Risk Classification and Adverse Selection

Evidence in LTCI Market

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I. Introduction

Adverse selection is one of two main sorts of market failure often associated with insurance. The other is moral hazard. Adverse selection can be a problem when there is asymmetric information between insurers and insureds. Ideally, insurance premiums should be set according to the average risk of the population. When there is adverse selection, high risks will buy the insurance, whereas low risks may decide it is too expensive to be worth buying. In this case, the insurance pool becomes not profitable for the insurers. Putting up the premium will not solve this problem, for as the premium rises the insurance policy will become unattractive to more low risks.

The seminal work of Rothschild and Stiglitz (1976) show that if consumers are better informed about their future risk than their insurers, and if insurers do not use all available information to set premiums according to different risk classes, adverse selection may cause an insurance market to be unstable, only under certain conditions can a separating equilibrium exist. These conditions include that insurers are able to offer different policies (i.e. coverage, unit price, etc.) thus higher risks end up buying full coverage at higher unit prices while lower risks end up buying partial coverage at lower unit prices. If insurers offer same policy for higher and lower risks, lower risks then subsidize the higher risks in that policy pool, resultantly lower risks want to drop and search for new policy that is actuarially fair to their risk type. This is a typical case similar to lemon cars drive out good cars in the used car market as described in Akerlof (1970).

Adverse selection renders the insurance market either underdeveloped, in which lower risks are not fully insured as described by Rothschild and Stiglitz (1976), or dynamically unstable (see, e.g. Buchmueller and DiNardo 2002) as “lemon” risks keep drive out “good” risks out of a preexisting policy pool. The dynamically instability is often called “dead spiral”, which refers to a vicious cycle that will eventually dry an insurance pool. It starts from higher risks dissembling into lower risk pool, then the premium of pool goes above actuarially fair premium for the lower risks, then the lower risks are motivated to drop out to search for fairly priced pool for their risk type, which is to the happiness of the insurer’s competitor. The premium of the old pool then has to go up further, and more low risks are motivated to drop, and so on. But higher risk will again tend to dissemble into the newly created lower risk pool, this vicious cycle continues, making the insurance pool dynamically unstable.

Because adverse selection, insurers want to categorize risks and underwrite accordingly. This is often termed as “risk classification”. Theoretically developed in the literature including Hoy (1982), Crocker and Snow (1985, 1986), Bond and Crocker (1991)[1], risk classification prevents higher risks from dissembling into lower risk pool, and gives both higher risks and lower risks their actuarially fair premium, therefore mitigates adverse selection.

Whether risk classification is an important weapon for the insurers to use to mitigate adverse selection remains to be confirmed empirically. To effectively control adverse selection via risk classification, an insurer must not be on the disadvantageous side of the informational game, which is against conventional wisdom that insureds know better about their own risk than insurers. The empirical researches on this issue are scarce, and the results are mixed. For example, Dionne, Gourieroux and Vanasse (2001) showed that, by an appropriate risk classification procedure, the insurers are able to significantly control for adverse selection in the automobile insurance market and does not need any additional self-selection mechanism in underwriting; But Buchmueller and DiNardo (2002) found that community rating, as an opposite underwriting method to the risk classification, does not induce adverse selection as expected in the health insurance market. In other words, they found that lack of risk classification has no conducive effect on adverse selection.

Using a unique dataset in the long term care insurance (LTCI) market, we test whether risk classification can effectively mitigate adverse selection in this still young market. We supply evidences that risk classification on insurer’s intention can effectively mitigate adverse selection. We also find that Insurers in the LTCI market as a whole can correctly anticipate the ex post claim costs, which means there is no asymmetric information (mainly adverse selection in the LTCI market) disadvantage on the overall insurers’ side. Asymmetric information, though theoretically intuitive, is no longer empirically relevant. This result brings doubts on the literature that test asymmetric

[1] For a theoretical overview, see Crocker and Snow (2000).

information based on the presence or absence of a positive correlation between insurance coverage and risk occurrence. A natural extension is that asymmetric information not being a factor as suggested by literature that leads to less than desired growth of LTCI market.

II. Literature Review

Risk Classification and Adverse Selection

Classic theories on adverse selection were developed after Akerlof's (1970) seminal paper. A general interpretation of the classic theories on adverse selection is that the stability of an insurance risk cohort depends on the proportion of high risks. If the proportion is lower than defined by Wilson (1977) and Grossman (1979), a strong form of subsidization holds, i.e., cross subsidization between different risks in the same pool holds, the contract is thus sustainable since the risks covered in that contract will be able to co-exist. If the proportion of higher risks in the pool is higher than Wilson (1977) and Grossman (1979) threshold, but lower than Miyazaki (1977) and Spence (1977) threshold, a weak form of subsidization holds, i.e., cross subsidization between different pools within same insurer as well as cross subsidization within a pool will hold, so that each pool can still remain stable. If the proportion is even higher, then according to Rothschild and Stiglitz (1976), insurance cohort will be unstable, only separating equilibrium can exist under certain conditions in which high risks end up buying full coverage at higher prices while low risks end up buying partial coverage at lower prices.

So the classic adverse selection theories tell us that if enough high risks sneak into an insurance cohort designed for low risks, so that the proportion of high risks in the insurance cohort is higher than certain threshold, then that insurance contract will become dynamically unstable, and, to the extremity, a death spiral. If the proportion is higher than the strong-form subsidization threshold, then that single contract can't exist without cross subsidization from other contract(s) of same insurer. If the proportion is higher than the cross-subsidization threshold, then the contract cohort will eventually collapse even there are other contracts within the same insurance company. This gives a natural cause for literature to propose that adverse selection, if not controlled, can be a serious cause for the underdevelopment of an insurance market, especially of a new market such as private long term care insurance market (see, e.g., Norton, 2000).

It is a natural logic extension from classic adverse selection literature that risk classification can offset the adverse selection. Classifying risks into different categories will help insurer limit the proportion of high risks within any insurance contract cohort, therefore make the proportion in that cohort lower than either the cross subsidization threshold or the strong form subsidization threshold. Therefore the insurance contract can be stable over the time. It is also possible that using risk classification in the underwriting process, an insurer can separate low risks from high risks completely, therefore Rothschild and Stiglitz separation equilibrium can be established from the beginning and sustained thereafter.

Based on this, theories on risk classification predict that risk classification can render adverse selection practically irrelevant in the insurance markets[2]. Hoy (1982) considers the effects of risk classification on market equilbria and finds the use of imperfect information to differentiate policies via risk categorization can lead to a Pareto-type welfare improvement, given certain initial and final equilibriums. Hoy (1989) later demonstrates that adverse selection will not exist in insurance markets if risk information is provided symmetrically to both insurers and insureds. Crocker and Snow (1986) show that when costless risk classification is possible, the market uses the information to treat high risk and low risk group differently, and two equilibriums are attained, one for each of the two risk groups. Bond and Crocker (1991) show that categorization based on the observed consumption of a product that is correlated with underlying risk alleviates and, in some instances, eliminates the problem of adverse selection.

A typical insurance market usually has both high and low risks. Unless the proportion of high risks in the market is extremely low, so that a stable pooling equilibrium kicks in, the market will have to rely on a Rothschild and Stiglitz type separating equilibrium. To do this the market should allow insurers to charge higher price for high risk pool than for the low risk pool in a sustainable manner. However, Grossman (1979) shows that in that case, high risks have incentives to pose as low risks

[2] For an overview of risk classification theories, see Crocker and Snow (2000).

to acquire the low risk contract. Thus the sustainability is destroyed by this human behavior. Without risk classification, Crocker and Snow (1985) show that low risks have to pay more than an actuarially fair premium in order to separate themselves from high risks and get a preferred contract. Their reasoning is that the portion paid by the low risks over the fair premium in the low risk pool is transferred to cross-subsidize the high risk pool, so that the premium paid by high risks in their pool is less than their fair premium, and resultantly the incentives of high risks to pose as low risks and migrate into low risk pool are limited.

However, assuming high risks behave rationally and ignoring the trading cost, the theoretical case in Crocker and Snow (1985) can't be an empirical equilibrium because it is incentive incompatible. As long as the premium paid in low-risk cohort is still preferred by low risks, it means the benefit of cross-subsidization for high risks staying in high-risk cohort is lower than the benefit for high risks dissembling and migrating into low-risk cohort to enjoy the low risk preferred contract. Thus the high risks will rationally keep migrating into the low risk cohort, which, after insurers' experience rating, will increase premium for the low risk cohort, this process will continue until those staying in the high risk cohort get same premium as those in the low risk cohort. The market then swings back to the initial mixed-risk pool, where, again, low risks want to drop, separating themselves from high risks to form a new, pure low risk cohort. And, high risks will then start to migrate into the low risk insurance cohort…the same cycle continues, market is always in unstable situation. This consequence of adverse selection is one of two problems that insurers have tried hard to overcome.

Theoretically, classification can stop high risks from dissembling and migrating into the low-risk contract cohort, thus reduce the adverse selection and stabilize the market. The use of risk classification is built on the logic that there are risk indicators that are highly correlated to the actual risk of the insureds, and these risk indicators are observable to insurers and can be used to categorize insurance applicants. In other words, insurers know risk as least as good as the insureds, as far as the classification they use are concerned (Jeleva and Villeneuve 2004). Therefore high risks encounter difficulty dissembling into a cohort that is designed for low risks. Adverse selection will thus be eliminated because asymmetric information no longer favors insureds (Chiappori and Salanie 2000). The adverse selection left, if any, which is sometimes called "residual adverse selection", becomes negligible. Thus any tendency of insurance market to enter disequilibrium because of adverse selection, as proposed in classical adverse selection theories, disappears. In other words, risk classification helps remove adverse selection thus helps insurance market achieve dynamic stability.

For risk classification to successfully mitigate adverse selection, insurers must not be at an informational disadvantage status compared to insured (Villeneuve 2000). Insureds can have access to more information about themselves than their insurers do, but information itself is not as critical as how to use it to predict claims. Even an individual with abundant information is in no position to select against his insurer if he cannot accurately forecast the occurrence of the event he is insuring against. On the contrary, insurers have thousands of actuaries working to correctly predict the risk from certain characteristics of an insured. This interesting phenomenon is well described in the literature. For example, Meehl (1954, 1996) and Grove & Meehl (1996) find that predictions of experts about the future behavior of a group of individuals are more accurate than the predictions of the individuals themselves. Their findings verify an important assumption for the proper functioning of insurers' risk classification.

That risk classification may mitigate adverse selection may explain why the empirical literature on adverse selection has mixed results. Cutler (2002) reviews a substantial literature that suggests the importance of adverse selection in health insurance markets, and Puelz and Snow (1994) and Cohen (2001) offer some evidence for adverse selection in U.S. automobile insurance markets. The evidence (Finkelstein and Poterba 2004) from annuity markets also indicates that the insured are at higher risk than the uninsured. However, there are numerous papers find that adverse selection is not a practically important feature of insurance markets. Among them, the studies that found evidence against the existence of adverse selection include Cawley and Philipson (1999), who study the U.S. life insurance market; Cardon and Hendel (2001), who study the U.S. health insurance market; and Chiappori and Salanie (2000), who study the French automobile insurance market, and etc.

The conflicting empirical results regarding adverse selection may be due to the omission of risk classification variables in the empirical study. Dahlby (1983) find evidence that the prohibition of risk classification in auto insurance markets forces safer drivers, i.e., female drivers, out of the market. Dionne, Gourieroux and Vanasse (1998) examined auto insurance markets and found that risk classification eliminates residual adverse selection. Dionne, Gourieroux, and Vanasse (2001) showed that one empirical test supporting adverse selection may be subject to model misspecification because classification factors are omitted. They specifically find that once a classification effects are added to the Puelz and Snow's 1994 model, residual adverse selection in each risk class is fully mitigated. Van de Ven & L'an Vliet (1995) examine health care costs and find that adverse selection is reduced by more than 80% once classification factors are incorporated into their model.

Indeed, when Cawley and Philipson (1999) cannot find adverse selection in life insurance market using policy-specific data, they suggest that one interpretation is that insurers can distinguish risks through underwriting and observing systematic patterns in claims over time. They suggest that insurers are likely to know their production costs better than insureds. Similarly, Chiappori and Salanie (2000) suggest that results from the French auto insurance market indicate that informational asymmetry, if anything, favors insurers.

In contrast to the previously discussed research, Buchmueller and DiNardo (2002) find that community rating did not induce adverse selection by comparing the health insurance markets of three states: New York, Pennsylvania, and Connecticut. Since community rating is antithetical to risk rating, their results suggest that there might be other factor other than risk classification that can reduce adverse selection if there is adverse selection in the health markets. Similarly, Schwarze and Wein (2005) find that risk classification in German auto insurance market during the 1990s did not improve the efficiency of contracting and the composition of insureds, they conclude risk classification is inefficient in this market.

The Long Term Care Insurance Market

Long term care expenditures currently represent one of the largest uninsured medical and financial risks faced by the elderly in the United States. One third of long term care expenditures are paid for out of pocket. This is double the proportion of overall health care expenditures paid for out of pocket (Congressional Budget Office 2004, National Center for Health Statistics 2002). As the baby boom generation ages and healthcare costs rocket, the nature of private long term care insurance market will have profound implications for the well-being of both the elderly and their children. Standard insurance theory suggests that the random and costly nature of long term care expenditures makes this precisely the type of risk for which rational individuals would find private long term care insurance (LTCI) valuable.

Though LTCI market is potentially big, its less developed reality deserves investigation. As of year 2002, only 10 percent of the elderly have any private long term care coverage (Brown and Finkelstein 2004), comparing 95 percent of health care penetration 55 percent of life insurance penetration (citation source).

A variety of theoretical explanations have been proposed for the limited size of the private long-term care insurance market (see Norton, 2000 for a review). Asymmetric information[3] is often raised as one potential explanation. Indeed, the relative newness of the market for LTC insurance and the still fairly small number of policies being sold, as well as less actuarial experience accumulated, suggest that the market may be affected by adverse selection (Doerpinghaus and Gustavson1999).

Finkelstein, McGarry and Sufi (2005) find evidence of risk-based dynamic selection; individuals who drop their LTCI contracts are, ex post, of substantially lower risk than otherwise identical-looking individuals who retain their LTCI coverage. This dynamic selection implies that over time the LTCI market becomes more adversely selected.

Finkelstein and McGarry (2004) find that, in the LTCI market, the insurance companies' actuarial model generates a prediction that is more highly correlated with subsequent nursing home use than the individual's reported self-assessment. Yet they conclude that the finding that the actuaries are more accurate, however, is not relevant for the issue of asymmetric information; as long as the individual has residual private information – conditional on the menu of choices offered by the insurance company – asymmetric information can operate in the insurance market as in the theoretical models. And they then find that individual does have residual private information about his risk type. Regardless of what set of controls for insurance company risk classification

[3] Rarely people would risk their health just to get long term care claim, we assume there is no moral hazard problem in the LTCI market.

or measure of the individual's beliefs is used, these beliefs are positive and statistically significant predictors of subsequent nursing home utilization. These results represent a key finding of their paper: conditional on the insurance company's risk classification, individuals still have private information that predicts their subsequent nursing home use.

III. Research Design

Research Data

The data comes from NAIC InfoPro databases of Long Term Care Insurance Reports and Life and Health Reports. These data include such items as direct premiums earned and loss experience, as well as the anticipated loss percentage and actual loss percentage for each policy form (cohort) and each calendar duration year. Cox and Ge (2004) gave detailed illustration of the dataset. The sample data encompass the period 1995 – 2003.

The uniqueness of the NAIC InfoPro LTCI dataset is that it provides direct measurement of adverse selection that is due to asymmetric information, rather than indirect measurement using the data such as whether those who buy higher insurance will incur more claims. Strictly saying, the latter is not adverse selection from asymmetric information between insurers and insurees. It is just a rational consumer behavior. More importantly, the methodology of using the positive correlation between risks and coverage may encounter a risk aversion problem. A low risk may buy high coverage just because that she is risk averse. As the result, the high coverage insurance pool might not necessarily be more risky than the low coverage insurance pool, despite the presence of asymmetric information about risk type between insurers and insureds (see, e.g. Finkelstein and McGarry 2004 for a similar argument). NAIC InfoPro LTCI dataset allows us to use insurer side data instead of the widely used insured side data to test on the adverse selection, which not only is more straightforward, but also avoids the risk aversion offset problem from insureds' side and therefore likely is more reliable. .

Another advantage of using LTCI data is that, unlike rating practice in auto insurance and most other insurance markets, currently the rating practice in LTCI market is virtually unregulated, thus there is no distortion in the data observation caused by regulations (see Brown and Finkelstein 2004). Previous work has argued that regulations may interfere with a market's functioning and be an important factor in the failure of markets to provide certain kind of insurance (see Cochrane 1995).

Key Variables

We define a variable shock as a proxy for adverse selection. Shock is measured as log (actual loss ratio / anticipated loss ratio)[4] and is adjusted with industry average of the respective year. Since actual loss ratio is a natural measure of the real information of insureds, while anticipated loss ratio is a natural measure of the information that insurers have assuming they anticipate rationally, the shock is therefore a natural measure for the asymmetric information between insureds and insurers[5].

The explanatory variables include:

1. Number of cohorts within the insurer's underwriting portfolio, which is our major proxy for the degree of risk classification; According to NAIC (2001) for LTCI statutory filing, a cohort is composed of policy forms that are issued under similar underwriting standards to substantially similar risk classes, and provide substantially similar coverage and provisions. This NAIC-prescribed grouping of reported experience by similar policy forms, as remarked by Cox and Ge (2004), "allows us to control for homogeneity of risk groups…" Clearly, the higher number of cohorts within an insurer, the higher degree of risk classification that insurer is practicing. If risk classification can mitigate adverse selection, then the coefficient estimated is expected to be negative at a quite significant level.

[4] We also test using (actual loss ratio – anticipated loss ratio)/anticipated loss ratio, the regression results are basically the same. Since this proxy is affected by the scales of actual loss ratio and anticipated loss ratio, especially anticipated loss ratio, we choose log (actual/anticipated) as final proxy.
[5] Assume no moral hazard in the health insurance market. It is really rare if an individual will intentionally destroy his/her own health just to be able to get into nursing home, which, otherwise he/she doesn't need.

2. Age of cohort. Shock is expected to be negatively related to age of cohort, i.e., duration of cohort. The reasons: 1. Insurer learns from the underwriting/claim experience in the cohort over the time (Hendel and Lizzeri 2003), they become understand better the risk of that cohort, better evaluate adverse selection, and better design the policy/class to control it; 2. Higher age of cohort leads to higher insured inertia and higher switch and/or drop cost on insured's part (see Pauly 1984, Society of Actuaries 2002), so overtime the cohort become more stable and easy to evaluate. Therefore we expect the sign to be negative.

3. Size of cohort. As the lives insured in the same cohort increase, the risk characters of that cohort is more statistically stable and credible, which help actuaries of the insurer better evaluate adverse selection, and better design the policy/class to control it. (a citation will be better). Therefore we expect the sign to be negative.

4. Level of premium, which is measured by log of premium per policyholder in a cohort. We take log to control the scale effect in the regression. Ercinosa and Sappington (1997) show that if there are positive sunk-costs there exist market equilibriums where the incumbent insurance company cross-subsidizes loss making contracts (those high-risk insurance pools) with profitable ones (those low-risk insurance pools). The intuition is that in presence of scale economies a firm that serves only low-risk faces higher average costs of production than a firm that serves both risk groups does. So, the potential advantage of screening risks may wither away. Based on this reasoning, we expect that low premium cohort enjoy less benefit of risk classification. If risk classification does mitigate adverse selection, then low premium cohort will tend to have higher adverse selection shock. The coefficient sign is expected to be negative if risk classification can mitigate adverse selection, under the same reason.

5. Level of claim, which is measured by log of actual claim per policyholder in a cohort. Level of claim proxies for the actual ex post risk of a cohort. The cohort

having higher level of claim has higher portion of high risk in the pool. Then according to Hoy (1982) and the classic adverse selection theories, this cohort have higher lapse ratio with lower risks withdrawing their policies from the cohort, which in turn increases the adverse selection shock. Based on this reasoning, we expect the sign to be negative.

6. Group dummy, which is equal to one if the cohort is a group policy; or zero if the cohort is an individual policy. NAIC requires that policy forms should be grouped by individual, group direct response and other group and reported on Lines 1, 2 and 3 of form-B, respectively. The subtotals for each of the three classes, i.e., individual, group direct response and other group, must be provided. Line 4 is the sum of Lines 1 through 3. Based on this information, we get our dummy group proxy. Participation in an employer-based LTC group insurance generally is voluntary and coverage is either guaranteed or subject to minimal underwriting (Pincus, 2000), so group plans could experience more adverse selection (Cox and Ge 2004). We expect group dummy has positive sign on adverse shock, everything else equal.

7. Interaction effects of group dummy, which include the interaction forms with classes, age of cohort, size of cohort, level of premium, and level of claim. (add something such as literature's typical argument for interaction effect)

8. Size of firm, which is measured by log of total assets of the insurer. Everything else equal, firm size may be a good indicator of an insurer's experience and expertise to accurately predict and control the potential adverse selection when offering a LTCI policy. Based on this reasoning, we expect sign to be negative.

Hypotheses and Adverse Selection Shock Model

Null Hypothesis

Risk classification utilized by insurers cannot mitigate the adverse selection.

Alternative Hypothesis:

Utilizing risk classification in the underwriting procedure, the insurers can render adverse selection irrelevant in the market. There is no such asymmetric information between insurers and insureds with regard to the actual long term care costs of a LTCI policy holder.

Based on the hypotheses, we have a function:

$$\text{Adverse Selection Shock}_{i,t} = f\,(\text{Risk Classification}_{i,t}, \text{Control Variables}_{i,t}).$$

And the full testing model is:

$$\text{Shock}_{i,t} = \beta_0 + \beta_1 * \text{Class}_{i,t} + \beta_2 * \text{CohortAge}_{i,t} + \beta_3 * \text{CohortSize}_{i,t} + \beta_4 * \text{PremiumLevel}_{i,t} + \beta_5 * \text{ClaimLevel}_{i,t} + \beta_6 * \text{GroupDummy}_{i,t} + \beta_7 * \text{FirmSize}_{i,t} + \beta_8 * \text{GroupDummy}_{i,t} * \text{CohortAge}_{i,t} + \beta_9 * \text{GroupDummy}_{i,t} * \text{CohortSize}_{i,t} + \beta_{10} * \text{GroupDummy}_{i,t} * \text{PremiumLevel}_{i,t} + \beta_{11} * \text{GroupDummy}_{i,t} * \text{ClaimLevel}_{i,t} + \varepsilon_{i,t}$$

IV. Regression Methods, Results and Analysis

Regression Methods

We estimate our regressions in a variety of ways. First, we estimate a simple pooled OLS regression on full model. Since we adjust each year's observation on variable shock with that year's industry average, we are able to pool all years together to increase the testing power because of the enlarged sample. This adjustment also allows us to control for the industry-wide change of any specific year as well as the regulatory environment of that specific year.

We also conduct regressions in the style of Fama and MacBeth (1969) in which we conduct regressions over sub-samples of each year from 1995 to 2003 and average the coefficients across years. We also conduct regressions over sub-samples of cohort durations (from one year to five years) and average the coefficients across the cohort durations. The Fama-MacBeth regressions serve two purposes. First, they check whether our results are driven by cross-sectional or time-series correlation in residuals. Second, they test whether our results are driven more by particular years. The year-by-year regression as well duration-by-duration results are quite similar as what we get from the pooled OLS regression, so the average of the coefficients across years and cohort durations are quite similar too.

Since the group dummy and its interaction effects are quite significant in the full model, we split full sample into two sub-samples. One sample consists of only individual policy cohorts; another sample consists of only group policy cohorts. Accordingly, the full testing model now for each sub-sample is reduced to:

$$Shock_{i,t} = \beta_0 + \beta_1 * Class_{i,t} + \beta_2 * CohortAge_{i,t} + \beta_3 * CohortSize_{i,t} + \beta_4 * PremiumLevel_{i,t} + \beta_5 * ClaimLevel_{i,t} + \beta_6 * FirmSize_{i,t} + \varepsilon_{i,t}$$

Regression Results

Summary Statistics (key variables)

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
Shock	5923	0.00032	0.93746	1.8682	-2.2581	2.88636
Cohortyear	5923	3.09336	1.36224	18322	1	5
Class	5923	13.2452	11.03456	78451	1	51
logTA	5767	27.8893	2.30806	160838	22.2799	32.797
logPremiumLevel	5923	7.07896	0.67349	41929	1.38629	13.3429
logClaimLevel	5923	5.51117	1.40498	32643	-0.0299	12.793
logCohortSize	5923	5.76746	2.43595	34161	0	11.5447

Table 1, Full Testing Model

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	3604.14304	300.34525	1197.32	<.0001
Error	5754	1443.37329	0.25085		
Corrected Total	5766	5047.51633			

Root MSE	0.50085	R-Square	0.7140
Dependent Mean	-0.00194	Adj R-Sq	0.7134
Coeff Var	-25758		

Dependent Variable: Shock

Number of Observations Used 5767

Variable	DF	Expected Sign	**Parameter Estimate**	Standard Error	t Value	**Pr > |t|**	**Variance Inflation**
Intercept	1	N/A	-0.35563**	0.11691	-3.04	0.0024	0
class	1	-	-0.00524**	0.00068	-7.65	<.0001	1.14724
CohortSize	1	-	-0.00635*	0.00318	-2	0.0457	1.3917
CohortYear	1	-	-0.30226**	0.00583	-51.83	<.0001	1.45137
DGroup	1	+	0.94866**	0.26383	3.6	0.0003	118.394
logppl	1	-	-0.70479**	0.01257	-56.06	<.0001	1.6251
logcpl	1	+	0.76094**	0.00674	112.88	<.0001	2.03507
g_class	1	N/A	0.00444	0.00351	1.26	0.2061	2.06736
g_cohortsize	1	N/A	-0.01495	0.01086	-1.38	0.1685	9.29629
g_cohortyear	1	N/A	-0.09842**	0.01951	-5.04	<.0001	7.69428
g_ppl	1	N/A	-0.15161**	0.0373	-4.07	<.0001	111.391
g_cpl	1	N/A	0.06994**	0.0228	3.07	0.0022	25.928
logTA	1	-	0.07888**	0.00343	22.99	<.0001	1.44132

Table 2, Testing Model for Individual Market

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	3229.58252	538.26375	2129.04	<.0001
Error	5296	1338.93411	0.25282		
Corrected Total	5302	4568.51663			

Root MSE	0.50281	R-Square	0.7069
Dependent Mean	-0.00791	Adj R-Sq	0.7066
Coeff Var	-6356.83277		

Dependent Variable: Shock

Number of Observations Used 5303

Variable	DF	Expected Sign	**Parameter Estimate**	Standard Error	t Value	**Pr > |t|**
Intercept	1	N/A	-0.44543**	0.12021	-3.71	0.0002
class	1	-	**-0.00523****	0.00069	-7.6	<.0001
CohortSize	1	-	-0.00761*	0.00321	-2.37	0.0177
CohortYear	1	-	-0.30345**	0.00586	-51.74	<.0001
logppl	1	+	-0.70632**	0.01263	-55.93	<.0001
logcpl	1	-	0.76282**	0.00679	112.35	<.0001
logTA	1	-	0.08253**	0.0036	22.91	<.0001

Table 3, Testing Model for Group Market

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	375.22836	62.53806	281.78	<.0001
Error	457	101.42589	0.22194		
Corrected Total	463	476.65425			

Root MSE	0.47110	R-Square	0.7872
Dependent Mean	0.06623	Adj R-Sq	0.7844
Coeff Var	711.28188		

Dependent Variable: Shock

Number of Observations Used 464

Variable	DF	Expected Sign	**Parameter Estimate**	Standard Error	t Value	**Pr > |t|**
Intercept	1	N/A	1.45138**	0.33928	4.28	<.0001
class	1	-	0.00206	0.00333	0.62	**0.5373**
CohortSize	1	-	-0.00201	0.01124	-0.18	0.8581
CohortYear	1	-	-0.39154**	0.01773	-22.08	<.0001
logppl	1	+	-0.82833**	0.03399	-24.37	<.0001
logcpl	1	-	0.82132**	0.02071	39.66	<.0001
logTA	1	-	0.04014**	0.011	3.65	0.0003

Table 4, Two Sample Test on Dummy Class

Analysis of Variance for Variable Shock

Classified by Variable DClass

DClass	N	Mean
1	2072	-0.029257
0	2037	0.034000

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Among	1	4.110201	4.110201	4.6442	0.0312
Within	4107	3634.756971	0.885015		

Wilcoxon Two-Sample Test

Statistic	4265147.0000
Normal Approximation	
Z	2.0807
One-Sided Pr > Z	0.0187
Two-Sided Pr > |Z|	0.0375
t Approximation	
One-Sided Pr > Z	0.0188
Two-Sided Pr > |Z|	0.0375

Median Two-Sample Test

Statistic	1047.0000
Z	1.7937
One-Sided Pr > Z	0.0364
Two-Sided Pr > |Z|	0.0729

Table 5, Two Sample Test on Dummy Group

Analysis of Variance for Variable Shock

Classified by Variable DGroup

DGroup	N	Mean
0	3744	-0.001247
1	365	0.036457

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F

Among	1	0.472775	0.472775	0.5337	0.4651
Within	4107	3638.394397	0.885901		

Wilcoxon Two-Sample Test

Statistic	760500.0000

Normal Approximation

Z	0.4818
One-Sided Pr > Z	0.3150
Two-Sided Pr > |Z|	0.6299

t Approximation

One-Sided Pr > Z	0.3150
Two-Sided Pr > |Z|	0.6299

Median Two-Sample Test

Statistic	190.0000
Z	0.8273
One-Sided Pr > Z	0.2040
Two-Sided Pr > |Z|	0.4081

Table 6, Summary Comparison between group cohort and individual cohort

group cohort vs. individual cohort	ratio
cohort Size (policyholder number per cohort)	131%
claim level (claim per policyholder in a cohort)	47%
premium level (premium per policyholder in a cohort)	53%
premium/claim	113%
adverse selection shock (actual claim/anticipated claim)	98%

With the way the variables are defined, the model is a semi-log model[6][7]. Result of the full model is shown in table 1, where all the variables except firm size have expected signs. All the variables except the interaction forms between dummy group and two variables, class and cohort size, are highly significant. Adjusted R-square is above 70%. Overall model specification test is less than 1%. Result of the model run on individual LTCI market is shown in table 2, where all the variables except firm size have expected signs at highly significant level. Adjusted R-square is above 70%. Overall model specification test is less than 1%. Result of the model run on group LTCI market is shown in table 3, where class variable and cohort size variable are no longer significant. Firm size also have unexpected signs at highly significant level. Adjusted R-square is above 70%. Overall model specification test is less than 1%.

Table 4 and table 5 show two sample test results on two dummy variables. Table 4 is a two sample test on variable shock with respect to dummy class, which we created to test whether it is risk classification other than other factors such as risk aversion that mitigate the adverse selection. Table 5 is a two sample test on variable shock with respect to dummy group. It is to test whether there is difference between group LTCI market and individual LTCI market regarding the residual adverse selection. We will explain the details in next section.

Preliminary Analysis

We use OLS method to get the preliminary results. OLS is a simple but very efficient regression method after model specification diagnosis shows there is no harmful heteroscedesticity and multicollinearity problem exist in our data.

[6] Since the dependent variable is in log form, and some of the explanatory variables also take log form while others not, the regression model is a semi-log form model. It is still a general type linear model. See Kennedy 2003, p123, and Greene 2003, p12.

[7] For semi-log, $\ln Y = alpha + beta*X + gama * \ln Z$, beta gives $\%\Delta Y$ due to ΔX, unless X is a dummy, in which case $\%\Delta Y$ is given by e to the power of beta – 1, gama gives $\%\Delta Y$ due to $\%\Delta Z$ (elasticity).

For the dependent variable, shock, to test robustness we also try other proxies, such as using shock not adjusted by that year's industry average, or using other proxies for shock, such as (actual loss ratio – anticipated loss ratio / anticipated loss ratio), or just (actual loss ratio – anticipated loss ratio), the regression results are basically the same as what we get from original definition of shock. Since those proxies may be distorted by different scales between actual loss ratio and anticipated loss ratio, we eventually choose log (actual loss ratio / anticipated loss ratio) as proxy. We also delete those observations that have actual loss ratio over ten times anticipated loss ratio, or have anticipated loss ratio over ten times actual loss ratio, as outliers. We end up with above five thousands observations.

The Pearson correlation coefficients for the independent variables show that: 1. Premium level and claim level are relatively highly correlated (absolute value above 50% at less than 1% significant level). 2. Firm size and cohort size are relatively highly correlated (absolute value above 40% at less than 1% significant level). 3. Dummy group and the interaction terms of dummy group are relatively highly correlated, which is natural according the way interaction term is calculated.

So we check multicollinearity. We first look at the Variance Inflation Factors (VIF). These factors measure the inflation in the variances of the parameter estimates due to multicollinearity that exist among the independent variables. There are no formal criteria for deciding if a VIF is large enough to affect the predicted values. VIF of premium level, claim level, firm size, and cohort size are not high, less than 3. VIF of dummy group and interaction form of dummy group and claim level are higher than 100, this is the side effect of adding interaction term to the model. We are cautious on this high VIF, and, when look at the regression results of individual and group sub-samples where there is no interaction form, the regression results are consistent with the full sample model. We also look at the Condition Index, another indicator for possible multicollinearity. Belsley, Kuh, and Welsch (1980) propose that a condition index of 30 to 100 indicates moderate to strong multicollinearity when a component associated with a high condition index contributes strongly to the variance of two or more variables. Rule of thumb is if condition index is bigger than 30, then identify those variables with proportion if index larger than 0.9 and study the effect of them. At Condition Index over 30, we don't have any proportion of variance bigger than 0.9 (not even closer than 0.9) except intercept appears one times. In addition, we intentionally drop and add independent variables, and the regression results on other variables are pretty stable. We rerun the regressions by years, by cohort durations, and the results are basically the same. Therefore, we conclude the model overall does not have severe multicollinearity problem.

We use White (1980)'s test on heteroscedasticity. The result confirms that there is no heteroscedasticity.

In the full testing model, we adjust each year's observations by that year's average. It helps control for external factors, such as changes in industry-wide supply and demand, and changes in the regulatory environment. It also enables us to pool each year's observations together to form a bigger sample to increase the testing power[8].

To test the robust, we rerun the same regressions by each year from 1995 to 2003, and the results of each year are basically the same as the results from the pooled sample.

For the same reason, we also rerun the regressions by cohort durations. We group data based on cohort durations, from one year duration to five year duration, to form five sub-samples. We then run the same regressions on these five sub-samples separately, and results are basically the same.

Since first year claim, premium experience might be distorted due to half-year effect, we delete the first year data from sample and rerun the regressions, and results are basically the same.

[8] For example, since multicollinearity problem can be viewed as equivalent to having a small sample (Kennedy 2003, p412), larger sample makes this problem less likely happen.

One strong assumption in our regressions is that adverse selection shock relates to risk classification in a log-linear manner. Considering the strength of the coefficients on our control variables, it may be worth examining the robustness of the results to the log-linearity assumption. To do so, we sort variable class into quintiles, and then, we define a dummy variable called DClass, which takes value 0 if the class observed is located in the first (lowest) quartile, and takes value 1 if the class observed is located in the fourth (highest) quartile. We then do a two-sample test with regard to DClass variable. The results are highly supportive for what we get from the full testing model, therefore the negative relationship between adverse selection shock and risk classification is robust to relaxing the log-linear specification[9].

The above robust tests show that our model estimation results are consistent over the ways data is tested. We also intentionally drop and add control variables, and the regression results do not affect the significance and sign of other variables left in the model. So our model estimation results are also consistent over the ways variables are tested.

Table 1 shows that overall, risk classification are able to mitigate the adverse selection. The coefficient is -0.00524, significant at less than 1% level. This means, preliminarily, everything else equal, for the number of cohorts that an insurer goes up by one, the industry adjusted (actual loss ratio/anticipated loss ratio) will be reduced to $e^{*-0.00524} = 0.9948$, a 0.5% reduction of shock. Considering the class ranges from a minimum 1 to a maximum 56, the maximum reduction of shock will be 25% between insurers who has least level of risk classification and insurers who has the most level of risk classification.

Table 1 also shows that cohort year is important in reducing the adverse selection. Basically, the longer a cohort exists in the market, whether in the individual or the group market, the less adverse selection shock. Over time it becomes harder for the policyholders to switch/cancel the policy because it means the forfeiture of the already

[9] See Coval and Shumway (2005 JF) for the explanation of a similar econometric treatment.

paid premium. So over time the cohort becomes stable thus easier to evaluate. On the other side, over time actuaries also learn from the experience of a cohort and are better able to evaluate that cohort.

The coefficient for dummy group is positive and significant at less than 1% level, which indicates that adverse selection in the group market is more severe than in the individual market. A result of the fact that in the group market there is much less risk classification than in the individual market. Weiss (2002) estimate that fifteen percent of non-group LTCI applications is denied, while group LTCI is guaranteed.

Tables 1, 2, and 3 show that premium level and claim level are both significant for individual and group cohorts. But surprisingly, the firm size always takes positive sign at consistently significant level as shown in tables 1, 2 and 3. It is counterintuitive, since bigger firm size should have better expertise to control adverse selection. To see if it is the wrong proxy (total asset) that causes the problem, we rerun the model using capital plus surplus and the proxy for firm size, the results are basically same.

Table 2 is the regression results in individual market. It shows that that risk classification did mitigate the adverse selection shock, so did cohort size. Table 3 is the regression results in group market. It shows that number of cohorts and cohort size did not have significant effect on reducing adverse selection shock. These differences between individual market and group market demand further investigation.

We think the fundamental reasons lie in that cohort size and number of cohorts in group market mean much differently than that in individual market. In individual market, insurers create cohorts to distinguish different risks and underwriting differently; in group market, a new cohort often is created to sell to a new group contract with little underwritings. In other words, insurer create different classes to identify different risks and underwriting them in the individual market, but insurer create different classes to cater to group buyers that have bargaining power and low administrative cost per head. Therefore, number of cohort matters with respect to risk classification in individual market while it is not true in group market. For the same reason, cohort size matters in individual market because, since each policyholder is underwritten into a individual policy cohort, bigger size means that the cohort is more statistically approachable, is more creditable to be evaluated (risk-classified) correctly; in group market, bigger cohort size might affect pricing through the group's bargain power, but, since little underwriting is involved for each policyholder in that group policy, bigger size does not bring better evaluation (risk classification) for the insurer's actuaries, thus has little to do with the control of adverse selection.

We want to see that, after underwriting (including risk classification), whether there is still residual adverse selection in the LTCI market. According to the summary statistics, the mean of adverse selection shock is almost zero, which shows that there is no residual adverse selection shock in this still young insurance market. To double check our results, we sum up total ex post actual claims of the industry and compared it to the total ex ante anticipated claims, again, total ex post claims actually is less than total anticipated claims, at around ninety percent[10]. This gives us evidence that basically adverse selection is rendered irrelevant.

We further want to see whether there is difference between group and individual market regarding to residual adverse selection. We split the pooled sample into group and individual sub-samples. Within each sample we calculate the mean of adverse selection shock, and also compare the total ex post actual claims with the total ex ante anticipated claims, we cannot reject that the there is no difference between group and individual market with respect to residual adverse selection. Both markets have no adverse selection left on the insurers' side. The result is in table 5 and table 6.

The evidence that in group market there is also no residual adverse selection does not contradict our earlier evidence that initial adverse selection is more severe in group

[10] The little difference between zero mean of adverse selection shock, and 90% of actual claims as of anticipated claims, are due to the different nature these two statistics are calculated. Our zero mean of adverse selection shock is also consistent with the results in Cox and Ge (2004), where they did a *t*-test for zero-mean prediction error, which suggests that insurers' expected loss ratios are unbiased estimators of both current year incurred loss ratios and reserve-adjusted loss ratios.

market than in individual market. The reason: group market has its own channels to counteract this initial severe adverse selection. Cox and Ge (2004) mentioned that "Mitigating factors such as economies of scale, better loss predictability over time because of cohort size…could counter the effects of adverse selection (in the group LTCI market)..." We conduct a summary comparison between group cohorts and individual cohorts. The finding is that group cohorts typically have bigger cohort size than individual cohorts. On average a group cohort has thirty one percent more policyholders than an individual cohort. Since cohort size contributes significantly to reduce adverse selection, the much bigger size of group cohort alleviates the initial adverse selection in the group market.

In addition, dummy group has extra significant interaction effects on cohort year, which means over the time the group cohorts respond more through experience rating to reduce adverse selection than individual cohorts. At the date of issuing policy, a group policy has much less underwriting than an individual policy, so group policy has much less information exposed to the actuaries than individual policy, and the actuaries of a group policy therefore have to rely more on experience of the cohort over years to better their evaluation.

Moreover, from summary comparison in table 6 we can see group cohort's premium level is 53% as of individual cohort, but the group cohort's claim level is even lower, a 47% as of individual cohort. Since low premium level correspondent to high adverse selection shock, and low claim level correspondent to low adverse selection shock, the combined effect here is mitigating the initial adverse selection effect for the group cohort[11].

The evidence that there is no residual adverse selection in the LTCI market help answer a question that literature (see Norton, 2000 for a review) [12] has for a long time pondering: whether adverse selection should be blamed for the less than desirable

[11] Note in table 1, the coefficient of logppl for group cohort is approximately - (0.70+0.15), which is about the same magnitude as the coefficient of logcpl for group cohort (0.76+0.069).
[12] Also see Doerpinghaus and Gustavson 1999.

development of private LTCI market. Since we don't find adverse selection from insurer's side, which means it is not adverse selection between insureds and insurers that hinders the insurer from issuing the right policies to the public. Our results suggest that further researches on this issue to be focused on the demand side in the private LTCI market, i.e., whether there is lack of demand for private LTCI, rather than on the supply side, i.e. whether the insurers are reluctant to supply LTCI due to adverse selection.

The evidence from two sample test grouping on dummy class as in table 4 suggests that pure risk aversion can not solely explain the disappearance of adverse selection in LTCI market, at least in the way we test the existence of adverse selection, i.e., whether there is adverse selection shock from insurers' side. Our results are different than that suggested by Finkelstein and McGarry (2004). After using the widely used testing method to find that adverse selection still exists in the LTCI market, i.e., those who purchased LTCI used more nursing home services afterward than those who didn't, Finkelstein and McGarry (2004) then posit that it is insureds' risk aversion that offset the adverse selection, therefore despite the presence of asymmetric information about risk type, in equilibrium the insureds on average have no higher risk profile than the uninsureds in any insurance pool. It follows that one may argue that it is insureds side risk aversion instead of insurers side underwriting (including risk classification) that contribute the disappearance of adverse selection. We now take a serious look at this.

If risk aversion can solely offset the adverse selection, then there should not be any significant difference of adverse selection shock for the two sub-samples. One is high-risk-classification sub-sample, another is low-risk-classification sub-sample. We therefore split the pooled sample into two sub-samples by grouping on a dummy variable called DClass, which takes value 1 if the number of cohorts is at top quartile and value 0 if the number of cohorts is at bottom quartile. We then do a two sample test accordingly. The result is shown in table 4. It rejects there is no significant difference of adverse selection shock between the two sub-samples.

In addition, for risk aversion to offset adverse selection, it implies that low risks are actually more risk-averse than high risks. Why? If low risks are less risk-averse than high risks, then high risks will buy more insurance than low risks. This in turn will intensify the adverse selection rather than offset it. Now without considering this implication as an untested issue, and assuming that low risks are truly more risk averse than high risks hence are more intended to buy insurance than high risks at any given premium level, then the link between premium level and claim level is cut off. However, a quick glimpse on the Pearson correlation coefficient between premium per person and claim level per person finds that it is not the case. The correlation coefficient between premium level and claim level are still closely correlated, with correlation coefficient over threshold 0.5 at less than 1% level. This shows that at least risk aversion does not work perfectly, if at all. There must be some other forces at insurers' side rather than insureds' risk aversion to mitigate adverse selection. That force is underwriting, which is risk classification in our case.

Overall, our results doubt that risk aversion itself can explain the disappearance of adverse selection; risk classification at least is a key factor that can mitigate the adverse selections. In this aspect we echoes Baranoff (2004, p77), "The business of insurance inherently involves discrimination; otherwise, adverse selection would make insurance unavailable." A byproduct suggestion is that, to get a whole picture of adverse selection in a special market, relying on testing whether three is positive correlation between coverage and risk occurrence as widely used is not enough, it could be confusing[13], if not misleading.

It is natural to wonder that it is firm size that purely contributes to the firm's ability to offset adverse selection, instead of risk classification. Bigger firm should have more cohorts, therefore be more intensive in classifying risks. So the significance of variable class might just represent the influence of firm size. To solve this question, we incorporate firm size as a control variable. The regression results show that after the firm size is controlled, there is no much difference on the variable class. And also from

[13] That's perhaps why the adverse selection literature by now has mixed results on the existence of adverse selection.

correlation of firm size and class, they are not highly correlated. In fact they are surprisingly negative correlated with a Pearson correlation coefficient of -0.14 at less than 1% significant level. We think total assets are better measurement for the firm's expertise than capital and surplus, because firm assets represents on the scale of business the insurer is covering. To be cautious, we also use capital + surplus instead of total assets to proxy firm size, the regression result is similar. But a puzzling thing is that the sign of the parameter estimated is positive, which is counterintuitive, since bigger firm usually should be better in analyzing information and evaluate the risks.

V. Summary and Conclusions

Literature has widely test asymmetric information basing on the presence or absence of a positive correlation between insurance coverage and risk occurrence. Using NAIC's LTCI data, we provide an alternative way to test the existence of adverse selection, and based on that, we answer the question whether risk classification can empirically mitigate adverse selection. The answer is yes in the individual LTCI market where the insurers practically identify risks and underwrite accordingly. Insurers do not identify individual risk in the group LTCI market, which results in adverse selection. However, insurers have other channels to counteract the adverse selection in the group market. Overall, adverse selection is rendered irrelevant in both individual and group market.

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