Essays on Empirical Contract Theory: Evidence from Car Insurance Data

Yong-Woo Lee

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Department of Economics

University College London

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ABSTRACT

In this thesis the central aim is to identify and appreciate a fuller understanding of possible market imperfections in the insurance market: I have focused on contributing to the existing empirical tests to determine the presence of asymmetric information, such as moral hazard and adverse selection. Further to this the intention is to explore and improve plausible policy implications in order to make adjustments to market welfare. In particular, the empirical analysis is enriched using 'car insurance panel data sets' obtained from two major Korean car insurance companies.

In the first chapter I review the detailed descriptions of the Korean car insurance market, and the data sets from the Korean car insurance companies are presented. Then, using the Korean data sets, I implement three pioneering empirical models for application within the field of empirical insurance economics. Namely: the conditional correlation approach (probit model/bivariate probit model); the occurrence dependence approach (duration model); and the Granger causality approach (dynamic bivariate probit model).

In the second chapter I have sought to detect the presence of moral hazard via the introduction of a regulatory change that occurred in the Korean car insurance market in the year 2000. Then using logit and nonparametric estimation I have investigated whether there was any change in accident

rates between, before, and then after the introduction of a stronger incentive system.

In the last chapter - with an aid of an improved, more substantive, data set - I have investigated the presence of asymmetric information; that is from a different direction from that previously employed within the literature. Firstly, with regards to the 'moral hazard problem', I have worked on the relationship between the purchase of coverage for damage to the policyholder car and the stated car value. Due to the presence of a 'missing data problem', I have implemented a bounds approach in estimating car value distribution. Secondly, regarding the identification of adverse selection I have introduced a simple conditional variance test to see whether there is a difference in risk level across policyholders.

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CHAPTER 1

INTRODUCTION

Since the seminal papers by Arrow [1963], Arrow [1965], Akerlof [1970] and Rothschild and Stiglitz [1976], the 'informational asymmetries' in various market contexts have been one of the main concerns in economics. Before these theoretical contributions exploring the (plausibly) catastrophic phenomenon, the general equilibrium theory was established quite solidly at the heart of the mainstream economics.

However, as Salanie [1998] points out, there are at least three major problems that challenged the general equilibrium theory: Firstly, each economic agent interacts between them, which is missing in the general equilibrium theory. Secondly, there are no appropriate considerations on the many established organisational institutions governing economic relationships. Finally, informational asymmetries are entirely neglected. Contract theory (economics of information, in general) has arisen naturally enough in response to these drawbacks in the general equilibrium theory[1].

Needless to say, the presence of informational asymmetries is not only a

[1]Stiglitz [2000] describes the contribution of economics of information as an intellectual revolution.

theoretical problem but also a fairly practical problem in the sense that it has affected individuals in society on the daily basis. For instance, as individuals, we are more or less all dependent on the professional services - such as those medical and legal services provided, becoming more and more specialised [2]. This is a very similar situation to the 'lemon' problem analysed by Akerlof [1970] since the buyers of these services are likely to have less information about the quality of services than experts have. Also, as an employee, most individuals in industrialised societies are affected by many different kinds of financial and non-financial motivational mechanisms devised by firms to take account of informational asymmetries (for the comprehensive discussions, see Milgrom and Roberts [1992]).

Although most economists have been aware of, and cognisant of, the importance of the presence of informational asymmetries in economic activities and trades between agents, there has been relatively little empirical research on this problem; especially when compared with the rather flourishing field of theoretical research. This, it has has been suggested, has been mainly due to the difficulties of obtaining the relevant data sets to develop the empirical work. With access to the Korean car insurance data set in this thesis, I focus on developing empirical tests for the presence of informational asymmetries in the car insurance market. In both developed and developing countries, as the size of economy grows, the car insurance contract has become more and more important: for the protection of individual lives; as well as for economy as a whole. For instance, Jun [2000] maintains that there is an identifiable

[2]An interesting question would begin by analysing how these agents have been trading in this market.

relationship between economic development and the occurrence of car accidents. His report cites that a quarter million people have died, and 6 million people have been injured, between 1960 and 1999 in Korea as a result of car accidents. As a result many households have been directly affected both economically and socially by the prevalence of such accidents. Further, the social cost due to car accidents in 1998 alone is estimated to be 50 million GBP, which was approximately 2.4% of GNP in 1998. From this perspective alone the research outcomes available here - through investigating the informational asymmetries in the car insurance market - provides economists, policymakers and insurance companies with many valuable insights as to how to enhance the safety and efficiency of the market.

This thesis presents as follows: In Chapter 2 I present the market characteristics in the Korean car insurance market, firstly identifying the data descriptions that are the prerequisite for any formal analysis. Then, I present the empirical results from the existing implementations, of the leading strategies in empirical insurance economics, using the Korean data set. In Chapter 3, I attempt to detect the presence of moral hazard by investigating the effect of regulatory change on the accident rates in the Korean car insurance market. This investigation and work contributes to a natural experimental approach as applied to empirical contract theory. In Chapter 4, I present a unique identification strategy to detect moral hazard based on a simple theoretical model and, subsequently, examine whether there is such a difference in accident rates across policyholders: Which will, therefore, imply the possible presence of adverse selection. Finally, in Chapter 5, I conclude along with a resume of promising directions for future research.

CHAPTER 2

FITTING DATA TO THE LEADING LITERATURES

2.1 Introduction

Within the field of insurance economics, the problem of informational asymmetries has been recognised for a long time for the following practical reasons: Borch [1990] presents two fundamental outcomes in the presence of informational asymmetries: adverse selection and moral hazard, as they were originally termed by various insurance industries. According to Borsch, the concept of adverse selection was first studied in connection with life insurance. During the early years of development life insurance companies ran their business models based on imprecise mortality tables because rating every risk correctly was prohibitively expensive. In economics, Arrow [1965] introduced and popularised 'asymmetric information', as well as the terms 'adverse selection' and 'moral hazard' along with the famous "Arrow-Pratt" measure of 'risk aversion'. One of the first studies of adverse selection - apart from life insurance field - is by Rothschild and Stiglitz [1976]. The important prediction in their self selection model is that there arises the positive relationship between 'insurance coverage' and 'accident probability', which has become a cornerstone for subsequent empirical research.

In turn, Borch [1990] remarks that the concept of moral hazard has its origin in marine insurance. Further he [Borsch], states it frequently appears in the related fields of fire insurance and health insurance literature. Arrow [1963] introduced the concept of moral hazard into economics and consequently announced the emergent discipline of information theory. The typical market outcome for the presence of moral hazard is a provision of partial insurance coverage to impose an incentive upon the policyholder's side as Shavelle [1979] shows.

So far, most empirical research on car insurance markets has explored the 'conditional correlation' approach based on the predictions by Rothschild and Stiglitz [1976] and Shavelle [1979]. Along with those presented in Chiappori [2000] and Chiappori and Salanie [2003], this method tests whether the choice of a contract is correlated with accident probability, controlling for observables (for instance, Chiappori and Salanie [1997], Chiappori and Salanie [2000], Dionne et al. [2001a], Richaudeau [1999] and Puelz and Snow [1994]). However, as research along these trajectories has emphasised, there is a 'reverse causality' between moral hazard and adverse selection. Therefore, within the static framework, it is almost impossible to distinguish between them except for the situation where a natural experiment can be applied (see Browne and Puelz [1999], Chiappori et al. [1998] and Dionne and Vanasse [1996]). As Chiappori [2000]points out, *in* practice the distinction between adverse selection and moral hazard may be crucial, especially from a normative point of view. For instance, if 'hidden action' is the main cause of the presence of asymmetric information, the introduction of a stronger incentive system[1] is likely to be useful and justified. However, if the selection is the main driving force, low risk types must sacrifice some desired insurance protection in order to avoid being pooled with high risk types. Thus, the problem is not resolved without cost as Doherty [2000] correctly points out. In this case, the introduction of a sophisticated risk classification mechanism tends to be MORE effective[2].

Given these circumstances there have been some recent empirical tests using dynamic data sets to attempt the separation of two phenomena. Abbring et al. [2003a] and Abbring et al. [2003b] take the contracts as given and concentrate on their implications for observed behaviour. Methodologically, these studies build on and extend the literature on 'state dependence' and 'unobserved heterogeneity' in 'event history data'. After controlling for unobserved heterogeneity, the principle identification is founded on 'negative occurrence dependence' especially given the existing experience rating scheme.

Further, Dahchour et al. [2004] has attempted to separate moral hazard from adverse selection using French longitudinal data. Within a longitudinal data framework controlling for unobserved heterogeneity, they show how Granger causality can be used to separate out moral hazard from adverse se-

[1]For instance reductions in the amount of coverage, or a stronger monetary penalty on behaviour correlated with accident occurrence.

[2]That is, insurance premiums should be based on many relevant observable individual and car characteristics.

lection. The empirical model used is an extension of Chiappori and Salanie [2000] model to the dynamic environment.

In this chapter, with access to the Korean car insurance data set, I test for informational asymmetries, implementing the three preceding empirical models described so far. That is, Conditional Correlation; Occurrence Dependence; and Granger Causality respectively. Primarily, this work contributes to the field of empirical contract theory by enlarging the applied area using the Korean data set. Secondly, I explore the appropriateness of previous models and as a result develop some alternative possibilities to improve current state-of-the-art models.

In section 2, I briefly discuss the features of the Korean car insurance market and the data set we have obtained. This review is an essential prerequisite before formal theoretical analysis. In section 3, 4 and 5, I describe the three models as implemented, and present the empirical results one by one. Then, briefly, conclude in the last section.

2.2 Market Characteristics and Data Description

2.2.1 Market Characteristics

There are four main features in the car insurance market that need to be understood before any formal analysis.

Firstly, there is 'exclusivity' and 'semi-commitment' in car insurance contracts. Like most car insurance contracts in other countries, the insurer can impose an exclusive relationship on the policyholder. Thus, a policyholder cannot have contracts with different insurers to insure the same risk in a given period. Further, there is no clause in insurance contracts forcing drivers to stay with the same insurance company once the contractual period is over, or even during a contractual period.

Secondly, there is an 'experience rating system', which works through 'bonus-malus' system[3] in the 'insurance premium calculation'. This mechanism is compulsory and uniform across insurance companies and policyholders.

Thirdly, all the information about each insurance contract is public information. All contract terms and claims filed by policyholders fall into the domain of public information through the Korean Insurance Development Institute [KIDI] to which rival companies have free access[4].

Lastly, broadly speaking, there are six types of insurance coverage. Details are given in table 2.1 below. Policyholders can freely choose insurance cover amongst the coverage available. However there are some points to mention:

1. Coverage [1] is compulsory by law so that every policyholder has to buy this coverage in order to drive a car.

2. Coverage [1] has a maximum possible reimbursement. When a policyholder is responsible for injury or death to a third party and this

[3]Shortly, I shall explain this system within the presentation of a premium calculation.

[4]It was in January 1990 when 'the rules for information circulation management' were introduced. This legislation allows for government institutes to collect the information about all the car insurance contracts, and in doing so provide all the car insurance companies with an access to this information pool.

Tab. 2.1: Types of Coverage

1. against the injuries or deaths inflicted on third party
2. against the remaining losses beyond the compensated amount made by the coverage 1
3. against the damages caused on the third party's property or car
4. against the damages or theft on policyholder's own car
5. against the injuries or death on policyholder or family members
6. against the injuries or deaths on policyholder or family members caused by the third party's car that is not sufficiently insured or kick and run car

exceeds coverage [1]'s maximum possible reimbursement - having not purchased coverage [2], a policyholder must pay the exceeding money by himself. Coverage [2] was introduced to compensate for this kind of loss.

3. Purchase of coverage [1, 2 and 3] altogether corresponds to 'third party' car insurance in some developed countries (for instance the French system).

4. Purchase of coverage [1, 2, 3, 4, 5, and 6] altogether is 'comprehensive' insurance in some developed countries (again, like that in France).

5. Purchase of coverage 6 is possible only given if the policyholder also purchases coverage [1, 2, 3 and 5].

2.2.2 Premium System

Another crucial prerequisite for analysis is to understand the 'insurance premium calculation'. Therefore, at this point, we should explain the mechanism in some detail. In the Korean car insurance market contracts are renewed and premiums are revised annually.

The final, and applied premium, for a policyholder is mainly a product of four factors, these are: the 'Base Premium'; the 'Limitation Policy'; the 'Individual Characteristics Coefficient'; and the 'Bonus-Malus Coefficient', respectively.

$$\text{premium} = \text{base premium} \times \text{limitation policy} \times \text{individual characteristics coefficient} \\ \times \text{bonus-malus coefficient.}$$

The base premium is computed at the beginning of the business relationship. It depends on the recognition of some observables and must be uniform across agents with identical characteristics. It cannot be modified during the relationship unless some observable characteristics change. The calculation for the base premium is mainly based on car characteristics such as car types, car size, car age, car use, gear types and so on. These variables used to be calculated by KIDI but, after the liberalisation of car insurance pricing in August 2001, it is now entirely up to a company's discretion as to how the base premium is calculated[5].

The 'individual characteristics coefficient' has two components: the 'contract experience coefficient' and the 'traffic law violation coefficient'. The

[5]Before this regulatory change the price of car insurance was more or less homogeneous across competing insurance companies.

contract experience coefficient reflects how long a policyholder has contracted the car insurance. When the policyholder begins an insurance contract for the first time, the coefficient is 1.4, in subsequent years it decreases to 1.15 and 1.05 respectively. After the policyholder has contracted the insurance for 3 or more years, this coefficient becomes 1.

Tab. 2.2: Contract Experiences Coefficient

experience period	coefficient
first or shorter than 1 year	1.4
longer than 1 year–shorter than 2 years	1.15
longer than 2 years–shorter than 3 years	1.05
3 years or longer than 3 years	1

The 'traffic law violation coefficient' was introduced in September 2000, deliberately intending to target a reduction in the number of accidents[6]. Not all traffic law violations are reflected in the update of insurance premiums. Research has revealed that six serious violations are most directly related to accident occurrence. It is those violations that are reflected in the 'traffic law violation coefficient'. When there is a relevant traffic law violation, the maximum possible increase in insurance premium is 5% – 15%. However, when there is no violation within the contract year, an insurer is allowed to discount the premium within 10%[7].

[6] Financial Supervisory Service (1999), "Regulation Changes in Car Insurance Market". Firstly, the serious traffic law violations that took place in April 1999 - May 2000 were reflected in the contracts beginning in September 2000.

[7] Later, the insurance companies were to all set this percentage to be 0.3%. Hence, they have been criticised for being collusive.

Tab. 2.3: Traffic Law Violations Coefficient

cohort	relevant items
penalty group	hit and run, drunk driving and driving without a licence (more than once): 10% trespass of center line, over-speed and traffic signal violation (more than twice): 5%
bonus group	no violations trivial violations that are not recorded

The experience rating system operates through the application of a fourth component - the 'bonus-malus coefficient'. The evolution of the law of the coefficient is identical across companies by regulation. The policyholder starts with a coefficient 100% at the beginning. Then, if maintained without an accident, this coefficient decreases more or less by 10%. There exists a floor for the bonus coefficient which is currently 40%; each accident incrementally increasing the coefficient. Malus coefficient operates in something of a complex way in the case of an accident: each is calculated into the score in terms of the severity and cause of an accident, with a score ranging from 0.5 to 4 discretely. There is also a cap for the malus coefficient, which is currently 200%.

In summary, when there is no accident in the current period, and in the last three years, the evolution of the coefficient is given in table 2.4. When there is no accident in the current period, yet there had been an accident in the last three years, the coefficient is the same as the previous coefficient. When there is an accident the evolution is given in table 2.5. When there

Tab. 2.4: Coefficient in No Accident Case

previous coefficient	applied coefficient
40 and 50	40
50 and 55	45
60	50
65-110	previous coefficient$-$10
over 115	100

Tab. 2.5: Coefficient in Accident Case

previous coefficient	applied coefficient
40	45 if score is 1 30+score$\times$10 if score is bigger than 2
45	40+score$\times$10
over 50	previous coefficient+score$\times$10

is an accident, and it is either no fault, or the score is less than 0.5, the coefficient is the same as the previously one.

The Korean experience rating system is distinctively different from other countries in the world. The chief difference is that the system takes account of the severity of each accident, as well as the number of accidents[8]. The other difference being that it is much faster to reach the floor than to arrive at the ceiling. Thus it has been acknowledged that insurance companies tend

[8]Korea is, apparently, the only country which takes account of the severity and cause of an accident in bonus-malus coefficient.

to avoid good policyholders because of this feature. The limitation policy will be explained in the data description below.

2.2.3 Data Description

I have obtained two panel data sets on car insurance contracts from two Korean car insurance companies (A and B) that have been operating since 1983[9]. Company A has a market share of approximately 13.20% of the total market. The data set from this company covers [5] calendar years between 01/01/1998 and 30/06/2002. This is equivalent to [4] entire contract years at maximum. The total number of policyholders contained within the data set is 607,824; samples are limited to those who are younger than 31 years old in 1998.

The data has [4] broad categories:

The first component is 'individual characteristics', this includes each policyholder's: gender, age, place of residence (by post code), job type, 'contract experiences coefficient' and 'bonus-malus' coefficient.

The second part is 'contract information', this consists of: dummy variables for family-limited policy and age-limited policy, contract starting and terminating date, deductible choices, coverage types and applied insurance

[9]Before 1983, there had been a monopoly within the car insurance market in Korea. As the number of cars increased and the market size got bigger this system was no longer compatible with the changing economic environment, both domestically and internationally. Thus, to enhance the competitiveness of the market, the government allowed 10 domestic and 2 foreign - [not-life] insurance companies - to operate in the car insurance market from 1983. Later, in 2000, one more domestic company entered the market.

premiums. If a policyholder buys a family-limited contract, those who can drive are limited to family members - prescribed in the clauses - as the name suggests. There is a discount in insurance premiums for this policy because this choice is supposed to reduce accident probability. With regards to age-limited policy there are three types: all ages, over 21 year's old, and over 26 year's old. There is also a discount whereby the 'over 26 year old contract' has the highest discount. A deductible is applied to a case where the damage on a policyholder's car occurs, given that the policyholder has purchased the fourth coverage in table 2.1. There are 6 types – 0, £25, £50, £100, £150 and £250[10]. Unless it is not at zero - 0, the policyholder should pay the amount that s/he chose at the beginning of the contract when there is a damage to his/her own car. Coverage types are recorded separately (from 1 to 6 in table 2.1). Finally, insurance premiums for each policyholder are recorded.

The third part concerns information on the car. This contains car age (measured by the production year), car size (measured by CC), gear types (automatic, semi-automatic or manual), dummy variable for ABS equipment and valuation of the car.

The final component is information on accident occurrence. This includes: accident place (by post code), accident date, fault rate, loss amount, accident type (17 types) and car loss type. Loss amount shows the actual amount of monetary compensation awarded to the policyholder when there was an accident. Car loss type inform us whether car was a total 'write off' or only partially damaged. Further to this it also separately shows whether a car

[10]Monetary measurement is shown in Korean Won in the data set. This is approximately converted to UK pounds sterling

was stolen.

Company B has a market share of 4.59%. The data set covers [4] calendar years between 01/01/1999 and 30/09/2002: These contain [3] full contract years at a maximum. The total number of policyholders in the data set is 990,199. The structure of the data set is the same as the data from company A. Some of the differences for each category are characterised by the following: That is within 'individual characteristics' the data set contains dummy variables for marital status, and employee status of 'company B'; however we do not have a contract terminating date. Also within contract information, we do not have a dummy variable for age-limited policy. For information on the cars, we only have car age variables in this data set. In accident records we have: accident place, accident date, fault rate, car loss types and loss types. Car loss types for this case is a dummy variable for theft accident only. Loss types correspond to each coverage type when there is an accident.

2.3 Conditional Correlation

2.3.1 Background

As Chiappori [2000] and Chiappori and Salanie [2003] have clearly stated, under moral hazard, transfers will be positively correlated to performance in a less volatile way in order to combine incentives and risk sharing; while under adverse selection the policyholder will typically be asked to choose a particular relationship between transfer and performance within a menu.

Applying adverse selection the client base are characterised by different levels of risk that will, ex-post, be translated into different accident probabilities; because of these discrepancies they will choose different contracts. Within the context of moral hazard policyholders will initially choose different contracts for a variety of exogenous reasons: they are then faced with different incentive schemes and consequently adopt a more or less cautious approach, this ultimately results in heterogeneous accident probabilities. The conclusion in both cases, controlling for observables, is that contract selection will inevitably be correlated with accident probability. More comprehensive coverage is associated with higher risk types. However, there is an instance of reverse causality between the moral hazard and the adverse selection models.

One explanation is that the contracts induce corresponding behaviour through their underlying incentive structure - the incentive effects of contracts. An alternative is that differences in behaviour simply reflects some unobserved heterogeneity across agents, and that this heterogeneity is also responsible for the variation in contract choices. In the presence of unobserved heterogeneity the matching of agents to contracts must be studied with care. If the outcome of the matching process is related to the unobservable heterogeneity variable then the choice of the contract is endogenous. In particular, any empirical analysis taking contracts as given will be biased[11].

Most empirical literatures in contract theory face a selection problem. Some papers explicitly recognise the problem and merely test for the presence of asymmetric information without exploring its nature. In most empirical

[11]The necessity of controlling for Unobservable Heterogeneity in Contract Theory is well shown inAckerberg and Botticini [2002].

insurance literatures, the aim of the test is straightforward. Conditional on all information available to the insurance company, they aim to test whether the choice of a particular contract is correlated to the risk as proxied ex post by the occurrence of an accident.

Puelz and Snow [1994] found evidence of positive relationship between insurance coverage and accident occurrence. They claim that the market for insurance entails the adverse selection and market signalling with no cross subsidisation between the contracts of the different risk classes. To obtain these results, they estimate two equations: firstly a demand equation for a deductible (as a function of an accident occurrence dummy, and an estimated deductible price): and secondly a premium function - as a function of various deductible level.

Conversly, Dionne et al. [2001a] found no evidence of the relationship. They argue that the insurer is able to control for adverse selection by using an appropriate risk classification procedure and that there is no residual adverse selection. Thus, the choice of deductible does not reveal any information about individual risk. They point out that the outcomes of Puelz and Snow [1994] could be spurious and due here to misspecification. In particular it is argued, the highly constrained functional form used by Puelz and Snow [1994] results in the omission of non-linearity and/or cross effects.

Chiappori and Salanie [1997] and Chiappori and Salanie [2000] also found no evidence of asymmetric information. To avoid non-linearity and complexity of experience rating, they consider a sub-sample of young drivers and introduce a large number of exogenous variables. Then, they simultaneously estimate two probit equations: One relates to the choice of deductible; the second equation takes the occurrence of an accident as the dependent variable. Asymmetric information should result in a positive correlation between the choice of deductible and the occurrence of an accident conditional on the exogenous variables; this is equivalent to a positive relationship between error terms. In addition, they also run the 'bivariate probit' and perform the 'chi-square test' for independence based on the fully nonparametric model.

Richaudeau [1999] also found no evidence of asymmetric information. In his paper, a 'two step maximum likelihood' method is used. Firstly, he computes a probit model to estimate the probability of taking out comprehensive versus third party insurance. He then calculates the generalised residual, which is included as an independent variable in a negative binomial model estimating the probability of having an accident. It is argued that the coefficient of this variable represents the presence of asymmetric information.

In summary, apart from the early work by Puelz and Snow [1994], there has been no evidence for the presence of asymmetric information.

In the following section I test for the presence of asymmetric information with the Korean car insurance data set using methods proposed by Chiappori and Salanie [2000].

2.3.2 Empirical Model

A general strategy for applying empirical model is described in Dionne et al. [2001a]. Let Y, X and Z respectively denote the endogenous variables under scrutiny (the occurrence of the accident, in this case), the initial exogenous variables and a decision variable (the choice of the insurance coverage). Let

$l(Y|X,Z)$ denote a probability density function of Y conditional on X and Z. If the decision variable provides no other information we have

$$l(Y|X,Z) = l(Y|X).$$

We can also have the equivalent form

$$l(Z|X,Y) = l(Z|X).$$

Further to this, we can even have

$$l(Z,Y|X) = l(Y|X)l(Z|X).$$

There *is* conditional independence of Y and Z in the last equation. The asymmetric information results in a positive correlation between Y and Z conditional on X.

Specifically, there are two probit models, one for 'contract choice' and the other for the 'occurrence of an accident'. Denote two independent errors following normal distributions with zero mean and unit variance by ϵ_i and η_i. Then we have

$$d_i = \mathbf{1}(X_i\beta + \epsilon_i > 0)$$

$$n_i = \mathbf{1}(X_i\gamma + \eta_i > 0).$$

d_i is a dummy dependent variable for contract choice. In the French data set used by Chiappori and Salanie [2000], there are two types of coverage: RC and TR. The former is the minimum legal coverage required to cover damage inflicted to other drivers or their cars. The latter is a comprehensive coverage which also indemnifies damage to the policyholder's car (or driver).

In their empirical model, if a policyholder bought a TR contract, then $d_i = 1$ and $d_i = 0$ otherwise.

As explained in section 2.2.1, the Korean coverage system is more sophisticated. I have formulated a dependent variable, d_i, according to whether a policyholder purchased below coverage [3] listed in table 2.1. This corresponds to RC contract in the French system. Thus, in our estimation, if a policyholder bought above coverage [3] in addition to coverage [1, 2 and 3], then $d_i = 1$ (equivalent to the TR contract in France) and $d_i = 0$ otherwise. Also n_i is a dummy variable for an accident occurrence. If a policyholder had at least one accident in which s/he were judged to be at fault, then, $n_i = 1$ and $n_i = 0$ otherwise.

As for the exogenous variables, the most relevant ones are included. In the French data set they are dummy variables for: gender (1), make of car (7), performance of the car (5), type of use (3), type of area (4), age of driver (8), profession of driver (7), age of car (11), and of region (9). This gives 55 exogenous variables plus a constant.

I estimate using both data sets described in section 2.2.3. Thus, for company A, I have dummy variables for gender (1), place of residence (15), gear type (2), ABS equipment (1), car age (12), job of driver (28) and car size (4). Overall, 63 exogenous variables are available. For company B, they are dummy variables for gender (1), employee status (1), marital status (1), place of residence (15), age of driver (6) and car age (11). Thus, in this case, the total number of exogenous variables are 35. Insurers use those variables in the determination of insurance premiums for each policyholder.

Finally, in their estimation, Chiappori and Salanie concentrate on young drivers[12]. According to them this has several advantages: One benefit being that the 'heteroscedasticity problem' is probably much less severe on a sample of young drivers since their experience is much more homogeneous than in a population in which different seniority groups are mixed up: And, more importantly, concentrating on young drivers avoids the problems linked to the experience rating (bonus-malus coefficient). If we include it, the test may be biased since this variable is likely to be correlated with η_i in the second equation. To prevent this problem, they selected 6,333 samples of drivers who obtained their driver's licence in 1988[13]. For the same reason, I choose young drivers using a 'contract experience coefficient'; in particular I selected drivers whose number of years of contract experience is [1] so that they do not have an extended driving record history. Given the model and variables, they first estimate two probits independently[14]. Then they compute the generalised residuals $\hat{\epsilon}_i$ and $\hat{\eta}_i$. For instance, $\hat{\epsilon}_i$ is given by

$$\hat{\epsilon}_i = \mathrm{E}(\epsilon_i | d_i, X_i) = \frac{\phi(X_i\beta)}{\Phi(X_i\beta)} d_i - (1 - d_i) \frac{\phi(X_i\beta)}{\Phi(-X_i\beta)},$$

where ϕ and Φ denote the probability density and cumulative distribution

[12]This usually means the most recent drivers in insurance industry.

[13]The French data set that they used covers the calendar year 1989.

[14]They weigh each individual by the number of days with insurance cover, ω_i due to the fact that they have data set in a calendar year. I have data sets also in contract years and almost all policyholders had complete one year of the contract. In case, I also take account of this factor in company A (this data has both contract starting and terminating dates), and I present the results for this case as well; and in my estimation this does not seem to drive the outcomes.

function of N(0, 1). Finally, they compute a test statistic by

$$W = \frac{(\Sigma_{i=1}^{n} \omega_i \hat{\epsilon}_i \hat{\eta}_i)^2}{\Sigma_{i=1}^{n} \omega_i^2 \hat{\epsilon_i}^2 \hat{\eta_i}^2}.$$

It is proposed that, under the null of conditional independence $\text{cov}(\epsilon_i, \eta_i) = 0$, W is distributed asymptotically as a $\chi^2(1)$[15]. This provides a test of symmetric information. Overall, the idea is that when there is asymmetric information this should result in a positive correlation between d_i and n_i (described in a general strategy), which is equivalent to a positive correlation between ϵ_i and η_i.

After testing two 'independent probits' they also estimate a 'bivariate probit' in which ϵ_i and η_i are jointly distributed. They argue that estimating the two probits independently is appropriate under conditional independence, but it is inefficient under the alternative. Thus, the 'bivariate probit estimation' is a reasonably complementary piece of work.

2.3.3 Empirical Results

Overall, Chiappori and Salanie [2000] found no evidence for the presence of asymmetric information. In their estimation, the test statistic, W, is 0.46 which is too small to reject for the conditional independence hypothesis. Furthermore, in 'bivariate probit', the estimate for the 'correlation coefficient'- ρ, is slightly negative, -0.029. The estimated standard error is 0.049. Although, ρ is not actually zero it is bound to be very small.

By contrast I have generated the following evidential conclusions: For Company A:- there are 205,627 contracts covering the contract year 1998.

[15]This is based on the results in Gourieroux et al. [1987].

This covers the contracts starting between 1/1/1998 - 31/12/1998, and terminating between 1/1/1999 - 31/12/1999 respectively. Among these contracts there are 31,839 beginners who purchased a car insurance contract for the first time. For this sample, I implement the same estimation as Chiappori and Salanie [2000]. The test statistic is 166.59, which is too big to accept for conditional independence. Further using the weight, it becomes 166.63, considerably larger than required to accept the null hypothesis. In bivariate probit estimation, the estimate for ρ is 0.2133891, for which the standard error is 0.0187869.

In the contract year 1999, there are 233,620 contracts which cover the contracts starting between 1/1/1999 - 31/12/1999 and terminating between 1/1/2000 - 31/12/2000. I have 44,396 beginners among these contracts. For this sample the test statistic, W, is 154.54 which is far from accepting 'conditional independence'. The weighted statistic is 134.58 that also rejects 'conditional independence'. In 'bivariate probit' the estimate for 'correlation coefficient', ρ, is 0.1827481 with an estimated standard error 0.0170097.

In the contract year 2000, I have 271,357 contracts that cover contracts starting between 1/1/2000 - 31/12/2000 and terminating between 1/1/2001 - 31/12/2001. Among these contracts there are 49,012 beginners. For this sample the test statistic turns out to be 109.19, that is again, too large to accept for conditional independence. The weighted statistic becomes 92.87, that is not so different from the unweighted one. In this case, the estimate for ρ is 0.1684491, and the estimated standard error is 0.0188084.

For company B, there are 512,365 contracts covering the contract year 1999. This contains the contracts starting from 1/1/1999 - 31/12/1999 and terminating between 1/1/2000 - 31/12/2000. Here there are 69,582 beginners. For this sample the test statistic is 3430.95. This is so large that we cannot accept conditional independence. In 'bivariate probit', the estimate for ρ is 0.5898179, with estimated standard error of 0.0067733.

The contract year 2000 includes 469,209 contracts that cover contracts starting between 1/1/2000 - 31/12/2000 and terminating between 1/1/2001 - 31/12/2001. Among them there are 55,339 beginners. The test statistic is again too large to accept for conditional independence. The estimate for ρ is 0.6324146 in the bivariate probit, the estimated standard error is 0.0069622.

Further, for each data set, I also do the same estimation for the sub-samples classified by individual characteristics. I estimate these sub-samples separately and calculate a test statistic, then add these up. In this case, I still achieve the same results: although test statistics here are slightly smaller than the results for the pooling samples[16].

Finally, a sceptic might argue that my finding is merely an artifact of the extremely large sample size of the data sets that comprise the study. To consider this critical possibility I also estimate the random sub-sample drawn from the full data, which is of sizes comparable to the existing study. The results are given in the following table 2.6, and the qualitative feature confirms my results from full data.

In summary, and in sharp contrast to Chiappori and Salanie [2000], I find - within the data set/s that I have used - evidence for the presence of

[16] For instance the test statistic for the first estimation of Company 'A'data becomes:- 162.86 from 166.59: and the results for the first estimation of the Company 'B'data becomes:- 3223.19 from 3430.95.

Tab. 2.6: Results from Subsaples

data	sample size	test statistic
company A (1998)	6,368	46.18
company A (1999)	6,659	18.97
company A (2000)	6,372	28.70
company B (1999)	6,958	350.50
company B (2000)	5,534	375.46

asymmetric information implementing the conditional correlation approach proposed by them. However, I do need to mention the fact that the insurer can only observe claims, not accidents. As pointed out in Chiappori [2000], this may cause a spurious correlation in the conditional correlation approach. In my case, even if losses are not affected by behaviour, it may be that certain losses are only covered under more comprehensive contracts and are only reported by a policyholder who has indeed bought this more comprehensive insurance! In this respect higher test statistics for data 'B' might indicate this as a plausible problem: that is since data 'B' contains many more policyholders who only purchased coverage [1] (see table C.1 in appendix C).

2.4 Occurrence Dependence

2.4.1 Background

There has been relatively little empirical research within dynamic contract theory considering the dynamic insurance relationship. Apart from the difficulties of obtaining data sets, mainly dynamic contract theory is often inconclusive, or relies on very strong assumptions that are difficult to maintain within an applied framework. Still, there are few works that study the qualitative features of existing contracts assuming that they are optimal in the relevant context. An important contribution from Dionne and Doherty [1994] addresses repeated adverse selection with semi-commitment and renegotiation. The key testable prediction is the presence of 'highballing'. In a repeated adverse selection framework, optimal contracts are such that the insurance company makes positive profits in the first period, compensated by low and below-cost second period prices. They test this property on Californian automobile insurance data. According to this theory - when various types of contracts are available - low risk policyholders are more likely to choose the 'experience rated policies'. Also, firms with a high growth rate will have a high proportion of new business with low loss to premium ratio [L/P], and therefore the recorded [L/P] for the book of business will be low. Conversely, firms with a low growth rate will have few of the newer, more profitable, policies, and so the [L/P] for the book of business will be high. Californian insurance companies are divided into three groups. The slope coefficient of premium growth on the [L/P] is negative, and significant for the group with 'lowest average loss per vehicle i.e. the best quality portfolio. This is both positive and significant for the group with highest average loss, and not significant for the intermediate group. With these results they conclude that the 'high-balling' prediction cannot be rejected.

In contrast, D'Arcy and Doherty [1990] identifies a 'low-balling' phenomenon focusing on informational asymmetries between insurers: their work is rather descriptive; with a significantly restricted data set. Firstly, they show that the loss ratio for cohorts of policyholders declines quite dramatically with policy age, consistent then with the predicted low-balling pattern. In addition, they show that the observed shift in market share from independent agent companies to direct writers is implied by the low-balling model. Direct writers contractually bind their policyholders from selling private information to their rivals.

Both Dionne and Doherty [1994] and D'Arcy and Doherty [1990] rely on the 'aggregate data set'.

Cohen [2005] studies adverse selection in the Israeli car insurance market focusing on a manifest policyholder learning process. The crucial feature of the market is that insurance companies are not required to, and do not, share information about their policyholders with other insurers[17]. Within this context she confirms the presence of the adverse selection. Firstly - examining the pool of new customer purchasing policies - she finds that policyholders choosing a low deductible are associated with more accidents, and higher total losses to the insurance companies. Interestingly, she also finds no such correlation for policyholders with little or no driving experience: stating that these policyholders might have had relatively little opportunity to obtain private information about their risk types and to gain an informational advantage over the insurer. However, such a correlation does exist for new policyholders who, having had three or more years of driving experience, have had an opportunity to absorb 'private' information concerning their risk

[17]That is, there is a private information structure, which is different form the Korean car insurance market where there is a public information structure.

types.

The other line of the empirical dynamic insurance research takes existing contracts as given and investigates the testable properties of induced individual behaviour. This is due to Abbring et al. [2003a] and Abbring et al. [2003b]. Methodologically, their studies build on and extend the literature on state dependence and unobserved heterogeneity in event history data (see Heckman and Borjas [1980] for a formal definition of occurrence dependence). They use a French data base and focus on the role of the existing experience rating system, working through the 'bonus-malus coefficient' in the contracts. With this system, the insurance premium associated with any particular contract depends, among other things, on the past history of the contracts. That is, particularly, after each year without an accident, the coefficient is decreased by a factor of, δ, which is between 0 and 1. However, if there is an accident occurrence, it increases by a factor of, $\gamma(> 1)$. The authors show that this scheme has a very general property: that is each accident increases the marginal cost of having accidents in the future. Therefore, under moral hazard, any accident increases cautious efforts, therefore reducing accident probability. That is - for any given individual - moral hazard induces a negative contagion phenomenon. The occurrence of an accident in the past reduces accident probability in the future. However, this prediction is only conditional upon individual characteristics, whether observable or unobservable. As is well known, 'unobserved heterogeneity' induces the opposite - positive contagion. Past accidents are typical of bad drivers and, as a result, are a good predictor of a higher accident probability in the future. Thus, the problem lies in controlling unobserved heterogeneity. Using a proportional hazard duration model controlling for unobserved heterogeneity, they accept the null hypothesis of no moral hazard.

2.4.2 Empirical Model

In this section, I implement the estimation strategy by Abbring et al. [2003a] andAbbring et al. [2003b]. Here, initially, I describe the theoretical and empirical models. It is the qualitative results of the formal theoretical model from which the empirical model is derived.

A brief sketch of the theoretical model is as follows: Time is discrete and infinite horizon. At each time t, the agent, receives some fixed income, W. With probability, $1 - p_t$ the policyholder has an accident and incurs a fixed monetary loss of, L. The policyholder is covered by an insurance contract involving a fixed deductible, D and a premium, Q_t. Thus, an individuals consumption for each period is $W - Q_t$ without an accident, and $W - Q_t - D$ if an accident occurs.

The premium Q_t depends on past experience, specifically, the evolution of Q_t is governed by the following 'bonus-malus coefficient',

$$Q_{t+1} = \begin{cases} \delta Q_t & \text{if no accident} \\ \gamma Q_t & \text{if an accident.} \end{cases}$$

The no accident probability p_t is subject to moral hazard. At each time t, the agent chooses an effort level, $e_t \geq 0$, for some deterministic function, p. It is assumed that p is twice differentiable with $p' > 0$ and $p'' < 0$. The cost of effort is assumed to be separable. That is, the agent attaches utility $u(x) - c(e)$ to an income x if he exerts effort e, where c is a cost function of making an effort. Thus, the agent's expected time, t utility is

$$v(e_t, Q_t) = p(e_t)u(W - Q_t) + (1 - p(e_t))u(W - Q_t - D) - c(e_t).$$

The agent is risk averse with an increasing and strictly concave utility function. The agent chooses effort levels, $e_1, e_2, \ldots$ so as to maximise expected discount utility, with discount factor, $0 < \rho < 1$. That is, the agent solves the program

$$\max_{e_1,\ldots} \sum_t \rho^t v(e_t, Q_t),$$

where Q_t satisfies the premium evolution described above.

This is a standard optimum control problem with one dimensional state variable Q_t and control variable e_t. The value function satisfies the following Bellman equation:

$$V(Q) = \max_e -c(e) + (1 - p(e))[u(W - Q - D) + \rho V(\gamma Q)] + p(e)[u(W - Q) + \rho V(\delta Q)].$$

The first crucial property of the value function is that it *is* decreasing in Q. Secondly, it is concave[18]. Apart from the formal proofs, I also implement numerical analysis using the value function iteration method[19]. For a numerical illustration, I specify the functional forms and numerical values as follows:

- utility function: $u(\cdot) = \ln(\cdot)$

[18]Proofs are provided here on the request. Also, the final version of the authors' working paper contains the proofs, which is a discrete-time model.

[19]The matlab code for numerical analysis is also available upon request. For the details of the value function iteration, there are many references. For the formal treatments, see Adda and Cooper [2003], Sargent [1987] or Stokey and Lucas [1989].

- probability of no accident: $p(e) = 1 - \frac{1}{1+e}$
- effort cost: $c(e) = e^2$
- $\rho = 0.9$, $\delta = 0.95$, and $\gamma = 1.25$.

The results from value-function-iteration are given by figure [1] & figure [2][20]. To attain qualitative results the authors derive the first order condition

$$p'(e) = \frac{c'(e)}{u(W-Q) - u(W-Q-D) + \rho(V(\delta Q) - V(\gamma Q))}.$$

By defining $\psi(e) = -p(e)$, we have

$$\psi(e) = \frac{c'(e)}{u(W-Q-D) - u(W-Q) + \rho(V(\gamma Q) - V(\delta Q))}.$$

Concavity of V implies that the right hand side of the last formula is increasing in Q. Since ψ is increasing, this implies, in turn, that e increases with Q. This is the main result for the negative occurrence prediction. If there is an accident, the agent faces higher premiums in the next period due to the experience rating scheme. Then, as a consequence of experience rating system a higher level of effort is induced in order to reduce accident occurrence under moral hazard.

Given this theoretical prediction, the empirical model is presented. The analysis focuses on the occurrence of car insurance contact claims in a single insurance contract year, i.e. the period bounded by two consecutive contract renewal dates.

[20]The authors have not done this part. However, this practice would be a useful supplement to the theoretical proofs. In figure 2, we can also see the pattern of a policy function clearly.

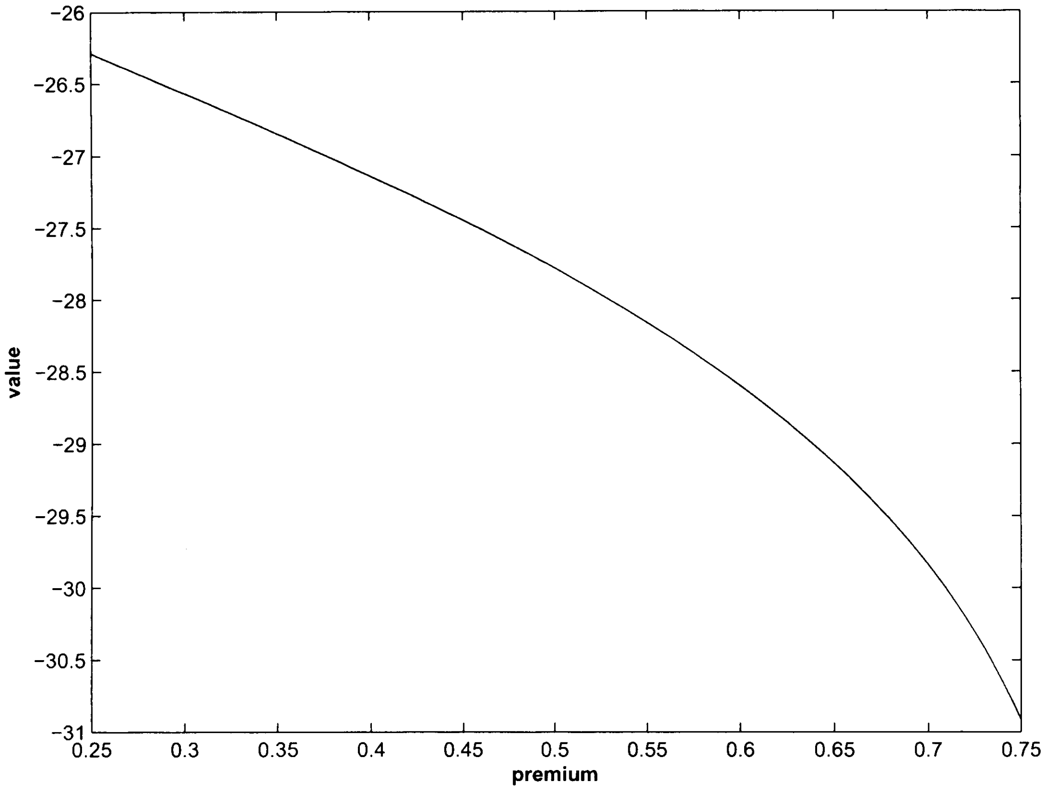


Fig. 2.1: Premium-Value

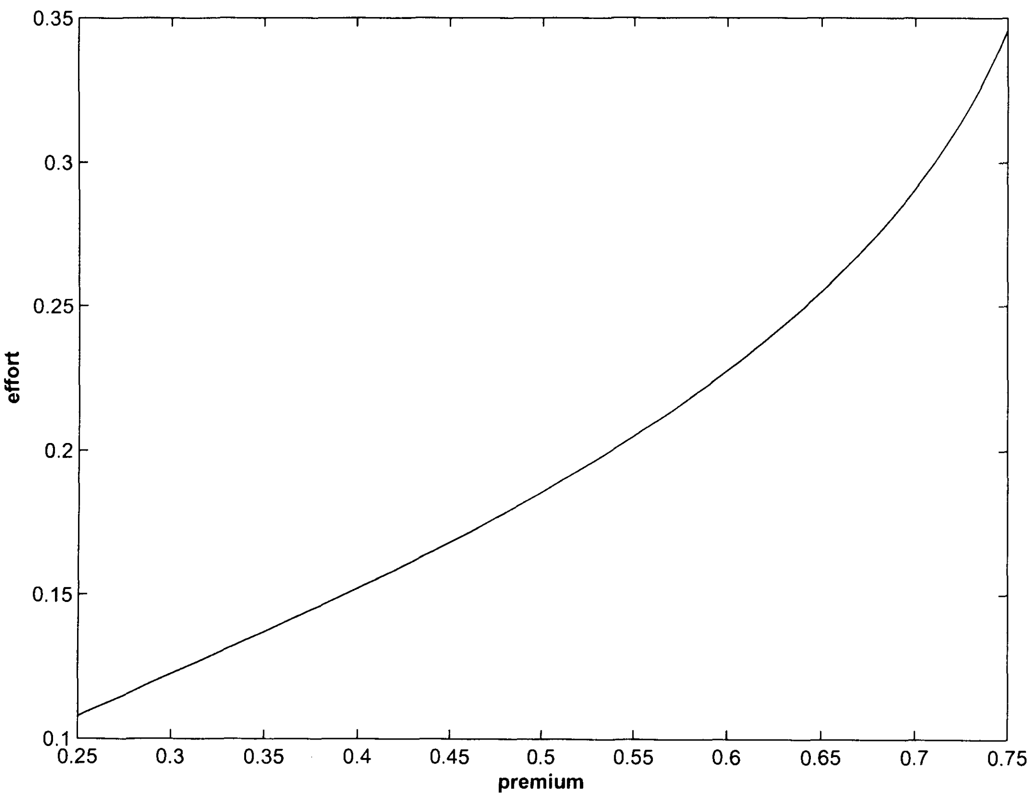


Fig. 2.2: Premium-Effort

Let time have its origin at the start of the contract year: Then, if a contract year is of length T, it can be represented by the interval $[0, T]$. Let T_k be the time of the k-th claim. Denote the corresponding counting process by $N[0,T] := \{N(t); 0 \leq t \leq T\}$, where $N(t) := \{k : T_k \leq t\}$ counts the number of claims in the contract year up to time t. $N[0,T]$ is the focus of the model and empirical analysis.

The intensity θ of claims at time t, conditional on the claim history $N[0,t) := \{N(u); 0 \leq u \leq t\}$ up to time t and a nonnegative unobservable covariate λ, is

$$\theta(t|\lambda, N[0,t)) = \lambda \beta^{N(t-)} \psi(t)$$

with $\beta : [0,\infty) \rightarrow (0,\infty)$ and $\psi : [0,T] \rightarrow (0,\infty)$ that captures the contract-time effects. Denote $\Psi(t) := \int_0^t \psi(u)du$. With normalisation $\Psi(T) = 1$, λ capturing the scale of θ. It is assumed that λ has marginal distribution of G.

The parameter β captures occurrence dependence effects in the French car insurance system. Moral hazard leads to a decline in the intensity of claims in relation to the number of previous claims ($\beta < 1$). Without Moral Hazard, $\beta = 1$ is expected. Distinguishing these two cases and estimating β is the focus of empirical analysis.

2.4.3 Empirical Results

The empirical model is estimated by maximum likelihood[21]. The authors have chosen piecewise-constant specifications of ψ. With $q \geq 1$ pieces, they

[21] Matlab code for this maximum likelihood estimation is provided on request. I implement quasi-Newton algorithm on matlab.

then partition the contract year, $[0, T]$, in q equally-sized intervals with ψ constant on each interval thus:

$$\psi(t) = \sum_{j=1}^{q} \psi_j I(\frac{j-1}{q} \leq \frac{t}{T} < \frac{j}{q}),$$

with $\psi_1, ..., \psi_q \geq 0$ parameters to be estimated up to the normalisation $\Psi(T) = (T/q) \sum_{j=1}^{q} \psi_j = 1$. For the distribution of λ_i, they use discrete distribution with two points of support. In this case they estimate the support points, λ^a, $\lambda^b > 0$, and one probability, $\Pr(\lambda = \lambda^a) = 1 - \Pr(\lambda = \lambda^b)$.

The authors use the insurance contracts from a French insurance company for a given and common calendar time period of two years, October 1, 1987 - September 30, 1989.

Tab. 2.7: French Data

number of observations by number of claims	
$M_{0,n}$(no claims)	74566
$M_{1,n}$(1 claim)	4831
$M_{2,n}$(2 claims)	270
$M_{3,n}$(3 claims)	15
$M_{4,n}$(4 claims)	2

Overall, using their own data set, they found no evidence of moral hazard. The estimate for β is 0.974 with an estimated standard error of 0.677. With regard to contract time effects, they do not reject the stationarity.

Conversely, I have detected the negative occurrence dependence phenomenon. I present here my results for the 1998 data set of Company [A] and the 1999 data set of Company [B] in table 9 and in table 10. In the appendix A.1, I present the remaining results for other contract years in both data sets[22]. However, there should be some caution exercised in the interpretation of empirical results. As presented in section 2.2.2, the Korean experience rating system is markedly different from the French system: which is a proportional system[23]. This implies that when I apply [the French] theory to the Korean data set this would suggests a possible changes in the interpretation of Abbring et al. [2003b]'s test for moral hazard. Particularly, depending on the policyholder's current experience rating state, under the presence of moral hazard, individual claim rates may also depend positively on the past claim if the experience rating system is nonproportional.

Further, as in the previous section, I estimate with sub-samples to see whether the sample size makes a difference to the results: especially with regard to t-values. In this exercise I construct sub-samples according to individual characteristics. In the following tables below are presented the results; here only coefficient βs are reported and we can clearly see that sample size does not make a difference.

Here I like to point out one thing regarding our results. In case of the year 2000 data set of Company [A] the estimated β is very small, being close to zero. This seems to be driven by the contracts-time effects.

[22]I also estimate sub-samples classified by some individual characteristics. I have divided the samples for Company [A] using 'gender' and for Company [B] using 'gender, marital status and age'. For these estimations, I have produced similar results to the pooled-data-sets; some results are presented in table 2.8.

[23]This is described in section 2.4.1 in details. Basically, the Korean system is nonproportional and much more complicated due to taking account of the severity of an accident as well as the number of accidents.

Tab. 2.8: Results from Subsamples

data	subsample	sample size	coefficient β
A (1998)	female	M_0: 29,448	0.4978 (0.1060)
		M_1: 2,498	
		M_2: 173	
		M_3: 17	
		M_4: 1	
B (2000)	married male &	M_0: 70,068	0.4325 (0.0318)
	$18 \leq$ age <40	M_1: 7,515	
		M_2: 1,017	
		M_3: 127	
		M_4: 35	
B (2000)	unmarried female &	M_0: 15,559	0.4886 (0.0892)
	age ≥ 40	M_1: 2,025	
		M_2: 268	
		M_3: 33	
		M_4: 5	

(standard errors are in parenthesis)

Tab. 2.9: Discrete heterogeneity; 12 time intervals (1998 A)

occurrence dependence	
β	0.5369(0.0399)
unobserved heterogeneity	
λ^a	0.0594(0.0010)
λ^b	1.5119(0.2154)
$\Pr(\lambda = \lambda^a)$	0.9878(0.1483)
$\Pr(\lambda = \lambda^b)$	0.0122(0.1483)
piecewise constant ψ	
ψ_1	1.1929(0.0342)
ψ_2	1.0799(0.0317)
ψ_3	1.0436(0.0304)
ψ_4	0.9935(0.0297)
ψ_5	1.0232(0.0300)
ψ_6	0.9792(0.0295)
ψ_7	0.9317(0.0289)
ψ_8	0.9585(0.0295)
ψ_9	0.9177(0.0291)
ψ_{10}	1.0043(0.0310)
ψ_{11}	0.9264(0.0297)
number of observations by number of claims	
$M_{0,n}$(no claims)	182441
$M_{1,n}$(1 claim)	12100
$M_{2,n}$(2 claims)	776
$M_{3,n}$(3 claims)	81
$M_{4,n}$(4 claims)	14
$M_{5,n}$(5 claims)	3
log-likelihood	−50502

Tab. 2.10: Discrete heterogeneity; 12 time intervals (1999 B)

occurrence dependence	
β	0.5356(0.0234)
unobserved heterogeneity	
λ^a	0.0821(0.0013)
λ^b	1.3936(0.1109)
$\Pr(\lambda = \lambda^a)$	0.965(0.0835)
$\Pr(\lambda = \lambda^b)$	0.035(0.0835)
piecewise constant ψ	
ψ_1	1.1990(0.0200)
ψ_2	1.1150(0.0180)
ψ_3	1.1054(0.0172)
ψ_4	1.0325(0.0163)
ψ_5	1.0245(0.0162)
ψ_6	1.0184(0.0162)
ψ_7	0.9976(0.0163)
ψ_8	0.9306(0.0159)
ψ_9	0.9249(0.0162)
ψ_{10}	0.8940(0.0162)
ψ_{11}	0.8809(0.0164)
number of observations by number of claims	
$M_{0,n}$(no claims)	396729
$M_{1,n}$(1 claim)	40635
$M_{2,n}$(2 claims)	4148
$M_{3,n}$(3 claims)	521
$M_{4,n}$(4 claims)	87
log-likelihood	-159260

2.5.1 Background

Abbring et al. [2003a] and Abbring et al. [2003b] have indeed made progress beyond the established static framework in attempting to distinguish two major phenomena in informational asymmetries. However, due to data limitations, they focus on the dynamics of the claims, and therefore not on the dynamics of contract choices. Given that, and applying specific assumptions about the wealth effects of accidents to policyholders who differ only in their claim records (and thus their experience rating), their model predicts that policyholders with worse claim records should try harder to drive carefully, and, *ceteris paribus*, file fewer claims in the future. Yet, they do not detect the presence of Moral Hazard.

Dahchour et al. [2004] proposes a methodology to disentangle the historical pathways which lead asymmetric information to a conditional correlation between the claims and the levels of coverage. Using a French longitudinal framework controlling for unobservables, they show how Granger causality can be used to disentangle moral hazard from adverse selection. They apply a dynamic bivariate probit model here as an empirical model.

2.5.2 Empirical Model

Basically, the model is an extension of the static bivariate probit model proposed in Chiappori and Salanie [2000]. Let us consider the case where we have T_i repeated observations on a contract (assume $T_i = T$). We can decompose the error terms in the static framework (see the error terms in choice equations from section 2.3.2) into an error component structure

$$\epsilon_i = \alpha_{di} + \epsilon_{dit}$$

$$\eta_i = \alpha_{ni} + \epsilon_{nit}.$$

Assume that the econometrician, insurance companies, and policyholders can observe the pair $\alpha_i = (\alpha_{di}, \alpha_{ni})$ where α_{di} represents specific contract characteristics and α_{ni} represents specific policyholder characteristics. The test for asymmetric information then adopts the form:

$$\mathrm{H}_0 : F(d_{it}, n_{it}|\mathbf{x}_{it}, \alpha_i; \theta) = F(d_{it}|\mathbf{x}_{it}, \alpha_i; \theta_d)F(n_{it}|\mathbf{x}_{it}, \alpha_i; \theta_n)\forall t,$$

where F is the cumulative distribution function.

Now include the history of each of the decision variables in the conditioning set such that:-

$$\begin{aligned}\mathrm{H}_0 : F(d_{it}, n_{it}|\mathbf{x}_{it}, d_{it-1}, n_{it-1}, \alpha_i; \theta) = F(d_{it}|\mathbf{x}_{it}, d_{it-1}, n_{it-1}, \alpha_i; \theta_d)\times \\ F(n_{it}|\mathbf{x}_{it}, d_{it-1}, n_{it-1}, \alpha_i; \theta_n)\forall t > 1.\end{aligned}$$

This still yields a test for residual asymmetric information given by the null hypothesis $\rho_\epsilon = 0$, where $\rho_\epsilon = \mathrm{Cov}[\epsilon_{dit}, \epsilon_{nit}]$. Looking at the marginals, the authors claim that the cross-sectional variation in contract choice d_{it-1}, holding α and n_{it-1} constant, effectively identifies the presence of moral hazard if n_{it} responds positively to such a variation. Under pure adverse selection, such variation in contract choice will not lead to a subsequent change in the distribution of claims in the next period. Thus, they propose to test for the presence of moral hazard by using Granger causality, crucially holding α fixed. Then, rejecting the null hypothesis:-

$$\mathrm{H}_0 : F(n_{it}|\mathbf{x}_{it}, d_{it-1}, n_{it-1}, \alpha_i; \theta_n) = F(n_{it}|\mathbf{x}_{it}, n_{it-1}, \alpha_i; \theta_n) \forall t > 1$$

will lead them to conclude that there *is* evidence of dynamic moral hazard.

One can distinguish moral hazard from adverse selection within this dynamic framework because changes in exogenous risk factors (adverse selection) are controlled over time. Therefore, access to longitudinal data is crucial. Since α is not observable and the cross-sectional variation in d_{it-1} and n_{it-1} is correlated with unobserved heterogeneity, one additional observation is needed in order to have two pairs of (n_{it}, d_{it}) and (n_{it-1}, d_{it-1}) from which we can separate the effect of unobserved heterogeneity. This is analogous to the identification argument that Heckman [1981] make for a dynamic binary choice model with an error component structure.

Given the discussion above, the parametric model for the evolution of claims and contract choice is given by

$$d_{it} = \begin{cases} 1 & \text{if } d^*_{it} = \mathbf{x}'_{it}\beta_d + \mathbf{w}'_{it}\gamma_d + \phi_{dd}d_{it-1} + \phi_{dn}n_{it-1} + \alpha_{di} + \epsilon_{dit} > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$n_{it} = \begin{cases} 1 & \text{if } n^*_{it} = \mathbf{x}'_{it}\beta_n + \mathbf{w}'_{it}\gamma_n + \phi_{nn}n_{it-1} + \phi_{nd}d_{it-1} + \alpha_{ni} + \epsilon_{nit} > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$i = 1, ..., N, t = 1, ..., T_i$$

$\mathbf{x}_{it}$ is a vector of the policyholder's characteristics that are observable to both insurance company and policyholder. $\mathbf{w}_{it}$ is a set of variables that are predetermined at t, such that $\mathrm{E}(\epsilon_{dit}\mathbf{w}_{it+s}) = 0$ and $\mathrm{E}(\epsilon_{nit}\mathbf{w}_{it+s}) = 0$ are assumed to hold for $s = 0$ but may not necessarily hold for $s > 1$. This plausibly allows for feedback from accidents and contract choice to certain variables such as the bonus-malus coefficient.

The dynamic test for moral hazard is:

$$\mathrm{H}_0 : \phi_{nd} \leq 0$$

$$\mathrm{H}_1 : \phi_{nd} > 0,$$

while the contemporaneous test for residual asymmetric information[24] is given by

$$\mathrm{H}_0 : \rho_\epsilon \leq 0$$

$$\mathrm{H}_1 : \rho_\epsilon > 0.$$

For a small panel, predetermining the binary choice with an error component structure will lead to the 'initial condition problem'. Since $(\alpha_{di}, \alpha_{ni})$ are unobserved, they must be integrated out from the conditional probabilities. Because contracts have a prior history which is hidden for the econometrician, it therefore requires an attempt to sort out the joint density of $(\alpha_{di}, \alpha_{ni})$ and the prior initial conditions since d_{i0} and n_{i0} are missing[25].

Authors follow the solution proposed by Wooldridge [2005] and, as a result, assume the mean of the distribution of $(\alpha_{di}, \alpha_{ni})$ to be a linear index $\mathbf{y}'_{i1}\zeta_d$ and $\mathbf{y}'_{i1}\zeta_n$ of endogenous variables and predetermined variables:

[24] Residual asymmetric information is interpreted as asymmetric information after controlling for all the observables.

[25] Wooldridge [2005] discusses that even when the econometrician has access to the entire history of the process, the problem still remains unresolved!

$\mathbf{y}_{i1} = (d_{i1}, n_{i1}, \mathbf{w}_{i1})'$. The parameters ζ_d and ζ_n do not capture causal effects and therefore cannot be used to test any of the relevant sources of asymmetric information. With this solution, we can decompose the unobserved heterogeneities by

$$\alpha_{di} = y_{i1}'\zeta_d + \omega_{di}$$

$$\alpha_{ni} = y_{i1}'\zeta_n + \omega_{ni}.$$

Replacing unobserved heterogeneity by their conditional means with error terms yields the following equations:-

$$d_{it} = \begin{cases} 1 & \text{if } d_{it}^* = \mathbf{x}_{it}'\beta_d + \mathbf{w}_{it}'\gamma_d + \phi_{dd}d_{it-1} + \phi_{dn}n_{it-1} + y_{i1}'\zeta_d + \omega_{di} + \epsilon_{dit} > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$n_{it} = \begin{cases} 1 & \text{if } n_{it}^* = \mathbf{x}_{it}'\beta_n + \mathbf{w}_{it}'\gamma_n + \phi_{nn}n_{it-1} + \phi_{nd}d_{it-1} + y_{i1}'\zeta_n + \omega_{ni} + \epsilon_{nit} > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$i = 1, ..., N, t = 2, ..., T_i$$

2.5.3 Empirical Results

The authors use the SOFRES longitudinal survey covering representative samples of French drivers from 1995 to 1997 (3 years). The information available in the database is composed of three elements: The first concerns information on driver characteristics: The second covers the vehicles: The third provides the bonus-malus coefficient, and the type of insurance coverage. Given this data structure, they use the unbalanced panel to improve the efficiency of the estimator although the identification of moral hazard will be mainly derived from contracts observed over three years; the total of these contracts is 1,049.

By implementing the empirical model[26], first of all, they found no evidence of residual asymmetric information. The coefficient, ρ_ϵ, is quite low, 0.014 and imprecisely estimated (t-value = 0.25). However, they did find evidence of dynamic moral hazard the estimate for ϕ_{nd} being 0.409. Indeed, they find that those switching from comprehensive coverage to third-party coverage tend to exhibit a 5.9 percentage point decrease in the probability that they will file a claim the next year. Finally, interestingly, they found the evidence of a positive contagion effect (positive state dependence) in the claim process. A policyholder filing a claim in a given period is 6.1% more likely to file another claim in the next year compared with another policyholder with a comparable risk profile who did not file a claim. This implies that not finding a negative contagion effect does not necessarily imply that moral hazard is absent under the experience rating system (compare with Abbring et al. [2003b]).

I use the data set from Company [B] for this estimation. As mentioned in the data description, this data set covers [4] calendar years from 1999 to 2002. Unlike the authors I use the balanced panel, since I have enough contracts that stayed for the entire time period. From this data set I have 11,645 contracts - equivalent to 34,935 observations - which remained for [4] years. For the random terms in the replacement of the unobserved heterogeneities, I

[26]They do not report the estimates for two random terms in the replacement of the unobserved heterogeneities.

assume that they follow a bivariate discrete distribution (see appendix). According to Michaud and Tatsiramos [2005], using a mass point heterogeneity distribution is an attractive alternative to parametric distributions. It is non-parametric and, particularly, the parametric alternative involves numerical methods that are not always precise when persistence is high. I implement the given model using a maximum likelihood estimation[27].

I partition the samples according to places of residence[28]. With this method, I have 13 sub-samples. In most estimations, I found out evidence of both residual (contemporaneous) asymmetric information and dynamic moral hazard. Here, I present the results for those who live in Seoul, the capital city in Korea. The remaining 12 results for other provinces are presented in appendix A.3.

As can seen in the table 2.11, my estimated 'rho' is 0.1238. That shows positive correlation between two contemporaneous error terms, which is different from the authors' results (but consistent with our results from the conditional correlation approach). Furthermore, the estimated coefficient, ϕ_{nd}, is 0.6118 (coefficient for LAGCON in our estimation). That is, there is a reduction in the future probability of filing a claim with regard to the decrease in coverage from the previous period. Also, in my case, there arises a positive state dependence phenomenon in the claim process. This is shown by

[27]Matlab code is again available on request. We implement a sequential quadratic programming (SQP) method using a quasi Newton algorithm.

[28]This is mainly due to technical considerations. In our case, the number of parameters to be estimated is 68 and the sample size is 34,935. Thus, it was not feasible to estimate the pooled sample. This method does have an advantage though: that is we could see some differences across the provinces in Korea regarding the aims of the estimation.

the estimated coefficient for LAGCLA in the claim equation. The estimated coefficient is 0.1747, which shows the positive contagion effect.

Although I found out the evidence of contemporaneous asymmetric information and dynamic moral hazard, identification of the latter in the model would be neither strong nor obvious. Particularly, whether the effects of lagged contract choices on the current claims corresponding to moral hazard effects is not obvious. As the authors stated, what would be informative may be the effects of the changes in contract choices between the previous period and the current period on current accident occurrence. In this regard an alternative model specification should be considered like.

2.6 Conclusion

Empirical contract theory has explored and studied many interesting economic phenomena with regard to informational asymmetries in the various market contexts. Also, this research area has constantly attracted the enthusiastic attentions from many economists. As described in the introduction, this interest reflects the fact that empirical research within contract theory compared with theoretical research in this area is lagging behind somewhat. Furthermore, and more importantly, economists have also realised that economic agents involved in the trades have become aware of the practical importance, and considerable welfare implications, of informational asymmetries.

In this chapter, with the availability of the Korean car insurance data set, I have focused on empirical aspects of insurance economics. Mainly, I have implemented the most path breaking empirical models in the empirical insurance literature.

First of all, I have sought to implement the conditional correlation approach. From this endeavour I have generated fairly interesting results. Unlike the most research that has applied similar methods (particularly, Chiappori and Salanie [2000]), I have discovered evidence for the presence of the asymmetric information within static frameworks.

Detecting the presence of the asymmetric information in terms of the potential application of the above research for welfare implications is neither sufficient nor comprehensive enough, as far as the involved trading parties are concerned. As I mentioned in the introduction, depending on the 'cause' of the information asymmetries, there should be different policy reactions.

In this regard there has been, recently, some pioneering research that has explored the possibilities of distinguishing two major phenomena: adverse selection and moral hazard, especially within the context of dynamic contractual relationship.

Therefore, secondly - and with regard to dynamic empirical contract theory - I have applied occurrence dependence methodology. As a result of this enquiry I discovered the negative occurrence dependence phenomenon which is different from the provision of 'no moral hazard' from Abbring et al. [2003b].

Finally, I have implemented the model based on Granger causality. This methodology has been made possible with useful panel data set. In accordance with Dahchour et al. [2004], I have been able to find evidence for the presence of dynamic moral hazard.

Overall, in virtually all my implementations, I have consistently discovered evidence for the presence of asymmetric information in the static framework, and evidence of dynamic moral hazard in the dynamic framework. However, we should be cautious here: That is we may not be entirely sure whether these results are a necessary consequence of the apparent existence of informational asymmetries within the Korean car insurance market or derived completely from misspecifications of the empirical models we have employed. Therefore, I would need a more diversified research approach, based on the different strategies, using enriched Korean car insurance data sets in order to further pursue this empirical research.

As previously mentioned in the introduction, I launch the 'natural experiment' research project exploiting the regulation change in 2000 in the

Korean car insurance market. With the provision of panel data sets, I explore the accident probability changes over time since the implementation of the regulation change holds individual characteristics unchanged. In this work, I aim at detecting moral hazard separately. This is the theme of the chapter 3.

Tab. 2.11: Dynamic Model of Contract Choice and Accident Occurrence

Variables	coverage	claims
GEN	0.0451 (0.0633)	0.1248 (0.0245)
MS	-0.0640 (0.0549)	-0.0214 (0.0234)
CAGE1	-0.5319 (0.0784)	-0.1133 (0.0360)
CAGE2	-0.1892 (0.0704)	-0.0300 (0.0290)
CAGE3	-0.2128 (0.0650)	0.0091 (0.0268)
AGE1	-0.3352 (0.0905)	0.1797 (0.0469)
AGE2	-0.0191 (0.0641)	-0.0044 (0.0266)
AGE4	-0.0818 (0.0798)	0.0334 (0.0287)
AGE5	-0.3247 (0.0961)	-0.0759 (0.0433)
CONS	-0.3752 (0.1240)	-1.6872 (0.0768)
Predetermined		
LAGCON	2.9795 (0.0975)	0.6118 (0.0854)
LAGCLA	0.1370 (0.0788)	0.1747 (0.0334)
BM	-0.9640 (0.1134)	0.1681 (0.0708)
Initial Conditions		
INICON	0.7864 (0.1033)	-0.2347 (0.0806)
INICLA	0.0061 (0.0917)	-0.0656 (0.0371)
INIBM	0.1402 (0.1146)	-0.1089 (0.0653)
Correlation Coefficient		
Rho	0.1238 (0.0460)	
Unobserved Heterogeneity Distribution	estimate	probability
(ω_d^1,ω_n^1)	(0, 0)	0.2497
(ω_d^2,ω_n^1)	(-0.0005, 0)	0.2501
(ω_d^1,ω_n^2)	(0, -0.0013)	0.2501
(ω_d^2,ω_n^2)	(-0.0005, -0.0013)	0.2501

CHAPTER 3

TESTING FOR THE PRESENCE OF MORAL HAZARD USING THE REGULATORY CHANGE

3.1 Introduction

It has been of some serious concern that there are a large number of car accidents in Korea compared with other developed countries. On average car accident rates[1] are twice as high as accident rates in other developed countries. For instance, in 1996, the accident rate in Korea was 2.9% whereas it was 1.1% in the USA, 1.1% in Japan, and 0.9% in the UK. Car accident occurrence has had a substantial effect on the whole economy as well as on individual lives. Under these circumstances, in April 1999, the Financial Supervisory Service (FSS) announced that it would introduce a new incentive system beginning May 1999 in order to reduce the number of car accidents

[1] Measured by 'the number of car accidents divided by the total number of registered cars'.

(FSS [1999]).

According to previous research (particularly, Lee [1997]) in Korea, it appears that those who have violated traffic laws tend to have more accidents, approximately 25 % higher, than those who have not[2]. In this regard, the records of traffic law violations are a very useful informational indicator reflecting driving habits: And further to this, there have been some concern with regard to the efficiency of the market: That is, given that those who violate serious traffic laws tend to exhibit higher accident probability - as is shown in both theoretical and empirical work - there does then exist an issue concerning the unfair subsidy provided by those who keep to the law to those who violate the law: That is an unfair disparity since there is no difference in insurance premiums between them. Thus, in addition to the actual accident occurrence, the FSS has decided to link traffic law violations records with car insurance premiums in an attempt to reduce the number of car accidents and enhance market efficiency.

In this chapter, I investigate the presence of the moral hazard phenomenon using the data generated by the regulatory change. With the implementation of new regulation the same people successively face different incentive structures that are exogenously given. Here, the selection process is no longer a problem. Any resulting change in behaviour can safely be attributed to the variation of incentives. Thus, the idea is that policyholders are expected to exert higher effort levels to avoid violations of the relevant traffic laws especially if there is hidden action on their side. Moreover, if those traffic laws

[2]Also, Korea Non-Life Insurance Association (KNIA) announced that this rate was 30% in FY 2002.

are significantly related to accident occurrence either directly or indirectly, the higher effort will cause lower accident probability in the end. Overall, using the new data provided by regulatory change I seek to focus on moral hazard only, controlling for unobserved heterogeneity.

Using the data sets from the Korean car insurance companies, I test the hypothesis described above. This work aims to contribute to the 'natural experiment' literature within the field of empirical contract theory. In section [2], I briefly present the related literature. In Section [3] I explain the details of regulatory change. I test the above hypothesis in both parametric and nonparametric ways in section [4]. Then I conclude discussing these results in the last section.

3.2 Related Literatures

In empirical contract theory, there has been some research using natural experiments to distinguish adverse selection and moral hazard.

Dionne et al. [2001b] study the effects of new incentive systems on average accident frequency in the Canadian car insurance market. They evaluate the effects of the 1992 changes in car insurance pricing in Québec by the SAAQ (the public monopoly insurer for bodily injuries)[3] on road safety. Before this structural change, the demerit points accumulated were not used in a pricing scheme ('memoryless'). Using a negative binomial model with random effects, they show that the new system provided strong incentives to increase prevention and, as a result, it reduced infractions and accidents

[3]Damage on property is covered by the private sector.

implying increased road safety. They conclude that changes in policyholders' behaviour, as triggered by the new incentives, did produce a significant effect on accident probabilities.

Browne and Puelz [1999] study the economic consequences of tort reform: Firstly, they test the relationship between tort reforms and claim severity for automobile liability incidents: Further, they test the effect of tort reforms on economic and non-economic damage separately: Using OLS, they show that many of the reforms have had a statistically significant effects on total, non-economic and economic damage. Secondly, they test the proposition that tort reforms, by reducing the damage available at trial, have reduced the likelihood that an injured party will seek legal remedy: Using the logit model they confirm that the presence of the reform is associated with a reduction in the likelihood of a claim being filed. Both aspects of the study are examined using individual data sources from a large sample of claims from 61 insurers in 1992.

An ideal experiment would involve a reference sample that is not affected by the change, and a treatment sample that is; Chiappori et al. [1998] employs this methodology. Following a change in regulation in 1993, French health insurance companies modified the co-payment rate in a non-uniform way. Their data set contains two subgroups, one for which a co-payment rate of 10% for physician visits was introduced and the other for which no change occurred during the period. They test if the number of visits per agent was modified by this co-payment rate. The data reject the hypothesis for office visits but does not for home visits. This suggests that there is moral hazard in demand for some physician services.

My approach is similar to the research noted above. Since regulatory change in Korea now applies to every policyholder uniformly, I do not have reference and treatment samples separately. In this case, as mentioned in Chiappori and Salanie [2003], it may establish a simultaneity rather than a causality. That is, when accident rates significantly change over a given period, and this evolution immediately follows a regulatory reform, the two phenomena might result from simultaneous and independent causes. For instance, the lower accident rates may be due to milder climate conditions. However, I think that external environments such as road condition do not change in a very fast way and, and as a result, I may still test for causality although it is hard to discard such a coincidences entirely.

3.3 Incentive System Change in Korean Car Insurance Market

The new regulation took effect with contracts starting in September 2000. Thus, it was traffic law violations records beginning from May 1999 to the end of April 2000 that were incorporated in the contracts starting from September 2000. Then, the previous 2 years records were reflected in the contracts since 2001. The reference to which this regulatory change is applied *is* the actual policyholders. The sequence is summarised as follows:

- 1999. 4: the introduction of new policy announced
- 1999. 5 - 2000. 4: traffic law violation recorded
- 2000. 9 - 2001. 8: previous year's records reflected
- 2000. 5 - 2001. 4: traffic law violation recorded

- 2001. 9 - 2001. 8: previous 2 years' records reflected

Not all traffic law violations are reflected in the insurance premium. It has been revealed that 6 serious violations are most directly related to car accidents happening[4]. It is those violations that are reflected in the records. Table 2.3 is reproduced below.

cohort	relevant items
penalty group	hit and run, drunk driving and driving without a licence (more than once): 10% trespass of center line, over-speed and traffic signal violation (more than twice): 5%
bonus group	no violations trivial violations that are not recorded

When there is are traffic law violations, the possible increase in insurance premiums is 5% - 15%. However when there is no violation within the contract year, an insurer is allowed to discount the premium within, 10%[5].

As mentioned above, and although there has been some basic research discovering the correlation between traffic law violations and car accident occurrence, there has been no research at the micro level regarding the impact of new regulation on the number of car accidents. Now, 'running' with the assumption that traffic law violations are related to the occurrence of

[4]It has been reported that, in 1995, the number of serious violations are 2.18 million out of total violations numbering 8.54 million: that is almost 25.5%.

[5]During the implementation stage, all the insurance companies set up 0.3% for a bonus. Thus, they have been criticised for being collusive.

accidents, I compare the outcomes from B/A [Before & After] design using the introduction of new regulation to see if individual behaviour in relation to accident probability alters, if anything. Given the exogenous feature of the above regulation change, we may have a 'natural experiment' opportunity. Therefore, I should here focus on the moral hazard phenomenon only.

3.4 Estimations

3.4.1 Parametric Estimation

Methodology

First of all, I estimate the average accident probability using the logit model (Cramer [1991]). In the logit model, the probability of having an accident is given by

$$p_i = \mathrm{E}(y_i = 1|x_i) = \frac{\exp(\alpha + x_i'\beta)}{1 + \exp(\alpha + x_i'\beta)}.$$

Accordingly, we have

$$1 - p_i = 1 - \mathrm{E}(y_i = 1|x_i) = \frac{1}{1 + \exp(\alpha + x_i'\beta)}.$$

Then, we can calculate the odd-ratio

$$\frac{p_i}{1 - p_i} = \exp(\alpha + x_i'\beta).$$

Finally, we derive the log-odds

$$L_i = \ln(\frac{p_i}{1 - p_i}) = \alpha + x_i'\beta.$$

The interpretation of α is the value of log-odds towards having an accident if regressors are zero. This term reflects the difference in levels across time periods in the accident probabilities. My identification of moral hazard is on the change in α over time. If α is decreasing after the introduction of the new incentive scheme, I would say that there *is* a moral hazard problem.

Data

Mainly, I concentrate on data [A] since it includes the contract periods both before and after the implementation of the new regulation. Thus, this data set is ideal for a B/A analysis. However, I also use the data [B] to generate a supplementary outcome. As mentioned in the data section, data [A] is only for young divers aged 18-30 years old at the very first contract year 1998. Since I focus on accident rate changes in subgroups constructed by established individual characteristics, I use regressors such as gear type, ABS equipment, car size and car production year in the parametric estimation. All of them are dummy variables. For data [B], I have a dummy regressor, and car production year for each policyholder in the parametric estimation.

Results

The very first samples that I use in data [A] are the observations from data for those individuals who 'contracted' for 2 years between May 1998 and April 1999 and, subsequently, between May 1999 and April 2000. This time period encompasses the periods both before and after the introduction of the new policy: There are 7,300 policyholders in this category.

The table 3.1 shows the change in the constant term in the logit estimation for each of the subgroups before and after the implementation. The subgroups are constructed by gender and residential location (table B.1 in appendix B). From table 3.1, we can see that there is no impact from the new regulation upon the level of the accident probability. Even so, the constant increased after the introduction of this regulation, apart from MK and FK.

Tab. 3.1: May Results 1

Logit	1998	1999
MS	-2.575006 (0.352)	-2.468639 (0.340)
MK	-2.496618 (0.315)	-2.852130 (0.312)
MKI	-2.101030 (0.279)	-2.075481 (0.268)
MCJ	-2.618433 (0.325)	-2.372962 (0.286)
FS	-2.783250 (0.699)	-2.246137 (0.729)
FK	-2.135783 (0.664)	-3.682417 (1.085)
FKI	-1.588030 (0.514)	-1.267515 (0.458)
FCJ	-3.470858 (1.162)	-1.300422* (0.722)

(standard errors in parenthesis)

* insignificant at 95 % level

To identify further the effects over a given time period, I also perform the same procedure for those who contracted for 3 years: That is between May 1998 and April 1999, between May 1999 and April 2000, and between May 2000 and April 2001: There are 4,560 policyholders included in this group.

Again, we can observe that the constant terms slightly increase year by year, after implementation for most subgroups as seen in table 3.2.

Now, I investigate the effect on those who contracted for [4] years. There are 2,568 policyholders in this category. Over time, the constant terms more or less increased again. Here, in table 3.3, I report for only male subgroups

Tab. 3.2: May Results 2

Logit	1998	1999	2000
MS	-2.829122 (0.469)	-2.275663 (0.410)	-2.506132 (0.396)
MK	-2.482830 (0.412)	-3.013533 (0.436)	-3.629039 (0.535)
MKI	-2.389946 (0.380)	-2.271980 (0.385)	-2.016814 (0.339)
MCJ	-2.799210 (0.415)	-2.637945 (0.401)	-2.163179 (0.339)
FS	-3.451613 (1.028)	-2.743998 (1.263)	-0.958689* (0.803)
FK	-2.408277 (0.460)	-2.57477 (0.484)	-2.638594 (0.553)
FKI	-1.501551 (0.677)	-0.943520* (0.620)	-3.589317 (0.963)
FCJ	-3.314352 (1.304)	-1.723058* (0.919)	-2.012149 (0.886)

* insignificant at 95 % level

because the number of female samples are too small to have reasonable estimates in the parametric estimation. I complement this with nonparametric results

Finally, I implement the estimation using those who contracted for [3] years. These observations began contracts beginning from May 1999 on-

Tab. 3.3: May Results 3

Logit	1998	1999	2000	2001
MS	-2.143663 (0.615)	-3.319481 (0.841)	-2.263120 (0.581)	-1.833864 (0.510)
MK	-2.663637 (0.623)	-3.592095 (0.714)	-3.446649 (0.806)	-1.857960 (0.466)
MKI	-2.969292 (0.769)	-2.089851 (0.550)	-1.493743 (0.409)	-1.557476 (0.414)
MCJ	-2.140236 (0.529)	-3.439654 (0.757)	-2.373685 (0.499)	-1.697384 (0.475)

Tab. 3.4: Overall Results A

Logit	1999	2000	2001
MS	-2.521661 (0.282)	-2.139879 (0.247)	-1.862629 (0.223)
MK	-2.489937 (0.252)	-2.306955 (0.242)	-2.180988 (0.215)
MKI	-2.057032 (0.247)	-1.907823 (0.216)	-1.585742 (0.187)
MCJ	-2.673128 (0.281)	-2.604255 (0.273)	-2.037970 (0.222)
FS	-2.763816 (0.570)	-2.344158 (0.528)	-1.392573 (0.463)
FK	-2.495490 (0.621)	-3.876313 (0.790)	-2.091269 (0.485)
FKI	-2.024095 (0.456)	-1.734645 (0.454)	-1.545056 (0.434)
FCJ	-1.803356 (0.524)	-2.252885 (0.560)	-1.285957 (0.407)

wards. These contracts are all affected by the introduction of the new policy: there are 10,580 policyholders in all. In this estimation, I use the samples contracted in May and June for each year to have complete spells for 3 years (please note that the last contract year in the data is truncated at the end of June).

In this outcome, not a single subgroup seems to be affected by the new regulation. Overall we do not see any significant change in the constant term from the logit estimations.

Additionally, I present the outcome for data [B] in table B.3 in appendix B. I have 34,328 observations initially contracted between May and September [1999]. Here, I have similar patterns to outcomes from data [A] apart from MMS, FMS and MuMS for which the constant terms decreased. However, overall, we again observe that there is no such change in constant term for logit estimation.

3.4.2 Nonparametric Estimation

Methodology

In this section, I implement the simple nonparametric analysis (Ichimura [2005]) using the same data set as used in the previous section.

For $i = 1, ..., n$ and a random variable Y_i and a K-dimensional random vector X_i, and $m(x) = E(Y_i|X_i = x)$,

$$Y_i = m(X_i) + \epsilon_i$$

$$E(\epsilon_i|X_i) = 0$$

$$E(\epsilon_i^2|X_i) \leq C < \infty.$$

I consider estimation of a function $m(\cdot) : R^K \to R$.

Let x be a point we wish to evaluate function $m(\cdot)$ at. In this case, what I want to estimate is $m(x)$, and that is just one number I want to estimate. Assume for a moment that X_i has repeated observations at x. Then,

$$\frac{\sum_{i=1}^{n} Y_i 1\{X_i = x\}}{\sum_{i=1}^{n} 1\{X_i = x\}}$$

would be a natural estimator of $m(x)$. In fact, if each element of K-vector is a discrete random variable, then I can estimate $m(\cdot)$ by the method just described. I just calculate cell means for each x.

I calculate average probability of accident for each subgroup described in the appendix and compare the accident probabilities over time.

Results

Through table 3.5 and table 3.8, I present the cell means for each subgroup over time. The outcomes display very similar patterns to the outcomes of the parametric estimation. That is, there is no such change in accident probability over time before and after the introduction of the new regulation.

There are some subgroups that exhibit possible effects: These are similar to the outcomes from the parametric estimation, in table 3.5, the average probability of accident decreased for FS and FK. However, in the subsequent tables, I cannot discover any substantial decrease in accident probability.

Again, the outcomes for data set [B] are presented in table B.4 in appendix B. For this particular sample, there is no effect at all.

Tab. 3.5: May Results1 A

Nonparametric	1998	1999
MS	0.07585	0.08149
MK	0.04778	0.06225
MKI	0.08328	0.08814
MCJ	0.06559	0.07605
FS	0.09810	0.06940
FK	0.06905	0.05755
FKI	0.10109	0.13388
FCJ	0.06620	0.08997

Tab. 3.6: May Results2 A

Nonparametric	1998	1999	2000
MS	0.07227	0.07537	0.08684
MK	0.04352	0.05535	0.04758
MKI	0.08297	0.08038	0.09129
MCJ	0.06279	0.07168	0.08108
FS	0.08780	0.06220	0.08134
FK	0.06498	0.06593	0.03636
FKI	0.11354	0.13656	0.06087
FCJ	0.04972	0.08743	0.08427

Tab. 3.7: May Results3 A

Nonparametric	1998	1999	2000	2001
MS	0.06651	0.05854	0.08983	0.10096
MK	0.02673	0.04581	0.04107	0.07643
MKI	0.04724	0.06464	0.10425	0.10795
MCJ	0.04771	0.04008	0.08097	0.08266
FS	0.05738	0.04237	0.08403	0.12069
FK	0.05479	0.07857	0.02920	0.07914
FKI	0.06349	0.13636	0.06015	0.10563
FCJ	0.00943	0.07273	0.08411	0.05825

Tab. 3.8: Overall Results A

Nonparametric	1999	2000	2001
MS	0.08519	0.09802	0.11927
MK	0.06474	0.06954	0.09512
MKI	0.09351	0.09951	0.13416
MCJ	0.06497	0.07067	0.09598
FS	0.09216	0.10338	0.12449
FK	0.07061	0.06755	0.09516
FKI	0.13419	0.11131	0.11321
FCJ	0.08054	0.07901	0.10502

3.5 Discussions

As can be seen from the results in the previous section, I conclude that there has been no significant effect concerning the introduction of new regulation on accident probabilities apart from a few subgroups (mainly women in some regions). Further, for some additional robustness, I also implement both parametric and nonparametric estimations for young drivers (defined by contract experience coefficient). From my point of view, it may be the case that old drivers (those who have driven a car for a long time) find it difficult to change their driving behaviour in response to the incentive system change. However, the results here display similar patterns to my previous results. As a result, we could say that there is not any phenomenon such as moral hazard in the car insurance market. Then, as many people have sought to critically point out, the net effect of the new regulation may have only been to increase insurance companies revenues without significantly reducing accident probability.

However, there should be some caution in putting forward this conclusion. In particular, in order to question this, I may need to propose a question such as:- whether the premium increase, due to traffic law violations, has been high enough to induce the drivers to change their habits. As the FSS have repeatedly announced the amount of premium increase due to traffic law violations in the new regulation may not have been effective at all. This may be shown by the following table which shows the penalty system of other countries where a similar system has been developed.

Tab. 3.9: Penalty System in Other Countries

	U.S	U.K.	Canada
penalty group	drunk driving, driving without a licence	drunk driving, over-speed, signal violation,	drunk driving, no seat belt, over-speed, driving without a licence
penalty rate	40-220%	25-50%	25-250%
application period	3 years	5 years	

As we can observe from this table, penalty rates are much higher than the rates in Korean system. Further, there is no bonus rate for those who keep to the traffic laws. Thus, given that the current penalty rates are not sufficiently punitive to induce change in driver behaviour, the FSS introduced a stronger incentive system in 2005. This has strengthened the current system in several ways:

First of all, and markedly different from the last system, it widens the relevant penalty group. In addition to [6] serious violations, a few more violations such as: protection of pedestrians, and overtaking laws have been included.

Secondly, in the modified regulation, the number of violations matter. Thus, it is 10% if there is one violation of the relevant law, this increases to 20% for 2 violations with a maximum possible penalty rate of 30%.

Finally, the application period is made longer, up to [3] years rather than the current [2] years.

My final judgement on the presence of moral hazard may be subject to future research: productively focussing on the effects of a modified and much stronger incentive system with regards to accident probability. If future research shows no evidence of hidden action, - from a policyholder perspective - then there *should* be a dramatic change in policy within the car insurance market.

Chapter 4

Tests for Moral Hazard and Adverse Selection in the Car Insurance Market

4.1 Introduction

Recent literature on empirical contract theory has been rapidly growing. Particularly, most empirical work has been facilitated by an intense use of insurance data sets. Here the primary concern has been to detect the presence of such phenomenon as moral hazard and adverse selection or both. In this chapter I attempt to contribute to the direction of this research using the Korean car insurance data set. Much research so far has investigated the relationship between contract choice and ex-post accident occurrence ('conditional correlation approach') in the car insurance market, most notably, Chiappori and Salanie [2000]. Here, in this chapter, I am taking a slightly different approach yet exploring the same problem.

Firstly, addressing the 'moral hazard phenomenon', with the aid of an enriched data set I perform a simple test where I analyse the relationship between a particular policyholder contract choice and their car value. In the Korean car insurance market policyholders can freely choose insurance coverage among six coverage types[1]. Here I focus on the choice of insurance coverage that specifically covers damage on the policyholder's own car. Chiefly, I investigate whether the choice of this particular coverage 'monotonically' increases in the car value. My intuition is that if policyholders cannot adjust their behaviour it would be rational for them to buy coverage for car damage when the car value is high. For this purpose, I use those who purchased all 6 coverage types and those who purchased all but the coverage that covers damage on the policyholder's own car. Then, I want to see whether the number of people in the first group is substantially higher as the car values increase.

A natural consequence of this, I estimate the distribution of car values, and I compute the proportion of the 2 policyholder groups in each quantile of the distribution. However, I need to solve a missing data problem in the estimation. Since the insurance company does not record car values for those who do not purchase car damage coverage, I face missing data problem as described in Manski [1994], Manski [1995] and Manski [2003]. To solve this problem, I use the bounds approach on the car value distribution. Using the bounds approach, I estimate the car distribution and compute the corresponding qunatiles in a nonparametric way.

Next, I implement a simple test to detect the presence of unobserved heterogeneity in risk levels across policyholders using conditional variance

[1] This is explained in detail in section 2.2, chapter 2.

identity. The idea is that, under *no* unobserved heterogeneity, the variance of accident occurrence is not attributed to the differences in accident probability across policyholders. Since adverse selection happens when there is a difference in policyholder risk levels, this process is a reasonable substitute for testing for the presence of adverse selection. Using repeated cross sectional samples, I compute the overall variance of accident occurrence probability over the entire sample and investigate how much the differences across policyholders contribute to the volatility of accident occurrence.

In what follows, I present the two works described above. Then working through each section in turn I describe the characteristics of the data used, the estimation methods, and the results.

4.2 Moral Hazard

4.2.1 Theoretical Basis

Here I follow a standard insurance economics model (for instance, see Mossin [1968] and Borch [1990]). Consider a policyholder owning and driving a car the value of which is V. In addition, he owns wealth with a total amount of y. It is assumed that during any specified time interval the car value will either be lost with probability p or suffer no damage at all with probability $1-p$ and the policyholder has the possibility of insuring his own car. The premium he would have to pay is denoted by q. The policyholder is assumed to be risk averse ($u'(\cdot) > 0$ and $u''(\cdot) < 0$).

The policyholder can freely choose the amount of insurance coverage.

Here, I define the contract that covers owner car damage as comprehensive. Otherwise, it is a non-comprehensive contract. Therefore, if s/he purchases comprehensive insurance, it would cover the damage to his/her own car when there is accident occurrence.

When a policyholder purchases non-comprehensive insurance, the expected utility is given by

$$\mathrm{EU}^{nc} = u(y_i - V_i - q_i^{nc})p_i^{nc} + u(y_i - q_i^{nc})(1 - p_i^{nc}),$$

where nc denotes a non-comprehensive insurance. The probability is superscripted by nc, which shows the induced probability by the given insurance coverage under the presence of moral hazard.

However, if he instead decides to buy comprehensive coverage, it becomes[2]

$$\mathrm{EU}^{c} = u(y_i - d_i - q_i^{c})p_i^{c} + u(y_i - q_i^{c})(1 - p_i^{c}).$$

When a policyholder buys a comprehensive policy, s/he can also choose the level of deductibles. Then, the reimbursement given to a policyholder, when there is an accident, becomes[3]:

$$R = \begin{cases} 0 & \text{if } L < d \\ L - d & \text{if } L \geq d \end{cases}$$

In the static framework, the condition for a policyholder's choosing non-comprehensive insurance contract is

$$u(y_i - d_i - q_i^{c})p_i^{c} + u(y_i - q_i^{c})(1 - p_i^{c}) \leq u(y_i - V_i - q_i^{nc})p_i^{nc} + u(y_i - q_i^{nc})(1 - p_i^{nc}).$$

[2] We could alternatively express $q_i^c = q_i^{nc} + q_i$, where q_i is an additional premium for coverage on owner car damage. Notice that q_i is a function of car value. However, this component is not linear in a car value.

[3] This system is called straight deductible (Lee et al. [1999]).

I state that there is no moral hazard if $p_i^c = p_i^{nc}$[4]. That is, there is no induced difference in the accident probability in both cases. Under this condition, if there is no moral hazard, I can derive the following conditions

1. $V_i + q_i^{nc} \leq d_i + q_i^c$

2. $q_i^{nc} \leq q_i^c$.

The second condition here is trivially satisfied and so I focus on the first condition, which functions as a base for the empirical work.

TESTABLE PREDICTION: If there is no moral hazard and car value is quite low being close to the deductible amount given that there is a difference in premiums between [2] different types of contract, it is rational for a policyholder to purchase a non-comprehensive contract. The testable implication is that the number of people who purchase cover for own car damage is quite small in the bottom quantiles of car value distribution and substantially higher in the upper quantiles.

In reality, this argument makes sense because if the car value is not so high it would be better to abandon the car rather than fixing and using it again. Under this circumstance, it is not rational to pay an additional premium to buy comprehensive coverage. However, it is worth buying the comprehensive for those who have high value cars in the presence of no moral hazard.

[4]In this case, when we assume the additive separable effort cost function, they are canceled out on both sides.

4.2.2 Data Description

In this analysis, as mentioned above, I define comprehensive coverage as purchasing all the coverage types and the non-comprehensive coverage as buying all but coverage [4].

With these coverage types, for my analysis, I use one (data A) of 2 data sets that I have obtained since the other data set (data B) does not contain information on the car values[5]. In my work, I use the contracts that were written between 01/01/1998 and 31/12/1998 (contract year 1998) from company [A]. In this sample, the contract choices are given by table 4.1[6]. The numerical value corresponds to the coverage type given in the table 2.1 in chapter 2. For instance, 123456 means that the policyholder purchased all 6 coverage.

In this sample, I use 123056 and 123456. The only difference between them is a purchase of coverage [4] that covers damage or theft on a policyholder's own car. As can be seen, these policyholders consist of nearly 80% of the total sample.

Next, I present the deductible choices among 123456 policyholders. Deductible choices available to policyholders are shown in the table 4.2[7].

[5]So far, only the Israeli data in Cohen [2005] contains information of car values. However, this data has only comprehensive contracts.

[6]As supplementary information, I also present the contract choices in data from company [B] in appendix C. We can see that this data set also displays a similar pattern as data [A]. The only difference is that, in data [B], the number of people who purchased compulsory coverage only is quite substantial.

[7]KW means Korean Won, which is the Korean currency unit. GBP is calculated using yearly average exchange rate in 1998.

Tab. 4.1: Tabulation of Coverage Choices

cover	Freq	Percent	Cum
100000	10	0.00	0.00
103000	1	0.00	0.01
103050	1	0.00	0.01
120000	15	0.01	0.01
123000	14,582	7.19	7.20
123050	26,518	13.07	20.27
123056	73,884	36.41	56.67
123400	310	0.15	56.82
123450	294	0.14	56.97
123456	87,325	43.03	100.00
Total	202,940	100.00	

Tab. 4.2: Tabulation of Deductible Choices

Deductible	Freq	Percent	Cum
0	8	0.01	0.01
KW 50,000 (22 GBP)	82,453	94.42	94.43
KW 100,000 (44 GBP)	2,733	3.13	97.56
KW 200,000 (88 GBP)	407	0.47	98.03
KW 300,000 (132 GBP)	1,109	1.27	99.30
KW 500,000 (220 GBP)	615	0.70	100.00
Total	87,325	100.00	

As shown, there are 5 types of deductible choice. It is shown that majority of the policyholders chose the lowest amount of deductible[8]. Due to this phenomenon, I perform my analysis based on the lowest deductible choice.

4.2.3 Nonparametric Analysis using Bounds

Mainly, I want to see changes in the ratio between 123056 and 123456 as car values increase. However, with obvious reason[9], the insurance company does not record information on car values for 123056 group. Therefore, the missing data problem naturally arises. As a result, I use 'bounds' on the car value distribution. Particularly, I compute bounds on the quantiles of the car value distribution for each cell. I make the small cells according to various individual characteristics and a car characteristic. Then, in the distribution, if the number of policyholders who purchased coverage for their own car damage is increasing, I may conclude that there is no moral hazard. My analysis is based on some previous research such as Manski [1994], Manski [1995] and Blundell et al. [2006][10].

In this section, I analyse car value dispersion allowing for the sample selection induced by individuals' non-purchase of coverage for own car damage. Further, I use bounds to the car value distribution and its quantiles to address the issue of selection without relying on strong assumptions.

First, I denote some variables as follows:

[8]In this respect, there has been a concern in the Korean insurance industry that the deductible does not work as it is supposed to.

[9]In case of an accident, the company does not have to cover the damage to the car.

[10]Also, Lee [2005] discusses the same problem in the program evaluation context.

- V: the dependent random variable
- X: the conditioning vector
- C indicates whether the individual purchases coverage for own car damage
- $P(C = 1|x)$: the probability of $C = 1$ given $X = x$
- $F(v|x)$: the cumulative distribution function (CDF) of V given $X = x$
- $F(v|x, C = 1)$: the CDF of V given $X = x$ and $C = 1$
- $F(v|x, C = 0)$: the CDF of V given $X = x$ and $C = 0$.

$F(v|x)$ is the object of our interest. However, it is not identified because of non-random sample selection. The sampling process does identify the selection probability $P(C = 1|x)$, the censoring probability $[1 - P(C = 1|x)]$, and the measure of v conditional on selection, $F(v|x, C = 1)$ below.

$$F(v|x) = F(v|x, C = 1)P(C = 1|x) + F(v|x, C = 0)[1 - P(C = 1|x)].$$

This is uninformative regarding the measure of v conditional on censoring, which is $F(v|x, C = 0)$. To overcome this problem, I use the worst case bounds, which is the most conservative one given that no other prior information on the distribution is available.

Worst case bounds

If I use the following inequality

$$0 \leq F(v|x, C = 0) \leq 1,$$

then, the bounds to the cumulative distribution function become:

$$F(v|x, C = 1)P(C = 1|x) \leq F(v|x) \leq F(v|x, C = 1)P(C = 1|x) + [1 - P(C = 1|x)].$$

The bounds then can be translated to give the worst case bounds on the conditional quantiles. Denoting by $v^q(x)$ the qth quantile of $F(v|x)$, we have

$$v^{q(l)}(x) \leq v^q(x) \leq v^{q(u)}(x),$$

where $v^{q(l)}(x)$ is the lower bound and $v^{q(u)}(x)$ is the upper bound that solve the equations

$$q(u) = F(v|x, C = 1)P(C = 1|x) \text{ and } q(l) = F(v|x, C = 1)P(C = 1|x) + [1 - P(C = 1$$

with respect to v, respectively. As known, unless there are restrictions on the support of V, we can only identify $q(l) \geq 1 - P(C = 1|x)$ and $q(u) \leq P(C = 1|x)$. Thus, when $P(C = 1|x)$ is higher, the bounds on quantiles become tighter.

Estimation

I estimate the bounds to the distribution of car values to compute the bounds to the quantiles using non-parametric methods proposed by Blundell et al. [2006].

The dependent variable is the car value. The conditioning vector includes policyholder's gender, policyholder's place of residence, car size (measured by CC) and car age, and gear type.

I construct the cells as follows. Regarding individual characteristics, I have [2] gender groups and [2] residential groups. For tractability, I divide the place of residence into the capital city areas and other areas. For a car characteristic, I have [4] car size groups and [3] car age groups. Additionally, I include [2] gear type groups. This is summarized in the table C.2 in the appendix C. Overall, I construct 96 cells.

Then, the probability of purchasing coverage [4] with characteristics x_k is estimated by

$$P(x_k) = \frac{\sum_{i=1}^{N} I(C_i = 1)\kappa_k(x_i)}{\sum_{i=1}^{N} \kappa_k(x_i)},$$

where $I(A)$ is the indicator function which equals one whenever A holds and the weights are defined by

$$\begin{aligned} \kappa_k(x_i) &= I(gender_i = gender_k)I(residence_i = residence_k)I(carsize_i = carcize_k) \\ & \quad I(carage_i = carage_k)I(geartype_i = geartype_k). \end{aligned}$$

This is just the calculation of cell means for each x_k.

To estimate empirical distribution of car values, I allow for smoothing. Thus, the estimator is given by

$$F(v|C_i = 1, x_k) = \frac{\sum_{i=1}^{N} \Phi(\frac{v-v_i}{h})I(C_i = 1)\kappa_k(x_i)}{\sum_{i=1}^{N} I(C_i = 1)\kappa_k(x_i)},$$

where Φ is a standardized normal CDF and a bandwidth, h, is set at a fifth of the standard deviation of car values.

4.2.4 Results

As described in the previous section, I have total 96 cells. Among them, 33 cells have a very low probability of purchasing the coverage [4]. Therefore, for those cells, quantiles are poorly identified. However, in the remaining 63 cells, I have fairly tight bounds. In this section, I present results for some cells because all the results display similar patterns. First, I present the result for those who are male and live in the capital city areas. The car characteristics for them are that the cars were made before 1995, the car size is equal to or greater than 1500CC and less than 2000CC, and the gear type is auto or semi-auto. This is presented in table 4.3.

Tab. 4.3: Upper and Lower Bounds for Quantiles

Quantile	Lower	Upper
10th quantile		KW 1,490,169 (£643)
20th quantile		KW 2,069,050 (£893)
30th quantile	KW 1,021,518 (£441)	KW 2,637,653 (£1,138)
40th quantile	KW 1,650,849 (£712)	KW 3,198,204 (£1,380)
50th quantile	KW 2,227,076 (£961)	KW 3,752,002 (£1,619)
60th quantile	KW 2,791,250 (£1,205)	KW 4,426,413 (£1,910)
70th quantile	KW 3,350,433 (£1,446)	KW 6,584,968 (£2,842)
80th quantile	KW 3,912,942 (£1,689)	
90th quantile	KW 4,699,657 (£2,028)	

Given this result, I first compute the number of policyholders who purchased 123456 coverage in each 10% in the estimated distribution using upper bounds. In this cell, it is given by 140, 151, 148, 142, 143, 158 and 141. Next, I also compute the same numbers using lower bounds. It is 145, 149, 152, 130, 176, 147 and 125. This is summarized in table 4.4. Notice that, in my testable prediction under *no* moral hazard, it must be seen that there are small number of policyholders who purchase the additional coverage [4] with low valued cars whereas there are large number of policyholders with

Tab. 4.4: Frequency of Purchasing Coverage 4

Values (£)	Lower	Values (£)	Upper
441 - 712	145	- 643	140
712 - 961	149	643 - 893	151
961 - 1,205	152	893 - 1,138	148
1,205 - 1,446	130	1,138 - 1,380	142
1,446 - 1,689	176	1,380 - 1,619	143
1,689 - 2,028	147	1,619 - 1,910	158
2,028 -	125	1,910 - 2,842	141

high valued cars in the upper quantiles. However, the number of people who bought this coverage is more or less uniform. Thus, we tend to reject the null hypothesis that there is no moral hazard.

I present some more results to see the similar changes for different car value levels. In what follows, the first one is for those who are male and live in the capital city areas. The car characteristics for this cell is that the cars were made before 1995, the car size is between 1000CC and 1500CC, and the gear type is manual. The second one is for those who are male and live in the capital city areas. The car characteristics are that the cars were made between 1995 and 1996, the car size is between 1500CC and 2000CC and the gear type is auto or semi-auto. Qualitatively, the results for these cells also show the similar results as the first cell.

I present some more results for female policyholders in appendix C.

Tab. 4.5: Upper and Lower Bounds for Quantiles

Quantile	Lower	Upper
10th quantile		KW 822,662 (£355)
20th quantile		KW 1,160,997 (£501)
30th quantile		KW 1,452,985 (£627)
40th quantile	KW 748,057 (£323)	KW 1,726,433 (£745)
50th quantile	KW 1,096,111 (£473)	KW 1,995,247 (£861)
60th quantile	KW 1,395,051 (£602)	KW 2,326,629 (£1,004)
70th quantile	KW 1,673,134 (£722)	
80th quantile	KW 1,939,630 (£837)	
90th quantile	KW 2,245,522 (£969)	

Tab. 4.6: Frequency of Purchasing Coverage 4

Values (£)	Lower	Values (£)	Upper
323 – 473	1355	0 – 355	1347
473 – 602	1403	355 – 501	1421
602 – 722	1431	501 – 627	1348
722 – 837	1282	627 – 745	1328
837 – 969	1513	745 – 861	1480
969 –	1316	861 – 1004	1561

Tab. 4.7: Upper and Lower Bounds for Quantiles

Quantile	Lower	Upper
10th quantile		KW 4,651,964 (£2,007)
20th quantile	KW 3,471,162 (£1,498)	KW 5,231,978 (£2,258)
30th quantile	KW 4,665,008 (£2,013)	KW 5,714,401 (£2,466)
40th quantile	KW 5,242,453 (£2,262)	KW 6,218,256 (£2,683)
50th quantile	KW 5,723,551 (£2,470)	KW 6,775,339 (£2,924)
60th quantile	KW 6,229,459 (£2,688)	KW 7,449,817 (£3,215)
70th quantile	KW 6,786,867 (£2,929)	KW 8,429,938 (£3,638)
80th quantile	KW 7,466,224 (£3,222)	KW 13,189,083 (£5,691)
90th quantile	KW 8,455,266 (£3,649)	

Tab. 4.8: Frequency of Purchasing Coverage 4

Values (£)	Lower	Values (£)	Upper
1,498 – 2,013	194	– 2,007	198
2,013 – 2,262	211	2,007 – 2,258	202
2,262 – 2,470	232	2,258 – 2,466	215
2,470 – 2,688	160	2,466 – 2,683	176
2,688 – 2,929	232	2,683 – 2,924	234
2,929 – 3,222	210	2,924 – 3,215	216
3,222 – 3,649	230	3,215 – 3,638	229
3,649 –	192	3,638 – 5,691	190

4.2.5 Discussions

Naturally, it could be asked why those who with low valued cars purchase the coverage 4 if there was no hidden action on the policyholders' side. Are they really wiling to fix a car and drive it again when there is an accident? Further, it increases the next year's premium by 10% when they use own car damage coverage. It may be very unlikely. However, there is a case where this sort of policyholders may have a gain. That is, total loss. This is defined as cash reimbursement because the accident is not repairable or fixing cost is greater than the car value. In my data, it is clearly shown as in table 4.9 that this indeed happens[11].

Tab. 4.9: Proportion of Total Loss

Values (£)	Total Loss/Total Number of Accident
0 - 355	0.41
355 - 501	0.24
501 - 627	0.25
627 - 745	0.17
745 - 861	0.12
861 - 1,004	0.05

In this respect, I could say that there may be moral hazard phenomenon at least in the bottom quantiles[12].

[11]There may be an argument that low car value is more likely to be declared a total loss without any effects on policyholder's behaviour. But, for a policyholder with a low car value, purchasing coverage for own car damage would cause a change in his behaviour since he knows that any accident occurrence will benefit him.

[12]Recently, I have found out the following sort of news articles quite frequently: "It has been reported that the car insurance companies are reluctant to insure own car damage

Overall, and with regards to the future research, I need to take explicit account of contract choice and effort choice in the dynamic context to have a more comprehensive picture (for instance, interaction between effort cost and accident severity or/and future premium increase and one shot gain from cash reimbursement). The latter component would determine not only accident occurrence but also the severity of an accident. For this purpose, the fully structural estimation based on dynamic programming seems promising[13].

4.3 Adverse Selection

4.3.1 Test Statistic

In this section, I investigate whether there is such a difference in policyholders' risk level. For this purpose, I use the following conditional variance identity theorem (Casella and Berger [2002]):

$$\mathrm{Var}(D_{it}) = \mathrm{E}[\mathrm{Var}(D_{it}|i)] + \mathrm{Var}[\mathrm{E}(D_{it}|i)],$$

where D_{it} is a binary random variable which takes [1] if there is an accident and [0] otherwise.

Given this, I state that adverse selection is very unlikely if $p_i = p$. That is, the accident probability is not different across policyholders. This is translated as $\mathrm{Var}[\mathrm{E}(D_{it}|i)] = 0$ in the theorem above.

To investigate this, I compute the following formula corresponding to the

for those whose car value is quite low." – Seoul Economic Daily (6 Feb 2006).

[13]The above listed developments are part of my future research.

right hand side and the first term on the left hand side of the identity

$$\frac{1}{nT}\sum_{i,t}(D_{it} - D_{..})^2 - \frac{1}{n}\sum_{i=1}^{n}(\frac{1}{T}\sum_{t=1}^{T}(D_{it} - D_{i.})^2),$$

where n is a number of policyholders, T is a time period, $D_{..}$ is an average accident occurrence across time and individual $D_{i.}$ is an average accident occurrence across time.

If this is close to zero, this implies that there may not be such a difference in the risk levels.

4.3.2 Data and Results

In the same data set A, I select the policyholders who repeatedly purchased insurance contracts over [4] contract years. I have 14,495 policyholders in this category.

Using this sample, I calculate the following magnitudes.

$$\text{Var}(D_{it}) = \frac{1}{nT}\sum_{i,t}(D_{it} - D_{..})^2 = 0.066748671$$

and

$$\text{E}[\text{Var}(D_{it}|i)] = \frac{1}{n}\sum_{i=1}^{n}(\frac{1}{T}\sum_{t=1}^{T}(D_{it} - D_{i.})^2) = 0.066449051.$$

The difference between them is 0.00029962. This amount is very close to zero. Also, the variance of accident occurrence is explained 99.55% by the first argument of the identity.

As a complementary work, I implement the same procedure using more data. In the same data set [A], I select those who bought insurance contracts repeatedly over 3 years (1999–2001). I have 32,491 policyholders in this group. The result using this sample displays a similar result

$$\mathrm{Var}(D_{it}) = \frac{1}{nT}\sum_{i,t}(D_{it} - D_{..})^2 = 0.083104449$$

and

$$\mathrm{E}[\mathrm{Var}(D_{it}|i)] = \frac{1}{n}\sum_{i=1}^{n}(\frac{1}{T}\sum_{t=1}^{T}(D_{it} - D_{i.})^2) = 0.082955403.$$

Again, this amount is very close to zero. Also, the variance of accident occurrence is explained 99.82% by the first argument of the identity.

For one more complementary work, I implement the same procedure using additional data. In the same data set [A], I select those who bought insurance contracts repeatedly over 3 years (1998–2000). I have 63,376 policyholders in this group. The result using this sample displays the similar result.

$$\mathrm{Var}(D_{it}) = \frac{1}{nT}\sum_{i,t}(D_{it} - D_{..})^2 = 0.074124326$$

and

$$\mathrm{E}[\mathrm{Var}(D_{it}|i)] = \frac{1}{n}\sum_{i=1}^{n}(\frac{1}{T}\sum_{t=1}^{T}(D_{it} - D_{i.})^2) = 0.074063946.$$

Again, this amount is very close to zero. Also, the variance of accident occurrence is explained 99.92% by the first argument of the identity.

Further, it may be interesting to see whether there is a difference among young drivers (possibly, due to the lack of driving experience). Thus, I compute what I have done before for young drivers. I have 2,019 policyholders who repeatedly purchased over [4] contract years

$$\mathrm{Var}(D_{it}) = \frac{1}{nT}\sum_{i,t}(D_{it} - D_{..})^2 = 0.081916245$$

and

$$\mathrm{E}[\mathrm{Var}(D_{it}|i)] = \frac{1}{n}\sum_{i=1}^{n}(\frac{1}{T}\sum_{t=1}^{T}(D_{it} - D_{i.})^2) = 0.081816357.$$

The variance of accident occurrence is explained 99.88% by the first argument of the identity.

Also, I have 6,951 policyholders who repeatedly purchased over [3] contract years (1999–2001)

$$\mathrm{Var}(D_{it}) = \frac{1}{nT}\sum_{i,t}(D_{it} - D_{..})^2 = 0.104527981$$

and

$$\mathrm{E}[\mathrm{Var}(D_{it}|i)] = \frac{1}{n}\sum_{i=1}^{n}(\frac{1}{T}\sum_{t=1}^{T}(D_{it} - D_{i.})^2) = 0.104465544.$$

The variance of accident occurrence is explained 99.94% by the first argument of the identity.

Further, there are 9,755 policyholders who repeatedly purchased over [3] contract years (1998–2000)

$$\mathrm{Var}(D_{it}) = \frac{1}{nT}\sum_{i,t}(D_{it} - D_{..})^2 = 0.092301588$$

and

$$\mathrm{E}[\mathrm{Var}(D_{it}|i)] = \frac{1}{n}\sum_{i=1}^{n}(\frac{1}{T}\sum_{t=1}^{T}(D_{it} - D_{i.})^2) = 0.092299402.$$

Again, this amount is very close to zero. Also, the variance of accident occurrence is explained 99.99% by the first argument of the identity.

From the results, we could state that there can be *no* adverse selection problem on the risk.

4.4 Conclusion

In this chapter, I have examined the existence of asymmetric information in the car insurance market.

Firstly, different from the conventional approach, I have investigated the existence of moral hazard phenomenon through the particular contract choice. So far, most research has focused on the relationship between contract choice and ex-post accident occurrence. Then, with this line of enquiry, it is feasible to identify the existence asymmetric information only using the conditional correlation method. In my own work here, it has been possible to focus on the moral hazard problem separately even in the static framework. Using the simple theoretical prediction, I have analysed whether the purchase of the particular coverage covering my own car damage increases in the car values under the hypothesis of *no* moral hazard. It appears that, in the Korean market, this purchase is more or less uniform in every cell that I have estimated; thus, likely to reject the null hypothesis.

Secondly, I also separately test for the existence of differences in the policyholder risk level (the main cause of adverse selection) in the car insurance market. I have attempted to find out whether there is a difference in policyholder accident probability using conditional variance identity. With access to the repeated cross sectional data I have computed the relevant quantities in the identity and have discovered that the variance of accident occurrence across policyholders and time is very unlikely to be attributed to the differences in policyholders.

Overall, my findings seem to be consistent with other results from empirical contract theory using car insurance data sets (see Chiappori [2000]). Most of them suggest that adverse selection may be no longer a problem by introducing very sophisticated prior screening devices. However, some research has detected the presence of moral hazard, which is the case here in my work.

CHAPTER 5

CONCLUSION

This thesis has investigated the presence of asymmetric information in the car insurance market using [2] panel data sets obtained from [2] leading insurance companies in Korea.

In the first chapter, I have attempted to fit my data set to the leading empirical strategies proposed within the field of empirical insurance economics. Initially, I have implemented the conditional correlation approach; from this work I have obtained fairly interesting results: unlike most research that adopts similar methods, I have discovered evidence for the presence of asymmetric information in this static framework. That is, it turns out that there is a positive correlation between contract choice and accident occurrence controlling for observable characteristics. Secondly, with regards to dynamic empirical contract theory, I have implemented occurrence dependence methodology. In this work I discovered the negative occurrence dependence phenomenon that is different from the findings of *no* moral hazard by the original authors. Finally, I have implemented a model based on Granger causality. This methodology has been made possible with a panel data set.

In accordance with the original authors, I have found evidence for the presence of dynamic moral hazard. Also, regarding contemporaneous asymmetric information, my results are consistent with the initial research where I also discovered the presence of asymmetric information. Overall, considering all the implementations, I have consistently discovered evidence for the presence of asymmetric information in the static framework, and evidence of the dynamic moral hazard in the dynamic framework.

In the second chapter, I have investigated the effects of the introduction of a stronger incentive system on the policyholder behaviour. As seen from the results by logit and non-parametric estimations, there was no such a change in accident occurrence before and after the introduction of the new regulation. In this respect, I may conclude that there is no such a phenomenon as moral hazard in the car insurance market. However, some may question whether the premium increase due to traffic law violations has been set high enough to induce changes in driver behaviour: That is the amount of premium increase due to traffic law violations in the new regulation may simply have not been effective on policyholder behaviour at all. Consequently there was a review, and an enhancement for this incentive system in 2005. Thus, there will be a further opportunity to reinvestigate the impact of this sort of exogenous institutional change in the future.

In the third chapter, and quite different from the previous approaches, I have investigated the presence of the moral hazard phenomenon that utilises particular contract choice. Based on a simple theoretical prediction, I have examined whether the purchase of particular coverage for own car damage increases in car value under the hypothesis of *no* moral hazard. It appears that this purchase is more or less uniform in the distribution of car value, for every cell that I have estimated using bounds approach. Therefore, it is likely for the moral hazard phenomenon to exist in the car insurance market. Adverse selection is due to unobservable differences in risk levels across policyholders. Thus, secondly, I test for the existence of differences in policyholder risk level in the car insurance market. I have attempted to find out whether there is a difference in policyholder accident probability using conditional variance identity. With access to the repeated cross sectional data, I have computed the relevant quantities in the identity and have discovered that the variance of accident occurrence across policyholders and time is very unlikely to be attributed to the unobservable differences amongst policyholders.

Overall, apart from the ambiguous results in chapter [2], I have, throughout this thesis, generated findings that seem to be consistent in the sense that I have discovered the existence of asymmetrical information and, further, the presence of moral hazard. These results are also more or less consistent with existing research. Particularly, within the context of insurance economics, most research has discovered evidence of moral hazard but not adverse selection.

The natural direction of future research would necessitate a fully structural estimation in the dynamic context. Since I have access to a panel data set, this work is likely to be addressed. Particularly, within this agenda, contract/effort choice needs to be explicitly incorporated: and further, an underlying unobserved heterogeneity would be considered in a more direct approach. Overall, the main aim is to quantify the moral hazard phenomenon. So far, most research has focused on detecting the presence of asymmetric information in the various market contexts. Even though the above constitutes original path breaking works, it may be the time to measure the magnitude of the asymmetric information. With all these developments future research will have good opportunity to design fairer and safer contracts for use in our everyday lives.

Appendix A

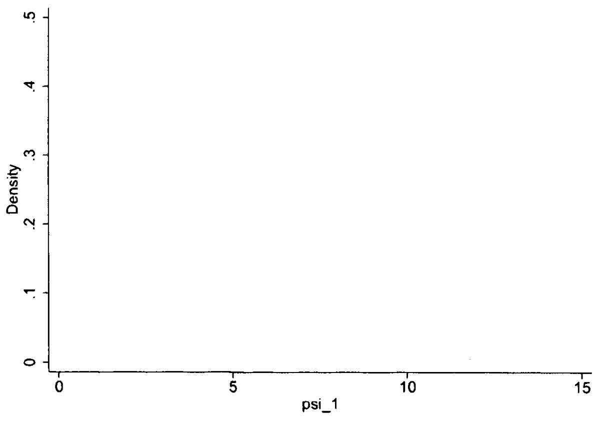
A.1 Empirical Results for Occurrence Dependence

Tab. A.1: Discrete heterogeneity; 12 time intervals (1999 A)

occurrence dependence	
β	0.4225(0.0178)
unobserved heterogeneity	
λ^a	0.0880(0.0016)
λ^b	1.8835(0.1618)
$\Pr(\lambda = \lambda^a)$	0.9728(0.0911)
$\Pr(\lambda = \lambda^b)$	0.0272(0.0911)
piecewise constant ψ	
ψ_1	1.3621(0.0305)
ψ_2	1.1838(0.0272)
ψ_3	1.1475(0.0263)
ψ_4	0.9953(0.0247)
ψ_5	1.0722(0.0257)
ψ_6	0.9991(0.0250)
ψ_7	0.9552(0.0247)
ψ_8	0.9074(0.0243)
ψ_9	0.8738(0.0241)
ψ_{10}	0.8340(0.0236)
ψ_{11}	0.8394(0.0239)
number of observations by number of claims	
$M_{0,n}$(no claims)	172766
$M_{1,n}$(1 claim)	18366
$M_{2,n}$(2 claims)	1653
$M_{3,n}$(3 claims)	198
$M_{4,n}$(4 claims)	30
$M_{5,n}$(5 claims)	6
$M_{6,n}$(6 claims)	1
$M_{7,n}$(7 claims)	1
log-likelihood	−69991

Tab. A.2: Discrete heterogeneity; 12 time intervals (2000 A)

occurrence dependence	
β	0.0800(0.0039)
unobserved heterogeneity	
λ^a	0.0010(0.0094)
λ^b	2.4885(0.2214)
$\Pr(\lambda = \lambda^a)$	0.8881(0.1007)
$\Pr(\lambda = \lambda^b)$	0.1119(0.1007)
piecewise constant ψ	
ψ_1	2.9020(0.1025)
ψ_2	1.7857(0.0650)
ψ_3	1.3487(0.0568)
ψ_4	1.0789(0.0545)
ψ_5	0.9172(0.0500)
ψ_6	0.7863(0.0455)
ψ_7	0.6894(0.0417)
ψ_8	0.6079(0.0386)
ψ_9	0.5385(0.0364)
ψ_{10}	0.4896(0.0335)
ψ_{11}	0.4557(0.0317)
number of observations by number of claims	
$M_{0,n}$(no claims)	194303
$M_{1,n}$(1 claim)	20260
$M_{2,n}$(2 claims)	1850
$M_{3,n}$(3 claims)	230
$M_{4,n}$(4 claims)	35
$M_{5,n}$(5 claims)	6
$M_{6,n}$(6 claims)	2
log-likelihood	−75358



Tab. A.3: Discrete heterogeneity; 12 time intervals (2000 B)

occurrence dependence	
β	0.5067(0.0161)
unobserved heterogeneity	
λ^a	0.0855(0.0014)
λ^b	1.6576(0.0980)
$\Pr(\lambda = \lambda^a)$	0.9547(0.0598)
$\Pr(\lambda = \lambda^b)$	0.0453(0.0598)
piecewise constant ψ	
ψ_1	1.3967(0.0210)
ψ_2	1.1963(0.0181)
ψ_3	1.1241(0.0169)
ψ_4	1.0391(0.0161)
ψ_5	1.0248(0.0160)
ψ_6	0.9742(0.0158)
ψ_7	0.9261(0.0156)
ψ_8	0.8790(0.0155)
ψ_9	0.9006(0.0161)
ψ_{10}	0.8347(0.0156)
ψ_{11}	0.8735(0.0165)
number of observations by number of claims	
$M_{0,n}$(no claims)	359452
$M_{1,n}$(1 claim)	40398
$M_{2,n}$(2 claims)	5321
$M_{3,n}$(3 claims)	763
$M_{4,n}$(4 claims)	168
log-likelihood	−160000

A.2 The Distribution of Random Terms in Dynamic Bivariate Probit

A.2.1 The distribution of random terms

We can formulate the probability as follows [1]:

	ω_d^1	ω_d^2
ω_n^1	$P_{1,1}$	$P_{1,2}$
ω_n^2	$P_{2,1}$	$P_{2,2}$

Therefore,

$$\mathrm{P}_{i,j} = \mathrm{prob}(\omega_d = \omega_d^i \text{ and } \omega_n = \omega_n^j) = \frac{\exp(\alpha_{i,j})}{\Sigma\Sigma \exp(\alpha_{i,j})}$$ [2]

Here, we normalize $\alpha_{1,1} = 0$.

Therefore, we have

$$\mathrm{P}_{1,1} = \mathrm{prob}(\omega_d = \omega_d^1 \text{ and } \omega_n = \omega_n^1) = \frac{1}{1 + \exp(\alpha_{1,2}) + \exp(\alpha_{2,1}) + \exp(\alpha_{2,2})}$$

By the same logic,

$$\mathrm{P}_{1,2} = \mathrm{prob}(\omega_d = \omega_d^2 \text{ and } \omega_n = \omega_n^1) = \frac{\exp(\alpha_{1,2})}{1 + \exp(\alpha_{1,2}) + \exp(\alpha_{2,1}) + \exp(\alpha_{2,2})}$$

$$\mathrm{P}_{2,1} = \mathrm{prob}(\omega_d = \omega_d^1 \text{ and } \omega_n = \omega_n^2) = \frac{\exp(\alpha_{2,1})}{1 + \exp(\alpha_{1,2}) + \exp(\alpha_{2,1}) + \exp(\alpha_{2,2})}$$

[1] This is an example for 4 mass points. It can be easily extended to multi-dimensional case.

[2] This formula is widely used to make sure that a probability lies between 0 and 1.

$$P_{2,2} = \text{prob}(\omega_d = \omega_d^2 \text{ and } \omega_n = \omega_n^2) = \frac{\exp(\alpha_{2,2})}{1 + \exp(\alpha_{1,2}) + \exp(\alpha_{2,1}) + \exp(\alpha_{2,2})}$$

Here, we have to estimate three arguments $\{\alpha_{1,2}, \alpha_{2,1}, \alpha_{2,2}\}$.

A.2.2 Normalization

We normalize $(\omega_d^1, \omega_n^1) = (0, 0)$. In this case, we need to estimate ω_d^2 and ω_n^2. Therefore, overall we have to estimate $\{\alpha_{1,2}, \alpha_{2,1}, \alpha_{2,2}, \omega_d^2, \omega_n^2\}$

A.3 Empirical Results for Granger Causality

A.3.1 Variables List

variable name	description
GEN	gender of the policyholder (1 = female)
MS	marital status (1 = not married)
CAGE1	car production year before 1993
CAGE2	car production year between 1993 and 1994
CAGE3	car production year between 1995 and 1996
CAGE4	car production year after 1996
AGE1	age younger than 30
AGE2	age 30 - 39
AGE3	age 40 - 49
AGE4	age 50 - 59
AGE5	age older than 59
CON	insurance coverage (1 = comprehensive)
CLA	accident occurrence (1 = claim)
BM	bonus-malus coefficient
LAGCON	lag CON
LAGCLA	lag CLA
INICON	initial value of CON
INICLA	initial value of CLA
INIBM	initial value of BM

A.3.2 Estimation Results

Tab. A.4: BUSAN

Variables	coverage	claims
GEN	0.3718 (0.1592)	0.1660 (0.0573)
MS	-0.2506 (0.1900)	0.0085 (0.0525)
CAGE1	0.2037 (0.2599)	-0.4896 (0.1045)
CAGE2	0.1879 (0.1969)	-0.3113 (0.0653)
CAGE3	0.1381 (0.3948)	-0.1673 (0.0545)
AGE1	0.5774 (0.1930)	0.0615 (0.1086)
AGE2	-0.2968 (0.2470)	-0.0764 (0.0588)
AGE4	-0.1907 (0.4079)	0.0162 (0.0629)
AGE5	0.1146 (0.9997)	0.1048 (0.0732)
CONS	-0.5356 (0.4828)	-1.3407 (0.1566)
Predetermined		
LAGCON	3.6628 (0.2993)	0.3752 (0.3095)
LAGCLA	-0.1334 (1.1791)	0.2659 (0.0861)
BM	-0.2229 (0.5809)	-0.0066 (0.1735)
Initial Conditions		
INICON	0.6832 (0.2672)	-0.2186 (0.2948)
INICLA	-0.1747 (1.1966)	0.0007 (0.1146)
INIBM	-1.0319 (0.6602)	-0.2115 (0.1733)
Correlation Coefficient		
Rho	0.2926(0.2260)	
Unobserved Heterogeneity Distribution	estimate	probability
(ω_d^1, ω_n^1)	(0, 0)	0.2501
(ω_d^2, ω_n^1)	(-0.0037, 0)	0.2491
(ω_d^1, ω_n^2)	(0, -0.0053)	0.2503
(ω_d^2, ω_n^2)	(-0.0037, -0.0053)	0.2505

Tab. A.5: INCHEON

Variables	coverage	claims
GEN	-0.1600 (0.1553)	-0.0121 (0.0489)
MS	-0.3158 (0.1031)	-0.0390 (0.0396)
CAGE1	-0.2207 (0.1403)	-0.2110 (0.0718)
CAGE2	-0.0678 (0.1148)	-0.0448 (0.0495)
CAGE3	0.2547 (0.1561)	0.1965 (0.0434)
AGE1	0.6791 (0.1735)	0.0104 (0.0808)
AGE2	0.1735 (0.1100)	0.0865 (0.0416)
AGE4	0.1195 (0.2789)	-0.0895 (0.0569)
AGE5	-0.2753 (0.2463)	-0.0346 (0.0795)
CONS	-0.7107 (0.2066)	-1.5558 (0.1180)
Predetermined		
LAGCON	3.0198 (0.1650)	0.2837 (0.1599)
LAGCLA	-0.5175 (0.1355)	-0.0581 (0.0593)
BM	-0.7503 (0.3676)	0.4100 (0.0917)
Initial Conditions		
INICON	0.8998 (0.1627)	-0.0210 (0.1465)
INICLA	0.6664 (1.2348)	-0.0103 (0.0602)
INIBM	0.1081 (0.2975)	-0.2905 (0.0969)
Correlation Coefficient		
Rho	0.1318 (0.1652)	

Unobserved Heterogeneity Distribution	estimate	probability
(ω_d^1,ω_n^1)	(0, 0)	0.2501
(ω_d^2,ω_n^1)	(-0.0016, 0)	0.2497
(ω_d^1,ω_n^2)	(0, -0.0005)	0.2503
(ω_d^2,ω_n^2)	(-0.0016, -0.0005)	0.2499

Tab. A.6: DAEJON

Variables	coverage	claims
GEN	-0.1720 (0.1451)	0.0915 (0.0529)
MS	-0.4232 (0.1411)	0.0386 (0.0501)
CAGE1	-0.4211 (0.2387)	-0.5524 (0.0766)
CAGE2	0.0138 (0.1650)	-0.2026 (0.0549)
CAGE3	-0.1746 (0.1885)	-0.1117 (0.0491)
AGE1	-0.1426 (0.2020)	-0.1541 (0.0885)
AGE2	-0.0261 (0.1360)	-0.1978 (0.0504)
AGE4	-0.3480 (0.2185)	-0.0689 (0.0544)
AGE5	-0.2516 (0.8403)	-0.1146 (0.0832)
CONS	-1.0963 (0.3142)	-1.5896 (0.1453)
Predetermined		
LAGCON	2.8964 (0.2504)	0.5292 (0.1989)
LAGCLA	0.9475 (0.3232)	0.1855 (0.0577)
BM	-0.0172 (0.5041)	-0.1182 (0.1076)
Initial Conditions		
INICON	1.1990 (0.2815)	-0.0100 (0.1739)
INICLA	-0.0761 (0.5015)	-0.1602 (0.0675)
INIBM	0.6168 (0.4755)	0.1415 (0.1137)
Correlation Coefficient		
Rho	0.1862 (0.1681)	
Unobserved Heterogeneity Distribution	estimate	probability
(ω_d^1,ω_n^1)	(0, 0)	0.2501
(ω_d^2,ω_n^1)	(0.0002, 0)	0.25
(ω_d^1,ω_n^2)	(0, -0.0003)	0.2499
(ω_d^2,ω_n^2)	(0.0002, -0.0003)	0.25

Tab. A.7: KYUNGGI PROVINCE

Variables	coverage	claims
GEN	-0.1040 (0.0679)	0.1148 (0.0271)
MS	-0.2411 (0.0580)	-0.1994 (0.0233)
CAGE1	-0.3658 (0.1020)	-0.2705 (0.0403)
CAGE2	-0.1230 (0.0887)	-0.0913 (0.0292)
CAGE3	0.0808 (0.0777)	-0.0799 (0.0264)
AGE1	-0.2343 (0.0923)	0.1433 (0.0462)
AGE2	0.2820 (0.0721)	-0.0067 (0.0261)
AGE4	-0.0070 (0.0843)	0.1079 (0.0322)
AGE5	-0.1216 (0.1208)	0.2237 (0.0406)
CONS	-0.8152 (0.1535)	-1.6472 (0.0721)
Predetermined		
LAGCON	3.3329 (0.1330)	0.5451 (0.1112)
LAGCLA	-0.2784 (0.0916)	0.0496 (0.0341)
BM	-0.0377 (0.2099)	0.0136 (0.0692)
Initial Conditions		
INICON	0.5535 (0.1357)	-0.0304 (0.0990)
INICLA	0.0211 (0.1023)	0.1278 (0.0371)
INIBM	-0.1463 (0.2197)	0.0221 (0.0694)
Correlation Coefficient		
Rho	0.2148 (0.0645)	
Unobserved Heterogeneity Distribution	estimate	probability
(ω_d^1,ω_n^1)	(0, 0)	0.2502
(ω_d^2,ω_n^1)	(0.0008, 0)	0.25
(ω_d^1,ω_n^2)	(0, -0.0009)	0.2499
(ω_d^2,ω_n^2)	(0.0008, -0.0009)	0.2499

Tab. A.8: KYUNGNAM PROVINCE

Variables	coverage	claims
GEN	1.1249 (0.1891)	0.0877 (0.0576)
MS	0.0990 (0.2532)	0.0534 (0.0492)
CAGE1	-0.4108 (0.2619)	-0.3579 (0.0863)
CAGE2	-0.1085 (0.2314)	-0.1920 (0.0542)
CAGE3	-0.2316 (0.2325)	-0.2131 (0.0507)
AGE1	0.6521 (0.2447)	0.0971 (0.0780)
AGE2	0.0301 (0.1807)	0.0304 (0.0523)
AGE4	0.2905 (0.2180)	0.0958 (0.0584)
AGE5	-0.1229 (0.8437)	-0.1385 (0.1029)
CONS	-0.0947 (0.3610)	-1.9264 (0.5717)
Predetermined		
LAGCON	3.1647 (0.4891)	-0.3506 (0.9710)
LAGCLA	-0.0534 (0.4264)	0.0101 (0.0737)
BM	-1.2270 (0.6208)	0.3806 (0.1477)
Initial Conditions		
INICON	1.1207 (0.5149)	0.8633 (0.9764)
INICLA	-0.3085 (0.4370)	-0.0308 (0.0759)
INIBM	-0.5954 (0.6445)	-0.1149 (0.1621)
Correlation Coefficient		
Rho	0.2451 (0.1574)	
Unobserved Heterogeneity Distribution	estimate	probability
(ω_d^1,ω_n^1)	(0, 0)	0.2494
(ω_d^2,ω_n^1)	(0, 0)	0.2502
(ω_d^1,ω_n^2)	(0, 0.0088)	0.2502
(ω_d^2,ω_n^2)	(0, 0.0088)	0.2502

Tab. A.9: KYUNGBUK PROVINCE

Variables	coverage	claims
GEN	0.0788 (0.1168)	0.2001 (0.0410)
MS	-0.1785 (0.1381)	0.0038 (0.0390)
CAGE1	-0.4642 (0.1817)	-0.3693 (0.0641)
CAGE2	-0.4361 (0.1203)	-0.1295 (0.0407)
CAGE3	-0.3162 (0.1268)	-0.1496 (0.0390)
AGE1	-0.0044 (0.1360)	-0.1650 (0.0700)
AGE2	0.0936 (0.1205)	-0.0164 (0.0400)
AGE4	-0.0610 (0.1332)	0.1367 (0.0452)
AGE5	0.1363 (0.1930)	0.1849 (0.0516)
CONS	-0.7203 (0.2721)	-1.5202 (0.1031)
Predetermined		
LAGCON	3.9003 (0.2092)	0.1369 (0.2859)
LAGCLA	0.2859 (0.1659)	0.1630 (0.0558)
BM	-0.4883 (0.3127)	-0.1842 (0.1160)
Initial Conditions		
INICON	0.1686 (0.2105)	0.0878 (0.2788)
INICLA	0.0569 (0.2776)	0.0553 (0.0681)
INIBM	-0.0627 (0.3581)	0.1163 (0.1140)
Correlation Coefficient		
Rho	0.2505 (0.1318)	
Unobserved Heterogeneity Distribution	estimate	probability
(ω_d^1, ω_n^1)	(0, 0)	0.2494
(ω_d^2, ω_n^1)	(-0.0012, 0)	0.2502
(ω_d^1, ω_n^2)	(0, -0.0001)	0.2502
(ω_d^2, ω_n^2)	(-0.0012, -0.0001)	0.2502

Tab. A.10: JUNNAM PROVINCE

Variables	coverage	claims
GEN	0.3740 (0.1930)	0.0784 (0.0516)
MS	-0.6215 (0.1223)	-0.2200 (0.0459)
CAGE1	-0.0868 (0.1650)	-0.4393 (0.0949)
CAGE2	-0.0942 (0.2064)	-0.0816 (0.0557)
CAGE3	-0.1261 (0.1311)	-0.0785 (0.0477)
AGE1	0.4318 (0.2027)	0.0164 (0.0821)
AGE2	0.0997 (0.1509)	-0.1334 (0.0491)
AGE4	-0.4918 (0.1663)	-0.0405 (0.0593)
AGE5	-0.1855 (0.1846)	-0.2952 (0.0861)
CONS	0.1797 (0.2358)	-1.7636 (0.1368)
Predetermined		
LAGCON	2.9345 (0.1867)	0.5166 (0.1658)
LAGCLA	0.3087 (0.5202)	0.2682 (0.0680)
BM	-0.2465 (0.2925)	-0.1951 (0.1533)
Initial Conditions		
INICON	0.9988 (0.2260)	-0.1013 (0.1355)
INICLA	-0.2991 (0.3280)	0.1819 (0.0706)
INIBM	-0.5820 (0.2973)	0.3928 (0.1505)
Correlation Coefficient		
Rho	-0.1603 (0.1229)	
Unobserved Heterogeneity Distribution	estimate	probability
(ω_d^1, ω_n^1)	(0, 0)	0.2494
(ω_d^2, ω_n^1)	(-0.0003, 0)	0.2502
(ω_d^1, ω_n^2)	(0, 0.0005)	0.2502
(ω_d^2, ω_n^2)	(-0.0003, 0.0005)	0.2502

Tab. A.11: JUNBUK PROVINCE

Variables	coverage	claims
GEN	-0.1274 (0.1560)	0.0823 (0.0591)
MS	-0.4173 (0.1733)	-0.0212 (0.0535)
CAGE1	-0.5785 (0.2689)	-0.1280 (0.0907)
CAGE2	-0.1789 (0.1670)	-0.0578 (0.0635)
CAGE3	-0.0196 (0.1596)	-0.0207 (0.0561)
AGE1	0.9498 (0.2151)	-0.0240 (0.1065)
AGE2	0.4387 (0.1277)	-0.0581 (0.0538)
AGE4	0.3953 (0.1825)	-0.1130 (0.0645)
AGE5	0.0313 (0.5787)	0.1020 (0.0704)
CONS	-0.6887 (0.4083)	-1.7815 (0.1437)
Predetermined		
LAGCON	2.9796 (0.2869)	1.0128 (0.1801)
LAGCLA	0.2550 (0.3610)	0.0456 (0.0823)
BM	-0.7628 (0.7253)	0.2323 (0.1542)
Initial Conditions		
INICON	1.2113 (0.3266)	-0.5772 (0.1536)
INICLA	-0.0995 (0.6425)	-0.0380 (0.1010)
INIBM	0.0298 (0.7797)	-0.0872 (0.1505)
Correlation Coefficient		
Rho	0.6134 (0.1302)	
Unobserved Heterogeneity Distribution	estimate	probability
(ω_d^1,ω_n^1)	(0, 0)	0.2505
(ω_d^2,ω_n^1)	(-0.0005, 0)	0.2498
(ω_d^1,ω_n^2)	(0, -0.0001)	0.2499
(ω_d^2,ω_n^2)	(-0.0005, -0.0001)	0.2498

Tab. A.12: CHUNGNAM PROVINCE

Variables	coverage	claims
GEN	-0.0063 (0.1511)	0.0579 (0.0563)
MS	0.2001 (0.1326)	-0.0895 (0.0543)
CAGE1	-0.2130 (0.1707)	-0.3191 (0.0760)
CAGE2	-0.2174 (0.1452)	-0.1737 (0.0582)
CAGE3	0.3116 (0.1446)	-0.1906 (0.0526)
AGE1	-0.5801 (0.1543)	-0.1528 (0.0860)
AGE2	-0.1158 (0.1445)	-0.2301 (0.0569)
AGE4	-0.1440 (0.1895)	-0.0990 (0.0575)
AGE5	-0.5151 (0.1655)	-0.2044 (0.0787)
CONS	-0.5221 (0.2789)	-1.2423 (0.1166)
Predetermined		
LAGCON	2.9930 (0.1900)	0.3708 (0.1473)
LAGCLA	0.4855 (0.2446)	-0.0896 (0.0681)
BM	0.6756 (0.4014)	0.1745 (0.1344)
Initial Conditions		
INICON	0.9609 (0.1950)	-0.3055 (0.1334)
INICLA	-0.6998 (0.3067)	0.3123 (0.0725)
INIBM	-1.4199 (0.4172)	-0.0136 (0.1186)
Correlation Coefficient		
Rho	0.1364 (0.0658)	
Unobserved Heterogeneity Distribution	estimate	probability
(ω_d^1,ω_n^1)	(0, 0)	0.25
(ω_d^2,ω_n^1)	(0.0003, 0)	0.25
(ω_d^1,ω_n^2)	(0, 0.0002)	0.25
(ω_d^2,ω_n^2)	(0.0003, 0.0002)	0.25

Tab. A.13: CHUNGBUK PROVINCE

Variables	coverage	claims
GEN	0.2459 (0.2988)	-0.0741 (0.0691)
MS	0.1248 (0.1767)	-0.0705 (0.0564)
CAGE1	0.2930 (0.3067)	-0.2618 (0.0860)
CAGE2	-0.2427 (0.2138)	-0.0742 (0.0660)
CAGE3	-0.0423 (0.2225)	0.0436 (0.0587)
AGE1	-0.2375 (0.2489)	-0.0027 (0.0965)
AGE2	1.0323 (0.2096)	0.0400 (0.0611)
AGE4	-0.0922 (0.1752)	0.0386 (0.0728)
AGE5	0.0465 (0.6291)	0.3366 (0.0866)
CONS	-1.0291 (0.3016)	-1.3870 (0.1553)
Predetermined		
LAGCON	2.4543 (0.2307)	0.6114 (0.2336)
LAGCLA	0.7821 (0.1945)	-0.1387 (0.0870)
BM	-1.3647 (0.4132)	0.6712 (0.1417)
Initial Conditions		
INICON	1.8032 (0.2642)	-0.4856 (0.2187)
INICLA	-0.1460 (0.2322)	-0.3535 (0.1057)
INIBM	0.1013 (0.3955)	-0.5747 (0.1564)
Correlation Coefficient		
Rho	0.2520 (0.1959)	
Unobserved Heterogeneity Distribution	estimate	probability
(ω_d^1,ω_n^1)	(0, 0)	0.2488
(ω_d^2,ω_n^1)	(0.0005, 0)	0.2504
(ω_d^1,ω_n^2)	(0, -0.0017)	0.2504
(ω_d^2,ω_n^2)	(0.0005, -0.0017)	0.2504

Tab. A.14: JEJU ISLAND

Variables	coverage	claims
GEN	2.9362 (1.3171)	0.3214 (0.1016)
MS	-0.5394 (0.9002)	-0.3259 (0.1115)
CAGE1	-0.6685 (1.8301)	-0.2381 (0.1683)
CAGE2	-0.0169 (0.7008)	0.0229 (0.1210)
CAGE3	2.5390 (1.4514)	-0.0178 (0.1155)
AGE1	3.9852 (1.3168)	-0.1238 (0.1804)
AGE2	1.0836 (0.7280)	-0.4472 (0.1163)
AGE4	1.3432 (1.2343)	0.0744 (0.1286)
AGE5	2.1244 (2.0029)	0.3965 (0.1483)
CONS	-0.3275 (1.4864)	-1.2292 (0.2639)
Predetermined		
LAGCON	2.8994 (0.7377)	-0.2367 (1.9243)
LAGCLA	2.7406 (0.6731)	-0.0890 (0.1668)
BM	-3.5726 (2.0491)	1.2727 (0.3326)
Initial Conditions		
INICON	4.0842 (1.8821)	0.4711 (1.9207)
INICLA	-0.5849 (0.3798)	-0.1364 (0.1498)
INIBM	-1.6338 (1.9211)	-0.9619 (0.3425)
Correlation Coefficient		
Rho	0.7858 (0.2039)	
Unobserved Heterogeneity Distribution	estimate	probability
(ω_d^1,ω_n^1)	(0, 0)	0.2501
(ω_d^2,ω_n^1)	(0.0124, 0)	0.2498
(ω_d^1,ω_n^2)	(0, 0.0034)	0.25
(ω_d^2,ω_n^2)	(0.0124, 0.0034)	0.2501

Tab. A.15: GANGWON PROVINCE

Variables	coverage	claims
GEN	0.3055 (0.2231)	-0.2234 (0.1114)
MS	-0.0727 (0.2528)	-0.3897 (0.0827)
CAGE1	0.2911 (0.2630)	-0.1311 (0.1446)
CAGE2	0.1111 (0.3220)	-0.0303 (0.1141)
CAGE3	0.3595 (0.1550)	0.1664 (0.0949)
AGE1	-0.1354 (0.2009)	0.1104 (0.0895)
AGE4	-0.2078 (0.3037)	0.0495 (0.1057)
AGE5	0.0721 (0.2313)	0.1662 (0.1209)
CONS	-1.0351 (0.3921)	-1.6167 (0.2152)
Predetermined		
LAGCON	3.4504 (0.4897)	0.1416 (0.3025)
LAGCLA	0.4405 (0.4990)	0.1431 (0.1495)
BM	-0.0860 (0.6562)	-0.3180 (0.3929)
Initial Conditions		
INICON	0.7193 (0.4532)	0.1082 (0.2775)
INICLA	1.2783 (1.0723)	0.0733 (0.1728)
INIBM	-0.4060 (0.5675)	0.2088 (0.3113)
Correlation Coefficient		
Rho	-0.3024 (0.6094)	
Unobserved Heterogeneity Distribution	estimate	probability
(ω_d^1,ω_n^1)	(0, 0)	0.2494
(ω_d^2,ω_n^1)	(-0.0002, 0)	0.2502
(ω_d^1,ω_n^2)	(0, -0.0006)	0.2502
(ω_d^2,ω_n^2)	(-0.0002, -0.0006)	0.2502

APPENDIX B

B.1 Subgroup Classification

Tab. B.1: Subgroup Classification A

Name	Description
MS	Male and Seoul Metropolitan City
MK	Male and Kyeongsang and Jeju Province
MKI	Male and Kyeonggi Province
MCJ	Male and Chungcheong/Jeolla/Gangwon Province
FS	Female and Seoul Metropolitan City
FK	Female and Kyeongsang and Jeju Province
FKI	Female and Kyeonggi Province
FCJ	Female and Chungcheong/Jeolla/Gangwon Province

Tab. B.2: Subgroup Classification B

Name	Description
MMS	Male and Married and Seoul Metropolitan City
MMK	Male and Married and Kyeongsang Province
MMC	Male and Married and Chungcheong
MMJ	Male and Married and Jeolla/Gangwon Province
MMI	Male and Married and Kyeonggi Province
MuMS	Male and Not Married and Seoul Metropolitan City
MuMK	Male and Not Married and Kyeongsang Province
MuMC	Male and Not Married and Chungcheong
MUMJ	Male and Not Married and Jeolla/Gangwon Province
MUMI	Male and Not Married and Kyeonggi Province
FMS	Female and Married and Seoul Metropolitan City
FMK	Female and Married and Kyeongsang Province
FMC	Female and Married and Chungcheong Province
FMJ	Female and Married and Jeolla/Gangwon Province
FMI	Female and Married and Kyeonggi Province
FuMS	Female and Not Married and Seoul Metropolitan City
FuMK	Female and Not Married and Kyeongsang Province
FuMC	Female and Not Married and Chuncheong Province
FuMJ	Female and Not Married and Jeolla/Gangwon Province
FuMI	Female and Not Married and Kyeonggi Province

B.2 Results B

Tab. B.3: Overall Results B

LOGIT	1999	2000	2001
MMS	-1.891289 (0.116)	-1.95818 (0.119)	-1.96361 (0.119)
MMK	-2.548328 (0.160)	-1.991781 (0.127)	-2.261763 (0.142)
MMC	-2.358155 (0.177)	-2.427748 (0.182)	-2.112964 (0.160)
MMJ	-2.691243 (0.211)	-2.400824 (0.188)	-2.091563 (0.166)
MMI	-2.177047 (0.112)	-2.069185 (0.107)	-2.062891 (0.107)
MuMS	-2.101484 (0.093)	-2.116737 (0.095)	-2.128038 (0.095)
MuMK	-2.295782 (0.097)	-2.232439 (0.094)	-2.122305 (0.090)
MuMC	-2.35601 (0.116)	-2.442347 (0.120)	-2.267133 (0.111)
MuMJ	-3.028522 (0.187)	-2.421625 (0.143)	-2.496741 (0.149)
MuMI	-2.051619 (0.083)	-2.224056 (0.088)	-2.207003 (0.087)
FMS	-1.680897 (0.210)	-2.04122 (0.238)	-2.098986 (0.243)
FMK	-2.531427 (0.393)	-1.58412 (0.274)	-1.742969 (0.290)
FMC	-1.667707 (0.345)	-2.097141 (0.401)	-1.386294 (0.310)
FMJ	-3.314186 (0.720)	-2.322388 (0.469)	-2.564949 (0.519)
FMI	-1.94591 (0.223)	-1.89085 (0.219)	-1.441864 (0.188)
FuMS	-2.072473 (0.177)	-2.0131 (0.175)	-2.0131 (0.175)
FuMK	-2.184802 (0.203)	-2.752864 (0.258)	-2.054124 (0.194)
FuMC	-2.085107 (0.226)	-1.951608 (0.214)	-1.857455 (0.207)
FuMJ	-3.654978 (0.585)	-2.09849 (0.294)	-1.926679 (0.276)
FuMI	-2.038056 (0.175)	-1.91482 (0.165)	-1.90176 (0.163)

(standard errors in parenthesis)

Tab. B.4: Overall Results B

Nonparametric	1999	2000	2001
MMS	0.12621	0.13386	0.12687
MMK	0.10459	0.11637	0.11146
MMC	0.10056	0.09912	0.11208
MMJ	0.07448	0.08366	0.10329
MMI	0.11549	0.12518	0.12614
MuMS	0.11102	0.11289	0.11973
MuMK	0.08791	0.10148	0.10774
MuMC	0.10321	0.09819	0.11286
MUMJ	0.06900	0.08588	0.08378
MUMI	0.12942	0.11840	0.12091
FMS	0.16578	0.13121	0.14801
FMK	0.12760	0.18229	0.14805
FMC	0.12054	0.15351	0.16450
FMJ	0.08658	0.10965	0.10132
FMI	0.17684	0.16220	0.16485
FuMS	0.12018	0.13283	0.13832
FuMK	0.11005	0.09958	0.11979
FuMC	0.10445	0.11963	0.14992
FuMJ	0.05339	0.10408	0.11157
FuMI	0.12903	0.13656	0.14224

Appendix C

C.1 Contract Choices in Data B

Tab. C.1: Tabulation of Coverage Choices

cover	Freq	Percent	Cum
100000	97,458	21.78	21.78
100050	66	0.01	21.80
100400	4	0.00	21.80
103000	71	0.02	21.82
103050	19	0.00	21.82
103400	3	0.00	21.82
120000	1,325	0.30	22.12
120050	52	0.01	22.13
120400	3	0.00	22.13
120450	1	0.00	22.13
123000	25,031	5.60	27.72
123050	46,831	10.47	38.19
123056	93,598	20.92	59.11
123400	468	0.10	59.22
123450	1,362	0.30	59.52
123456	181,080	40.48	100.00
Total	447,372	100.00	

C.2 Variables Description

Tab. C.2: Variables Discription

Variable	Description
dg1	male
dg2	female
dr1	seoul/kyunggi/incheon
dr2	other provinces
dca1	–1994
dca2	1995–1996
dca3	1997–
dcs1	<1000cc
dcs2	1000cc<= <1500cc
dcs3	1500cc<= <2000cc
dcs4	>=2000cc
dgt1	manual
dgt2	auto/semi-auto

C.3 Results for Female Policyholders

Tab. C.3: Female/capital city areas/–1994/<1000CC/manual

Quantile	Lower	Upper
10th quantile		KW 607,192 (£262)
20th quantile		KW 708,851 (£306)
30th quantile	KW 508,744 (£220)	KW 819,132 (£353)
40th quantile	KW 658,487 (£284)	KW 954,459 (£412)
50th quantile	KW 754,039 (£325)	KW 1,081,652 (£467)
60th quantile	KW 882,929 (£381)	KW 1,237,990 (£534)
70th quantile	KW 1,013,378 (£437)	KW 1,439,347 (£621)
80th quantile	KW 1,147,963 (£495)	
90th quantile	KW 1,319,680 (£569)	

Tab. C.4: Frequency of Purchasing Coverage 4

Values (£)	Lower	Values (£)	Upper
220 – 284	21	– 262	21
284 – 325	26	262 – 306	25
325 – 381	30	306 – 353	29
381 – 437	18	353 – 412	19
437 – 495	25	412 – 467	34
495 – 569	30	467 – 534	17
569 –	21	534 – 621	26

Tab. C.5: Female/capital city areas/–1994/1000≤<1500/auto or semi-auto

Quantile	Lower	Upper
10th quantile		KW 1,546,802 (£667)
20th quantile	KW 1,042,988 (£450)	KW 2,122,291 (£916)
30th quantile	KW 1,712,218 (£739)	KW 2,692,283 (£1,162)
40th quantile	KW 2,299,035 (£992)	KW 3,141,151 (£1,355)
50th quantile	KW 2,826,925 (£1,220)	KW 3,557,967 (£1,535)
60th quantile	KW 3,260,529 (£1,407)	KW 4,007,187 (£1,729)
70th quantile	KW 3,678,075 (£1,587)	KW 4,665,008 (£2,013)
80th quantile	KW 4,157,914 (£1,794)	KW 6,950,332 (£2,999)
90th quantile	KW 4,983,286 (£2,150)	

Tab. C.6: Frequency of Purchasing Coverage 4

Values (£)	Lower	Values (£)	Upper
450 – 739	44	– 667	44
739 – 992	44	667 – 916	47
992 – 1,220	46	916 – 1,162	36
1,220 – 1,407	48	1,162 – 1,355	52
1,407 – 1,587	36	1,355 – 1,535	35
1,587 – 1,794	50	1,535 – 1,729	60
1,794 – 2,150	50	1,729 – 2,013	44
2,150 –	38	2,013 – 2,999	39

Tab. C.7: Female/capital city areas/95–96/1000≤<1500/auto or semi-auto

Quantile	Lower	Upper
10th quantile		KW 4,600,152 (£1,985)
20th quantile	KW 4,414,477 (£1,905)	KW 5,114,550 (£2,207)
30th quantile	KW 4,965,378 (£2,143)	KW 5,581,120 (£2,408)
40th quantile	KW 5,444,410 (£2,349)	KW 6,033,875 (£2,604)
50th quantile	KW 5,894,911 (£2,544)	KW 6,535,765 (£2,820)
60th quantile	KW 6,374,397 (£2,751)	KW 7,167,016 (£3,093)
70th quantile	KW 6,960,765 (£3,004)	KW 7,912,070 (£3,414)
80th quantile	KW 7,674,395 (£3,312)	KW 9,056,561 (£3,908)
90th quantile	KW 8,595,935 (£3,709)	

Tab. C.8: Frequency of Purchasing Coverage 4

Values (£)	Lower	Values (£)	Upper
1,905 – 2,143	96	– 1,985	82
2,143 – 2,349	80	1,985 – 2,207	77
2,349 – 2,544	88	2,207 – 2,408	78
2,544 – 2,751	82	2,408 – 2,604	89
2,751 – 3,004	77	2,604 – 2,820	89
3,004 – 3,312	77	2,820 – 3,093	72
3,312 – 3,709	78	3,093 – 3,414	75
3,709 –	79	3,414 – 3,908	94

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