ADVERSE SELECTION AND ADVANTAGEOUS SELECTION IN INSURANCE MARKETS

A Dissertation

by

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ABSTRACT

This dissertation consists of three essays about adverse selection and advantageous selection in life insurance and health insurance markets.

Firstly, I confirm the advantageous selection in voluntary private health insurance markets in Europe and detect the sources of such advantageous selection by using data from Survey of Health, Ageing and Retirement in Europe (SHARE). Specifically, I find, on the extensive margin, individuals with symptom are less likely to own VPHI than those without any symptom; on the intensive margin, the more the number of symptoms the individual has, the less likely she has VPHI. Same conclusion can be obtained when using a subjective measure of health. The sources of this advantageous selection include asset, education, longevity expectations, as well as cognitive ability. Conditional on these factors, individuals whose health is worse are more likely to purchase VPHI.

Secondly, I identify the adverse selection problem in life insurance markets in the presence of both adverse and advantageous private information. Conventional theory for private information of adverse selection predicts a positive correlation between insurance coverage and *ex post* risk. However, Cawley and Philipson (1999) reported a neutral or even negative correlation between mortality risk and insurance coverage in the life insurance market. A recent growing literature has shown that such puzzle could be attributed to the multiple dimensions of private information coexisting in the market. Specifically, I provide evidence of the existence of private information both on mortality risk and on life insurance preferences. I show that these two dimensions of private information have an offsetting effect on the relationship between subsequent mortality and life insurance purchases, which makes the identification of the private information on mortality risk difficult under the traditional setting. Instead, I apply the mixture density model and successfully detect a positive correlation between individual mortality and insurance coverage.

Moreover, I examine the mortality risk related to each of the two main types of life insurance contracts – term and whole life insurance. Our two-period model shows that, given an individual, the relative income, rather than the risk, dominates the choice between whole and term life insurance policies, indicating that a systematic risk difference between these two pools should not be observed. Moreover, when the income of these two periods are the same, whole life insurance policies, the one with more capability of avoiding reclassification risk, would be always favored if the individual is risk averse. Empirical results support the conclusions made in the theoretical model. This paper also, empirically confirms the partial lock-in of consumers embodied in the more front-loading contract as proposed by Hendel and Lizzeri (2003). Specifically, I find as a more front-loaded contract, whole life insurance policy is associated with a lower lapsation rate and thus retains a healthier pool after 65 years old.

DEDICATION

To My Parents

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1. 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. In my research, I study the voluntary private health insurance and life insurance markets, respectively, to detect the adverse selection or advantageous selection existing in these markets.

In Section 2, I explore the voluntary private health insurance (VPHI) markets and find that there is an advantageous selection in this market. Specifically, I find individuals who are healthier, which is measured by both objective and subjective health condition, are more likely to purchase VPHI. I next find such advantageous selection can be attributed to different assets, education level, and cognitive abilities.

Similar phenomena can be also found in life insurance markets. In Section 3, I examine the life insurance markets and find individuals who are more educated, risk averse, in employment, and with stronger bequest motives are more likely to purchase life insurance but less likely to die. However, although we clearly know the existence of adverse selection in this market, a positive correlation still cannot be obtained even after controlling a series of proxy variables for the above factors. I solve this problem and get a direct evidence for the existence of private information on mortality risk by applying the mixture density model.

In the last section, I examine the mortality risk related to each of the two main types of life insurance contracts – term and whole life insurance. I offer a two-period model showing that, given an individual, the relative income dominates the choice between whole and term life insurance policies. Moreover, when the income of these two periods are the same, whole life insurance policies, the one with more capability of avoiding reclassification risk, would be always favored if the individual is risk averse. Empirical results are perfectly matched to the predictions made in the theoretical model. I also empirically confirms the partial lock-in of consumers embodied in the more front-loading contract as proposed by Hendel and Lizzeri (2003). Specifically, I find as a more front-loaded contract, whole life insurance policy is associated with a lower lapsation rate and thus retains a healthier pool after 65 years old. As far as I know, this is the first empirical paper using an individual-level dataset to test this lock-in effect existing in the front-loading contract.

2. ADVANTAGEOUS SELECTION OF VOLUNTARY PRIVATE HEALTH INSURANCE IN EUROPE: EVIDENCE FROM SHARE

Public health systems of most European countries cover the majority of expenditure on health, however, individuals are still exposed to the potential risk on large costs of obtaining health care utilization due to the partial coverage or no reimbursement from the public system at all. Aiming at reducing consumers' out-of-pocket (OOP) as well as easing the burden of public health care financing, voluntary private health insurance (VPHI), as possible means of addressing these challenges in public health system in European countries and improving the access to health care which also includes reduction of waiting time, is introduced (Mossialos and Thomson, 2004).

Although the share of VPHI still remains small in today's European Union, the long-term availability of public financed health care keeps getting challenged (Klevmarken and Lindgren, 2008; Gerdtham *et al*, 1992). The VPHI market, therefore, may aggrandize dramatically. In this paper, we focus on detecting the adverse selection, which is one of the central problems to economic models of insurance, in the European VPHI market.

Rothschild and Stiglitz (1976) argue that individuals may still have residual information about their own eventual risk even after controlling a bunch of observables to insurers, resulting in those who believe they have higher risk would purchase more insurance than those lower-risk individuals. Therefore, the standard test used in most literature for detecting asymmetric information is to test for a positive correlation between the insurance ownership and *ex post* risk (Chiappori and Salanié 1997, 2000; Chiappori *et al*, 2006).

The empirical results, however, are mixed. Cawley and Philipson (1999) find a neutral or even negative correlation between life insurance purchase and subsequent mortality. Chiappori and Salanie (2000) study the automobile insurance market, and find that after controlling for the observables for insurers, there is no significant difference in accident rates between those who choose comprehensive contracts and those who choose the statutory ones. Finkelstein and McGarry (2006) confirm that there is no adverse selection in long-term care insurance market. Fang, Keane, and Silverman (2008) show the evidence of the existence of advantageous selection in Medigap insurance market and argue that instead of risk aversion, individuals' cognitive ability is the key source for such advantageous selection. Cardon and Hendel (2001) find that the demographic gap, income elasticity, and estimated price are the main factors for the existence of differences in the medical expenditure between the insured and the uninsured people; therefore, they argue that no significant adverse selection exists. In the annuity market, Finkelstein and Poterba (2004) find there is no substantive mortality difference by the annuity size, indicating that there is no adverse selection problem in this market. In contrast, Cohen (2005) shows the presence of asymmetric information in automobile insurance market. While, such positive correlation between insurance coverage and accident rates only exists for those who have enough years of driving experience. He (2009) finds that individuals who have purchased life insurance indeed have a higher mortality risk, even after controlling for individuals' risk classification. Specifically, individuals who died within a 12-year time frame were 19% more likely to have life insurance in the base year than those who did not die during that time frame. Puelz and Snow (1994) study the car insurance and find that individuals with lower risk are more likely to choose a contract with higher deductible; also, contracts with higher deductible has a lower average price. These two facts are consistent with adverse selection.

Recent theoretical literature, for example, de Meza and Webb (2001) contribute such puzzle to the existence of multiple dimensions of private information. They assume that individuals have two types of private information – the private information on *ex-post* risk and the private information on risk-aversion. They argue that the advantageous selection will show up if individuals who are more likely to purchase insurance, which is usually induced by risk aversion, are less likely to experience the insured event. Therefore, the positive correlation between insurance coverage and the insured event induced by the private information on risk may no longer hold when the second type of private information is not controlled. In fact, any private information which is positively related to insurance ownership and negatively related to *ex post* risk could serve as a source of advantageous selection (Fang *et.al*, 2008).

Since then, empirical literature has started to test this multiple dimensions of private information theory: Finkelstein and McGarry (2006) study the long-term care insurance market. They find after controlling insurers' risk categories, a positive correlation between the purchase of long-term care insurance and the usage of nursing home, in fact, could not be observed. However, by taking advantage of the question on self-perceived probability of being in nursing home in the 1995 AHEAD questionnaire, they confirm the existence of asymmetric information on the risk of being in a nursing home. Specifically, they find that even after controlling for insurers' risk classification, individuals who believe they are more likely to enter in a nursing home are more likely to purchase long-term care insurance; at the same time, they are also more likely to use the nursing home. These two positive correlations, combined, suggest that there exists the private information-induced adverse selection in the LTC market. Second, they find more risk-averse individuals (characterized by more likely to take preventative health activity and wear seatbelt) are more likely to own long-term care insurance but less likely to enter a nursing home. All together, these two types of private information – the private information on risk categories and the private information on risk aversion– offset each other, resulting in a neutral correlation or even negative correlation they observed in the first part of their paper.

Our paper contributes to the literature from the following two aspects: We examine the evidence for and the sources of advantageous selection in voluntary private health insurance market in Europe. Specifically, we first find a statistically significant negative correlation between the ownership of VPHI and health status, indicating that an evidence of multiple dimensions of private information as well as an evidence of advantageous selection. We next explore the potential sources of this advantageous selection and find individuals' cognitive ability is the key determinant. Moreover, after conditional on a series of proxy variables for cognitive ability, such as, memory, math performance, reading and writing abilities, we find a positive and significant correlation between the holding of VPHI and health status.

The remainder of this paper is organized as follows. Section 2.1 describes the data we use to analyze in this paper and some detailed background about European health system and voluntary private health insurance. Section 2.2 provides the direct evidence of advantageous selection as well as its source in VPHI markets using the SHARE data. Section 2.3 concludes.

2.1 Background and Data

2.1.1 Institutional Background

There are different types of VPHI, but they, generally, can be classified into three major types based on how they integrate the public health insurance system: *duplicate*, *complement*, and *supplement*. Duplicate coverage targets to increase the number of choice of different health services, in which most are already covered by statutory health insurance. Complementary coverage provides insurance to some services that are not freely covered by the statutory health insurance. This type of coverage firstly is widely used in France and now is available for the whole population in all countries in our analysis. Supplementary health insurance, which also named as double coverage, provides full or partial coverage to the services that are excluded by statutory health insurance. In Netherlands and Switzerland, VPHI is only in the supplementary form.

We next describe the pricing issue of VPHI. Although it varies with different types, generally, it includes age, gender, occupation, household size, and medical history. Group policies which is with a given premium for a certain population can be found in Denmark and Sweden. In Belgium, mutual associations can sell policies with flat rate premium, however, it is not widespread.

2.1.2 Data Description

To explore the existence of adverse/advantageous selection in VPHI markets, we use the first wave of Survey of Health, Aging and Retirement in Europe (SHARE). The first wave of the survey covered more than 30,000 individuals in 11 countries. The SHARE dataset is multidisciplinary which contains information on individuals' physical health and socioeconomic status. The health information includes self-perceived health status, activities of daily living (ADL) limitations, and a large set of objective measures.

Equally important, the advantage of SHARE for studying advantageous selection in the voluntary private health insurance in Europe lies in the fact that it contains detailed information which includes measures of risk attitudes, self-evaluated health condition and several measures of cognitive ability.

VPHI

The dependent variable is a dummy variable indicating whether the respondent has any type of voluntary private health insurance or not. It takes the value 1, if the individual had any VPHI in 2004, and 0 otherwise. In general, voluntary coverage varies a lot in different countries: in France, the coverage rate is as high as 78 percent; contrast to the 3 percent in Sweden. All together, approximately 30 percent of population had some form of VPHI.

Subjective Measurement of Health Status

In the SHARE dataset, individuals are asked to use a number from 1 to 5 to (subjectively) evaluate her health status, where 1 represents poor and 5 represents excellent. We therefore use this individual self-evaluated health condition as the proxy variable for the risk of using health care. And the key parameter we are interested in is the effect of this subjective-measured health condition on the likelihood of holding VPHI; in particular, a positive (negative) correlation between individual self-assessed health and VPHI ownership if there is advantageous (adverse) selection.

Observable Health Conditions

The SHARE dataset also includes detailed information on health-related variables such as BMI, cancer, diabetes, heart problem, high blood pressure, stroke, lung diseases, arthritis, etc. In the later analysis, we also use whether have any symptom as well as how many symptoms the individual has as the objective measurement of health condition, besides the subjective self-assessed health above.

Cognitive Ability

The measure of an individual's cognitive ability includes education level, the performance on four different tests: the number of words she can recall, math performance, reading and writing abilities. We use these variables to proxy the individual's ability to make a rational decision for whether or not to purchase VPHI.

Demographics

Demographic control variables include age, gender, the interaction terms between age and gender, marriage status, employment status and country dummies to indicate which country the respondent lives in. Country dummy variables are also used in order to eliminate fixed effects in health care systems and other unobservable factors across countries. Furthermore, variables related to asset and income are also included.

For more details on the data and our sample see Table A.1.

2.2 Empirical Strategy and Results

Our study essentially is composed of two steps. We first estimate a series of probit, ordered probit, and Ordinary Least Square models to explore the correlation between health status and VPHI ownership. Different measurements of health (self-assessed health and activities of daily living (ADL) limitations) are used for a robust result; and we indeed find a negative correlation between health status and VPHI ownership. In the second step, we discuss the sources of this advantageous selection. Specifically, we find that after controlling asset, education, and cognitive abilities, individuals with worse self-assessed health are more likely to purchase VPHI.

We provide direct evidence for the existence of advantageous selection in the VPHI market: individuals who purchase VPHI are healthier.

Table A.2 reports two panels of results examining the relationship between self-evaluated health status and VPHI ownership from Ordinary Least Squares regression and ordered probit model, respectively. Each reports results from estimating a full sample as well as the male and female subsamples. In both panels, we find a significantly negative relationship between individual self-evaluated health status and ownership of VPHI, indicating the advantageous selection in VPHI market. Specifically, for the full sample, individuals who have VPHI are 1.1 percentage points more likely to report an excellent health condition; while, 0.65 percentage point less likely to report a poor health.

Table A.3 confirms such advantageous selection from detecting the relationship between ADL limitations and VPHI coverage. Similarly, we find the individuals who have VPHI are less likely to have any ADL limitation.

Table A.4 and Table A.5 show this advantageous selection from extensive and intensive margin, respectively. Specifically, Table 4 shows that individuals who have VPHI are less likely to have any symptom; and Table 5 shows that individuals who have VPHI are having less symptoms than those who do not have.

Table A.6 shows that education level and cognitive abilities are positively correlated to VPHI purchase. After conditional on these factors, the coefficient for self-perceived health status is significantly negative—individuals who believe they are healthier are less likely to purchase VPHI. We therefore conclude that there does exist the private information on risk-induced adverse selection.

2.3 Conclusion

Using data from Survey of Health, Ageing and Retirement in Europe (SHARE), we provide evidence of advantageous selection in the voluntary private health insurance (VPHI) markets for individuals aged over 50, in twelve European countries. Specifically, we find, on the extensive margin, individuals with symptom are less likely to own VPHI than those without any symptom; on the intensive margin, the more the number of symptoms the individual has, the less likely she has VPHI. Same conclusion can be obtained when using a subjective measure of health. The sources of this advantageous selection include asset, education, and individuals' cognitive ability. After controlling for these factors, individuals whose health is worse are more likely to purchase VPHI.

3. MULTIPLE DIMENSIONS OF PRIVATE INFORMATION IN LIFE INSURANCE MARKETS

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. 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 extensive 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, the most widely used and standard test for detecting asymmetric information is to test for a positive correlation between the insurance coverage and *ex post* risk (Chiappori and Salanié 1997, 2000; Chiappori *et al*, 2006).

Existing empirical literature on asymmetric information in life insurance markets, however, is mixed.[1] Cardon and Hendel (2001) find no adverse selection between health insurance choice and health care demand. Cawley and Philipson (1999) find 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, as shown in Table B.1, using HRS data during the period 2000~2008. The mortality rate for people who have

[1] Cohen and Siegelman (2010) review the recent literature in this field.

life insurance in year 2000 is 18%--a much lower rate than those who do not have, whose mortality rate is 25%. In contrast, He (2009) finds that individuals who have purchased life insurance indeed have a higher mortality risk, conditional on individuals' risk classification. Specifically, individuals who died within a 12-year time frame after a base year were 19% more likely to have taken up life insurance in that base year than those who survived for that time frame. Browne and Doerpinghaus (1993) confirm the presence of adverse selection in the individual medical expense insurance market. Cohen (2005) studies the automobile insurance markets in Israel and find evidence that is consistent with the informational asymmetries: low-deductible contracts are associated with more accidents and greater losses for new customers who have enough years of driving experience.

Various explanations for this interesting phenomenon are offered in the literature. Pauly *et al* (2003) explain such inexistence of private information with individuals' sufficiently low risk elasticity. They argue that even if buyers indeed know more than insurers, serious adverse selection will not occur if those buyers are sluggish in their willingness to respond to that information. He (2009), however, attributes such difference between her finding and previous literature 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. Thus, instead of using an entire cross-sectional sample, He's conclusion holds only if the sample is restricted to the potential new life insurance buyers.

Recent theoretical research suggests that the correlation between insurance purchases and risk occurrence is not necessarily positive 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; Finkelstein and Poterba, 2002; Jullien *et al*., 2002; Cohen and Einav, 2007; Chiappori *et al*., 2013).

We use a subsample of the HRS dataset to illustrate this point. It is possible that people are different in their preference for insurance. Two groups are considered. The first group consists of people who take flu shot; take care of their grandkids; and have religion preferences. These people are likely to have high demand for life insurance. In contrast, the second group *only* contains individuals who do neither of the activities that the first group do at all. The second group is likely to have a lower demand for life insurance than the first group.

Figure B.1 illustrates the behavior of these two groups. We find that 83% of individuals in the first group own life insurance while only 52% in the second group does. However, the mortality rate in the first group is only 8%, which is much lower than 28% in the second group. Therefore, if we put these two groups together, it is not surprise to see a negative correlation between life insurance ownership and subsequent mortality. Specifically, as shown in the top panel of Table B.2, we find the mortality rate for individuals who do not have life insurance is 13%, which is 3% higher than those who have life insurance.

However, if we compare the mortality rate between individuals who have life insurance and those who do not have *within* a certain group, the positive correlation holds *within* each subsample. Specifically, as shown in the bottom panel of Table B.2, for individuals who belong to the first group, the mortality rate for individuals who have life insurance is 8%, which is 1% higher than those who do not have life insurance. Similarly, for individuals who are in the second subsample, the mortality rate for those who have life insurance is 29%, contrast to 27% for the individuals who do not have.

Empirically, Fang *et. al* (2008) find there exists advantageous selection in Medigap insurance market; and the main sources of such advantageous selection is individuals' cognitive ability; after conditional on these factors, adverse selection is revealed -- total medical expenditure for individuals who have Medigap is higher than that for those who do not have. Olivella and Vera-Hernández (2013) investigate UK's private health insurance market and find the innate probability of taking medical care for the insured is indeed higher than the average; while, it is caused by differences in preferences instead of the differences in underlying health. Cutler *et.al* (2008) show that individuals who do not take risky activities have more propensity to hold life insurance but less likely to experience *ex-post* mortality. Finkelstein and McGarry (2006) demonstrate that there are more than one type of private information in long-term care insurance markets—the private information on risk type and the private information on individual insurance preferences. 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 has three main contributions. 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 *et al* (2008). Specifically, individuals who have stock, houses, and loans, as well as those who have employment are more inclined 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, a positive correlation between life insurance purchases and subsequent mortality still cannot be observed.

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 is organized as followings. In section 3.1, we illustrate the identification strategy used to identify this private information in life insurance market and describe our data. Section 3.2 presents the results and specification test. The final section concludes.

3.1 Empirical Approach

The empirical strategy is composed of three steps. First, we show 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 suggests that there is no private information on mortality risk. 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 the heterogeneity of individuals' insurance preferences is conditioned by distinguishing people into two groups based on the series of factors we mentioned above.

3.1.1 Econometric Model

We characterize the market for life insurance with the following two equations. The first equation is about the individual characteristics and his probability of mortality. The second relates the same characteristics to whether or not to purchase life insurance.

$$\begin{aligned} Die &= 1(c_\beta + X\beta_X + H\beta_H + SS\beta_{SS} + u > 0) \\ LFI &= 1(c_\delta + X\delta_X + H\delta_H + SS\delta_{SS} + v > 0) \end{aligned} \tag{3.1}$$

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. X denotes the individual characteristics that are public–information that can be available for both individuals and insurers. SS is individuals' subjective survival probability for the next 10 to 15 years, so that $\beta_{SS} < 0$. Also, everything equal, individuals with higher expectation on their longevity are less likely to purchase life insurance, thus $\delta_{SS} < 0$. The variable H represents the unobserved individual preferences for life insurance. Without losing generality, we assume δ_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., β_H <0.

Our analysis firstly explores 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*). HRS asked individuals about their subjective belief of the probability of being alive in next 10 to 15 years. Previous literature (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*:

$$\begin{aligned} Die &= 1(c_\beta + X\beta_X + SS\beta_{SS} + u^* > 0) \\ LFI &= 1(c_\delta + X\delta_X + SS\delta_{SS} + v^* > 0) \end{aligned} \qquad (3.2)$$

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

We next implement the positive correlation test for private information. Chiappori and Salanié (1997, 2000) point out that a positive correlation can serve as a necessary and sufficient condition for the presence of adverse selection. Chiappori *et al.* (2006) as well as Chiappori and Salanié (2012) further theoretically analyze the robustness of this positive correlation property and show that its application 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 risk aversion. However, under the imperfect competition, if risk aversion is public, then the positive correlation property still holds; while, the correlation between the insurance coverage and *ex post* risk can take any sign when individuals' risk aversion is private information. Similar analyses are also provided in Jullien, Salanié, and Salanié (2007). According to our judgment, the structure of life insurance markets is more like an imperfect competition: Data in the American Council of Life Insurers (2010) show that 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 (2012) also point out that perfect competition does not well approximate insurance markets due to differentiation on fixed cost, product characteristics and switching cost. We estimate the following bivariate probit model and the variable we are interested is the sign of the correlation between error terms (ρ).

$$\begin{aligned} Die &= 1(c_\beta + X\beta_X + u^{**} > 0) \\ LFI &= 1(c_\delta + X\delta_X + v^{**} > 0) \end{aligned} \tag{3.3}$$

Where, $u^{**} = H\beta_H + Z\beta_Z + u$ and $v^{**} = H\delta_H + Z\delta_Z + v$.

Clearly, error terms in equation (2.3) include not only private information but also individual 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. Again, Chiappori *et al* (2006) as well as Chiappori and Salanié (2012) state that such positive correlation property does not necessarily hold if the market is imperfectly competitive and risk aversion cannot be fully controlled for. A formal discussion can be found in Gan *et al* (2011), in which they show that this test may fail to detect the private information on risk type when individuals have heterogeneous insurance preferences.

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 (2004):

$$\Pr(Die = 1) = \Phi\,(X\beta_x + \theta\, LFI) \tag{3.4}$$

The positive correlation predicts $\theta > 0$. One potential problem is that due to the simultaneous determination between mortality and the purchase of life insurance, 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) incorporate beneficiaries' preferences into the model, which shows that the probability of owning life insurance is positively correlated to the wage earners' death, the present value of the beneficiaries' consumption, and the degree of risk aversion; simultaneously, this probability is negatively correlated to the household's net wealth. Walliser and Winter (1998) report that tax advantages and bequest motives are the two key factors determining life insurance demand in Germany. Cutler *et al* (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) study the factors affecting life insurance demand across 45 countries. They find education as well as income are the two main factors for the life insurance purchase. Beck and Webb (2003) report that economic indicators, religion preferences are the determinant of the life insurance ownership; while, education level seems not have significant effect on life insurance purchase.

Following the literature discussed above, we suggest W includes: *(i) number of years of education*—a proxy variable for knowledge about life insurance; *(ii) whether an individual is employed* — 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; *(iii) income of the insured*—for the individual who inherits or builds significant wealth, whole life insurance is especially advantageous regarding taxes or estate settlement costs. For example, in the case of permanent life insurance policies, cash values accumulate on an income tax-deferred basis; *(iv) whether an 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; *(v) risk aversion,* which is represented by decision to practice preventative health activities such as getting a flu shot or blood test for cholesterol; as well as *(vi) 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.

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

$$\begin{aligned} Die &= 1(c_\beta + X\beta_X + W\beta_W + u^{***} > 0) \\ LFI &= 1(c_\delta + X\delta_X + W\delta_W + v^{***} > 0) \end{aligned} \tag{3.5}$$

Again, if we assume H can be written as $H_i = W_i + \delta_i$, where $W_i \perp \delta_i, \delta_i \perp u^{***}$, and $\delta_i \perp v^{***}$ for all $i = 1, \cdots\cdots, N$, a positive sign of the correlation between the two error terms in equation (3.5) indicates the existence of private information. However, more commonly, the set W_i can be written in terms of W_i=(W_{io}, W_{iu}), where we only observe W_{io} but not W_{iu}. Further, W_{io} and W_{iu} are often correlated, i.e., $corr(W_{io}, W_{iu}) \neq 0$. Obviously, the 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: $H = (H_1, H_2, ..., H_K)$, based on their different life insurance preferences. Without loss of generality, we assume $H_k < H_{k+1}$. Also, a greater value of H indicates a stronger preference on life insurance. For individuals belong to the k-th type ($H = H_k$):

$$\begin{aligned}
Die &= 1(c_\beta + X\beta_X + SS\beta_{SS} + H_k\beta_k + u_k > 0) \\
&= 1(c_\beta^k + X\beta_X + SS\beta_{SS} + u_k > 0) \\
&= 1(c_\beta^k + X\beta_X + u_k^* > 0) \\
LFI &= 1(c_\delta + X\delta_X + SS\delta_{SS} + H_k\delta_k + v_k > 0) \\
&= 1(c_\delta^k + X\delta_X + SS\delta_{SS} + v_k > 0) \\
&= 1(c_\delta^k + X\delta_X + v_k^* > 0)
\end{aligned} \tag{3.6}$$

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 $1 \leq m < n \leq K$, 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:

$$\Pr(Die = p, LFI = q \mid X, W) = \sum_{k=1}^{K} \Pr(Die = p, LFI = q \mid X, H = H_k) * \Pr(H = H_k \mid W) \quad (3.7)$$

3.1.2 Identification of Finite Mixture Density Model

The model in equation (3.7) is a standard mixture density model, whose identification issue has been well studied in much literature (Hu, 2008; Lewbel, 2007; Chen, Hu, and Lewbel, 2008, 2009; Mahajan, 2006; Gan and Henandez, 2013; Henry, Kitamura and Salanié, 2014). In particular, Henry, Kitamura, and Salanié (2014), HKS for short, show that under the following assumptions, the mixture density model with unobserved heterogeneity in equation (3.7) is non-parametrically identified.

Assumption 1 (Dependency Condition). The probability of being a certain type does depend on the value of W.

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

$$W_o, W_u \perp Die_k | X, H = H_k \text{ and } W_o, W_u \perp LFI_k | X, H = H_k, \text{ for any } k \in \{1, 2, ..., K\} \quad (3.8)$$

Or, can be equivalently represented by:

$$Pr(Die = p, LFI = q \mid X, H = H_k) = Pr(Die = p, LFI = q \mid X, H = H_k, W_o, W_u) \quad (3.9)$$

In particular, equation (2.8) implies:

$$W_o, W_u \perp u_k^* \,|X, H = H_k \text{ and } W_o, W_u \perp v_k^* |X, H = H_k \text{ for any } k \in \{1, 2, ..., K\} \quad (3.10)$$

Such property of W in equation (3.10) 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 "type" variable but not correlated with the error term.

It is worth noting that Assumption 2 in HKS (2014) implies that life insurance preferences (Type) can be *fully* controlled by only using a *partial* set of proxy variables W.[2]

This property has inspired the specification test of this paper. Specifically, we successively drop each one of these 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.

All the assumptions needed for the identification of mixture density model and the validity of specification test in this paper have been well discussed. HKS (2014) argue that under Assumption 1 and 2, a sharp boundary for both the probability of being each type (also named mixture weights) and the probability of the outcome conditional on a certain type

[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.

(also named mixture components) can be obtained. Moreover, in the two-component case (i.e., heterogeneity in life insurance preference is divided into two categories), point identification can be achieved under Assumption 1, 2 as well as an additional restriction. For instance, one component dominates in the left tail and the other component 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.

Argument 1. Under Implication 1, Assumption 1, and Assumption 2, the mixture density model, as shown in equation (3.7) 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)*) and construct the likelihood function with the assumption that the error terms have a standard joint normal distribution to jointly identify the parameter set ($c_\beta^h, c_\beta^l\ , c_\delta^h, c_\delta^l, \beta_X, \delta_X$,). The probability of being each type and the correlations between the error terms for each type can also be estimated simultaneously.

3.1.3 Data

We use the HRS cohort of the Health and Retirement Study (HRS) data during the period 2000 to 2008 to explore the adverse selection problem in life insurance markets. We apply the data from year 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 sample is followed from 2000 to 2008, allowing us to record whether this individual is dead during these eight years. Twenty-one percent of our sample die at some point during this eight-year time window. 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, *et al* (2005). For simplicity, we employ the binary variable as the record of the occurrence of insured event in the rest of our analysis. Moreover, to be comparable across various specifications, we delete the samples with any missing information for any utilized variable in our analysis.

The HRS cohort of the HRS data contains information such as 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; Gan, *et al*, 2005). 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 *et al*., 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 we would like to use to distinguish individuals' different preferences in life insurance: the number of years of education; employment status; whether own stock, loan, and house; loss of income if the insured dies; proxy variables for risk tolerance and bequest motives. 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 B.3.

3.2 Results

3.2.1 Private Information about Mortality Risk and Its Relation to Insurance Coverage as well as Subsequent Mortality

Column (2) of Table B.4 shows the estimated results from the bivariate probit model as shown in equation (3.2). It shows the relationship between individual subjective survival probability and subsequent mortality and the relationship between this subjective 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 percent of increase in self-perceived probability of being alive for next ten to fifteen years 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 positive correlation between private information on mortality risk and life insurance purchase as well as subsequent mortality we stated at the beginning of this part, when we apply the standard test, we obtain a significantly negative estimate for the correlation between the two error terms at -0.0341. In other words, the standard test suggests that there is no private information on mortality risk. 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.

3.2.2 Private Information about Insurance Preferences and Its Relation to Life Insurance Ownership as well as Subsequent Mortality

The third column of Table B.4 represents the results of model (3.5), in which we add the proxy variables for individuals' preferences for life insurance. These proxy variables, as displayed in Table B.4, are dummy variables for employment status: whether take care of grandkids if they have; whether the individual has a religion preference; whether take preventative health activities such as flu shot and blood test for cholesterol; whether have stock, loan, and house; as well as the loss of income if the insured dies and the number of years of education. 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 opposite effect on the correlation between life insurance ownership and subsequent mortality. 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 B.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).

3.2.3 Life Insurance and Individual's Mortality

Another approach, suggested by Finkelstein and Poterba (2004), is also applied to confirm this negative or neutral relationship between life insurance purchases and the mortality we derived above. Table B.5 shows the estimated coefficients from probit estimation of subsequent mortality on the ownership of life insurance (equation (3.3)). In column (1) of Table B.5, we control for the public information that is known 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 B.5, proxy variables for private information is added, i.e., the self-perceived risk of mortality. A similar result is obtained. The third and fourth columns in Table B.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.

3.2.4 Identification of Private Information about Mortality Risk using Mixture Density Model

We now estimate the mixture density model as shown in equation (3.7), 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. W consists of employment status, the number of years of education, the loss of the income if the insured dies, whether have loan, stock, and house; whether take care of grandkids if they have; whether the individual has a religion preference; as well as whether take preventative health activities such as flu shot and blood test for cholesterol. We then use ML method to estimate our log likelihood function.

Column (1) of the top panel of Table B.6 represents the estimated coefficients of these socioeconomic factors on predicting the probability of being an *h*-type. 86 percent of individuals can be categorized as the *h* type.

Not surprisingly, different types of individuals 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 comparison of constant terms between these two types. 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} , which is 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 correlation between the error terms in *Die* model and *LFI* model is, respectively, 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.

In the second column of Table B.6, we include one proxy variable for the private information on mortality risk, 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 B.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 B.6.

3.2.5 A Test of the Mixture Density Model

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:

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

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

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 Henry, Kitamura and Salanié (2014). 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' socioeconomic factors from five aspects: employment status, education level, a series of proxy variables for risk tolerance, bequest motives and financial conditions. We would like to respectively exclude each of these five aspects in our specification tests.

Table B.7 (a), (b), (c), (d) and (e) reports the result when proxy variables for bequest motives, risk attitudes, the number of years of education, individuals' 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 are consistent with the predictors of two-type model; parameters in both *Die* and *LFI* equations are similar to the corresponding parameters estimated in Table B.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 B.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 B.8

with each of the five cases in Table B.9. Results under five specifications, which correspond to the specification test in Table B.9, are reported. In the first to fifth set of columns, we compare the estimates from the base model (the model with all five aspects) 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.

3.2.6 A Model with Three-types of Heterogeneity in Life Insurance Preferences

Section 3.2.4 and 3.2.5 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 B.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 among these three models. Results are shown in Table B.10. First, we find the (one-type) bivariate probit model is supported by neither AIC nor BIC. Second, 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.

3.3 Conclusions

This paper has three main contributions. 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 suggest that there exists asymmetric information on mortality risk. 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 opposite 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.

4. SELECTION OF DIFFERENT LIFE INSURANCE CONTRACTS: THEORETICAL PERSPECTIVES AND EMPIRICAL ANALYSIS

4.1 Introduction

Life Insurance Markets. As one of the most widely held financial products, by the end of 2012, total individual life insurance coverage in the United States has achieved $11.2 trillion (ACLI, 2013). Basically, there are two main types of individual life policies: term and whole life insurance policies. Basically, according to the life insurance ownership information from Health and Retirement Study (HRS) data year 2000, 32% does not have any form of life insurance; 36% is in the form of term life insurance; 20% is in the form of whole life insurance; and 12% have both types of life insurance contracts.

A term life insurance differs from a whole life insurance in terms of premium and the coverage period. Specifically, term insurance policies provide life insurance coverage for a specified period, at a fixed annual premium. The life insurance company will pay the face value of the policy to her beneficiaries, as long as the insured dies during the valid period and pays premium when she was alive. If the event of death does not occur before the term expires, term policies provide no further benefits, and no buildup of cash value occurs. When the term is expired, insurers will re-categorize insured's risk and a new premium will be set for another period. Unlike term insurance, the whole (cash-value) life insurance policies cover a person's entire life at a fixed pre-specified annual premium throughout the life of the policy. Besides for the pure insurance protection, which functions exactly as the term life insurance, whole life policies also have a saving component. Specifically, there is a cash value that grows each year, tax-deferred, until it matches the face value of the policy.

Individuals can access to their cash value in the case of financial emergencies or pay for special goals, through loan and withdraw options after paying premium for a certain years.

Front-loading, Lapsation and Mortality Risk. As suggested in H&L (2003), all life insurance contracts, by different extent, are front-loaded. This can be attributed to the one-sided commitment, i.e., consumers can terminate at any time but insurers respect to the contract. Consider a contract that *fully* insures the second-period reclassification risk. Since buyers can always lapse a contract at any time, such a contract implies its second-period premium should be equal or smaller than the fair premium for the healthiest consumer. However, this would lead to a second-period loss which is equal to the difference between the premium and the average cost of covering the whole pool. Therefore, consumers must be surcharged in the first period to obtain this insurance against reclassification risk in the second period. Front-loading therefore can be considered as consumers pay in advance (a premium which is higher than the current period fair price) to “exchange” for a lower price in the future, which keeps them stay in the contract. In reality, different premium profile reflects different degrees of front-loading. Whole life insurance policy can be considered as the most front-loaded contract due to its flat premium for the whole life. In earlier years, the annual premium for whole life policies is higher than that for term life policies; while, in later years, it becomes substantially lower. Basically, the excess amount of premium in earlier years accumulates, in reserve as the cash value, providing funds for the cost of coverage in the older age.

Due to this one-sided commitment, in period 2, after the new health status is revealed, the policyholder has two options: she can either stay in the current life insurance contract or lapse the current policy and go to the spot market for a better rate. Since a more front-loaded contract in the first period indicates a lower premium in the second period by insurers earning a zero profit (there definitely exists a time point after which the premium for whole life insurance contract is lower than the term contract premium; otherwise, at the very beginning, no one will choose the whole contract), and a lower premium will lock in (good risk) consumers to a greater extent (a lower lapsation rate); the more front-loaded contracts insure more (a wider range of) reclassification risk and are associated with a healthier pool. Therefore, by H&L (2003), one implication is that the mortality risk in whole life insurance should be lower than that in the term life insurance.

This paper makes three contributions to the literature. First, although the individual demand for life insurance has been discussed by a large volume of literature (e.g. Yaari (1965), Campbell (1980), Lin and Grace (2007)), few studies explore the determinants of choosing between different life insurance contracts; and literature discussing the relative risk between these contracts is even less. In this paper, we first present a theoretical model to understand individuals' heterogeneity in insuring against reclassification risk (the risk of being reclassified into a higher risk category due to symmetric learning) by choosing different front-loaded life insurance contracts. We find that, although when there is no friction, all individuals would like to purchase a more front-loaded contract to insure the future reclassification risk as proposed in H&L (2003), front-loading is costly; as a result, buyers with more resources (higher income) in the first period will choose to purchase a more front-loaded contract (correspondingly, the whole life insurance contract) and obtain a lower premium cap in the second period. Since only the relative level of income of these two periods matters, one implication of our model is that there is no systematic difference in the mortality risk between the whole and term life insurance contract pool. Empirical test supports the prediction of our model.

Second, as an extension for H&L (2003), we show that when the income level of these two periods are the same, individuals who are risk averse will choose to purchase a more front-loaded contract (whole life insurance) to insure against the future reclassification risk. Empirical results show that with everything equal, individuals who do not smoke; take seatbelt; and take preventative cholesterol are more likely to purchase a whole life insurance contract.

To our knowledge, it is the first time in the literature to provide empirical evidence for the sources of individuals' heterogeneity in avoiding reclassification risk.

Third, in accordance with H&L (2003), we confirm that front-loading improves consumer commitment (lower lapsation); and therefore, the more front-loaded contract retains a healthier pool. Specifically, contrast to the aggregate-level dataset used in H&L (2003), we use the Health and Retirement Study (HRS) which is an individual-level dataset to look at the relationship between lapsation and front-loading as well as the relation between front-loading and mortality risk, respectively. As expected, we find *(i)* more front-loaded contract has lower lapsation rate; *(ii)* for the sample whose age is greater than 65, conditional on having whole life insurance, individuals who are less likely to die, indeed, are less likely to lapse their contracts; and *(iii)* the mortality risk for those who are covered by whole life insurance contract is lower than that for the term life insurance after 65 years old. We therefore suggest the lock-in effect potentially is revealed at the age of 65. To our knowledge, it is the first time in the literature to empirically test this lock-in effect embodied in the more front-loaded contract using an individual-level data.

The remainder of this section proceeds as followings. In section 4.2, we provide a theoretical model to illustrate the identification strategy used to detect the private information in life insurance market and describe our data. Section 4.3 describes the data. Section 4.4 presents the empirical results. The final section concludes.

4.2 Theoretical Model

Consider a two-period model. Following H&L (2003), two key assumptions in our paper are: *(i)* symmetric learning of health status over time to all market participants; *(ii)* one-sided commitment, that is, insurance companies respect the contract but buyers can lapse at any time.

Whole life insurance, as its name implies, provides a whole-life protection (an amount of *m* is guaranteed to be paid to the beneficiaries at the moment the insured dies) so long as the fixed premium q_i^W is paid annually until the insured *i*'s death. In contrast, term life insurance policy protects only for a few years; and the benefit *m* is paid only if the insured dies prior to the expiration date. Consequently, if the individual chooses a term life insurance in the first period and is still alive at the expiration date (the end of the first period), to insure the second period, she has to re-contract a new term life insurance. And the premium adjustment will be based on her newly revealed health condition at the beginning of the second period. To be comparable, we assume the new policy is still with a face value of *m*. However, the annual premium will be adjusted to q_{i2}^T based on his health status at the beginning of the second period. In the rest of this subsection, we will show why and when individuals would prefer a less front-loaded contract which let her exposed to the future reclassification risk.[3]

We now describe consumers' behavior under the expected utility-maximizing framework. The utility function is assumed to be composed of two aspects: the consumption of composite good conditional on she is alive during the period; and the face value of the life insurance she would leave to her beneficiaries at the end of the period when the death is realized. We assume that there is a perfect competition between insurance companies.

At the beginning of period 1, individual *i* chooses a contract *j*, where $j \in (T, W)$, to maximize her expected utility as represented in equation (4.1):

$$E[U_i^j] = (1-p_{i1})U(y_{i1} - q_{i1}^j) + p_{i1}B(m)$$

$$+(1-p_{i1})(1-p_{i2})U(y_{i2} - q_{i2}^j) + (1-p_{i1})p_{i2}B(m) \quad (4.1)$$

subject to the zero profit condition,

$$(1-p_{i1})q_i^W + (1-p_{i1})(1-p_{i2})q_i^W = p_{i1}m + (1-p_{i1})p_{i2}m, \quad (4.2)$$

if whole life insurance is purchased;

Or,

$$(1-p_{i1})q_{i1}^T = p_{i1}m, \quad (4.3)$$

And $$(1-p_{i2})q_{i2}^T = p_{i2}m, \quad (4.4)$$

if term life insurance is purchased.

Where,

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[3] As suggested by H&L (2003), without no other friction, all consumers would purchase a contract that is sufficiently front-loaded to guarantee that they have no incentive to drop out of from their contract in the future (full insurance against the reclassification risk).

$U(.)$ is a strictly increasing and strictly concave function, which is second-order continuous differentiable;

$p_{it} =$ $i's$ probability of die during period *t (t=1,2)*. Particularly, we assume that

$p_{i1} < p_{i2}$ ($p_{i2}^T \in (0,1)$), since health is getting worse over time.

$q_{it}^j =$ premium of policy *j* at period *t*. (*t*=1, 2. *j=T, W*). Specifically, if whole life insurance is chosen, then $q_{i1}^W = q_{i2}^W = q_i^W$.

$y_{it} =$ income of i, (*t*=1, 2);

$m =$ face value of life insurance;

$B(.) =$ utility from bequest.

Notice that the utility form in equation (4.1) indicates that *(i)* inter-temporal borrowing is not allowed; and *(ii)* individuals would use up all their disposable income before they die, in other words, life insurance is the only bequest left to their beneficiaries.

By solving the model, we have the following propositions that are the main testable implications of the model.

Proposition 1. Under zero profit condition, the whole life insurance contract is more front-loaded in the first period but involved with a lower premium in the second period.

Proof: By equation (4.2), (4.3) and (4.4), we have,

$$q_i^W - q_{i1}^T = \frac{p_{i1}m + (1-p_{i1})p_{i2}m}{(1-p_{i1})(2-p_{i2})} - \frac{p_{i1}m}{(1-p_{i1})}$$

$$= \frac{(p_{i2}-p_{i1})m}{(1-p_{i1})(2-p_{i2})} \tag{4.5}$$

$$q_i^W - q_{i2}^T = \frac{p_{i1}m + (1-p_{i1})p_{i2}m}{(1-p_{i1})(2-p_{i2})} - \frac{p_{i2}m}{(1-p_{i2})}$$

$$= \frac{(p_{i1}-p_{i2})m}{(1-p_{i1})(2-p_{i2})(1-p_{i2})} \tag{4.6}$$

Since $p_{i1} < p_{i2}$, we therefore have $q_{i1}^T < q_i^W < q_{i2}^T$. Intuitively, on one hand, the first period premium for term life policy would be less than the whole life premium; otherwise, purchasing a whole life insurance policy will be always the dominant strategy; on the other hand, q_i^W must be smaller than q_{i2}^T, otherwise, zero profit condition does not hold.

Proposition 2. Buying a whole (term) life insurance policy is always optimal if the first-period income is greater (less) than that in the second period.

Proof: By equation (4.1), (4.5), and (4.6), take first-order Taylor expansion, we have,

$$U_i^W - U_i^T \approx (1-p_{i1})U'(y_{i1})(q_{i1}^T - q_i^W) + (1-p_{i1})(1-p_{i2})U'(y_{i2})(q_{i2}^T - q_i^W)$$

$$= (1-p_{i1})U'(y_{i1})(q_{i1}^T - q_i^W) + (1-p_{i1})U'(y_{i2})(q_i^W - q_{i1}^T)$$

$$= (1-p_{i1})(q_{i1}^T - q_i^W)[U'(y_{i1}) - U'(y_{i2})] \tag{4.7}$$

Obviously, since $(1-p_{i1}) > 0$, and $q_{i1}^T < q_i^W$; when $y_{i1} > y_{i2}$ $(y_{i1} < y_{i2})$, which is equivalent to $U'(y_{i1}) < U'(y_{i2})$ $(U'(y_{i1}) > U'(y_{i2}))$, we will always have $U_i^W > U_i^T$ $(U_i^W < U_i^T)$.

Intuitively, front-loading implies a give-up of current consumption, to achieve consumption smoothing, a higher income in period 1 makes the individual have incentive to pay more in the first period to "exchange" for a lower premium by avoiding reclassification risk in the second period when the income is also lower. However, when the second-period income is greater, although buying a term life insurance contract implies facing a higher premium for the second period; it could be attenuated by the higher income for that period.

Proposition 3. Buying a whole life insurance policy is optimal for a risk-averse individual when the income of the two periods is the same.

As shown in equation (4.7), when $y_{i1} = y_{i2} = y_i$, the first-order Taylor expansion is not enough to determine the sign of $(U_i^W - U_i^T)$, we therefore do the second-order Taylor expansion:

$$U_i^W - U_i^T \approx 0 + (1-p_{i1})(-\frac{U''(y_i)}{2})[(q_{i1}^T)^2 - (q_i^W)^2]$$

$$+(1-p_{i1})(1-p_{i2})(-\frac{U''(y_i)}{2})[(q_{i2}^T)^2 - (q_i^W)^2]$$

$$= (1-p_{i1})(-\frac{U''(y_i)}{2})[(q_{i1}^T)^2 - (q_i^W)^2 + (1-p_{i2})(q_{i2}^T)^2 - (1-p_{i2})(q_i^W)^2]$$

$$= (1-p_{i1})(-\frac{U''(y_i)}{2})[(q_{i1}^T - q_i^W)(q_{i1}^T + q_i^W) + (1-p_{i2})(q_{i2}^T - q_i^W)(q_{i2}^T + q_i^W)]$$

$$= (1-p_{i1})(-\frac{U''(y_i)}{2})(q_{i1}^T - q_i^W)(q_{i1}^T - q_{i2}^T) \tag{4.8}$$

Obviously, equation (4.8) will be greater than zero so long as individual *i* is risk aversion.

Sum up, without any friction, all consumers would like to purchase a more front-loaded contract to avoid the future reclassification risk; while, front-loading is costly. In this paper, we show that, the relative income level between the two periods is the determinant for what type of life insurance contract would be purchased. Specifically, we find if the income of first period is greater, then purchasing a whole life policy is better off; otherwise, term life policy is optimal. Moreover, we show that when there is no difference between the income of the two periods, risk aversion or not becomes the key factor that determines the type of policy purchased; moreover, more risk aversion, more incentive to purchase a whole life insurance contract.

Proposition 4. Whole life insurance contracts lock consumers to a greater extent in the second period, resulting in a better risk pool than the term life insurance.

Proof: By Proposition 1, whole life policy is a more front-loaded contract, which involves a lower second-period premium, resulting in a greater extent of lock-in (good) consumers (lower lapsation by the good risk) in the second period and therefore retains a better risk pool.

4.3 Data

We apply the HRS cohort of the Health and Retirement Study (HRS) data during the period 2000 to 2008. The data contains information such as insurance status, the types of life insurance individuals hold, mortality, and a series of public information on individual demographics and health conditions. We restrict our analysis to the sample who do not have any life insurance and those who only have term or whole life insurance policies. The average age of our respondents when we observe them in 2000 is 66. 63.8 percent have life insurance. Among those who have life insurance, 64.8% hold term life insurance contracts; and 35.2% choose whole life contracts. Same respondents are followed over time, allowing us to observe actual mortality from 2000 to 2008. Twenty-five percent of our sample died at some point during this eight-year time window. 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, we employ the binary variable as the record of the occurrence of insured event in the rest of our analysis. The data also contains detailed information on the lapsation of life insurance contract.

To record whether the individual voluntarily terminated a policy since last wave, the specific questions we use are: *(i)* "Since (previous wave interview) have you allowed any life insurance policies to lapse or have any been cancelled?" and *(ii)* Was this lapse or cancellation something you chose to do, or was it done by the provider, your employer, or someone else? If the respondent replies "yes" to the first and "my decision" to the second, he is recorded as the one who lapsed a policy since last interview. For what type of life insurance contract is lapsed, we use the question: "Did you receive any cash when the policy was cancelled or allowed to lapse?" If the respondent answers "yes", we consider him to have a whole life insurance policy lapsed. Moreover, to be comparable across various specifications, we drop the samples with any missing information for any utilized variable in our analysis.

The data also contain information on all of the variables we would like to apply to identify whether an individual is risk averse or not. Specifically, the proxy variables we use for risk tolerance include whether take preventative health activities such as flu shot and blood test for cholesterol; as well as whether take seatbelt. For more details on the data and our sample see Table C.1.

4.4 Empirical Testing for the Implications of the Model

4.4.1 The Comparison of Mortality Risk between Term and Whole Life Policies

Proposition 2 shows that given an individual, the determinant of purchasing which type of life insurance contract is the relative value of her two periods' income, indicating that at the beginning of the first period when individuals make their decisions, there is no selection based on the risk. We therefore propose that whole and term life policies share the same risk pool.

Table C.2 shows the unconditional relationship between mortality risk and ownership of different life insurance contracts. We find although the mortality risk for whole life policy which is 19.8% is a little bit higher than that for the term which is 18.7%; there is no significant difference between these two contracts.

To further examine the relation between mortality risk and different life insurance contract ownership, we estimate the following Multinomial Logit model for the whole sample and Probit model for the subsample who have life insurance:

$$\Pr(insurance_i = j) = \frac{\exp(V_{ij})}{\sum_{k=0}^{J} \exp(V_{ik})}, \quad j = 0,1,2 \tag{4.9}$$

$$\Pr(Die_i = 1) = \Phi(\beta_0 + \beta_1 WLI_i + \beta_2 X) \tag{4.10}$$

where, Die is an indicator variable for whether the individual died during the period 2000~2008. $Insurance$ is equal to zero if individuals do not have any life insurance in year 2000; equal to 1 if the individual only holds term life insurance; and equal to 2 if he only holds whole life insurance. We use not purchasing any life insurance as our baseline. WLI is a binary variable which equals to one if the individual has whole life insurance policy; and equals to zero if she has a term life policy. X denotes the individual characteristics that are public information – information that is both available for individuals and insurers.

Table C.3 reports the results. Column (1) and (2)'s dependent variable is whether to buy a life insurance or not; and if yes, what type of life insurance contract would be chosen. Coefficients of "die" in term life and whole life equations are the parameters we are interested in. We find the estimated marginal effect of die in both term and whole life insurance equations is negative and statistically significant, indicating that individuals who are more likely to die are less likely to purchase life insurance. While, a significant difference on the mortality risk between term and whole life policies cannot be observed. Column (3) reports the estimation from a Probit model, where die is the dependent variable. Similarly, we find although the coefficient for whole life insurance ownership is -0.045 with a marginal effect of -0.010, it is not significantly different from zero; indicating that the risk pool of term and whole have no significant difference.

4.4.2 Risk Aversion and Choice of Whole Life Insurance Contract

In Proposition 3, we show that if the individual has the same income for each period, then she will choose to purchase a whole life insurance contract if she is risk averse. We therefore estimate the following Probit model and the interested parameter is the coefficients of W :

$$\Pr(WLI_i = 1) = \Phi(\beta_0 + \beta_1 X_i + \beta_2 W) \tag{4.11}$$

Where, W is a series of proxy variable to indicate whether the individuals is risk averse or not, which includes whether annually take preventative test for cholesterol; whether take seatbelt; and whether smoke or not. Table C.4 reports the result. We find individuals who are more likely to take preventative health activities; take seatbelts; and do not smoke are more likely to purchase a whole life insurance contract to avoid the reclassification risk.

4.4.3 The Negative Relation between Front-loading and Lapsation

We have shown that, in Proposition 1, compared to the term life insurance, whole life insurance contract is more front-loaded. Based on the argument in H&L (2003), a more front-loaded contract will be associated with a lower premium for the second period, thus lock in (good-risk) consumers to a greater extent. We then apply the HRS dataset which is an individual-level data, contrast to the aggregate level dataset used in H&L (2003), to test this implication.

Table C.5 shows that *(i)* there is a significantly negative correlation between whole life insurance holding and lapsation. *(ii)* Conditional on being in whole life insurance contract, individuals who are less likely to die (healthier) are less likely to lapse their contract, which is highly in accordance with the fact that the more front-loaded contracts keep good-risk consumers to a greater extent. The signs of all the other variables are as expected.

To further investigate this stronger lock-in effect embodied in whole life insurance contract, we separate our sample into two groups by age. We confirm this lock-in effect does not show before 65 years old but is quite strong after 65. It is, actually, consistent with the fact that after 65 years old, although switching from one term contract to another may have the consumer to obtain a less expensive premium; whole life policy provides the best price after this age.

4.4.4 The Negative Relation between Front-loading and Mortality Risk

Proposition 4 argues that as a result of the lower lapsation rate, which locks in more good-risk individuals, whole life insurance should be involved with a healthier pool. We therefore estimate a probit model as shown in equation (4.10) to directly see the relationship between mortality risk and whole life insurance ownership. Column (1) of Table C.6 reports the same results as represented in column (3) of Table C.3—for the whole sample, there is no significant difference in the mortality risk between whole and term life insurance contract. According to our results reported in Table C.5, such lock-in effect existing in whole life policies does not show up until 65 years old. We therefore separate individuals into two groups using the standard of whether she is younger than 65 or not. We confirm that, for the group whose age is greater than 65, the time when the lock-in effect emerges, whole life insurance does retain a healthier pool than the term life insurance.

4.5 Conclusion

In this paper, we first present a theoretical model to understand individuals' heterogeneity in insuring against reclassification risk (the risk of being reclassified into a higher risk category due to symmetric learning) by choosing different front-loaded life insurance contracts. We find that, although when there is no friction, all individuals would like to purchase a more front-loaded contract to insure the future reclassification risk as proposed in H&L (2003), front-loading is costly; as a result, buyers with more resources (higher income) in the first period will choose to purchase a more front-loaded contract (correspondingly, the whole life insurance contract) and obtain a lower premium cap in the second period. Since only the relative level of income of these two periods matters, one implication of our model is that there is no systematic difference in the mortality risk between the whole and term life insurance contract pool. Empirical test supports the prediction of our model.

Second, as an extension for H&L (2003), we show that when the income level of these two periods are the same, individuals who are risk averse will choose to purchase a more front-loaded contract (whole life insurance) to insure against the future reclassification risk. Empirical results show that with everything equal, individuals who do not smoke; take seatbelt; and take preventative cholesterol are more likely to purchase a whole life insurance contract.

Third, in accordance with H&L (2003), we confirm that front-loading helps improve consumer commitment (lower lapsation); and therefore, the more front-loaded contract retains a healthier pool. Specifically, contrast to the aggregate-level dataset used in H&L (2003), we use the Health and Retirement Study (HRS) which is an individual-level dataset to look at the relation between lapsation and front-loading as well as the relation between front-loading and mortality risk, respectively. As expected, we find *(i)* more front-loaded contract has lower lapsation rate; *(ii)* for the sample whose age is greater than 65, conditional on having whole life insurance, individuals who are less likely to die, indeed, are less likely to lapse their contracts; and *(iii)* the mortality risk for those who are covered by whole life insurance contract is lower than that for the term life insurance after 65 years old. We therefore suggest the lock-in effect potentially is revealed at the age of 65. To our knowledge, it is the first time in the literature to empirically test this lock-in effect embodied in the more front-loaded contract using an individual-level data.

5. CONCLUSION

My work focuses on the detecting and quantifying the adverse selection and advantageous selection in life insurance and health insurance markets. I confirm that there exists an advantageous selection in voluntary private health insurance markets. I next identify the sources of such advantageous selection which include assets, education level, and cognitive abilities. This is consistent with the arguments by recent theoretical researches, that is, there are multiple dimensions of private information coexist on the market which offset each other, resulting in a neutral or negative correlation between insurance ownership and *ex post* risk, even in the presence of adverse selection. I find the similar phenomena in the life insurance markets, in which individuals are heterogeneous in their preferences in life insurance. I successfully identify this adverse selection under the framework of mixture density model, which distinguishes the second-dimension of private information, allowing the private information on risk revealed. Moreover, I move one step forward to see the mortality risk related to different life insurance contracts and find that the more front-loaded contract (whole life insurance) is involved with a lower risk than the less front-loaded contract (term life insurance). This provides an empirical evidence for Hendel and Lizzeri (2003).

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APPENDIX A

APPENDIX OF SECTION 2

Variables	Observations	Mean	Std. Deviation	Min	Max
VPHI	23922	.327	.469	0	1
Symptom	25100	.345	.476	0	1
self-perceived health	25096	3.120	1.065	1	5
Marriage	25100	.757	.429	0	1
Heart	25100	.116	.320	0	1
Stroke	25100	.033	.179	0	1
Drink	25082	.128	.334	0	1
smoke now	25099	.202	.402	0	1
smoke ever	25100	.481	.500	0	1
Diabetes	25100	.096	.294	0	1
Depression	25089	.364	.481	0	1
Age	25100	63.161	10.124	26	104
Sex	25100	.457	.498	0	1
Education	24930	2.577	1.512	0	6
Work	25100	.360	.480	0	1
Income	22888	15879.7	791318.2	0	1.19e08
House	24227	.721	.448	0	1

kid	25100	.896	.305	0	1
numkid	24667	2.231	1.507	0	17
grandkid-	25100	.595	.491	0	1
numgrandkid	25049	2.419	3.263	0	20
sib	25100	.893	.309	0	1

Table A.1: Summary of Statistics

	Ordinary Least Squares Regression			Ordered Probit Model		
Variable	(1) Full Sample	(2) Female	(3) Male	(4) Full Sample	(5) Female	(6) Male
VPHI	0.042***	0.055***	0.023	0.046***	0.060***	0.026
	(0.018)	(0.024)	(0.026)	(0.019)	(0.026)	(0.028)
age	-0.064	-0.054	0.214***	-0.077*	-0.066	--
	(0.047)	(0.047)	(0.089)	(0.051)	(0.052)	--
age^2	0.001	5.90e-04	-0.003***	0.001	0.001	0.003***
	(0.001)	(7.30e-04)	(0.001)	(0.001)	(0.001)	(0.001)
age^3	-4.47e-06	-3.22e-06	1.32e-05***	-5.62e-06	-4.30e-06	1.4e-05***
	(3.73e-06)	(3.72e-06)	(6.51e-06)	(4.04e-06)	(4.07e-06)	(6.91e-06)
sex	-6.870***	--	--	-7.578***	--	--
	(2.192)	--	--	(2.357)	--	--
age*sex	0.298***	--	--	0.329***	--	0.229***
	(0.010)	--	--	(0.107)	--	(0.095)
age^2*sex	-0.004***	--	--	-0.005***	--	--
	(0.002)	--	--	(0.002)	--	--
age^3*sex	1.99e-05***	--	--	2.2e-05***	--	--
	(7.41e-06)	--	--	(7.97e-06)	--	--
marriage	0.074***	0.086***	0.045**	0.080***	0.094***	0.049**
	(0.016)	(0.020)	(0.026)	(0.017)	(0.022)	(0.028)
work	0.409***	0.350***	0.471***	0.438***	0.379***	0.499***

	(0.017)	(0.023)	(0.026)	(0.018)	(0.025)	(0.028)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,918	12,996	10,922	23,918	12,996	10,922

Standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15

Table A.2: Results of Self-Evaluated Health Condition on “VPHI” Coverage

Variable	(1) Full Sample	(2) Female	(3) Male
VPHI	-0.054***	-0.035	-0.082***
	(0.022)	(0.030)	(0.032)
age	0.202***	0.211***	--
	(0.076)	(0.077)	--
age^2	-0.003***	-0.003***	-9.25e-05
	(0.001)	(0.001)	(0.002)
age^3	1.57e-05***	1.6e-05***	-1.08e-06
	(6.05e-06)	(6.18e-06)	(1.02e-05)
sex	3.055	--	--
	(3.471)	--	--
age*sex	-0.169	--	0.020
	(0.159)	--	(0.139)
age^2*sex	0.003	--	--
	(0.002)	--	--
age^3*sex	-1.68e-05	--	--
	(1.19e-05)	--	--
marriage	0.132***	0.056**	0.247***
	(0.026)	(0.033)	(0.041)
work	0.168***	0.164***	0.160***
	(0.027)	(0.037)	(0.040)
Country Dummies	Yes	Yes	Yes

Observations	23,921	12,995	10,922

Standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15

Table A.3: Results of ADL Limitations on "VPHI" Coverage

Variable	(1) Full Sample	(2) Female	(3) Male
VPHI	-0.045**	-0.035	-0.056*
	(0.024)	(0.033)	(0.036)
age	0.159***	0.134***	--
	(0.068)	(0.068)	--
age^2	-0.002***	-0.002**	0.002
	(0.001)	(0.001)	(0.002)
age^3	1.22e-05***	9.58e-06**	-5.23e-06
	(5.30e-06)	(5.32e-06)	(8.62e-06)
sex	6.790***	--	--
	(3.037)	--	--
age*sex	-0.306***	--	-0.133
	(0.138)	--	(0.120)
age^2*sex	0.004***	--	--
	(0.002)	--	--
age^3*sex	-1.97e-05**	--	--
	(1.01e-05)	--	--
marriage	-0.087***	-0.085***	-0.076***
	(0.021)	(0.026)	(0.035)
work	-0.263***	-0.167***	-0.388***
	(0.023)	(0.030)	(0.036)

Country Dummies	Yes	Yes	Yes
Observations	23,922	12,996	10,926

Standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15

Table A.4: Probit Model of Symptom on "VPHI" Coverage

Variable	(1) Full Sample	(2) Female	(3) Male
VPHI	-0.053***	-0.030	-0.076***
	(0.027)	(0.041)	(0.035)
age	0.034	0.007	-0.135
	(0.072)	(0.079)	(0.119)
age^2	-5.791e-04	-1.056e-04	0.001
	(0.001)	(0.001)	(0.002)
age^3	5.53e-06	2.94e-06	-1.90e-06
	(5.69e-06)	(6.22e-06)	(8.70e-06)
sex	4.953*	--	--
	(3.344)	--	--
age*sex	-0.199	--	--
	(0.152)	--	--
age^2*sex	0.002	--	--
	(0.002)	--	--
age^3*sex	-1.07e-05**	--	--
	(1.13e-05)	--	--
marriage	-0.157***	-0.187***	-0.105***
	(0.024)	(0.034)	(0.035)
work	-0.361***	-0.285***	-0.450***
	(0.026)	(0.038)	(0.035)

Country Dummies	Yes	Yes	Yes
Observations	23,922	12,996	10,926

Standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15

Table A.5: Ordinary Least Squares Regression Results of the Number of Symptoms on "VPHI" Coverage

Variable	Without Health Control		With Health Control	
	(1)	(2)	(3)	(4)
Self-perceived	0.030***	-0.024***	0.020*	-0.027**
health	(0.010)	(0.012)	(0.013)	(0.015)
education		0.034***		0.027***
		(0.011)		(0.011)
Total Income		-1.37e-08		-1.36e-08
		(2.52e-08)		(2.50e-08)
House		0.102***		0.096***
		(0.030)		(0.031)
Stock		0.108***		0.106***
		(0.034)		(0.034)
Mutual fund		0.135***		0.134***
		(0.036)		(0.036)
Mortgage		-0.076***		-0.076***
		(0.034)		(0.034)
Math		0.031***		0.028***
		(0.013)		(0.013)
Read		0.027		0.024
		(0.020)		(0.020)
Write		0.048***		0.047***
		(0.019)		(0.019)

Recall Word		0.039***		0.038***
		(0.008)		(0.008)
Country Dummies	Yes	Yes	Yes	Yes
Observations	23,918	20,078	23,465	19,995

Standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15

Note: The dependent variable is VPHI ownership. In both column (3) and (4), a total of 44 health indicators are included.

Table A.6: Sources of Advantageous Selection

APPENDIX B

APPENDIX OF SECTION 3

		Life insurance ownership	
		0	1
Die	0	3384 (22.7%)	8465 (56.7%)
	1	1160 (7.8%)	1916 (12.8%)
Mortality Rate		26%	18%

Table B.1: Unconditional Relationship between Life Insurance Ownership and Subsequent Mortality

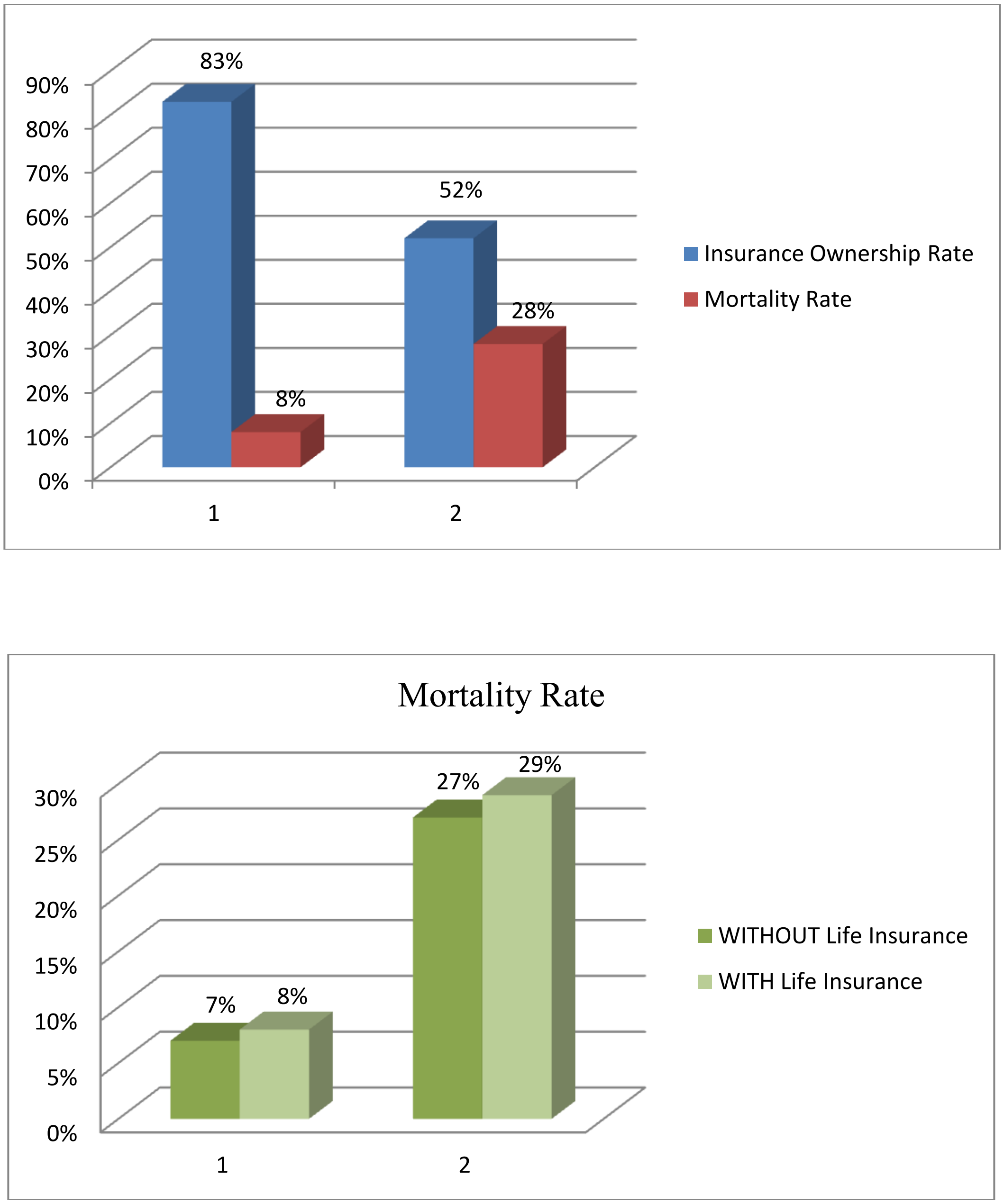

Figure B.1: Economic Identification

		Life Insurance Ownership			
		0		1	
Die	0	194		744	
	1	30		82	
Mortality Rate		13%		10%	
		High Life Insurance Preferences		Low Life Insurance Preferences	
		0	1	0	1
Die	0	142	689	52	55
		(15.25%)	(76.40%)	(30.88%)	(32.35%)
	1	11	60	19	22
		(0.91%)	(7.43%)	(14.71%)	(22.06%)
Mortality Rate		7%	8%	27%	29%

Table B.2: The Relationship between Life Insurance Ownership and Mortality Conditional on Insurance Preferences

Variables	Observations	Mean	Std. Deviation	Min	Max
Die	14925	.21	.41	0	1
LFI	14925	.70	.46	0	1
self-perceived risk	14925	49.51	31.75	0	100
Marriage	14925	.69	.46	0	1
Spouse age	14925	44.49	30.87	0	99
age	14925	65.92	9.97	27	90
age^2	14925	4444.13	1333.99	729	8100
age^3	14925	306172.3	137460.9	19683	729000
black	14925	.12	.32	0	1
age*black	14925	7.60	21.01	0	90
age^2*black	14925	498.97	1430.33	0	8100
age^3*black	14925	33481.92	101660.60	0	729000
age*gender	14925	26.56	33.14	0	90
age2gender	14925	1803.79	2353.33	0	8100
age3gender	14925	124801.1	174154.1	0	72900
male	14925	.40	.49	0	1
arthritis	14925	.56	.50	0	1
high blood pressure	14925	.48	.50	0	1
lung	14925	.09	.29	0	1

cancer	14925	.12	.33	0	1
heart	14925	.21	.41	0	1
stroke	14925	.06	.23	0	1
drink	14925	.06	.24	0	1
smoke now	14925	.16	.36	0	1
smoke ever	14925	.60	.49	0	1
diabetes	14925	.17	.44	0	1
incontinent	14925	.17	.38	0	1
psych	14925	.14	.34	0	1
depression	14925	.23	.42	0	1
back	14925	.33	.47	0	1
self-reported-health	14925	3.30	1.11	1	5
BMI	14743	27.25	5.34	12.6	75.5
take drugs	14925	.77	.42	0	1
home care use	14856	.05	.23	0	1
nursing home	14924	.01	.12	0	1
hospital	14921	.23	.42	0	1
number of kid	14925	3.25	2.15	0	20
kid	14925	.94	.25	0	1
No of siblings	14925	2.59	2.31	0	17
siblings	14925	.85	.36	0	1

No of grandkids	14925	5.07	5.43	0	80
grandkid	14925	.80	.40	0	1
caregrandkid	14925	.20	.40	0	1
cargkidmissing	14925	.28	.45	0	1
religion	14925	.95	.23	0	1
education	14903	12.47	3.02	0	17
flu shot	14925	.61	.49	0	1
test for blood cholesterol	14925	.77	.42	0	1
employment	14925	.40	.49	0	1
stock	14925	.36	.48	0	1
loan	14925	.08	.27	0	1
income ($)	14925	21793	33167	0	2000000

Table B.3: Summary of Statistics

	(1) Public information	(2) Subjective Survival & Public information	(3) Public information & Type info	(4) Subjective Survival & Public info & Type info
		Die equation		
Subjective survival probability		-0.0011***		-0.0010***
		(0.0005)		(0.0005)
education			-0.0004	-0.0002
			(0.0052)	(0.0052)
work			-0.159***	-0.156***
			(0.0361)	(0.0361)
religion			-0.0986**	-0.0989**
			(0.0600)	(0.0600)
care of grandkid			-0.0948***	-0.0945***
			(0.0344)	(0.0344)
flu shot			0.0135	0.0138
			(0.0316)	(0.0316)
preventive test for blood cholesterol			-0.217***	-0.215***
			(0.0354)	(0.0354)
stock			-0.0887***	-0.0887***
			(0.0320)	(0.0320)
income			-1.31e-06**	-1.33e-06**
			(7.21e-07)	(7.21e-07)
loan			-0.0060	-0.0043
			(0.0587)	(0.0587)
own house			-0.134***	-0.134***
			(0.0368)	(0.0368)
Constant	0.0658	0.160	-0.882	-0.792
	(3.1753)	(3.189)	(3.185)	(3.196)

LFI equation				
Subjective survival probability		-0.0008***		-0.0011***
		(0.0004)		(0.0004)
education			0.0278***	0.0284***
			(0.0044)	(0.0044)
work			0.334***	0.335***
			(0.0285)	(0.0285)
religion			0.230***	0.230***
			(0.0496)	(0.0496)
take care of grandkid			0.0807***	0.0814***
			(0.0279)	(0.0279)
flu shot			0.0674***	0.0679***
			(0.0256)	(0.0256)
Preventive test for blood cholesterol			0.0657***	0.0677***
			(0.0287)	(0.0287)
stock			0.0413*	0.0418*
			(0.0261)	(0.0262)
income			2.94e-06***	2.94e-06***
			(3.91e-07)	(3.91e-07)
loan			0.188***	0.190***
			(0.0466)	(0.0467)
own house			0.257***	0.256***
			(0.0316)	(0.0316)
Constant	-5.1930***	-5.084***	-3.417**	-3.272**
	(1.8514)	(1.852)	(1.925)	(1.926)
Correlation 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 B.4: One Type Bivariate Probit Model

	(1) Public Information	(2) Individual Prediction& Public Information	(3) Public Information & Other Private Info	(4) Individual Prediction& Public Information & Other Private Info
Coefficient from probit of Mortality on LFI	-.0529**	-.0546**	-.0109	-.0126
	(.0294)	(.0294)	(.0301)	(.0301)
Observations	14,605	14,605	14,586	14,586

Standard errors in parentheses

*** p<0.05, ** p<0.10, * p<0.15

Table B.5: The Relationship between Life Insurance and Subsequent Mortality

	(1) Company Information only	(2) Self-perceived risk & Company Information
Type equation		
education	0.0334***	0.0343***
	(0.0086)	(0.0086)
work	0.3990***	0.3925***
	(0.0631)	(0.0628)
religion	0.5295***	0.5216***
	(0.1075)	(0.1060)
take care of	0.1686***	0.1679***
grandkid	(0.0563)	(0.0558)
caregrandkidmising	-0.0634	-0.0587
	(0.1251)	(0.1228)
flu shot	0.0988***	0.0995***
	(0.0492)	(0.0488)
preventive test for	0.1764***	0.1767***
blood cholesterol	(0.0577)	(0.0571)
stock	0.1057***	0.1062***
	(0.0534)	(0.0530)
income	3.52e-05***	3.5e-05***
	(4.38e-06)	(4.31e-06)
loan	0.3656***	0.3665***
	(0.1120)	(0.1114)
own house	0.4276***	0.4226***
	(0.0607)	(0.0560)
Constant	-1.5840***	-1.569***
	(0.2459)	(0.2436)

Die equation				
	Type 1	Type 2	Type 1	Type 2
Self-perceived risk			-0.0011***	
			(0.0005)	
Constant	-0.2888	0.2451	-0.1787	0.3522
	(3.1764)	(3.1754)	(3.1831)	(3.1821)
LFI equation				
	Type 1	Type 2	Type 1	Type 2
self-perceived risk			-0.0014***	
			(0.0005)	
Constant	-3.8322*	-5.5241***	-3.671	-5.389***
	(2.5344)	(2.5530)	(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	

Standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15

Table B.6. Mixture density model (Two-type)

	Drop ‘Care’	
	(1)	(2)
Type equation		
education	0.033***	0.034***
	(0.008)	(0.008)
work	0.379***	0.371***
	(0.0619)	(0.0615)
flushot	0.0985***	0.0996***
	(0.048)	(0.0477)
preventivechol	0.1730***	0.1727***
	(0.057)	(0.056)
religion		
caregrandkid		
caregrandkidmisg		
Income	0.0000359***	0.0000356***
	(4.51e-06)	(4.45e-06)
stock	0.112***	0.113***
	(0.053)	(0.053)
loan	0.357***	0.358***
	(0.113)	(0.112)
Own house	0.430***	0.425***
	(0.059)	(0.058)
Constant	-0.980***	-0.968***
	(0.181)	(0.179)

	Type 1	Type 2	Type 1	Type 2
Die				
r5liv10			-0.0011***	
			(0.00046)	
Constant	-0.0168	0.4897	0.093	0.594
	(3.166)	(3.165)	(3.171)	(3.171)
LFI				
r5liv10			-0.0015***	
			(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)	(0.0804)	(0.052)	(0.082)
Observation	14,586		14,586	

Standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15

Table B.7 (a): Specification Test

	Drop 'Risk Averse'	
	(3)	(4)
Type equation		
education	0.035***	0.036***
	(0.0086)	(0.008)
work	0.371***	0.365***
	(0.062)	(0.062)
flushot		
preventivechol		
religion	0.523***	0.516***
	(0.107)	(0.106)
caregrandkid	0.168***	0.167***
	(0.056)	(0.056)
caregrandkidmisg	-0.069	-0.065
	(0.120)	(0.117)
Income	0.000036***	0.000036***
	(4.55e-06)	(4.48e-06)
stock	0.116***	0.116***
	(0.0526)	(0.052)
loan	0.370***	0.371***
	(0.112)	(0.111)
Own house	0.427***	0.423***
	(0.061)	(0.060)
Constant	-1.392***	-1.377***
	(0.242)	(0.240)

	Type 1	Type 2	Type 1	Type 2
Die				
r5liv10			-0.001***	
			(0.0005)	
Constant	-0.266	0.225	-0.162	0.327
	(3.178)	(3.177)	(3.183)	(3.182)
LFI				
r5liv10			-0.0014***	
			(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)
Observation	14,586		14,586	

Standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15

Table B.7 (b): Specification Test

	Drop ‘education’	
	(5)	(6)
Type equation		
education		
work	0.432***	0.428***
	(0.064)	(0.063)
flushot	0.102***	0.102***
	(0.0503)	(0.050)
preventivechol	0.194***	0.195***
	(0.0594)	(0.059)
religion	0.522***	0.516***
	(0.110)	(0.109)
caregrandkid	0.175***	0.175***
	(0.057)	(0.057)
caregrandkidmisg	-0.065	-0.062
	(0.137)	(0.136)
Income	0.000036***	0.000036***
	(4.31e-06)	(4.26e-06)
stock	0.140***	0.141***
	(0.053)	(0.053)
loan	0.3837***	0.386***
	(0.113)	(0.112)
Own house	0.446***	0.443***
	(0.062)	(0.062)
Constant	-1.308***	-1.294***
	(0.225)	(0.224)

	Type 1	Type 2	Type 1	Type 2
Die				
r5liv10			-0.001***	
			(0.0005)	
Constant	-0.599	-0.053	-0.499	0.046
	(3.185)	(3.184)	(3.194)	(3.193)
LFI				
r5liv10			-0.001***	
			(0.0005)	
Constant	-3.852*	-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)
Observation	14,605		14605	

Standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15

Table B.7 (c): Specification Test

	Drop 'work'	
	(7)	(8)
Type equation		
education	0.044***	0.045***
	(0.009)	(0.009)
work		
flushot	0.086*	0.087**
	(0.053)	(0.052)
preventivechol	0.161***	0.160***
	(0.062)	(0.061)
religion	0.569***	0.553***
	(0.120)	(0.117)
caregrandkid	0.167***	0.165***
	(0.061)	(0.060)
caregrandkidmisg	-0.096	-0.085
	(0.127)	(0.123)
Income	0.000047***	0.000046***
	(5.24e-06)	(5.13e-06)
stock	0.141***	0.141***
	(0.061)	(0.060)
loan	0.419***	0.417***
	(0.125)	(0.124)
Own house	0.467***	0.459***
	(0.064)	(0.063)
Constant	-1.660***	-1.624***
	(0.261)	(0.255)

	Type 1	Type 2	Type 1	Type 2
Die				
r5liv10			-0.001***	
			(0.0005)	
Constant	0.128	0.590	0.231	0.690
	(3.151)	(3.152)	(3.160)	(3.160)
LFI				
r5liv10			-0.0014***	
			(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)
Observation	14,586		14,586	

Standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15

Table B.7 (d): Specification Test

	Drop ‘financial conditions’	
	(9)	(10)
Type equation		
education	0.084***	0.084***
	(0.017)	(0.018)
work	0.935***	0.921***
	(0.179)	(0.181)
flushot	0.178***	0.177***
	(0.067)	(0.066)
preventivechol	0.336***	0.333***
	(0.097)	(0.096)
religion	0.581***	0.572***
	(0.167)	(0.167)
caregrandkid	0.248***	0.245***
	(0.082)	(0.082)
caregrandkidmisg	0.173	0.180
	(0.213)	(0.213)
Income		
stock		
loan		
Own house		
Constant	-1.973***	-1.958***
	(0.607)	(0.620)

	Type 1	Type 2	Type 1	Type 2
Die				
r5liv10			-0.001***	
			(0.0005)	
Constant	-1.115	-0.531	-1.000	0.420
	(3.297)	(3.297)	(3.299)	(3.299)
LFI				
r5liv10			-0.0013***	
			(0.0005)	
Constant	-2.824	-4.035**	-2.652	-3.884**
	(2.215)	(2.259)	(2.232)	(2.281)
Correlation of two error terms	0.225***	0.114	0.223***	0.118
	(0.082)	(0.104)	(0.082)	(0.110)
Observation	14,586		14,586	

Standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15

Table B.7 (e): Specification Test

	Baseline model v.s. drop “care” variable		Baseline model v.s. drop “risk averse” variable		Baseline model v.s. drop “financial conditions” variables	
	Company prediction	Both prediction	Company prediction	Both prediction	Company prediction	Both prediction
Die equation	5.46 (1.000)	5.13 (1.000)	4.12 (1.000)	4.19 (1.000)	9.58 (0.999)	0.79 (1.000)
LFI equation	16.24 (0.991)	11.31 (1.000)	18.06 (0.977)	17.76 (0.980)	9.93 (0.999)	6.20 (1.000)

	Baseline model v.s. drop “work” variable		Baseline model v.s. drop “education” variable	
	Company prediction	Both prediction	Company prediction	Both prediction
Die equation	5.87 (1.000)	5.62 (1.000)	0.06 (1.000)	6.87 (1.000)
LFI equation	11.94 (1.000)	14.73 (0.996)	14.74 (0.996)	14.60 (0.996)

Table B.8: Hausman Test-- Baseline Model v.s. Robustness Check

	(1) Company Information only	(2) Self-perceived risk & Company Information
Type equation(1)		
education	-0.176	0.229***
	(0.168)	(0.0548)
work	1.472***	-0.144
	(0.412)	(0.323)
religion	1.041***	0.252
	(0.335)	(0.663)
take care of	0.757***	-0.222
grandkid	(0.340)	(0.231)
caregrandkidmising	0.373	-0.431
	(0.394)	(0.310)
flu shot	0.0360	0.355**
	(0.195)	(0.199)
Preventive test for	-0.0016	0.352*
blood cholesterol	(0.863)	(0.221)
stock	-0.286	1.120***
	(0.809)	(0.470)
income	5.19e-05***	6.39e-05***
	(1.00e-05)	(1.13e-05)
loan	0.977	0.212
	(0.715)	(0.374)
own house	0.254	0.917***
	(0.675)	(0.193)
Constant	1.102	-2.949***
	(4.118)	(0.988)

Type equation(2)		
education	-0.380***	0.371***
	(0.0574)	(0.0473)
work	1.434***	-1.584***
	(0.586)	(0.412)
religion	0.592	-0.804
	(0.952)	(0.842)
take care of	0.886***	-0.937***
grandkid	(0.349)	(0.307)
caregrandkidmising	0.700**	-0.766***
	(0.380)	(0.365)
flu shot	-0.252	0.336
	(0.472)	(0.301)
preventive test for	-0.437	0.172
blood cholesterol	(1.104)	(0.463)
stock	-1.398**	1.259***
	(0.748)	(0.554)
income	-1.18e-05	1.12e-05
	(1.51e-05)	(1.54e-05)
loan	0.772	-0.648
	(0.799)	(0.716)
own house	-0.681	0.536*
	(0.628)	(0.362)
Constant	4.395	-3.171*
	(4.695)	(2.013)
	Die equation	

	Type 1	Type 2	Type 3	Type 1	Type 2	Type 3
self-perceived risk					-0.0011***	
					(0.0005)	
Constant	-0.3561	0.1580	0.0984	-0.460	0.0629	0.00904
	(3.2554)	(3.2928)	(3.1874)	(3.216)	(3.206)	(3.226)

LFI equation

	Type 1	Type 2	Type 3	Type 1	Type 2	Type 3
self-perceived risk					-0.0016***	
					(0.0006)	
Constant	-3.727	-5.728***	-5.304***	-3.496	-5.071**	-5.666***
	(2.6242)	(2.6661)	(2.6470)	(2.6393)	(2.6538)	(2.6652)
Correlation of two	0.164***	0.342***	0.202	0.161***	0.252***	0.347***
error terms	(0.0688)	(0.1511)	(0.3478)	(0.0677)	(0.1226)	(0.3473)
Observations		14,586			14,586	

Standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15

Table B.9: Three-type model

AIC

	One-Type Model	Two-Type Model	Three-Type Model
w/o private information	27630.3	27456.9	27375.7
With private information	27621.5	27447.8	27365.5

BIC

	One-Type Model	Two-Type Model	Three-Type Model
w/o private information	28389.1	28170.2	28195.1
With private information	28395.5	28176.3	28200.1

Table B.10: A Comparison of the Goodness of Fit among One-type (Bivariate Probit) model Two-type model and Three-type model via Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC)

APPENDIX C

APPENDIX OF SECTION 4

Variables	Observations	Mean	Std. Deviation	Min	Max
Die	14925	.21	.41	0	1
LFI	14925	.70	.46	0	1
Self-perceived risk	14925	49.51	31.75	0	100
Marriage	14925	.69	.46	0	1
Spouse age	14925	44.49	30.87	0	99
age	14925	65.92	9.97	27	90
age^2	14925	4444.13	1333.99	729	8100
age^3	14925	306172.3	137460.9	19683	729000
black	14925	.12	.32	0	1
age*black	14925	7.60	21.01	0	90
age^2*black	14925	498.97	1430.33	0	8100
age^3*black	14925	33481.92	101660.6	0	729000
age*gender	14925	26.56	33.14	0	90
age2gender	14925	1803.79	2353.33	0	8100
age3gender	14925	124801.1	174154.1	0	72900
Male	14925	.40	.49	0	1

arthritis	14925	.56	.50	0	1
High blood pressure	14925	.48	.50	0	1
Lung	14925	.09	.29	0	1
cancer	14925	.12	.33	0	1
Heart	14925	.21	.41	0	1
stroke	14925	.06	.23	0	1
Drink	14925	.06	.24	0	1
smoke now	14925	.16	.36	0	1
smoke ever	14925	.60	.49	0	1
diabetes	14925	.17	.44	0	1
incontinent	14925	.17	.38	0	1
psych	14925	.14	.34	0	1
depression	14925	.23	.42	0	1
back	14925	.33	.47	0	1
self-reported-health	14925	3.30	1.11	1	5
bmi	14743	27.25	5.34	12.6	75.5
take drugs	14925	.77	.42	0	1
home care use	14856	.05	.23	0	1
nursing home	14924	.01	.12	0	1
hospital	14921	.23	.42	0	1

number of kid	14925	3.25	2.15	0	20
kid	14925	.94	.25	0	1
number of sib	14925	2.59	2.31	0	17
sib	14925	.85	.36	0	1
number of grandkids	14925	5.07	5.43	0	80
grandkid	14925	.80	.40	0	1
caregrandmi~g	14925	.20	.40	0	1
caregrandkid	14925	.28	.45	0	1
religion	14925	.95	.23	0	1
education	14903	12.47	3.02	0	17
flu shot	14925	.61	.49	0	1
test for blood cholesterol	14925	.77	.42	0	1
employment	14925	.40	.49	0	1
stock	14925	.36	.48	0	1
loan	14925	.08	.27	0	1
income	14925	21793.37	33167.40	0	2000000

Table C.1: Summary of Statistics

	Life insurance ownership		
	No Insurance	Only TLI	Only WLI
Die 0	3384	4222	2267
1	1160	971	560
Mortality Rate	25.5% (.436)	18.7% (.390)	19.8% (.398)

Table C.2: Unconditional Relationship between Mortality Risk and Ownership of Different Life Insurance Contracts

	Multinomial Logit Model				Probit Model	
	(1)		(2)		(3)	
Dependent Variable	insurance		insurance		Die	
	Term Only	Whole Only	Term Only	Whole Only		
Die	-0.399***	-0.328***	-0.089*	-0.179***	WLI	-0.045
	(0.049)	(0.058)	(0. 056)	(0.066)		(0.037)
Age			0.515***	0.109	Age	0.189
			(0.160)	(0.208)		(0.255)
Age^2			-0.008***	-7.704e-04	Age^2	-0.003
			(0.003)	(0.003)		(0.004)
Age^3			4.11e-05***	-9.87e-07	Age^3	1.9e-05
			(1.29e-05)	(1.67e-05)		(1.88e-05)
Male			4.228	0.173	Male	1.031
			(6.111)	(9.299)		(9.439)
Age*Male			-0.219	-0.116	Age*Male	-0.043
			(0.285)	(0.424)		(0.422)
Age^2*Male			0.004	0.003	Age^2*Male	8.348e-04
			(0.004)	(0.006)		(0.006)
Age^3*Male			-1.94e-05	-2.08e-05	Age^3*Male	-4.72e-06
			(2.23e-05)	(3.18e-05)		(3.04e-05)
Marriage			0.294***	0.424***	Marriage	-0.282***

	(0.049)	(0.058)		(0.042)
Race	6.422	-4.699	Race	-10.186
	(8.554)	(10.746)		(12.529)
Age*Black	-0.391	0.248	Age*Black	0.511
	(0.410)	(0.515)		(0.571)
Age^2*Black	0.007	-0.004		-0.008
	(0.006)	(0.008)	Age^2*Black	(0.009)
Age^3*Black	-4.28e-05	1.59e-05	Age^3*Black	4.02e-05
	(3.35e-05)	(4.2e-05)		(4.25e-05)
Kid	0.163*	0.647***	Kid	-0.191***
	(0.103)	(0.127)		(0.089)
Num of Kid	-0.025**	-0.091***	Num of Kid	-0.002
	(0.014)	(0.017)		(0.012)
Grandkid	0.122**	0.036	Grandkid	0.047
	(0.070)	(0.081)		(0.062)
Num of	4.375e-04	9.866e-04	Num of	0.009***
Grandkid	(0.006)	(0.007)	Grandkid	(0.005)
Sib	-0.023	0.163***	Sib	-0.112***
	(0.066)	(0.079)		(0.054)
Num of Sib	-0.010	-0.011	Num of Sib	-0.010
	(0.011)	(0.012)		(0.009)
Income	2.15e-05***	1.5e-05***	Income	-6.1e-06***

			(1.32e-06)	(1.49e-06)		(9.8e-07)
Constant	0.221***	-0.401***	-10.574***	-5.042	Constant	-5.658
	(0.023)	(0.027)	(3.339)	(4.373)		(5.631)
Observations	12,564		12,564		8,020	

Standard errors in parentheses

*** p<0.05, ** p<0.1, * p<0.15

Note: Insurance=0 is baseline.

Table C.3: The Relationship between Mortality Risk and Different Life Insurance Contracts

	(1)
	WLI euqation
Age	0.071***
	(0.022)
Age^2	-0.0005***
	(0.0002)
Male	-3.042***
	(1.332)
Age*Male	0.084***
	(0.040)
Age^2*Male	-0.0005**
	(0.0003)
Marriage	0.084***
	(0.036)
Black	2.442*
	(1.664)
Age*Black	-0.054
	(0.051)
Age^2*Black	0.0003
	(0.0004)
Kid	0.312***
	(0.076)

Num of Kid	-0.045***
	(0.010)
Grandkid	-0.058
	(0.047)
Sib	0.120***
	(0.047)
Num of Sib	-0.002
	(0.007)
Income	-4.72e-06***
	(6.62e-07)
preventive test for blood cholesterol	0.067**
	(0.036)
seatbelt	0.089***
	(0.044)
Ever Smoke	-0.037
	(0.031)
Constant	-3.197***
	(0.738)
Observations	7,981

Standard errors in parentheses

*** $p<0.05$, ** $p<0.1$, * $p<0.15$

Table C.4: Risk Aversion Based Selection

Dependent Variable Lapsation	(1)	(2)		(3)	(4)	
		Age<65	Age>=65		Age<65	Age>=65
WLI holding	-0.205***	-0.23***	-0.122	-0.18***	-0.23***	-0.136
	(0.060)	(0.079)	(0.095)	(0.061)	(0.080)	(0.096)
Die	-0.297***	-0.183	-0.223**	-0.21***	-0.168	-0.198**
	(0.089)	(0.157)	(0.116)	(0.094)	(0.158)	(0.121)
WLI*	0.355***	-0.105	0.393***	0.340***	-0.097	0.397***
Die	(0.142)	(0.334)	(0.174)	(0.143)	(0.335)	(0.175)
Age				-0.01***	0.005	-0.011*
				(0.003)	(0.007)	(0.007)
Gender				0.053	-0.050	0.152**
				(0.053)	(0.073)	(0.081)
Race				-0.22***	-0.159*	-0.39***
				(0.085)	(0.102)	(0.166)
Income				5.37e-07	6.36e-07	4.45e-07
				(8.4e-07)	(9.3e-07)	(1.9e-06)
Constant	-1.641***	-1.56***	-1.786***	-1.09***	-1.84***	-1.08***
	(0.032)	(0.039)	(0.057)	(0.186)	(0.396)	(0.499)
Observations	8,140	4,101	4,039	8,140	4,101	4,039

Table C.5: Reduced-Form Probit Regression on the Probability of Life Insurance Lapsation, Conditional on Having Life Insurance in the Previous Wave

Dependent Variable Die	(1)	(2)	
		Age<65	Age>=65
WLI	-0.045	0.020	-0.073*
	(0.037)	(0.065)	(0.045)
Age	0.189	-1.867	4.053**
	(0.255)	(1.340)	(2.213)
Age^2	-0.003	0.039*	-0.054**
	(0.004)	(0.025)	(0.029)
Age^3	1.9e-05	-0.0003*	0.0002**
	(1.88e-05)	(0.0002)	(0.0001)
Male	1.031	-14.695	178.178***
	(9.439)	(51.129)	(77.420)
Age*Male	-0.043	0.833	-7.101***
	(0.422)	(2.794)	(3.084)
Age^2*Male	0.0008	-0.016	0.094***
	(0.006)	(0.051)	(0.041)
Age^3*Male	-4.72e-06	0.0001	-0.0004***
	(3.04e-05)	(0.0003)	(0.0002)
Marriage	-0.282***	-0.329***	-0.266***
	(0.042)	(0.072)	(0.052)
Black	-10.186	-105.175	158.244

	(12.529)	(125.742)	(120.265)
Age*Black	0.511	5.763	-6.302
	(0.571)	(6.718)	(4.793)
Age^2*Black	-0.008	-0.104	0.083
	(0.009)	(0.119)	(0.063)
Age^3*Black	4.02e-05	0.0006	-0.0004
	(4.25e-05)	(0.0007)	(0.0003)
Kid	-0.191***	-0.223*	-0.148
	(0.089)	(0.148)	(0.117)
Num kid	-0.002	-0.005	0.0001
	(0.012)	(0.021)	(0.015)
Sib	-0.112***	-0.079	-0.127***
	(0.054)	(0.104)	(0.065)
Num sib	-0.010	-0.028**	-0.0003
	(0.009)	(0.015)	(0.013)
Grandkid	0.047	-0.015	0.053
	(0.062)	(0.089)	(0.089)
Num Grandkid	0.009***	0.028***	0.003
	(0.005)	(0.009)	(0.005)
Income	-6.11e-06***	-5.09e-06***	-7.57e-06***
	(9.76e-07)	(1.27e-06)	(1.53e-06)

Constant	-5.658	27.397	-102.753**
	(5.631)	(23.335)	(55.671)
Observations	8,020	4,038	3,982

Table C.6. Revisit the Relationship between Whole Life Policy Holding and Mortality Risk