insured event.

The dataset contains information on insurance status, mortality, and a series of public information on individual demographics and health conditions, all of which may be used to determine risk classifications by insurers. The data also contain information that is only available to individuals but not to insurers. Specifically, HRS asks respondents about their self-perceived likelihood of being alive for next 10 to 15 years. The specific question is: "Using a number from 0 to 100, where 0 means absolutely no chance and 100 equals absolutely certain, what do you think are the chances that you will live to be 80 to 100?" These subjective survival probabilities have been shown in the literature to carry additional information on individual actual mortality (Hurd and McGarry, 1995) and performs better in predicting individuals' behavior (Gan, Gong, Hurd, and McFadden, 2013). We, therefore, use the self-perceived likelihood of being alive for next 10 to 15 years as a proxy variable for private information, Z, which captures a subset of private information of individuals. It is worth noting that the higher the value is, the lower probability of mortality the individual believes.

One well-known potential problem with self-perceived risk is that individuals have propensity to report figures 0, 50, and 100 percent (Hurd and McGarry, 2002; Gan, Hurd, and McFadden, 2005). These focal responses suggest that individual subjective probabilities on subsequent mortality can only serve as a noisy proxy for private information.

The data also contain information that is potentially useful to distinguish individuals' different preferences in life insurance: bequest motives; risk tolerance; the number of years of education; employment status; and financial variables such as whether own stock, loan, and house. The proxy variables for risk tolerance include whether an individual practices preventative health activities such as flu shot and blood test for cholesterol. The proxy variables for bequest motives include whether individuals take care of grandkids if they have and whether they have religion preferences. For more details on the data and our sample see Table 3.

III. Results

A. Private information about mortality

Column (2) of Table 4 shows the estimated results from the bivariate probit estimation of equation (2). They show the relationship between individual beliefs and subsequent mortality and the relationship between individual beliefs and purchases of life insurance, controlling the public information used by insurance companies for determining the classification of risk.

We find that an individual's belief about the likelihood of being alive for next ten to fifteen years is a significant, negative predictor of insurance purchases as well as subsequent mortality. This indicates that the individuals who have higher self-perceived probability of being alive for next 10 to 15 years are less likely to have life insurance and are also less likely to experience mortality. The estimated coefficients for individual beliefs in *Die* and *LFI* equation are -0.0011 and -0.00078, respectively, and corresponding to marginal effects of -0.00025 and -0.00027. That is, every 10 percentage point increase in self-perceived survival probability is associated with a 0.25% decrease in the probability of mortality between 2000 and 2008 and a 0.27% decrease in the probability of holding life insurance in the year 2000, respectively. Reasons for this statistically significant but economically trivial effect may be ascribed to focal point responses and problem of noisy reports, which are quite common in these subjective questions. Nevertheless, these results provide direct evidence for the existence of private information in life insurance markets.

In addition, we also include “self-reported health status (SRH)”, which is a subjective but more comprehensive judgment for current health condition, into the public information, *X*. The specific question we use is: “Would you say your health is excellent, very good, good, fair, or poor?” People are asked to use number 1 to 5, which represent poor, fair, good, very good, and excellent, respectively, to evaluate his/her current health condition. We find the estimated coefficients for SRH in *Die* equation is significantly negative, while, in *LFI* equation, it is positive. This indicates that individuals who are in a better state of health are less likely to die but more likely to be included in the pool of individuals holding life insurance.

However, except for the direct evidence for the existence of private information we stated at the beginning of this part, when we apply the standard test, we obtain a significantly negative estimate at -0.0341 for the correlation between the two error terms. In other words, the standard test does not provide evidence for the existence of private information. These findings are consistent with the conclusions made by Cawley and Philipson (1999), in which they confirm a neutral relationship between subjective mortality risk and life insurance ownership.

B. Private information about insurance preferences

The third column of Table 4 represents the results of model (5), in which we add the proxy variables for individuals’ preferences for life insurance. We confirm that the signs of these variables are opposite in these two equations, indicating that compared to private information on risk type, these factors can have an offsetting effect on the correlation between insurance coverage and risk occurrence. Specifically, individuals who have wealth, employment, low risk tolerance, strong bequest motives, and more years of education, who own stock, house, and loan are more likely to purchase life insurance but less likely to experience the insured events. However, even after controlling these variables, the correlation between the two error terms is still negative and not significantly different from zero.

Column (4) of Table 4 report the results from the same probit model, with self-perceived risk of mortality added. All the results are similar to what reported in column (3).

C. Life insurance and individual's mortality

Another approach, suggested by Finkelstein and Poterba (2004), is also applied here to confirm this negative or neutral relationship between life insurance purchases and the mortality we derived above. Table 5 shows the estimated coefficients from probit estimation of subsequent mortality on the ownership of life insurance (equation (3)). In column (1) of Table 5, we control for the public information that is available to insurers. The coefficient for life insurance is negative and statistically significant at -0.053 (0.029), indicating that individuals who have life insurance are 2% less likely to die than those who do not. In the second column of Table 5, we add proxy for private information, i.e., the self-perceived risk of mortality. A similar result is obtained. The third and fourth columns in Table 5 report the results with proxies for individuals' preferences in life insurance added, where the fourth column includes self-perceived risk while column (3) does not. We find that the estimated coefficient for life insurance, unsurprisingly, is still not significantly different from zero.

D. Identification of private information about mortality using mixture density model

We now estimate the mixture density model as shown in equation (7), assuming individuals can be categorized into two types based on their different insurance preferences. Let H=1 be h type, and H=0 be l type. As discussed before, we cannot observe which type the individual belongs to, but we can use a series of proxy variables W which are related to H to probabilistically determine the type of an arbitrary individual. We then use ML method to estimate our log likelihood function (10).

Column (1) of the top panel of Table 6 reports the estimated effects of the series of socioeconomic factors predicting the type of an individual. Overall, 86 percent of individuals belong to the h type.

Not surprisingly, people who belong to different types are quite different in their behaviors. As expected, with everything equal, individuals who are *h* type are more likely to purchase life insurance but less likely to experience mortality. For an *h*-type individual, the average likelihood of purchasing life insurance is 0.779 and the probability of mortality is 0.079; while, for an *l*-type person, the average likelihood of purchasing life insurance is 0.178 and the probability of mortality is 0.19. In other words, the *h* type is 60 percentage points more likely to purchase life insurance but 11 percentage points less likely to experience mortality than the *l* type.

The conclusion above can also be confirmed from the perspective of the magnitude of constant terms. For the *Die* model, with everything equal, the magnitude of the estimated constant for the *h* type c_β^h is -0.2888 (3.1764), which is smaller than the estimated constant for the *l* type c_β^l at 0.2451 (3.1754). However, for the *LFI* model, with everything equal, the magnitude of the estimated constant for *h* type c_δ^h is -3.8322 (2.5344), which is larger than the estimated constant for the *l* type c_δ^l at -5.5241 (2.5530), although they are not significantly different. It is worth mentioning here that all the results are consistent with the predictions made in *Implication* 1, the assumption that guaranteed the point identification of this model.

Most importantly, by distinguishing individuals into *h* and *l* types based on their different preferences in life insurance, we obtain direct evidence of private information from the standard test. The estimated correlation between the error terms in *Die* model and *LFI* model is, respectively, positive at 0.114 (0.0568) for *h*-type and 0.327 (0.0777) for *l*-type individuals, which are both statistically significant at the 5 percent level. Note that such positive correlation is achieved without using any data on private information.

In the second column of Table 6, we include one dimension of private information, the self-perceived probability of being alive for next ten to fifteen years, in both the *Die* equation and *LFI* equation. Consistent with the results reported in one type model in Table 4, the coefficient of this variable is negative and statistically significant in both equations, indicating that private information still plays a key role in determining the purchases of life insurance and predicting subsequent mortality after controlling the classification of risk calculated by insurance companies. We find when adding one proxy variable for private information, the correlation between the two error terms for *h* type and *l* type are still significantly positive at 0.112 (0.0564) and 0.334 (0.0790), respectively. All other estimates are similar to the results reported in column (1) of Table 6.

E. A specification test

In this section, we focus on the test of the key assumption (Assumption 2) which ensures the *full* exclusion of such heterogeneity in insurance preferences through the mixture density model. Given the above assumptions, the probability of mortality and life insurance purchases conditional on each type can be expressed in the following forms:

$$\Pr(Die=1|X,H=H_h)=\Phi(c_\beta^h+X\beta_X)\text{, and }\Pr(LFI=1|X,H=H_h)=\Phi(c_\delta^h+X\delta_X);$$

$$\Pr(Die=1|X,H=H_l)=\Phi(c_\beta^l+X\beta_X)\text{, and }\Pr(LFI=1|X,H=H_l)=\Phi(c_\delta^l+X\delta_X).$$

Provided that $corr(X,W)\neq 0$, Assumption 2 holds if and only if for any arbitrary two sets of proxy variable, say W_a and W_b, there is no significantly different estimation of c_β^h, c_β^l, c_δ^h, c_δ^l, β_X and δ_X when using W_a and W_b to determine the types of individuals, respectively. This enlightens the specification test which is similar to the over-identification test in the instrumental model when more than one dimension of instrumental variables *W* is available. Such method to test Assumption 2 in our paper is also suggested by HKS. We therefore vary the variables we used in the type equation as a test of Assumption 2. Specifically, in the present setting, the set of *W* includes individuals' characteristics from five aspects: bequest motives, risk aversion, education, employment status, and financial conditions. We would like to respectively exclude each of these five aspects in our specification tests.

Table 7 (a), (b), (c), (d) and (e) reports the result when proxy variables for bequest motives, risk attitudes, the number of years of education, employment status and financial conditions are excluded, respectively, where the first column only includes public information, *X*, while the second column includes both public information, *X*, and private information on subsequent mortality in next ten to fifteen years, *Z*. We see under all of these five settings, the constants in both equations satisfy the predictors of two-type model; parameters in both *Die* and *LFI* equations are similar to the corresponding parameters estimated in Table 6, when a full set of *W* is used. Moreover, the correlations between the error terms in *Die* and *LFI* equations are still significantly positive for most of specifications; although such positive correlation is not significant in case (d) for *h* type and case (e) for *l* type.

Table 8 presents a formal Hausman-type test comparing the estimated parameters of interest in the *Die* and *LFI* equations (i.e., c_β^h, c_β^l, c_δ^h, c_δ^l, β_X and δ_X) presented in Table 7 with each of the five cases in Table 8. Results under five specifications, which correspond to the specification test in Table 8, are reported. In the first to fifth set of columns, we compare the estimates from the full model with the bequest motive-excluded model, risk aversion-excluded model, education-excluded model, employment status-excluded model, and financial conditions-excluded model, respectively. The first and second rows compare the parameter estimates in *Die* equation and *LFI* equation, respectively. As expected, estimates in the *Die* and *LFI* equations in all five settings are not significantly different from the parameters estimated from the full model.

F. A three-type model

Section D and E present results from of the mixture density model with the assumption that individuals' heterogeneity in life insurance preferences (*H*) is categorized into two types, although, it is possible to categorize them into three or more types. We distinguish people into three types based on their high, medium, or low preference for life insurance by using the same set of variables we employed when separating individuals' preferences in life insurance into two types, with the assumption that the probability of being each type has a multinomial logit distribution. Meanwhile, we make the same restrictions in the two-type model: β_X and δ_X are set to be identical for each type, while the correlation between the two error terms in each type as well as the constant terms are allowed to differ. Table 9 shows the results estimated from a three-type model, where column (1) includes only public information and column (2) contains both public information as well as self-perceived probability of being alive for next 10 to 15 years.

We find the correlations between the error terms in *Die* and *LFI* equation in each type are still significantly positive, which are 0.164 (0.069), 0.342 (0.151), and 0.202 (0.348), respectively, when only public information is included. However, compared to the two-type model, many of the variables used to distinguish people's heterogeneous preferences in life insurance in the three-type model become insignificant, indicating the delimitation of individuals' different preferences for life insurance is not that clear when separating individuals into three types by the same set of variables we used for two types. In other words, there exists much more in common on the taste for life insurance between each two types of individuals when we categorize individuals into three types than when we separate them into two.

Next, we apply the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) as a further comparison of the relative goodness of fit between two-type and three-type model. Results are shown in Table 10. We find that when there is only public information added into the *Die* and *LFI* equations, the value of AIC is 27375.7 for three-type model, while for two-type model is 27456.9, suggesting that the three-type model minimizes the information loss compared to the two-type model and thus is preferred by AIC. However, after introducing a larger penalty term for the number of parameters, the two-type model is more favorably suggested by BIC. The corresponding value of BIC for two-type model is 28170.2, while for three-type model it is 28195.1. The same conclusions can be made when both public and private information are included in *Die* and *LFI* equations. However, since the difference of values between Two-type and Three-type model measured by both AIC and BIC is quite small, we may conclude that increasing the number of types does not help improve the model a lot.

IV. Conclusions

This paper makes three contributions to the literature. First, we find after controlling the insurer's risk classification, an individual's subjective belief of being alive for next 10 to 15 years still is a significantly negative predictor on subsequent mortality, indicating the existence of residual private information in life insurance markets. Besides, this residual private information is negatively correlated with the purchase of life insurances. Combined, these two results provide direct evidence of the asymmetric information. However, this private information cannot be directly detected by the standard test which is widely used in most literature.

Second, this paper demonstrates that a series of socioeconomic factors such as education level, employment status, risk attitudes, bequest motives as well as financial conditions which result in individuals' heterogeneity in insurance preferences all have offsetting effects on life insurance coverage and risk occurrence. Specifically, individuals who are employed, wealthier, more risk averse, with strong bequest motives and higher education level as well as those who have stock, loans and houses are more likely to purchase life insurance but less likely to die. However, even after controlling these variables, we still cannot observe a positive correlation between life insurance ownership and subsequent mortality.

Third, by applying the mixture density model, in which we distinguish people into two unobserved categories based on their different preferences in insurance, we successfully detect a significantly positive correlation between life insurance purchases and subsequent mortality, providing a direct evidence of private information suggested by the standard test.

One direction for future work is to use more diverse distribution assumptions on the error terms to serve as a further test of our result. In this paper, we estimate our model by assuming a standard normal distribution of error terms; however, more extensive distribution assumptions on error terms are welcomed to be applied to secure a more robust result.

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Table 1. Unconditional Relationship between Life Insurance

		Life insurance ownership		
		0	1	Sum
Die	0	22.7%	56.7%	79.4%
	1	7.8%	12.8%	20.6%
	Sum	30.5%	69.5%	

Table 2. Thought Experiment

	Group Number	Probability of Mortality	Purchase of Life Insurance
Low insurance preference group (*l*)	1	20	1
	2	30	1
	3	40	2
	4	50	3
	5	60	4
High insurance preference group (*h*)	A	10	1
	B	20	2
	C	30	2
	D	40	3
	E	50	4
All together		10	1
		20	2
		30	3
		40	5
		50	7
		60	4

Table 3. Summary of Statistics

Variables	Mean	Std. Deviation	Min	Max
Die	0.21	0.41	0	1
LFI	0.7	0.46	0	1
Subjective survival	49.51	31.75	0	100
Marriage	0.69	0.46	0	1
Spouse age	44.49	30.87	0	99
age	65.92	9.97	27	90
age square	4444	1334	729	8100
age cubic	306172	137461	19683	729000
black	0.12	0.32	0	1
age x black	7.6	21.01	0	90
age square x black	499	1430	0	8100
age cubic x black	33482	101661	0	729000
age x gender	26.56	33.14	0	90
age square x gender	1804	2353	0	8100
age cubic x gender	124801	174154	0	72900
male	0.4	0.49	0	1
arthritis	0.56	0.5	0	1
high blood pressure	0.48	0.5	0	1
lung	0.09	0.29	0	1
cancer	0.12	0.33	0	1
heart	0.21	0.41	0	1
stroke	0.06	0.23	0	1
drink	0.06	0.24	0	1
smoke now	0.16	0.36	0	1
smoke ever	0.6	0.49	0	1
diabetes	0.17	0.44	0	1
incontinent	0.17	0.38	0	1
psych	0.14	0.34	0	1
depression	0.23	0.42	0	1
back	0.33	0.47	0	1
self-reported-health	3.3	1.11	1	5
BMI	27.25	5.34	12.6	75.5
take drugs	0.77	0.42	0	1
home care use	0.05	0.23	0	1
nursing home	0.01	0.12	0	1
hospital	0.23	0.42	0	1
number of kid	3.25	2.15	0	20
kid	0.94	0.25	0	1

No of siblings	2.59	2.31	0	17
siblings	0.85	0.36	0	1
No of grandkids	5.07	5.43	0	80
grandkid	0.8	0.4	0	1
care grandkid missing	0.2	0.4	0	1
care for grandkid	0.28	0.45	0	1
religion	0.95	0.23	0	1
education	12.47	3.02	0	17
flu shot	0.61	0.49	0	1
test for blood	0.77	0.42	0	1
employment	0.4	0.49	0	1
stock	0.36	0.48	0	1
loan	0.08	0.27	0	1
income ($)	21793	33167	0	2000000

Table 4. One Type Bivariate Probit Model

	(1)	(2)	(3)	(4)
	public information	subjective survival and public information	public information and proxies for insurance preference	public information and individual survival and proxies for insurance demand
Die equation				
subjective survival		-0.0011***		-0.0010***
		(0.0005)		(0.0005)
care for grandkids			-0.0948***	-0.0945***
			(0.0344)	(0.0344)
religion			-0.0986**	-0.0989**
			(0.0600)	(0.0600)
flu shot			0.0135	0.0138
			(0.0316)	(0.0316)
preventive test for blood cholesterol			-0.217***	-0.215***
			(0.0354)	(0.0354)
education			-0.0004	-0.0002
			(0.0052)	(0.0052)
employment status			-0.159***	-0.156***
			(0.0361)	(0.0361)
income			-1.31e-06**	-1.33e-06**
			(7.21e-07)	(7.21e-07)
have loan			-0.0060	-0.0043
			(0.0587)	(0.0587)
own house			-0.134***	-0.134***
			(0.0368)	(0.0368)
have stock			-0.0887***	-0.0887***
			(0.0320)	(0.0320)
constant	0.0658	0.160	-0.882	-0.792
	(3.1753)	(3.189)	(3.185)	(3.196)
LFI equation				
subjective survival		-0.0008***		-0.0011***
		(0.0004)		(0.0004)
care for grandkids			0.0807***	0.0814***
			(0.0279)	(0.0279)
religion			0.230***	0.230***
			(0.0496)	(0.0496)
flu shot			0.0674***	0.0679***
			(0.0256)	(0.0256)

preventive test for blood cholesterol			0.0657***	0.0677***
			(0.0287)	(0.0287)
education			0.0278***	0.0284***
			(0.0044)	(0.0044)
Employment status			0.334***	0.335***
			(0.0285)	(0.0285)
income			2.94e-06***	2.94e-06***
			(3.91e-07)	(3.91e-07)
have loan			0.188***	0.190***
			(0.0466)	(0.0467)
own house			0.257***	0.256***
			(0.0316)	(0.0316)
have stock			0.0413*	0.0418*
			(0.0261)	(0.0262)
constant	-5.1930***	-5.084***	-3.417**	-3.272**
	(1.8514)	(1.852)	(1.925)	(1.926)
corr of two error terms	-0.0331**	-0.0341**	-0.00573	-0.00678
	(0.0178)	(0.0178)	(0.0182)	(0.0182)
observations	14,605	14,605	14,586	14,586

Standard errors in parentheses: *** p<0.05, ** p<0.1, * p<0.15

Table 5. The Relationship between Life Insurance and Subsequent Mortality

	(1) public information	(2) subjective survival and public information	(3) public information and proxies for insurance preference	(4) public information and individual survival and proxies for insurance demand
coefficient from probit of mortality on LFI	-.0529** (.0294)	-.0546** (.0294)	-.0109 (.0301)	-.0126 (.0301)
Observations	14,605	14,605	14,586	14,586

Standard errors in parentheses: *** p<0.05, ** p<0.1, * p<0.15

Table 6. Mixture density model (Two-type)

	(1) Public information		(2) Public information and Subjective survival	
Type equation				
care for grandkids	0.1686***		0.1679***	
	(0.0563)		(0.0558)	
religion	0.5295***		0.5216***	
	(0.1075)		(0.1060)	
flu shot	0.0988***		0.0995***	
	(0.0492)		(0.0488)	
preventive test for blood cholesterol	0.1764***		0.1767***	
	(0.0577)		(0.0571)	
education	0.0334***		0.0343***	
	(0.0086)		(0.0086)	
Employment status	0.3990***		0.3925***	
	(0.0631)		(0.0628)	
Income	3.52e-05***		3.5e-05***	
	(4.38e-06)		(4.31e-06)	
Have loan	0.3656***		0.3665***	
	(0.1120)		(0.1114)	
Own house	0.4276***		0.4226***	
	(0.0607)		(0.0560)	
Have stock	0.1057***		0.1062***	
	(0.0534)		(0.0530)	
constant	-1.5840***		-1.569***	
	(0.2459)		(0.2436)	
Die Equation				
	High-type	Low-type	High-type	Low-type
Subjective survival			-0.0011***	-0.0011***
			(0.0005)	(0.0005)
constant	-0.2888	0.2451	-0.1787	0.3522
	(3.1764)	(3.1754)	(3.1831)	(3.1821)
LFI Equation				
Subjective survival			-0.0014***	-0.0014***
			(0.0005)	(0.0005)
Constant	-3.8322*	5.5241***	-3.671	-5.389***
	(0.0568)	(0.0777)	(2.5556)	(2.5751)
Correlation of two error terms	0.114***	0.327***	0.112***	0.334***
	(0.0568)	(0.0777)	(0.0564)	(0.0790)
observations	14,586	14,586	14,586	14,586

Standard errors in parentheses: *** p<0.05, ** p<0.1, * p<0.15

Table 7a: Specification Tests: Drop "Bequest motives"

	(1) Public information		(2) Public information and Subjective survival	
Type equation				
care for grandkids				
religion				
flu shot	0.0985***		0.0996***	
	(0.048)		(0.0477)	
preventive test for blood cholesterol	0.1730***		0.1727***	
	(0.057)		(0.056)	
Education	0.033***		0.034***	
	(0.008)		(0.008)	
Employment status	0.0379***		0.371***	
	(0.0619)		(0.0615)	
Income	0.0000359***		0.0000356***	
	(4.51e-06)		(4.45e-06)	
Have loan	0.357***		0.358***	
	(0.113)		(0.112)	
Own house	0.430***		0.425***	
	(0.059)		(0.058)	
Have stock	0.112***		0.113***	
	(0.053)		(0.053)	
constant	-0.980***		-0.968***	
	(0.181)		(0.179)	
Die Equation				
	High-type	Low-type	High-type	Low-type
Subjective survival			-0.0011***	-0.0011***
			(0.0004)	(0.0004)
constant	-0.0168	0.4897	0.093	0.594
	(3.166)	(3.165)	(3.171)	(3.171)
LFI Equation				
Subjective survival			-0.0015***	-0.0015*
			(0.0005)	(0.0005)
Constant	-4.857**	-6.632***	-4.729**	-6.543**
	(2.597)	(2.626)	(2.622)	(2.654)
Correlation of two error terms	0.106***	0.338**	0.103***	0.348***
	(0.0529)			
observations	14,586	14,586	14,586	14,586

Standard errors in parentheses: *** p<0.05, ** p<0.1, * p<0.15

Table 7b. Specification Tests: Drop "Risk Averse"

	(1) Public information		(2) Public information and Subjective survival	
Type equation				
care for grandkids	0.168***		0.167***	
	(0.056)		(0.056)	
religion	0.523***		0.516***	
	(0.107)		(0.106)	
flu shot				
preventive test for blood cholesterol				
education	0.035***		0.036***	
	(0.0086)		(0.008)	
Employment status	0.371***		0.365***	
	(0.062)		(0.062)	
Income	0.000036***		0.000036***	
	(4.55e-06)		(4.48e-06)	
Have loan	0.370***		0.371***	
	(0.112)		(0.111)	
Own house	0.427***		0.423***	
	(0.061)		(0.060)	
Have stock	0.116***		0.116***	
	0.052)		(0.052)	
constant	-1.392		-1.377	
	(0.242)		(0.240)	
Die Equation				
	High-type	Low-type	High-type	Low-type
Subjective survival			-0.001***	-0.001***
			(0.0005)	(0.0005)
constant	-0.266	0.225	-0.162	0.327
	(3.178)	(3.177)	(3.183)	(3.182)
LFI Equation				
Subjective survival			-0.0014***	-0.0014***
			(0.0005)	(0.0005)
Constant	-3.911*	-5.650***	-3.760*	-5.524***
	(2.567)	(2.591)	(2.588)	(2.613)
Correlation of two error terms	0.110***	0.307***	0.107***	0.313***
	(0.056)	(0.083)	(0.055)	(0.084)
observations	14,586	14,586	14,586	14,586

Standard errors in parentheses: *** p<0.05, ** p<0.1, * p<0.15

Table 7c. Specification Tests: Drop "Education"

	(1) Public information		(2) Public information and Subjective survival	
Type equation				
care for grandkids	0.175***		0.175***	
	(0.057)		(0.057)	
religion	0.522***		0.516***	
	(0.110)		(0.109)	
flu shot	0.102***		0.102***	
	(0.0503)		(0.0503)	
preventive test for blood cholesterol	0.194***		0.195***	
	(0.0594)		(0.0591)	
education	0.432***		0.428***	
	(0.064)		(0.063)	
Employment status				
Income	0.000036***		0.000036***	
	(4.31e-06)		(4.26e-06)	
Have loan	0.3837***		0.3860***	
	(0.113)		(0.112)	
Own house	0.446***		0.443***	
	(0.062)		(0.062)	
Have stock	0.140***		0.141***	
	(0.053)		(0.053)	
constant	-1.308***		-1.294***	
	(0.225)		(0.224)	
Die Equation				
	High-type	Low-type	High-type	Low-type
Subjective survival			-0.001***	-0.001***
			(0.0005)	(0.0005)
constant	-0.599	-0.053	-0.499	0.046
	(3.185)	(3.184)	(3.194)	(3.193)
LFI Equation				
Subjective survival			-0.001***	-0.001***
			(0.0005)	(0.0005)
Constant	-.852***	-5.456***	-3.677***	-5.296***
	(2.458)	(2.471)	(2.470)	(2.483)
Correlation of two error terms	0.118***	0.301***	0.116**	0.305***
	(0.060)	(0.074)	(0.060)	(0.074)
observations	14,586		14,586	

Standard errors in parentheses: *** p<0.05, ** p<0.1, * p<0.15

Table 7d. Specification Tests: Drop "Employment Status"

	(1) Public information		(2) Public information and Subjective survival	
Type equation				
care for grandkids	0.161***		0.165***	
	(0.061)		(0.060)	
religion	0.569***		0.553***	
	(0.120)		(0.117)	
flu shot	0.086*		0.087**	
	(0.053)		(0.052)	
preventive test for blood cholesterol	0.161***		0.160***	
	(0.062)		(0.061)	
education	0.044***		0.045***	
	(0.009)		(0.009)	
Employment status				
Income	0.000047***		0.000046***	
	(5.24e-06)		(5.13e-06)	
Have loan	0.419***		0.417***	
	(0.125)		(0.124)	
Own house	0.467***		0.459***	
	(0.064)		(0.063)	
Have stock	0.141***		0.141***	
	(0.060)		(0.060)	
constant	-1.660***		-1.624***	
	(0.261)		(0.255)	
Die Equation				
	High-type	Low-type	High-type	Low-type
Subjective survival			-0.001***	-0.001***
			(0.0005)	(0.0005)
constant	0.128	0.590	0.231	0.690
	(3.151)	(3.152)	(3.160)	(3.160)
LFI Equation				
Subjective survival			-0.0014***	-0.001***
			(0.0005)	(0.0005)
Constant	-4.916***	-6.555***	-4.786***	-6.472***
	(2.460)	(2.479)	(2.500)	(2.515)
Correlation of two error terms	0.052	0.313***	0.052	0.325***
	(0.041)	(0.080)	(0.041)	(0.082)
observations	14,586		14,586	

Standard errors in parentheses: *** p<0.05, ** p<0.1, * p<0.15

Table 7e. Specification Tests: Drop “Financial Conditions”

	(1) Public information		(2) Public information and Subjective survival	
Type equation				
care for grandkids	0.248***		0.245***	
	(0.082)		(0.082)	
religion	0.581***		0.572***	
	(0.167)		(0.167)	
flu shot	0.178***		0.177***	
	(0.067)		(0.066)	
preventive test for blood cholesterol	0.336***		0.333***	
	(0.097)		(0.096)	
education	0.084***		0.084***	
	(0.017)		(0.018)	
Employment status	0.935***		0.921***	
	(0.179)		(0.181)	
Income				
Have loan				
Own house				
Have stock				
constant	-1.973***		-1.958***	
	(0.607)		(0.620)	
Die Equation				
	High-type	Low-type	High-type	Low-type
Subjective survival			-0.001	-0.001
			(0.0005)	(0.0005)
constant	-1.115	-0.531	-1.000	0.420
	(3.297)	(3.297)	(3.299)	(3.299)
LFI Equation				
Subjective survival			--0.0013***	--0.0013***
			(0.0005)	(0.0005)
Constant	-2.284	-4.035***		-3.884
	(2.215)	(2.259)		(2.281)
Correlation of two error terms	0.225***	0.114	0.223***	0.118
	(0.082)	(0.104)	(0.082)	(0.110)
observations	14,586	14,586	14,586	14,586

Standard errors in parentheses: *** p<0.05, ** p<0.1, * p<0.15

Table 8. Hausman Tests: The Baseline Model *vs* Models with Only a Subset of Proxy Variables for Insurance Demand

	Baseline model *vs* Drop "Bequest Motives"		Baseline model *vs* Drop "Risk Averse"		Baseline model *vs* Drop "Education"	
	Public information	Public and subjective survival	Public information	Public and subjective survival	Public information	Public & subjective survival
Die	5.46	5.13	4.12	4.19	0.06	6.87
equation	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
LFI	16.24	11.31	18.06	17.76	14.74	14.60
equation	(0.991)	(1.000)	(0.977)	(0.980)	(0.996)	(0.996)

	Baseline model *vs* Drop "Employment status"		Baseline model *vs* Drop "Financial Condition"	
	Public information	Public and subjective survival	Public information	Public and subjective survival
Die	5.87	5.62	9.58	0.79
equation	(1.000)	(1.000)	(1.999)	(1.000)
LFI	11.94	14.73	9.93	6.20
equation	(1.000)	(0.996)	(0.999)	(1.000)

Table 9. Three-type model

	(1) Public information	(2) Public information and Subjective survival
	Type equation (high-type)	
care for grandkids	0.757***	-0.222
	(0.340)	(0.231)
religion	1.041***	0.252
	(0.335)	(0.663)
flu shot	0.0360	0.355**
	(0.195)	(0.199)
preventive test for cholesterol	-0.0016	0.352*
	(0.863)	(0.221)
education	-0.176	0.229***
	(0.168)	(0.055)
Employment status	1.472***	-0.144
	(0.412)	(0.323)
Income	5.19e-05***	6.39e-05***
	(1.00e-05)	(1.13e-05)
Have loan	0.977	0.212
	(0.715)	(0.374)
Own house	0.254	0.917***
	(0.675)	(0.193)
Have stock	-0.286	1.120***
	(0.809)	(0.470)
constant	1.102	-2.949***
	(4.118)	(0.988)
	Type equation (medium type)	
care for grandkids	0.886***	-0.937***
	(0.349)	(0.307)
religion	0.592	-0.804
	(0.952)	(0.842)
flu shot	-0.252	0.336
	(0.472)	(0.301)
preventive test for cholesterol	-0.437	0.172
	(1.104)	(0.463)
education	-0.380***	0.371***
	(0.057)	(0.047)
Employment status	1.434***	-1.584***
	(0.586)	(0.412)
Income	-1.18e-05	1.12e-05
	(1.51e-05)	(1.54e-05)
Have loan	0.772	-0.648
	(0.799)	(0.716)
Own house	-0.681	0.536*
	(0.628)	(0.362)

Have stock		-1.398***			1.259***	
		(0.748)			(0.554)	
constant		4.395			-3.171	
		(4.695)			(2.013)	
Die Equation						
	High type	Medium type	Low Type	High Type	Medium Type	Low type
Subjective survival				-0.001***	-0.001***	-0.001***
				(0.0005)	(0.0005)	(0.0005)
Constants	-0.356	0.158	0.098	-0.460	0.0629	0.0090
	(3.255)	(3.293)	(3.187)	(3.216)	(3.206)	(3.226)
LFI Equation						
	High type	Medium type	Low Type	High Type	Medium Type	Low type
Subjective survival				-0.002***	-0.002***	-0.002***
				(0.0006)	(0.0006)	(0.0006)
Constants	-3.727	-5.728***	-5.30***	-3.496	-5.071**	-5.666***
	(2.624)	(2.666)	(2.647)	(2.639)	(2.654)	(2.665)
Corr of two Error terms	0.164***	0.342***	0.202	0.161***	0.252***	0.347***
	(0.069)	(0.151)	(0.348)	(0.068)	(0.1223)	(0.347)
Observations		14,586			14,586	

Standard errors in parentheses: *** p<0.05, ** p<0.1, * p<0.15

Table 10. A Comparison of the Goodness of Fit between Two-type model and Three-type model via Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC)

AIC

	Two-Type Model	Three-Type Model
w/o private information	27456.9	27375.7
With private information	27447.8	27365.5

BIC

	Two-Type Model	Three-Type Model
w/o private information	28170.2	28195.1
With private information	28176.3	28200.1