Testing for Hidden Information and Action in Automobile Insurance Market[1]

Juan P. García R.[2]

Universidad del Rosario

March 2, 2011

[1] I am highly indebt with my advisor David Bardey, his guidance, encouragement and patience immensely improved present research. Carlos Varela and Fasecolda allowed me to access to their data base and helped me understand the Colombian auto insurance market. I would like to thank the enlightening conversation held with the members of the thesis committee Manuel Ramírez, Darío Maldonado and José E. Gómez, the comments to an early draft by Jesús Otero, Andrés Álvarez, Ángela Luna and the comments of seminar participants at the Universidad del Rosario. An extended abstract of this paper was published in the *XIV Latin Ibero-American Congress on Operations Research – Book of Extended Abstracts*.

[2] Facultad de Economía – Universidad del Rosario. Casa Pedro Fermín de Vargas, Calle 14 # 4-69, Bogotá–Colombia. E-Mail: jpgarciar@gmail.com.

Abstract

I test the presence of hidden information and action in the automobile insurance market using a data set from several Colombian insurers. To identify the presence of hidden information I find a common knowledge variable providing information on policyholder's risk type which is related to both experienced risk and insurance demand and that was excluded from the pricing mechanism. Such *unused* variable is the record of policyholder's traffic offenses. I find evidence of adverse selection in six of the nine insurance companies for which the test is performed. From the point of view of hidden action I develop a dynamic model of effort in accident prevention given an insurance contract with *bonus* experience rating scheme and I show that individual accident probability decreases with previous accidents. This result brings a testable implication for the empirical identification of hidden action and based on that result I estimate an econometric model of the time spans between the purchase of the insurance and the first claim, between the first claim and the second one, and so on. I find strong evidence on the existence of unobserved heterogeneity that deceives the testable implication. Once the unobserved heterogeneity is controlled, I find conclusive statistical grounds supporting the presence of moral hazard in the Colombian insurance market.
JEL Classification: D82, G22, C41, C14.
Keywords: Insurance, Adverse selection, Moral hazard, Empirical tests of contract theory.

1 Introduction

Several theoretical models show that asymmetric information generates inefficiencies in insurance markets. However the existence of such asymmetry in real life markets is a controversial issue. In this paper I test the presence of hidden information and action in the automobile insurance market using data sets from several Colombian insurers.

Former empirical studies test the presence of asymmetric information in form of adverse selection or moral hazard searching for a positive correlation between the policyholders' experienced risk and their insurance demand. The so–called positive correlation test confound the source of asymmetric information since correlation is uninformative on causality. Thus, following Rothschild & Stiglitz (1976) the presence of hidden information on risk type induces a positive correlation between risk and insurance demand and causality runs from the former to the latter. On the contrary, following Shavell (1979) under moral hazard there exists a positive correlation between insurance demand and experienced risk with causality running in the opposite direction. The empirical methods employed here take into account the identification problem posted above through comparing the behavior implied by the presence of each source of asymmetric information with policyholder's observed conduct.

To identify the presence of hidden information I use the method proposed by Finkelstein & Poterba (2006) for UK's annuity market. The test is based on the idea that under symmetric information there should not exist common knowledge variables providing information on policyholder's risk type that also explain both his experienced risk and insurance demand and that were excluded from pricing contracts. The existence of at least one variable filling previous conditions provide grounds to sustain the presence of *asymmetrically used information* configuring the phenomena of policyholders holding private information on their risk type or adverse selection. Here I use traffic offenses as the *unused* observable that identifies adverse selection. I find evidence of adverse selection in six of the nine insurance companies for which the test is performed suggesting that offenses should be included in their pricing mechanism in order to reduce the informational asymmetry and improve risk allocations.

For the identification of hidden action I extract a testable implication of moral hazard from a dynamic model of effort in accident prevention given an insurance contract with a *bonus* experience rating scheme.[1] The testable implication states that the occurrence of

[1] *Bonus* and *bonus–malus* are insurance market mechanisms designed to take into account policyholder's claim record. Thus, in a *bonus–malus* scheme, if in the previous year the policyholder was involved (resp. not)

a claim launch prevention incentives reducing accident probabilities and the need to file claims, a result closely related to the one found in Abbring, Chiappori & Pinquet (2003). In econometric terms the testable implication propose that under the presence of moral hazard the time spans between claims are increasing in previous claims causing negative state dependence in the claim process. However, the existence of unobserved heterogeneity can mislead the test's results through positive dynamic selection effects that confound the negative state dependence effect. For instance, assume the presence of a costly recognizable driving characteristic randomly distributed among the population that affects accident probability. Such characteristic cannot be changed over time neither it is affected by driving experience. Therefore in terms of such characteristic high–risk policyholders are accident–prone at anytime and the observed claim process reflects dynamic selection effects caused by unobserved heterogeneity. I use a flexible parametric model that allows for both occurrence dependence and unobserved heterogeneity, in order to account for the testable implication and to solve the deceiving problem respectively. I find strong evidence on the existence of unobserved heterogeneity that deceives the testable implication. Once the unobserved heterogeneity is controlled I find conclusive statistical grounds supporting the presence of moral hazard in the Colombian insurance market.

Notice that from the theoretical point of view nothing prevents an agent from suffering of both hidden information and action. Such overlap of problems appears as asymmetric information in the positive correlation test but it will be undistinguishable in the individual tests because of their specific nature. Indeed, the rejection of the null hypothesis of symmetric information, no presence of hidden information or action (resp.), only allow conclusions of symmetrically imperfect information instead of ensure the presence of hidden action of information (resp.).

The data set used here is provided by the federation of Colombian insurers Fasecolda and contains information on insurance market covering car damage, theft and legal liability where eleven companies provide 236,582 contracts that were signed on 2006 and then renewed during the next year. Data base contains information on policyholder's details as well as their car's characteristics together with a record of traffic offenses.

The structure of this thesis is the following. The next section presents a brief review of the related literature. The third section describes the Colombian car insurance market and presents the used data set. Sections four and five are devoted to the identification of hidden information and action respectively. The last section concludes.

in a claim, his next year's risk premium increases (resp. decreases) in a common known percentage.

2 Related Literature

The following section is divided in three parts: the first and second ones review the theory of hidden information and action respectively and their effects on the insurance market while the third section focuses on the empirical works testing previous theoretical findings. Since the objective in this paper is foremost empirical, the emphasis of the theoretical review is put on report on the main intuitions underlying the empirical tests.

2.1 The Theory of Hidden Information

Hidden information appears in insurance markets when policyholders have information that affect the risk insured but that remain unknown to the insurer. A prevalent conflict arises because high–risk policyholders have no incentives to reveal his risk type since that revelation increases his premium. As pointed out by Akerlof (1970) in the *lemons* market and Rothschild & Stiglitz (1976) for the insurance market, the presence of hidden information impairs efficiency and may shut down the market. Many authors propose mechanisms to reduce the inefficiencies associated with adverse selection; Dionne, Doherty & Fombaron (2001) suggest three main classes of mechanisms: (i) self–selection mechanisms (Rothschild & Stiglitz (1976), Wilson (1977), Miyazaki (1977)); (ii) risks categorization (Crocker & Snow (1985)); and (iii) multi–period contracts (Cooper & Hayes (1987), Dionne & Lasserre (1985), Dionne & Doherty (1994), Fombaron (2000)).

Since the empirical test of adverse selection is based on the models describing self–selection and risk categorization I focus the attention on their seminal work. Rothschild & Stiglitz (1976) develop a model of competitive insurance market with hidden information on expected loss and investigate market equilibria. In a two stage game, uninformed insurers offer a menu of contracts in the first stage and in the second the informed policyholders self–select themselves among offered contracts. Authors assume that insurers know the proportions of bad and good risks in the population but cannot identify such characteristic individually. Provided the competitive environment, authors assume that firms reactions take as given the other's offers. The main conclusions are that the only possible Nash outcome is a separating equilibrium that may fail to exist and if it does it is not necessarily a second–best outcome.

Together with self–selection mechanisms, risk categorization provides explanation of insurance contracts in the static framework. Risk categorization (or statistical discrimination in terms of Dahlby (1983)) appears when risk segments are defined by an observable variable. Crocker & Snow (1985) analyze that contractual strategy and show that costless imperfect categorization enhances market efficiency if used variables are correlated with hidden information.

Previous contractual strategies suggest that the presence of hidden information induces high–risk policyholders to demand more insurance and because of their risk status to be accident–prone. Furthermore, risk categorization provides a clear intuition behind the empirical test implemented here to test the existence of hidden information. Thus, if the *unused* variable is correlated with hidden information then its inclusion into the pricing mechanism reduces the effect of asymmetric information through a better risk categorization of policyholders.

2.2 The Theory of Hidden Action

Hidden action arises in insurance markets because insurers offer contracts contingent to the occurrence of a claim, however they cannot observe policyholders'effort and thus write effort–contingent contracts. Once established the conflict between the principal and the agent (the more coverage the former offers, the lower effort in prevention by the latter), there exists the classical trade–off between risk–bearing and incentives posted by Arnott & Stiglitz (1991). Several articles deal with hidden action on insurance markets: Shavell (1979) treats single–period insurance markets while Rubinstein & Yaari (1983) treat dynamical issues.

On the effects of static hidden action on the insurance market, Shavell (1979) shows that as long as insurers cannot observe actions taken by policyholders their incentives to prevent loss are distorted. As a solution to this agency problem Shavell proposes insurance contracts with deductible in order to increase prevention effort. In terms of the empirical test, the presence of moral hazard suggest that once the insurance contract is acquired the prevention effort is reduced which increases risk.

Rubinstein & Yaari (1983) address the effects of dynamic hidden action on the insurance market using a multi–period principal–agent model that explains the existence of experience rating schemes. They find that one period contracts do not hold incentive compatibility thus policyholders always exert less prevention effort than the social desirable and hence the first–best is not enforceable. However, authors also show that repetition of isolated spot contracts allow reward strategies that may generate reputational effects that enforce in the long run a social optimal level of care in every period.[2] The existence of

[2] In some of the theoretical literature a no–claims discount strategy is used to describe an experience rating

such reward strategies (or contracts with *bonus–malus*) induces a characteristic behavior under moral hazard: once a claim is occurred the prevention effort increases and a reduction subsequent in claims is observed. I exploit that intuition in the empirical test of the presence of hidden action.

2.3 The Empirical Tests

Former empirical analysis on contract theory used the so–called positive correlation test to assess the presence of asymmetric information within the insurance market.[3] As pointed out before, the positive correlation test is informative on the presence of asymmetric information but is uninformative on causality and therefore it cannot differentiate hidden information from hidden action. First, under the presence of hidden information on risk, high–risk policyholders demand more coverage that low-risk ones and the former realize more claims than the latter generating a positive correlation between coverage choice and experienced risk with causality running from revealed risk to insurance demand. Second, if there exist hidden action, coverage from insurance reduces the cost to the insured's bad outcome inducing less prevention effort which increases accident risk. There is also a positive correlation between coverage and experienced accident risk but this time with the opposite causality.

A canonical positive correlation estimation uses two reduced–form econometric equations, one for the insurance coverage named c, and the other for the experienced risk of loss l. In both equations the explanatory variables are the information of policyholder i used for pricing by the insurance company named X_i. Linear versions of both econometric equations are displayed below:

$$c_i = X_i\beta + \epsilon_i, \tag{1a}$$
$$l_i = X_i\lambda + \mu_i. \tag{1b}$$

Under the null of hypothesis of symmetric information the residuals of those equations are uncorrelated. Otherwise, a statistical significant positive correlation implies the presence of information not taken into account by the pricing mechanism that affects both coverage decision and risk and leads to a rejection of the symmetric information hypothesis.

scheme.

[3] See Chiappori (2001), Chiappori & Salanié (2003) and Cohen & Siegelman (2009) for two complete surveys on empirical contract theory.

The findings of the positive correlation approach within the automobile insurance market are mixed: while Puelz & Snow (1994) and Cohen (2005) find evidence supporting the presence of asymmetric information, Chiappori & Salanié (2000), Dionne, Gouriéroux & Vanasse (2001) and Chiappori, Jullien, Salanié & Salanié (2006) cannot reject the null hypothesis of symmetric information.

The work of Puelz & Snow (1994) develops a system of hedonic premium and demand equations for a local company in USA and find evidence supporting the presence of adverse selection, a result that is the focus of several critics. First, as argued by Chiappori & Salanié (2000) and Dionne, Gouriéroux & Vanasse (2001), the highly constrained linear forms used and the lack of individual information suggest an omitted variable bias.[4] Second, Puelz & Snow use data of different individuals from the point of view of the insurer and the econometrician and do not control such heterogeneity leading to heteroscedasticity problems that again bias the estimation. Finally, the records of accidents are common information to the contract but they are treated as private information in the econometric analysis. Altogether that problems causes bias with unknown direction nor measure on the level of adverse selection.

Aware of the difficulties of separating adverse selection and moral hazard, Chiappori & Salanié (2000) address the presence of asymmetric information testing for a positive correlation between coverage and experienced risk and find no evidence supporting the rejection of the hypothesis of symmetric information. Authors use information on young drivers which circumvent both the identification and the learning problems though also is their major drawback because the harsh sample selection.[5]

In addition to the identification problem, Finkelstein & Poterba (2006) and Chiappori *et al.* (2006) question the robustness of the correlation approach. If individuals have different risk preferences, the correlation between ϵ_i and μ_i cannot longer be attributed only to unobserved differences in loss risk. For instance, suppose that individuals have private information on their risk type Z_1, and on their risk aversion Z_2, it is possible to write the

[4] Indeed, using the same data set Dionne, Gouriéroux & Vanasse (2001) find that controlling the accident probability breaks down the adverse selection evidence.

[5] Selecting the sample on young drivers eliminates two main problems: (i) contracts with high coverage are bought by high–risk costumers (prediction valid only for contracts within the same menu *i.e.*, for observationally identical agents); and (ii) focusing on young drivers eliminates the possibility of learning effects derived from driving experience.

following equations for the residuals of (1a) and (1b) respectively:

$$\epsilon_i = Z_{1,i}\pi_1 + Z_{2,i}\pi_2 + \varepsilon_i, \tag{2a}$$

$$\mu_i = Z_{1,i}\rho_1 + Z_{2,i}\rho_2 + \nu_i. \tag{2b}$$

If risk aversion is positively correlated with insurance coverage but has a negative correlation with risk of loss *i.e.,* $\pi_2 > 0$ and $\rho_2 < 0$, the correlation between ϵ_i and μ_i can be zero or negative, even under the presence of asymmetric information on risk type.

The theoretical and empirical relevance of individual attitudes toward risk within insurance markets were recently corroborated. Chiappori *et al.* (2006) argue through a theoretical model that under the presence of private information on risk preferences, the correlation test may fail to reject the null of symmetric information despite the presence of private information on risk type. From the empirical point of view, Cohen & Einav (2005) find that asymmetric information on risk preferences is positively correlated with private information on risk type which reinforces the positive correlation between coverage and *ex–post* risk.

2.3.1 Adverse selection and unused observables

Finkelstein & Poterba (2006) test the presence of adverse selection within the UK annuity market and reject symmetric information using the test of *unused* observables *i.e.,* variables observed by both parts of the contract related with both risk experience and insurance demand but not used by the pricing mechanism. The *unused* observable test has two major characteristics: (i) it is able to distinguish hidden information from hidden action; and (ii) it is robust to heterogeneity in individual preference parameters influencing insurance demand such as risk aversion.

The empirical strategy is based on the idea that under symmetric information, the pricing mechanism takes into account all the observed variables that provide information relevant to the insurance contract. Otherwise, informative observed variables are wasted and the error terms of (1a) and (1b) contain information on the policyholder's risk–type that were ignored by the pricing mechanism. The method of unused variables may be formalized as follows. Letting W be the unused variable, the econometric equations are for insurance coverage and risk of loss are:

$$c_i = X_i\beta + W_i\alpha + \epsilon'_i, \tag{3a}$$

$$l_i = X_i\lambda + W_i\phi + \mu'_i. \tag{3b}$$

The test's null hypothesis of symmetric information is that both α and ϕ are equal to zero. Rejecting the tests' null hypothesis means that there is evidence supporting the presence of asymmetric information. Moreover, the test provides evidence of adverse selection (or identifies adverse selection from moral hazard) if there exists a positive correlation between risk type and the *unused* variable for individuals with differential insurance coverage. Hence distinguishing adverse selection from moral hazard is based on the availability of information on how risk and *unused* observable characteristics are related among individuals regardless of their insurance coverage. Following Finkelstein & Poterba (2006) I test the presence of adverse selection proving as *unused* observable policyholders' traffic offenses providing both external an internal evidence of the link between offenses and accidents.

2.3.2 Moral hazard and the experience rating mechanism

The method used to identify moral hazard is based on the idea that under hidden action on effort and the existence of experience rating schemes the occurrence of a claim changes completely the discounted cost of future accidents making them more expensive and implying a reaction in policyholder's prevention behavior.

Abbring *et al.* (2003) propose the former empirical work implementing this methodology. They develop a theoretical model of dynamic moral hazard under *bonus–malus* experience rating and prove that under conventional assumptions the experience rating scheme affects the policyholder's behavior: the occurrence of a claim induces more prevention effort reducing the probability of accident and in turn claim's intensity. They use this testable prediction on data form a French insurer and find no significant evidence of moral hazard. Abbring, Chiappori & Zavadil (2007) propose a similar test for moral hazard based on the time span of a policyholder on an experience rating class. Authors find some evidence supporting the existence of moral hazard using data from a Dutch insurance company.

Following Abbring *et al.* (2003) I propose a theoretical dynamic model of moral hazard and prove that under a *bonus* mechanism the occurrence of a claim changes the prevention incentives reducing accident probability. I modify the environment proposed by Abbring *et al.* to adjust the market practice in Colombia where the experience rating scheme is based only on *bonus* rather than *bonus–malus* devices. Using a new data set I develop an empirical model of the time span between the purchase of the insurance contract and the first claim, and between the first claim and the second one, and so on. Thus I estimate a mixed proportional hazards model using as covariate the number of previous claims. This model accounts the misleading unobserved heterogeneity by including a *shared frailty* device that is related to random–effects models.[6]

3 Colombian Car Insurance Market

In the present section I briefly describe the functioning of the Colombian car insurance market and then I describe the used data set.

Two markets provide products of car insurance in Colombia. One market offers compulsory insurance covering from first to third party physical injury liability. The other market, where data set comes from, offers insurance contracts covering car damage (total or partial), car theft (total or partial) and legal liability. The latter market is not compulsory and every policyholder chooses his coverage level and type (any combination between total or partial damage, total or partial theft and legal liability is allowed). During the sample period, where eleven insurance companies provided approximately one million of policies, insurance companies used a common knowledge *bonus* experience rating scheme. Such no–claims discount device does not obey to an agreement between insurance companies, and yet it is a generalized market practice.

Fasecolda, the federation of Colombian insurers grants access to the administrative records of insurance companies which contains information on signed contracts. Each record includes policyholders and their cars' characteristics used for pricing, the amounts of coverage, deductible and premium contracted. The data set also contains information on the sample period claims record. Finally, the personal identification number of each insured provides a link to the traffic offenses database that contains information on the date, the punishable behavior and the pecuniary payment charged after an offense. I collect offenses information from three years before the purchase of the contract in the data base in order to build a consistent record of driving behavior. Table 2 on Appendix A contains a brief description of the variables available in the data set. As long as companies have pricing mechanisms based on different variables they do not collect the same information and some variables are available for some contracts while others are not. Information on the pricing variables is private and two of the eleven companies refused to

[6] For a detailed explanation of the methodology see: van den Berg (2001), Gutierrez (2002), Cameron & Trivedi (2005, Ch. 17–19) and Kleinbaum & Klein (2005, Ch. 5)

provide it. Table 3 in Appendix A presents variables used for pricing purposes by each insurance company whom revealed me that information.

I observe information on insurance contracts signed in a period of two years starting on January 1 2006. Observations are the flow of contracts written or renewed during the first sample year that were renewed in the next. This sample design ensures that the policyholder faces the effects of experience rating scheme on his premium schedule and therefore the second observed year provides no additional information and it is dropped.[7] Descriptive statistics of the survival data set are displayed in Table 4 on Appendix A and reveals that 236.582 subjects enter into the study with mean entry date July 12 of 2006. Information on subjects does not suffer from gaps in the time of the study and in total policyholders were 86’352.430 days at risk. Every subject stayed in the study 365 days and together made 12.894 claims with mean number of claims equal to 0,05 claims per subject.

The initial database suffers from different attrition sources that reduce its size from one million to 236.582 contracts. The attrition sources are the following. First, collective contracts are a market practice in Colombia, however contract theory used here works at the individual level instead of collective level, hence I drop joint policies taking away almost 60% of the initial contracts. Second, insurance contracts bought by firms are identified in the database by firm identification number, however traffic offenses are charged to the individuals involved in the offense, hence those policies cannot be linked to traffic offenses. Thus policies bought by firms are discarded causing a loss of 25% of the remaining contracts. Finally insurance contracts covering cars used for public service are discarded provided their greater exposure to risk when compared to private used cars. This attrition takes 8% of the remaining contracts.

Colombian transit law punishes with pecuniary payments 96 different types of driver’s behavior with a system that does not include memory of traffic offenses like demerit point systems. In order to solve the multidimensional issue arising from the diversity of traffic offenses I propose two variables that condensate such information: (i) the number of offenses imposed to a policyholder; and (ii) the number of minimum wages charged after an offense. Both variables increase with offenses but the second accounts for the fault’s severity, is steeper and more dispersed. Figures 1 and 2 on Appendix A respectively depict the distribution of the number of offenses and minimum wages charged by insurance

[7] In the best scenario a contract is signed in the first sample year, were not altered and renewed without changes during the next year. Now, if a contract were signed during the first year and changed during it, I observe the contract since it change.

company. The distribution of traffic offenses variables is stable between insurers, depends on their market share and is highly concentrated in zero.

4 Identification of Hidden Information

I apply the *unused* variable test on Colombian vehicle insurance market using traffic offenses variables. In order to assess the presence of adverse selection the *unused* observable have to be positively correlated with risk and be a good predictor of both experienced risk and insurance demand. In the following section I discuss the offenses variables and assess the correlation between offenses and accidents. Then I test the predictive power of policyholder's traffic offenses on both experienced risk and insurance demand conditional in both cases on pricing characteristics.

4.1 Testing Traffic Offenses as an Unused Observable

The *unused* variables test is able to distinguish between adverse selection and moral hazard if exist evidence supporting a relationship between the *unused* variable and driver's risk type for agents with differential coverage. In the following paragraphs I provide both external and internal evidence supporting such relationship.

A substantial body of empirical evidence suggests a relationship between traffic offenses and accident rates.[8] Those works test the predictive properties of offenses records on accidents for sample populations with differential coverage. There are two potential explanations for the positive correlation between offenses and accidents: (i) causality runs from offenses, which are correlated with unobserved characteristics, to accidents; and (ii) risky behavior induced by insurance coverage expose the policyholder to both offenses and accidents. The second explanation is sustained by the presence of moral hazard and requires changes in prevention behavior conditional on owning an insurance contract. However, with an extended traffic offenses database containing individuals with and without insurance coverage I find a significative positive correlation between offenses and accidents for both insurance status showing that offenses are correlated with risk and

[8] This evidence includes Coppin, McBride & Peck (1971), Burg (1975), Peck & Kuan (1983), Boyer, Dionne & Vanasse (2001), Gebers & Peck (1994), Chen, Cooper & Pinili (1995), Gebers (1998), Gebers (1999), Gebers & Peck (2003), between others.

suggesting that the explanation for that correlation is not the presence of moral hazard. Table 5 on Appendix B provides the results of such estimations.

4.1.1 Traffic offenses and policyholder accident rate

In the automobile insurance context the risk of loss is defined to be the risk of filing a claim. To analyze the relationship between the unused observables and the claim patterns, I estimate a proportional hazards model of the time span between the purchase of an insurance contract and the occurrence of a claim. The estimating equation is given by (4) below:

$$h(t|X_i) = h_0(t)\exp(X_i\beta), \tag{4}$$

where $h(t|X_i)$ denotes the hazard function for the probability that a policyholder with characteristics X files a claim t periods after the purchase of the policy.

To estimate 4 I apply the Cox proportional hazards method that allows to estimate parameters on β without imposing any parametric assumption on the form of the baseline hazard function $h_0(t)$. The covariates of interest are insured's characteristics used in pricing and the variable proposed to be the unused observable.

Notice that policyholders can report various claims during a contract year thus the estimation method should take into account the possible correlation structure behind the failure process.[9] Estimation techniques under the name of multiple failure or recurrent event survival analysis deal with the violation of the assumption in classical survival analysis that failure times are independent. Provided that multiple claim events possess a natural order –the first claim, the second claim and so on, I adopt here the counting process approach of Andersen & Gill (1982) where the problem reduces to the analysis of time to the first event, time to the second and so on. Moreover, I use the modification proposed by Prentice, Williams & Peterson (1981) known as the conditional risk set model where a policyholder is not at risk of a second claim until he files the first one, and so on.

Tables 6 to 14 on Appendix B present the results after estimating a Cox model for each insurer. Column (1) shows the results controlling only for the variables used in pricing while columns (2) and (3) show the results after estimating a model adding as covariates the number of offenses and the number of minimum wages charged respectively. For simplicity, tables present only the estimated coefficients of car's model and the unused

[9] Car insurance differs for example from annuity markets where the failure process posses a state from which an agent will never leave (the death of the insured).

variables though complete estimation tables are available upon request. Each estimation is followed by the number of subjects and fails that entered in the study, the log likelihood and the pseudo–R squared statistics, the statistic of likelihood–ratio test and its probability. Finally I present the statistics of the test of the proportional hazards assumption based on Schoenfeld residuals.

I find a significative positive correlation between the number of offenses and the experienced risk conditional on characteristics used in pricing for six insurance companies: 101, 161, 351, 431, 451 and 501 (Table 1 below or Columns (2) of Tables 6, 7, 9, 11, 13, 14 on Appendix B). The effect of one–offense increase in the number of offenses increases the hazard of filing a claim in a range of 9% (Company 451) to 24% (Company 351) showing the importance of the number of offenses in predicting the experienced risk. I also find significative evidence of positive correlation between the number of minimum wages charged and experienced risk for five insurance companies: 101, 161, 351, 451 and 501 (Table 1 below or Columns (3) of Tables 6, 7, 9, 13, 14 on Appendix B). The effects of one–minimum wage increase in the number of minimum wages charged increases in a modest amount the hazard of filing a claim, the range of increase is between 0.1% (Company 351) and 1% (Company 501). Altogether, the models are overall significant and respects the proportional hazards assumption measured by the LR–test and the Shoenfeld residuals statistic respectively.

Table 1: Summary of hidden information models

	Company								
	101	**161**	**311**	**351**	**381**	**431**	**441**	**451**	**501**
	Number of offenses								
Cox	1,15*	1,19*	0,96	1,25*	1,05	1,12-	1,04	2,51*	1,17*
OLS	0,24*	0,01*	0,01-	0,02*	0,01+	0,02*	0,01+	0,01	0,01-
	Number of minimum wages								
Cox	1,01*	1,01*	1	1,01*	1	1	1	1,01*	1,01*
OLS	0,0013*	0,0005*	0,0009+	0,0014*	0,0005	0,0010*	0,0003	0,0009-	0,0006-

Note: Summary table of results of the *unused* variable test. Cox coefficients correspond to hazard ratios. Statistical significance at 1%, 5% and 10% are displayed by (*), (+) and (-) respectively. For estimation details see Tables 6 to 14 on Appendix B.

4.1.2 Traffic offenses and coverage

Once the relationship between traffic offenses and survival rates were stated, the next step in the unused variables test is to assess the relationship between insurance demand and offenses conditional on observables used in pricing. Together with previous results, statistical evidence on the latter relationship provides evidence supporting the presence of adverse selection in the sense of Rothschild & Stiglitz (1976): informed high–risk agents, self–select themselves by choosing comprehensive coverage contracts and hence a positive relationship between offenses and coverage controlled by the pricing variables provides evidence of adverse selection.

In order to assess such relationship I estimate an OLS model of log–coverage against pricing and offenses variables. The estimating equation is displayed below:

$$c_i = X_i\beta + W_i\alpha + \epsilon_i', \tag{5}$$

where W_i stands for the unused observable. Tables 6 to 14 on Appendix B reports results of that estimations for each insurer. Column (4) shows the results when the covariates are the pricing variables while columns (5) and (6) show the results after estimating models adding offenses variables as covariates. Again tables present only the estimated coefficients of the model of car and the unused variables though complete estimation tables are available upon request. Each estimation is accompanied by the number of observations, the log likelihood statistic, the adjusted–R squared and the overall significance test.

I find significant though modest evidence on the relationship between insurance demand and the number of offenses for all insurance companies except for Company 451 for which I find no evidence of such relationship. The effect of one–offense increase in the number of offenses lies in a range of 1% to 2% increases in the demand for coverage. The results for the minimum wages charged variable are even more modest though statistically significant for seven of the nine companies for whom the test is conduced: 101, 161, 311, 351, 431, 451 and 501 (Table 1 above or Columns (6) of Tables 6, 7, 8, 9, 11, 13, 14 or Table 1 (summary) all on Appendix B).

The important finding that traffic offenses variables are correlated with insurance demand for all the insurance companies together with the earlier finding of a link between these characteristics and claim rates constitutes a rejection of the null hypothesis of symmetric information. More importantly, the evidence of a relationship between offenses variables and accidents across differential insurance coverage allows conclusion for the presence of adverse selection in the companies for which the symmetric information hypothesis has been rejected. Hence conclusions of the presence of adverse selection are reduced to six companies: 101, 161, 351, 431, 451 and 501 (Table 1 above or Tables 6, 7, 9, 11, 13, 14 on Appendix B).

A caveat in the estimation method arises if unused observables are correlated with pricing variables. I test that possibility by using an OLS regression of offenses against pricing variables for each insurer and then performing the unused test with the predicted values of that regression. I find no differences in the test's results and the reason for that is the little association between offenses and pricing variables in the linear model. Test for specification were conducted and revealed no important problems of misspecification.

5 Identification of Hidden Action

The following section tests the presence of hidden action. I derive a testable implication of the existence of hidden action from a dynamic model of moral hazard under a *bonus* experience rating scheme and then I develop an econometric model that tests the previous implication.

5.1 Dynamic Moral Hazard under a Bonus Scheme

In the following section I propose a dynamic model of moral hazard under a *bonus* scheme of experience rating and derive a testable implication that identify the presence of hidden action. It is worth noticing that the following model and its conclusions are highly related to Abbring *et al.* (2003).

5.1.1 The model

Time takes place discretely on $\mathcal{T} = \{0, \ldots, T\}$ with T positive and finite. The wealth of an agent i at time t is noted by $w_{i,t}$ which is strictly positive for every $t \in \mathcal{T}$. Wealth cannot be transferred from one period to the next *i.e.,* there are no saving or banking devices. An agent has an accident in t with probability $p_{i,t}$, such probability depends on the agent's effort in accident prevention. I assume that $p_{i,t}(e_{i,t})$ is twice differentiable with $p'_{i,t}(\cdot) < 0$ and $p''_{i,t}(\cdot) > 0$, therefore investments in accident prevention reduce accident probability with decreasing returns. If an accident occurs, the agent incurs in a monetary loss covered by an insurance policy with fixed deductible d_i and premium $q_{i,t}$.[10] Under a *bonus* scheme

[10] As long as accidents not caused by the agent are completely covered and have no impact on his future premiums *i.e.,* the experience rating scheme does not apply, such accidents are disregarded in the econometric analysis.

of experience rating, the premium depends on past experience following the path:

$$q_{i,t+1} = \begin{cases} \delta q_{i,t} & \text{if no accident occurred at } t \\ \gamma q_{i,t} & \text{if an accident occurred at } t, \end{cases} \tag{6}$$

where $0 < \delta < 1$ and $\gamma = 1$.

Hidden action is available to the policyholder, so at each time t, the agent chooses his effort in accident prevention $e_{i,t} \in [0, \bar{e}_i]$ at a disutility cost $c_i(e_{i,t})$, with $c_i^{'}(\cdot) > 0$ and $c_i^{''}(\cdot) > 0$, thus, increases in prevention effort are costly and every effort increase has an even higher cost. Agent's expected utility at time t is given by:

$$v_i(e_{i,t}, q_{i,t}) = p_{i,t}(e_{i,t})u_i(w_{i,t} - d_i - q_{i,t}) + (1 - p_{i,t}(e_{i,t}))u_i(w_{i,t} - q_{i,t}) - c_i(e_{i,t}), \tag{7}$$

where $u_i(\cdot)$ is increasing and strictly concave, capturing the policyholders' risk aversion. I assume for simplicity that utility is separable between income and cost of effort in accident prevention in spite of its restrictiveness. This assumption is widespread in the literature. For the sake of simplicity, I assume that the agent perfectly foresees his income path, thus he is only concerned with forming expectations on future accidents and their effects on his available income. Therefore, the agent chooses his effort in accident prevention path $\{e_{i,t}\}_{t=0}^{T}$, to maximize expected discounted utility with discount factor $\beta_i \in (0,1)$. He solves the program:

$$\max_{\{e_{i,t}\}_{t=0}^{T}} \sum_{t=0}^{T} \beta_i^t v_i(e_{i,t}, q_{i,t}). \tag{8}$$

Agent's preferences and effort in prevention cost functions are defined both in a wide sense and fully individual, therefore the model sustains any kind of unobserved heterogeneity in these primitives of the model.

5.1.2 The testable implication

To drop the individual index is convenient for notational purposes and leaves all results valid at the individual level irrespective of the form and degree of unobserved heterogeneity as mentioned above. The first result is stated in the Lemma 1 below.

Lemma 1. *At each t the optimal effort in accident prevention $e_t^{\star}$, only depends on the past history through the current premium q_t.*

Proof. See Appendix C.1.1. ■

In other words Lemma 1 states that current behavior is only affected by past accidents through their impact on the incentive scheme faced by the agent, for which the current premium contains the necessary information. Assuming a prevention technology that does not directly depend on previous accidents disregards many ways in which the driver's accident history could influence his current prevention choice (*e.g.*, learning effects or fear after an accident).[11]

The program in (8) is a dynamic optimization program with state variable q_t; let $V_t(\cdot)$ denote the value function of this program at date t.[12] The Bellman equation is given by:

$$V_t(q_t) = \max_e \Big\{ p(e)\left[u(w_t - d - q_t) + \beta V_{t+1}(q_t)\right] + \left(1 - p(e)\right)\left[u(w_t - q_t) + \beta V_{t+1}(\delta q_t)\right] - c(e) \Big\}. \tag{9}$$

The interest in what follows is to establish the qualitative properties of both the value function and the optimal effort with respect to current premium, instead of finding the optimal effort path. With that objective in mind, it is necessary to establish the relationship between the value function and premium's level. Lemma 2 below states that relationship.

Lemma 2. *The value function $V_t(\cdot)$ is decreasing in q_t for all t.*

Proof. See Appendix C.1.3. ■

Now, I can derive a testable implication of moral hazard under a *bonus* scheme that relates current premium and optimal effort in accident prevention. To analyze the impact of the current premium on the optimal effort lets focus on situations where the premium is small with respect to agent's income.[13] Proposition 1 below states that for such small levels of premium, prevention effort (or the optimal accident probability) decreases with the premium.

Proposition 1. *If the value function $V_t(\cdot)$ is differentiable in a neighborhood of $q_t = 0$ for all t, for small values of q_t, the accident probability associated to optimal effort in accident prevention $p_t(e_t^\star(q_t))$ decreases with q_t for all t.*

[11] Learning effects may have important consequences in the empirical test for the presence of moral hazard, for a complete treatment of such effects see Abbring *et al.* (2003, Sec. 3).

[12] For a detailed explanation of the argument that allows the Bellman equation representation see Appendix C.1.2.

[13] Notice that if the number of accidents is large enough, premium could exceed the agent's current income, current wealth or even lifetime wealth, however that situation is of no interest given that the agent could choose stop driving and his accident probability becomes zero. In this case, accident probability does not depend anymore on premium.

Proof. See Appendix C.1.4. ■

A simple testable implication is provided by Proposition 1. If moral hazard exists under a *bonus* scheme, the occurrence of an accident induces an abrupt drop in the optimal accident probability path, hence the accident process exhibits negative occurrence dependence.

The previous theoretical model provides a useful tool in the analysis of moral hazard under an experience rating scheme. It was designed at the individual level and it allows any distribution of preferences and prevention technologies across agents. However, as long as the empirical test relies on interpersonal comparisons, the issue of unobserved heterogeneity becomes crucial. It is also important to stress that the model does not take into account the real fact that the *bonus* scheme has a floor (a fall in 10% in the premium per year of no accidents until the 5th year). It also ignores the nonmonetary consequences of an accident.

5.2 Empirical Analysis of Hidden Action

Based on the testable implication found in the previous section I test the presence of hidden action by using dynamic data on claims in a market ruled by a *bonus* experience rating scheme. Hence if moral hazard exists, negative occurrence dependence in the claim process should be observed: the occurrence of an accident launches efforts in accident prevention and reduces claims. However, policyholders in possession of hidden information on risk could be accident–prone precisely for unobserved factors that cannot be controlled and the test for hidden action could be deceiving. Indeed, the negative occurrence dependence created by hidden action and experience rating could be countered by the positive effect on occurrence dependence produced by hidden information. The model used here allows for the identification of occurrence dependence and controls the deceiving unobserved heterogeneity through a survival–data model with random effects.

As the exact date of each claim is provided by the data set I follow the method proposed by Abbring *et al.* (2003) and estimate a model of the time span between the purchase of insurance and the first claim, and between subsequent claims using as only covariate the number of previous claims. The estimating equation is given by (10) below:

$$h(t|X_i, \alpha_i) = h_0(t) \exp(\beta X_i) \alpha_i, \tag{10}$$

where X_i is the counting process of the number of claims and α_i is a nonnegative individual–specific effect. The multiple records structure of the data base allows a flexible parametric estimation method that estimate β and the frailty variance θ. The frailties are shared among the policyholders and are assumed to follow a gamma distribution with mean one an variance θ to be estimated from the data measuring the variability of frailty across groups. Notice that if $\theta = 0$ the frailty effect disappears.

Empirical implementation of the above econometric model requires to assume explicit forms for both the baseline hazard $h_0(t)$ and a distribution of the unobserved heterogeneity. Following van den Berg (2001) the assumptions made over the distribution of the unobserved heterogeneity not necessarily depends on the economic theory behind the empirical implementation, however the explicit form of the baseline hazard should be theoretically sustained. Here I choose the exponential form for the baseline hazard because it assumes that the failure process lack of memory which provides the adequate environment for proving the testable implication. Notice that different assumptions on the form of the baseline should constrain the evidence of occurrence dependence and deceive the empirical test. Besides, I choose the gamma distribution for the shared frailty component as mentioned above.

Tables 15 to 17 of Appendix C presents results after the estimation of the model above mentioned. Column (1) presents results of a model with no shared frailty but clustered at the individual level while column (2) to (6) presents results of models with gamma distributed shared frailty at the individual level. Estimations in column (2) are calculated for the entire sample while results of columns (3) and (4) are calculated from stratifying the sample to males and females policyholders respectively. Finally columns (4) and (5) stratify for policyholders below 25 years and above 26. In Tables 16 and 17 I present results after stratifying for each insurance company. Below each estimation is presented the logarithm of the shared frailty variance, the number of subjects and their fails, the log–likelihood and finally the statistics of the log–likelihood ratio testing both the overall significance and significance of the frailty effect ($H_0 : \theta = 0$).

If I estimate the model without unobserved heterogeneity there is no evidence of moral hazard since an increase of one–claim increases the hazard of filing a claim in 87%, which breaks any possibility of negative occurrence dependence. However once the unobserved heterogeneity is controlled through the shared frailty, the estimated hazard ratio of β drops to 0.0437 meaning a reduction of 95% of the hazard of filing a claim and sustaining the presence of moral hazard in the Colombian insurance market. This result clearly illustrates the pervasive effect of unobserved heterogeneity on the sign of occurrence dependence changing it spuriously from negative to positive. The overall significance of the model is ensured together with the significance of the frailty effect.

The sample stratification confirms in several ways the previous result and permits further interpretations. Both males and females suffers of negative occurrence dependence together with drivers with and without experience. In spite of the modest differences found between females and males, females reduce more than males their hazard of filing a claim after the occurrence of an accident. In terms of driving experience, less experienced subjects reduce their hazard of filing a claim in 2% more than experienced ones, suggesting the existence of learning effects on young drivers. The stratification for insurance company reinforce the preceding conclusions and shows an interesting heterogeneity. While the reduction of hazard in two companies were close to 93% (Company 101 and 311), a reduction of 98% on the hazard of filing a claim is observed for company 211.

6 Conclusions

This thesis test for the identification of both hidden information and action in Colombian car insurance market. For the identification of hidden information I apply the test proposed by Finkelstein & Poterba (2006). Such test uses individual characteristics that are not used in the pricing mechanism but correlated with both insurance coverage and risk occurrence.

I use information on individual traffic offenses as an unused observable that is not priced. To provide evidence of asymmetric information I show that offenses are correlated with both survival probability and the amount of purchased coverage, controlling for used variables. Since each company use different variables in the pricing mechanism the test is conducted for each insurance company. I also provide external evidence of a positive relationship between offenses and accidents no matter the coverage levels. That evidence allows me to interpret previous results as supporting the presence of adverse selection. I find evidence of the presence of adverse selection in six of the nine companies for which the test is performed suggesting the inclusion of offenses variables in their pricing mechanism in order to reduce the informational asymmetry and improve risk allocations.

For the identification of hidden action I show that *bonus* experience rating schemes serves to identify the presence of moral hazard by implying negative occurrence dependence for individual claim process. The major drawback of this approach appears with the existence of intrinsically bad drivers that are more likely to be accident–prone and to have more accidents in the future. This positive selection effect can mislead the negative occurrence effect and hence deceive the test for moral hazard. I build on the work of Abbring *et al.* (2003) that deals with both the statistical identification of the parameter measuring negative dependence and the empirical distinction between unobserved heterogeneity that causes the positive selection effect and the negative state dependence caused by moral hazard. Using a parametric survival model with shared frailty I show the existence of negative occurrence dependence and hence of moral hazard in the Colombian insurance market. Stratified analysis on males and females and on experienced and not experienced drivers confirm previous result. Finally, analysis for each insurance company reinforces the previous results and suggest the need for modifications on the deductible mechanism applied by the insurance companies.

References

Abbring, J., Chiappori, P. & Pinquet, J. (2003), 'Moral Hazard and Dynamic Insurance Data', *Journal of the European Economic Association* **1**(4), 767–820.

Abbring, J., Chiappori, P. & Zavadil, T. (2007), Better Safe than Sorry? Ex Ante and Ex Post Moral Hazard in Dynamic Insurance Data. Mimeo.

Akerlof, G. (1970), 'The Market for Lemons: Quality Uncertainty and the Market Mechanism', *The Quaterly Journal of Economics* **84**(3), 488–500.

Andersen, P. & Gill, R. (1982), 'Cox's Regression Model for Counting Processes: A Large Sample Study', *Annals of Statistics* **10**(4), 1100–1120.

Arnott, R. & Stiglitz, J. (1991), 'Equilibrium in Competitive Insurance Markets with Moral Hazard', *NBER Working Paper* (3588).

Boyer, M., Dionne, G. & Vanasse, C. (2001), Econometric Models of Accident Distributions, *in* G. Dionne, ed., 'Contributions to Insurance Economics', Springer, pp. 169–213.

Burg, A. (1975), 'Traffic Violations in Relation to Driver Characteristics and Accident Frecuency', *Working Paper, UCLA: Institute of Trasportation and Traffic Engineering* (Report: 74–55).

Cameron, C. & Trivedi, P. (2005), *Microeconometrics: Methods and Applications*, Cambridge University Press.

Chen, W., Cooper, P. & Pinili, M. (1995), 'Driver Accident Risk in Relation to the Penalty Point System in British Columbia', *Journal of Safety Research* **26**(1), 9–18.

Chiappori, P. (2001), Econometric Models of Insurance under Asymmetric Information, *in* G. Dionne, ed., 'Handbook of Insurance', Kluwer Academic Publishers, pp. 365–394.

Chiappori, P., Jullien, B., Salanié, B. & Salanié, F. (2006), 'Asymmetric Information in Insurance: General Testable Implications', *Rand Journal of Economics* **37**(4), 783–798.

Chiappori, P. & Salanié, B. (2000), 'Testing for Asymmetric Information on Insurance Markets', *Journal of Political Economy* **108**(1), 56–78.

Chiappori, P. & Salanié, B. (2003), Testing Contract Theory: a Survey of Some Recent Work, *in* M. Dewatripont, L. Hansen & P. Turnovsky, eds, 'Advances in Economics and Econometrics - Theory and Applications, Eighth World Congress', Econometric Society Monographs, Cambridge University Press, pp. 115–149.

Cohen, A. (2005), 'Asymmetric Information and Learning in the Automobile Insurance Market', *Review of Economics and Statistics* **87**(2), 197–207.

Cohen, A. & Einav, L. (2005), 'Estimating Risk Preferences from Deductible Choice', *NBER Workig Paper* (11461).

Cohen, A. & Siegelman, P. (2009), 'Testing for Adverse Selection in Insurance Markets', *NBER Workig Paper* (15586).

Cooper, R. & Hayes, B. (1987), 'Multi–Period Insurance Contracts', *International Journal of Industrial Organization* **5**(2), 211–231.

Coppin, R., McBride, R. & Peck, R. (1971), 'The Distribution and Prediction of Driver Accident Frecuencies', *Accident Analysis and Prevention* **2**(4), 243–299.

Crocker, K. & Snow, A. (1985), 'The Efficiency of Competitive Equilibria in Insurance Market with Adverse Selection', *Journal of Public Economics* **26**(2), 207–219.

Dahlby, B. (1983), 'Adverse Selection and Statistical Discrimination', *Journal of Public Economics* **20**(1), 121–130.

Dionne, G. & Doherty, N. (1994), 'Adverse Selection, Commitment and Renegotiaation with Application to Insurance Markets', *Journal of Political Economy* **102**(2), 209–235.

Dionne, G., Doherty, N. & Fombaron, N. (2001), Adverse Selection in Insurance Markets, *in* G. Dionne, ed., 'Handbook of Insurance', Kluwer Academic Publishers, pp. 185–243.

Dionne, G., Gouriéroux, C. & Vanasse, C. (2001), 'Testing for Adverse Selection in the Automobile Insurance Market: A Comment', *Journal of Political Economy* **109**(2), 444–453.

Dionne, G. & Lasserre, P. (1985), 'Adverse Selection, Repeated Insurance Contracts and Announcement Strategy', *Review of Economic Studies* **52**(4), 719–723.

Finkelstein, A. & Poterba, J. (2006), 'Testing for Adverse Selection with Unused Observables', *NBER Working Paper* (12112).

Fombaron, N. (2000), 'Renegotiation–proof Contracts in Insurance Markets with Asymmetric Information', *Working Paper, THEMA* .

Gebers, M. (1998), 'Explanatory Multivariate Analysis of California Driver Record Accident Rates', *Transportation Reseach Record* (1635), 72–80.

Gebers, M. (1999), 'Strategies for Estimating Driver Accident Risk in Relation to California's Negligent–Operator Point System', *Working Paper, California Department of Motor Vehicles* (183).

Gebers, M. & Peck, R. (1994), 'An Inventory of California Driver Accident Risk Factors', *Working Paper, California Department of Motor Vehicles* (144).

Gebers, M. & Peck, R. (2003), 'Using Traffic Conviction Correlates to Identify High Accident–Risk Drivers', *Accident Analysis and Prevention* **35**(6), 903–912.

Gutierrez, R. (2002), 'Parametric Frailty and Shared Frailty Survival Models', *The Stata Journal* **2**(1), 22–44.

Kleinbaum, D. & Klein, M. (2005), *Survival Analysis: A Self–Learning Text*, 2 edn, Springer.

Miyazaki, H. (1977), 'The Rat Race and Internal Labour Markets', *Bell Journal of Economics* **8**(2), 394–418.

Peck, R. & Kuan, J. (1983), 'A Statistical Model of Individual Accident Risk Prediction Using Driver Record, Territory and other Biographical Factors', *Accident Analysis and Prevention* **15**(5), 371–393.

Prentice, R., Williams, B. & Peterson, A. (1981), 'On the Regresion Analysis of Multivariate Failure Time Data', *Biometrika* **68**(2), 373–379.

Puelz, R. & Snow, A. (1994), 'Evidence on Adverse Selction: Equilibrium Signalling and Cross–Subsidization in the Insurance Market', *Journal of Political Economy* **102**(2), 236–257.

Rothschild, M. & Stiglitz, J. (1976), 'Equilibrium in Competitive Insurance Markets: an Essay on the Economics of Imperfect Information', *The Quarterly Journal of Economics* **90**(4), 629–649.

Rubinstein, A. & Yaari, M. (1983), 'Repeated Insurance Contracts and Moral Hazard', *Journal of Economic Theory* **30**(1), 74–97.

Shavell, S. (1979), 'On Moral Hazard and Insurance', *The Quarterly Journal of Economics* **93**(4), 541–562.

van den Berg, G. (2001), Duration Models: Specification, Identification and Multiple Durations, *in* J. Heckman & E. Leamer, eds, 'Handbook of Econometrics', Vol. 5, Elsevier, pp. 3382–3460.

Wilson, C. (1977), 'A Model of Insurance Markets with Incomplete Information', *Journal of Economic Theory* **16**(2), 167–207.

A Colombian Car Insurance Market: Appendix

Table 2: Variables available in the data set

Variable	Value label	Description
ph_start_date		policy start date
ph_sex	0 male 1 female	sex
ph_age		age
ph_ocupation	0 self employed 1 employed 2 student 3 housewife 4 other	occupation
ph_marital_status	0 single 1 married 2 widowed 3 divorced 4 living together	marital status
ph_offenses_num		number of offenses
ph_offenses_mw		number of minimum wages charged
c_brand		car brand
c_model		car model (year)
c_alarm	0 no alarm 1 alarm	car with alarm
c_locator	0 no locator 1 locator	car with locator
c_class		car class
c_weight		car weight (in Kg)
c_imported	0 national 1 imported	national or imported car
c_power		car power (in HP)
c_ec		car engine capacity (in c3)
c_pcapacity		car passenger capacity
c_lcapacity		car load capacity
c_doors		number of car doors
c_air	0 no 1 yes	car air system
c_gearbox	0 Mec 1 Aut	car type of gearbox
c_fueltype	0 Gas 1 Diesel	car fuel type
c_cartrain	0 2x1 1 4X2 2 4+X4	car type of train
p_premium		premium
p_bonus		bonus %
p_coverage		policy coverage
cl_date		accident date

Table 3: Variables used in the pricing mechanism by company

	Company								
Variable	**101**	**161**	**311**	**351**	**381**	**431**	**441**	**451**	**501**
Sex	N	N	N	Y	N	Y	Y	N	N
Age	N	N	Y	Y	Y	Y	Y	N	N
Occupation	N	N	Y	N	Y	N	Y	N	N
Marital Status	N	N	Y	N	N	N	N	N	N
Brand	Y	Y	Y	Y	Y	Y	Y	Y	Y
Model	Y	Y	Y	Y	Y	Y	Y	Y	Y
Alarm	N	Y	Y	N	Y	N	Y	N	N
Locator	Y	Y	N	Y	Y	Y	Y	Y	Y
Class	N	N	Y	N	N	N	N	N	Y
Weight	Y	Y	N	N	N	N	Y	Y	N
Imported	Y	Y	Y	N	N	N	N	Y	N
Power	N	Y	N	N	N	N	Y	N	N
c3	N	Y	N	N	N	N	N	N	N
P Capacity	N	Y	N	N	N	N	Y	N	Y
L Capacity	N	Y	N	N	N	Y	Y	N	Y
Doors	N	Y	N	N	Y	N	Y	N	N
Air	N	Y	N	N	Y	N	N	N	N
Gearbox	N	Y	N	N	Y	N	N	N	N
Gas	N	Y	N	N	Y	N	N	N	N
Train	N	Y	N	N	Y	N	Y	N	Y

Note: Pricing information provided by insurance companies through Fasecolda. A N means that the company do not use that variable in its pricing mechanism while a Y means that it is used.

Table 4: Description of the survival data set

			Per subject		
Category	**Total**	**Mean**	**Min**	**Median**	**Max**
no. of subjects	236582				
(first) entry time		Jul/12/2006	Jan/01/2006	Jul/18/2006	Dec/01/2006
(final) exit time		Jul/12/2007	Jan/01/2007	Jul/18/2007	Dec/01/2007
subjects with gap	0				
time at risk	86352430	365	365	365	365
failures	12894	.0545012	0	0	5

Figure 1: Number of offenses by insurance company

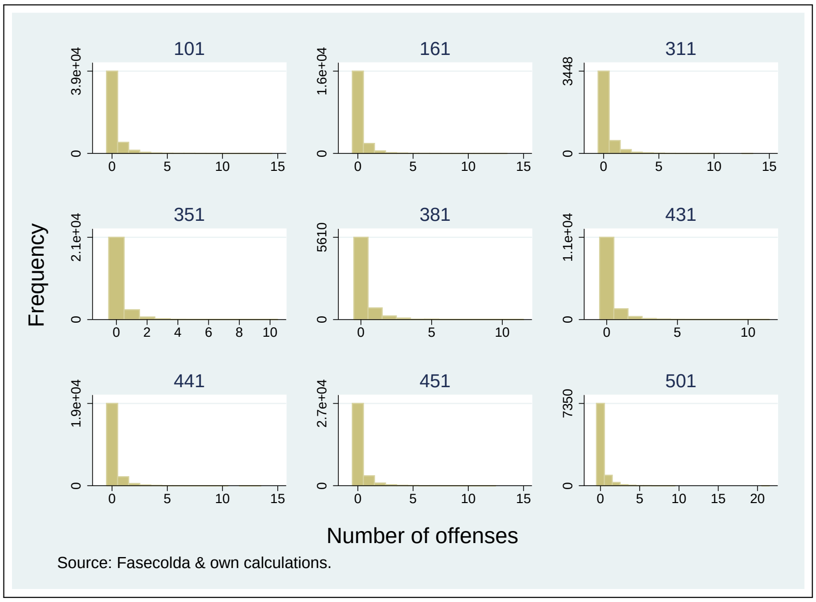
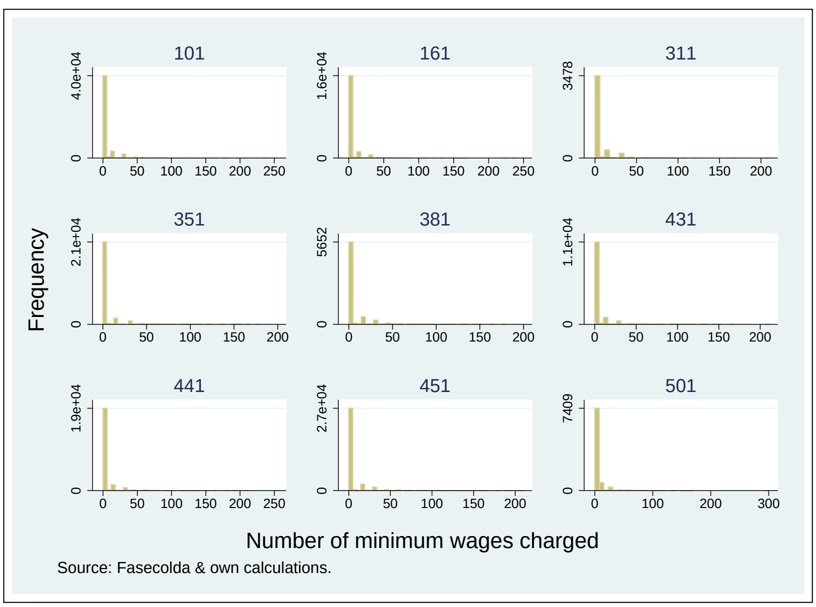


Figure 2: Minimum wages charged by insurance company



B Identification of Hidden Information: Appendix

Table 5: Correlation between traffic offenses and accidents

	Accidents	
	With Insurance	Without Insurance
Number of offenses	0.6041	0.5014
	(0.0480)	(0.047)
Minimum wages charged	0.5836	0.4863
	(0.0495)	(0.0469)

Note: Pairwise correlation coefficients between the offense variables and the number of accidents. Coefficients obtained from an extended database with subjects with and without insurance contracts. P-values displayed in parenthesis.

Note for Tables 6 to 14: Coefficients in columns (1) to (3) are from Cox proportional hazard model of time spans between insurance purchase and subsequent claims (equation 4). In order to interpret coefficients from Cox regression as hazard ratios they must be exponentiated. Coefficients in columns (4) to (6) are from OLS models of log–coverage (equation 5). Additional to the coefficients shown in the table, all models use as covariates the policyholder information used by the pricing mechanism. Standard errors clustered at the number of claims are shown in parenthesis. Statistical significance at 1%, 5% and 10% are displayed by (*), (+) and (-) respectively.

Table 6: Model comparison company 101

	Cox (1)	Cox Num (2)	Cox MW (3)	OLS (4)	OLS Num (5)	OLS MW (6)
Dependent Variable	Time spans			Log-Coverage		
Model	.0527*	.0521*	.0521*	.0776*	.0775*	.0775*
	(.00426)	(.00426)	(.00426)	(.00031)	(.00031)	(.00031)
No. offenses		.144*			.0236*	
		(.019)			(.00206)	
No. min. wages offenses			.00866*			.00133*
			(.00107)			(.00012)
Cons				-139*	-138*	-138*
				(.63)	(.629)	(.629)
N	50162	50162	50162	47009	47009	47009
No. of subjects	47009	47009	47009			
No. of fails	3153	3153	3153			
Log lik.	-30865	-30842	-30839	-15459	-15394	-15395
Pseudo r2	.00503	.00578	.00589			
LR chi2	312	359	365			
Prob LR	8.7e-51	1.1e-59	6.0e-61			
Prop. Hazdrs. Test	27.8	28.8	28.5			
Prob P.H. Test	.366	.372	.387			
Adjusted r2				.667	.668	.668
F				3617	3497	3497
Prob F				2.7e-42	1.1e-43	1.1e-43

Note: For a detailed information of the estimation procedure see the note of page 29.
Statistical significance at 1%, 5% and 10% are displayed by (*), (+) and (-) respectively.

Table 7: Model comparison company 161

	Cox (1)	Cox Num (2)	Cox MW (3)	OLS (4)	OLS Num (5)	OLS MW (6)
Dependent Variable	Time spans			Log-Coverage		
Model	.0233+	.0221+	.0221+	.0779*	.0779*	.0779*
	(.00992)	(.00994)	(.00993)	(.00048)	(.00048)	(.00048)
No. offenses		.17*			.0096*	
		(.0367)			(.00277)	
No. min. wages offenses			.00948*			.00045*
			(.00219)			(.00016)
Cons				-140*	-140*	-140*
				(.956)	(.956)	(.956)
N	16525	16525	16525	15750	15750	15750
No. of subjects	15750	15750	15750			
No. of fails	775	775	775			
Log lik.	-6908	-6900	-6901	981	987	985
Pseudo r2	.0028	.00396	.00384			
LR chi2	38.8	54.9	53.3			
Prob LR	.223	.013	.0188			
Prop. Hazdrs. Test	33.7	33.9	34.4			
Prob P.H. Test	.433	.471	.45			
Adjusted r2				.83	.83	.83
F				2334	2267	2267
Prob F				3.9e-50	2.1e-51	2.1e-51

Note: For a detailed information of the estimation procedure see the note of page 29.
Statistical significance at 1%, 5% and 10% are displayed by (*), (+) and (-) respectively.

Table 8: Model comparison company 311

	Cox (1)	Cox Num (2)	Cox MW (3)	OLS (4)	OLS Num (5)	OLS MW (6)
Dependent Variable	Time spans			Log-Coverage		
Model	.0838*	.0839*	.0839*	.0788*	.0788*	.0787*
	(.018)	(.018)	(.018)	(.00136)	(.00136)	(.00136)
No. offenses		-.0375			.0131-	
		(.0901)			(.00754)	
No. min. wages offenses			-.00118			.00094+
			(.00513)			(.00044)
Cons				-141*	-141*	-141*
				(2.73)	(2.73)	(2.73)
N	2362	2362	2362	2133	2133	2133
No. of subjects	2133	2133	2133			
No. of fails	229	229	229			
Log lik.	-1555	-1555	-1555	-273	-271	-270
Pseudo r2	.0145	.0146	.0145			
LR chi2	45.8	46	45.8			
Prob LR	.00472	.0065	.00673			
Prop. Hazdrs. Test	26.9	27.6	27			
Prob P.H. Test	.31	.328	.357			
Adjusted r2				.69	.69	.69
F				199	191	191
Prob F				5.0e-24	9.4e-25	9.2e-25

Note: For a detailed information of the estimation procedure see the note of page 29.
Statistical significance at 1%, 5% and 10% are displayed by (*), (+) and (-) respectively.

Table 9: Model comparison company 351

	Cox (1)	Cox Num (2)	Cox MW (3)	OLS (4)	OLS Num (5)	OLS MW (6)
Dependent Variable	Time spans			Log-Coverage		
Model	.0496*	.0478*	.0483*	.0846*	.0845*	.0845*
	(.015)	(.015)	(.015)	(.00099)	(.00098)	(.00098)
No. offenses		.223*			.0245*	
		(.0575)			(.00664)	
No. min. wages offenses			.0112*			.00144*
			(.00335)			(.00037)
Cons				-152*	-152*	-152*
				(1.97)	(1.97)	(1.97)
N	5968	5968	5968	5681	5681	5681
No. of subjects	5681	5681	5681			
No. of fails	287	287	287			
Log lik.	-2232	-2226	-2227	-1765	-1758	-1757
Pseudo r2	.00856	.0111	.0105			
LR chi2	38.5	50	47.2			
Prob LR	.0159	.00092	.00209			
Prop. Hazdrs. Test	18.6	19.9	18.9			
Prob P.H. Test	.671	.645	.707			
Adjusted r2				.615	.616	.616
F				413	397	397
Prob F				1.2e-25	1.5e-26	1.5e-26

Note: For a detailed information of the estimation procedure see the note of page 29.
Statistical significance at 1%, 5% and 10% are displayed by (*), (+) and (-) respectively.

Table 10: Model comparison company 381

	Cox (1)	Cox Num (2)	Cox MW (3)	OLS (4)	OLS Num (5)	OLS MW (6)
Dependent Variable	Time spans			Log-Coverage		
Model	.0266	.0264	.0264	.0715*	.0715*	.0715*
	(.0211)	(.0211)	(.0211)	(.00124)	(.00124)	(.00124)
No. offenses		.0473			.013+	
		(.101)			(.00612)	
No. min. wages offenses			.00261			.00053
			(.00552)			(.00034)
Cons				-126*	-126*	-126*
				(2.49)	(2.49)	(2.49)
N	2847	2847	2847	2679	2679	2679
No. of subjects	2679	2679	2679			
No. of fails	168	168	168			
Log lik.	-1164	-1164	-1164	-113	-111	-112
Pseudo r2	.00817	.00826	.00826			
LR chi2	19.2	19.4	19.4			
Prob LR	.864	.886	.886			
Prop. Hazdrs. Test	27.9	28.9	28.6			
Prob P.H. Test	.414	.419	.434			
Adjusted r2				.754	.754	.754
F				305	295	294
Prob F				2.3e-29	3.5e-30	3.6e-30

Note: For a detailed information of the estimation procedure see the note of page 29.
Statistical significance at 1%, 5% and 10% are displayed by (*), (+) and (-) respectively.

Table 11: Model comparison company 431

	Cox	Cox Num	Cox MW	OLS	OLS Num	OLS MW
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Time spans			Log-Coverage		
Model	.0364*	.0359*	.0361*	.0883*	.0881*	.0881*
	(.00974)	(.00974)	(.00974)	(.00061)	(.00061)	(.00061)
No. offenses		.112-			.0189*	
		(.0572)			(.00402)	
No. min. wages offenses			.00312			.00096*
			(.00348)			(.00023)
Cons				-160*	-159*	-159*
				(1.21)	(1.21)	(1.21)
N	10140	10140	10140	9648	9648	9648
No. of subjects	9648	9648	9648			
No. of fails	492	492	492			
Log lik.	-4094	-4092	-4093	-1519	-1508	-1511
Pseudo r2	.00634	.00675	.00643			
LR chi2	52.2	55.6	53			
Prob LR	.00112	.00063	.00136			
Prop. Hazdrs. Test	26.6	27.8	27.7			
Prob P.H. Test	.375	.371	.373			
Adjusted r2				.738	.739	.739
F				1089	1050	1049
Prob F				3.3e-34	2.6e-35	2.6e-35

Note: For a detailed information of the estimation procedure see the note of page 29.
Statistical significance at 1%, 5% and 10% are displayed by (*), (+) and (-) respectively.

Table 12: Model comparison company 441

	Cox	Cox Num	Cox MW	OLS	OLS Num	OLS MW
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Time spans			Log-Coverage		
Model	.0435+	.0434+	.0434+	.0558*	.0558*	.0558*
	(.0179)	(.0179)	(.0179)	(.00047)	(.00047)	(.00047)
No. offenses		.036			.00937+	
		(.145)			(.00426)	
No. min. wages offenses			.00167			.00034
			(.00795)			(.00022)
Cons				-95*	-95*	-95*
				(.95)	(.949)	(.95)
N	4595	4595	4595	4408	4408	4408
No. of subjects	4408	4408	4408			
No. of fails	187	187	187			
Log lik.	-1407	-1407	-1407	2341	2344	2342
Pseudo r2	.0115	.0115	.0115			
LR chi2	32.6	32.7	32.7			
Prob LR	.209	.247	.248			
Prop. Hazdrs. Test	19.2	19.3	19.5			
Prob P.H. Test	.864	.888	.883			
Adjusted r2				.874	.874	.874
F				1132	1093	1092
Prob F				4.8e-37	3.8e-38	3.8e-38

Note: For a detailed information of the estimation procedure see the note of page 29.
Statistical significance at 1%, 5% and 10% are displayed by (*), (+) and (-) respectively.

Table 13: Model comparison company 451

	Cox (1)	Cox Num (2)	Cox MW (3)	OLS (4)	OLS Num (5)	OLS MW (6)
Dependent Variable	Time spans			Log-Coverage		
Model	.0434*	.0429*	.0429*	.103*	.103*	.103*
	(.00489)	(.00489)	(.00489)	(.00098)	(.00098)	(.00098)
No. offenses		.0919*			.0111	
		(.0307)			(.00845)	
No. min. wages offenses			.00503*			.00086-
			(.00172)			(.00047)
Cons				-189*	-189*	-189*
				(1.95)	(1.96)	(1.96)
N	33001	33001	33001	31186	31186	31186
No. of subjects	31186	31186	31186			
No. of fails	1815	1815	1815			
Log lik.	-17285	-17281	-17282	-45375	-45374	-45373
Pseudo r2	.00408	.00431	.0043			
LR chi2	142	150	149			
Prob LR	6.6e-18	5.7e-19	6.6e-19			
Prop. Hazdrs. Test	16.2	18.9	19.8			
Prob P.H. Test	.932	.875	.838			
Adjusted r2				.309	.309	.309
F				536	516	517
Prob F				1.6e-31	1.8e-32	1.8e-32

Note: For a detailed information of the estimation procedure see the note of page 29.
Statistical significance at 1%, 5% and 10% are displayed by (*), (+) and (-) respectively.

Table 14: Model comparison company 501

	Cox (1)	Cox Num (2)	Cox MW (3)	OLS (4)	OLS Num (5)	OLS MW (6)
Dependent Variable	Time spans			Log-Coverage		
Model	.0612*	.0603*	.0601*	.084*	.0839*	.0839*
	(.0108)	(.0108)	(.0108)	(.00075)	(.00075)	(.00075)
No. offenses		.153*			.00997-	
		(.0445)			(.00548)	
No. min. wages offenses			.01*			.00058-
			(.00282)			(.00032)
Cons				-151*	-151*	-151*
				(1.5)	(1.5)	(1.5)
N	7275	7275	7275	6871	6871	6871
No. of subjects	6871	6871	6871			
No. of fails	404	404	404			
Log lik.	-3197	-3193	-3192	-2127	-2126	-2126
Pseudo r2	.00946	.0107	.0109			
LR chi2	61.1	68.9	70.1			
Prob LR	2.7e-05	3.2e-06	2.1e-06			
Prop. Hazdrs. Test	16.5	16.8	16.8			
Prob P.H. Test	.833	.857	.857			
Adjusted r2				.677	.677	.677
F				626	600	600
Prob F				8.0e-29	8.6e-30	8.6e-30

Note: For a detailed information of the estimation procedure see the note of page 29.
Statistical significance at 1%, 5% and 10% are displayed by (*), (+) and (-) respectively.

C Identification of Hidden Action: Appendix

C.1 Dynamic Moral Hazard under a Bonus Scheme

C.1.1 Proof of Lemma 1

Lemma. *At each t the optimal effort in accident prevention $e_t^\star$, only depends on the past history through the current premium q_t.*

Proof. Differentiating $v_t(\cdot)$ in (7) with respect to e_t and searching for an optimum:

$$\frac{\partial v_t(\cdot)}{\partial e_t} = p'(e_t)\left[u(w_t - d - q_t) - u(w - q_t)\right] - c'(e_t) = 0$$

$$\left[u(w_t - d - q_t) - u(w - q_t)\right] = \frac{c'(e_t)}{p'(e_t)} = \Delta(e_t^\star).$$

Given the assumptions over $c'(\cdot)$ and $p'(\cdot)$, $\Delta(\cdot)$ is increasing and has an inverse and hence there exists an optimal effort in accident prevention $e_t^\star$ that depends on the past only through the premium q_t defined by (6). ■

C.1.2 Bellman Equation Argument

As the premium is the state variable of the problem, the state space is named $Q \subset \mathbb{R}_+$. The effort in accident prevention is the control variable, hence the action space is named $E = [0, \bar{e}]$. Let v_t be the period–t reward function which is continuous over $Q \times E$ and given that $u''(\cdot) < 0$, is bounded on $Q \times E$. Let q_{t+1} defined by (6) be the period–t transition function which is continuous on $Q \times E$. Finally, let $\Phi_t(q) : Q \rightrightarrows \wp(E)$ be the period–t feasible action correspondence. As the problem does not impose any restriction on the action space, $\Phi_t(\cdot)$ is continuous on Q and compact valued. Given this, the problem satisfies the Bellman Principle of Optimality, and accepts the Bellman Equation representation.

C.1.3 Proof of Lemma 2

Lemma. *The value function $V_t(\cdot)$ is decreasing in q_t for all t.*

Proof. By mathematical induction. Starting in T, for any $q' < q$, let $p(\cdot)'$ and $p(\cdot)$ denote the respective accident probability associated to optimal effort in accident prevention for each q' and q.

$$
\begin{aligned}
V_T(q') &= p(e)'u(w_T - d - q'_T) + (1 - p(e)')u(w_T - q'_T) - c(e) \\
&\geq p(e)u(w_T - d - q'_T) + (1 - p(e))u(w_T - q'_T) - c(e) \\
&\geq p(e)u(w_T - d - q_T) + (1 - p(e))u(w_T - q_T) - c(e) \\
&= V_T(q)
\end{aligned}
$$

Now assume that $V_{t+1}(q)$ is decreasing; by backward induction, for any $q' < q$:

$$
\begin{aligned}
V_t(q') &\geq p(e)\big[u(w_t - d - q'_t) + \beta V_{t+1}(q'_t)\big] + (1 - p(e))\big[u(w_t - q'_t) + \beta V_{t+1}(\delta q'_t)\big] - c(e) \\
&\geq p(e)\big[u(w_t - d - q_t) + \beta V_{t+1}(q_t)\big] + (1 - p(e))\big[u(w_t - q_t) + \beta V_{t+1}(\delta q_t)\big] - c(e) \\
&= V_t(q)
\end{aligned}
$$

And $V_t(\cdot)$ is also decreasing. ■

C.1.4 Proof of Proposition 1

Proposition. *If the value function $V_t(\cdot)$ is differentiable in a neighborhood of $q_t = 0$ for all t, for small values of q_t, the accident probability associated to optimal effort in accident prevention $p_t(e^\star_t(q_t))$ decreases with q_t for all t.*

Proof. Rewriting the Bellman equation in (9):

$$
\begin{aligned}
V_t(q_t) = \max_e \Big\{ & u(w_t - q_t) + \beta V_{t+1}(\delta q_t) + \\
& p(e)\big[u(w_t - d - q_t) - u(w_t - q_t) + \beta V_{t+1}(q_t) - \beta V_{t+1}(\delta q_t)\big] - c(e) \Big\}.
\end{aligned}
$$

Notice that as assumed before $u'(\cdot) > 0$, and as stated in Lemma 2, $V_{t+1}(\cdot)$ is decreasing in q; given this, the maximand is concave in e and the first order approach is sufficient. The optimal effort in accident prevention at q_t satisfies:

$$
\frac{c'(e^\star_t(q_t))}{p'(e^\star_t(q_t))} = u(w_t - d - q_t) - u(w_t - q_t) + \beta\big[V_{t+1}(q_t) - V_{t+1}(\delta q_t)\big].
$$

By implicit derivation it is possible to find $\frac{de^\star_t}{dq_t}$:

$$
\frac{d}{dq_t}\left[\frac{c'(e^\star_t(q_t))}{p'(e^\star_t(q_t))}\right] = u'(w_t - q_t) - u'(w_t - d - q_t) + \beta\big[V'_{t+1}(q) - \delta V'_{t+1}(\delta q)\big].
$$

Asumming that q_t is small enough and taking the first order aproximation:

$$\frac{de_t^\star}{dq_t} \approx \frac{u'(w_t) - u'(w_t - d) + \beta(1-\delta)V'_{t+1}(0)}{\frac{p'(e_t^\star(0))c''(e_t^\star(0)) - p''(e_t^\star(0))c'(e_t^\star(0))}{p'(e_t^\star(0))^2}} > 0.$$

Finally, by the chain rule $\frac{dp}{dq} = \frac{dp}{de} \cdot \frac{de}{dq}$ and given the assumptions over $\frac{dp}{de}$, it is possible to conclude that $\frac{dp}{dq} < 0$. ■

C.2 Empirical Analysis of Hidden Action

Table 15: Testing for the presence of moral hazard

	Cluster (1)	Frailty (2)	Frailty Sex=0 (3)	Frailty Sex=1 (4)	Frailty Age≤25 (5)	Frailty Age>26 (6)
Dependent Variable	Time spans					
No. of Claims	.628*	-3.13*	-3.06*	-3.2*	-3.7*	-3.12*
	(.0289)	(.039)	(.0581)	(.0675)	(.283)	(.0393)
Cons	-8.84*	-7.75*	-7.75*	-7.63*	-7.11*	-7.76*
	(.00917)	(.0209)	(.0313)	(.0382)	(.155)	(.0211)
$\ln(\theta)$		3.6*	3.53*	3.66*	3.45*	3.6*
		(.0179)	(.0275)	(.0305)	(.111)	(.0182)
N	249476	249476	106717	76371	3686	245790
No. of subjects	2.4e+05	2.4e+05	1.0e+05	72344	3425	2.3e+05
No. of fails	12894	12894	5713	4027	261	12633
Log lik.	-671	1483	824	656	137	1363
LR chi2	472	3990	1673	1434	129	3867
Prob LR	1.e-104	0	0	0	6.8e-30	0
$\theta = 0$		36.5	34.3	38.8	31.5	36.6
LR Chi2 $\theta = 0$		4309	1816	1547	133	4181
Prob LR $\theta = 0$		0	0	0	5.6e-31	0

Note: Coefficients are from exponential hazard model of time spans between insurance purchase and subsequent claims (equation 10). Column (1) assumes that the frailty effect have variance zero and present standard errors clustered at individual level. Columns (2) to (6) are from exponential hazard models with individual shared frailty gamma distributed. In order to interpret coefficients from exponential regression as hazard ratios they must be exponentiated. Statistical significance at 1%, 5% and 10% are displayed by (*), (+) and (-) respectively.

Table 16: Testing for the presence of moral hazard

	Frailty 101 (1)	Frailty 151 (2)	Frailty 161 (3)	Frailty 211 (4)	Frailty 311 (5)	Frailty 351 (6)
Dependent Variable	Time spans					
No. of Claims	-2.72*	-3.22*	-3.02*	-4.36*	-2.71*	-2.91*
	(.0699)	(.107)	(.153)	(.22)	(.187)	(.11)
Cons	-7.57*	-7.83*	-8.01*	-8.08*	-7.13*	-7.7*
	(.0429)	(.0542)	(.0759)	(.0813)	(.109)	(.0621)
$\ln(\theta)$	3.41*	3.61*	3.57*	4.12*	2.82*	3.5*
	(.0368)	(.0477)	(.0734)	(.0643)	(.1)	(.0543)
N	50349	37960	19869	25296	4711	25939
No. of subjects	47184	36087	18944	24464	4242	24482
No. of fails	3165	1873	925	832	469	1457
Log lik.	1032	110	-30.7	-263	371	291
LR chi2	885	571	221	363	128	419
Prob LR	2.e-194	3.e-126	4.8e-50	6.4e-81	1.3e-29	4.4e-93
$\theta = 0$	30.2	37	35.5	61.9	16.8	33
LR Chi2 $\theta = 0$	1002	610	240	368	137	464
Prob LR $\theta = 0$	3.e-220	4.e-135	2.5e-54	2.5e-82	5.0e-32	4.e-103

Note: Coefficients are from exponential hazard model of time spans between insurance purchase and subsequent claims (equation 10) with individual shared frailty gamma distributed. Statistical significance at 1%, 5% and 10% are displayed by (*), (+) and (-) respectively.

Table 17: Testing for the presence of moral hazard

	Frailty 381 (1)	Frailty 431 (2)	Frailty 441 (3)	Frailty 451 (4)	Frailty 501 (5)
Dependent Variable	Time spans				
No. of Claims	-3.52*	-3.72*	-3.56*	-3.39*	-3.41*
	(.219)	(.193)	(.192)	(.112)	(.208)
Cons	-7.42*	-7.65*	-8.24*	-7.66*	-7.62*
	(.113)	(.096)	(.0829)	(.0563)	(.109)
$\ln(\theta)$	3.5*	3.81*	3.92*	3.53*	3.62*
	(.0889)	(.0731)	(.0758)	(.0477)	(.088)
N	7282	13195	22378	33261	9236
No. of subjects	6835	12569	21598	31435	8742
No. of fails	447	626	780	1826	494
Log lik.	150	48.9	-244	321	83.9
LR chi2	186	277	232	601	180
Prob LR	2.5e-42	3.8e-62	2.2e-52	1.e-132	5.4e-41
$\theta = 0$	33.3	45	50.4	34.2	37.4
LR Chi2 $\theta = 0$	193	286	245	630	191
Prob LR $\theta = 0$	3.1e-44	1.6e-64	1.3e-55	2.e-139	1.1e-43

Note: Coefficients are from exponential hazard model of time spans between insurance purchase and subsequent claims (equation 10) with individual shared frailty gamma distributed. Statistical significance at 1%, 5% and 10% are displayed by (*), (+) and (-) respectively.