Evidence of Adverse Selection in Automobile Insurance Markets

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Abstract

In this paper, we propose an empirical analysis of the presence of adverse selection in an insurance market. We first present a theoretical model of a market with adverse selection and we introduce different issues related to transaction costs, accident costs, risk aversion and moral hazard. We then discuss an econometric modeling based on latent variables and we derive its relationship with specification tests that may be useful to isolate the presence of adverse selection in the portfolio of an insurer. We discuss in detail the relationship between our modeling and that of Puelz and Snow (1994). Finally, we present some empirical results derived from a different data set. We show that there is no residual adverse selection in the studied portfolio since appropriate risk classification is made by the insurer. Consequently, the insurer does not need a self-selection mechanism such as the deductible choice to reduce adverse selection.

Keywords : *Adverse selection, empirical test, risk classification, transaction costs.*
JEL classification: D80.

Résumé

Dans cet article, nous proposons une analyse empirique sur la présence de l'antisélection dans un marché d'assurance. Dans un premier temps, nous présentons un modèle théorique d'un marché avec antisélection et nous introduisons différentes discussions reliées aux coûts de transaction, aux coûts des accidents, l'aversion au risque et le risque moral. Puis, nous discutons d'une modélisation économétrique avec variables latentes et nous décrivons sa relation avec des tests de spécification qui peuvent être utiles pour isoler la présence de l'antisélection dans le portefeuille d'un assureur. Nous discutons en détail des liens entre notre modélisation et celle de Puelz et Snow (1974). Finalement, nous présentons des résultats empiriques obtenus d'une banque de données différente. Nous montrons qu'il n'existe pas d'antisélection résiduelle dans le portefeuille étudié parce qu'une classification appropriée des risques est effectuée par l'assureur. Ce résultat implique que l'assureur n'a pas besoin d'utiliser un mécanisme d'autosélection, comme un choix de franchise pour réduire l'antisélection.

Mots clés : *Antisélection, test empirique, classification des risques, coûts de transaction.*
Classification JEL : D80.

Introduction

Adverse selection is potentially present in many markets. In automobile insurance, it is often documented that insured drivers have information not available to the insurer about their individual risks. This explains the presence of many instruments like risk classification based on observable characteristics (Hoy, 1982 and Crocker and Snow, 1985, 1986), deductibles (Rothschild and Stiglitz, 1976 and Wilson, 1977) and bonus-malus schemes (Dionne and Lasserre, 1985, Dionne and Vanasse, 1992 and Pinquet, 1998). But the presence of deductibles can also be documented by moral hazard (Winter, 1992) or simply by transaction costs proportional to the actuarial premium, and the bonus-malus scheme is often referred to moral hazard. It is then difficult to isolate a pure adverse selection effect from the data. However, the presence of adverse selection is necessary to obtain certain predictions that would not be obtained with only transaction costs and moral hazard.

This difficulty of isolating a pure adverse selection effect is emphasized by the absence in the published literature of theoretical predictions when both problems of information are present simultaneously. Very few models consider both information problems (see however Dionne and Lasserre, 1988 and Chassagnon and Chiappori, 1996). The literatures on moral hazard and adverse selection were developed separately and traditionally faced different theoretical issues : in the adverse selection literature, the emphasis was put on the existence and efficiency of competitive equilibria with and without cross-subsidization between different risk classes while in the moral hazard one the emphasis was on the endogenous determination of contractual forms with few discussion on equilibrium issues (see however Arnott, 1992). The same remarks apply to multi-period contracting. Moreover, both literatures have neglected accident cost distributions : the discussion was mainly on the accident frequencies with few exceptions (Winter, 1992; Dionne and Doherty, 1992 and Doherty and Schlesinger, 1995).

What are then the most interesting predictions for empirical research ? If we limit the discussion to single-period contracting[1] and adverse selection, the presence of separating contracts with different insurance coverages to different risk classes remains the most interesting one. This is the Rothschild-Stiglitz result obtained from a model describing a simple competitive insurance market with two different risk types and two states of nature : when the proportion of high risk individuals is sufficiently high, a separating equilibrium exists with less insurance coverage for the low risk individuals. There is no subsidy between the different risk classes and private information is revealed by contracting choices. Recently Puelz and Snow (1994) obtained results from the data of a single insurer and concerning collision insurance : they verified that individuals of different risk type self-selected through their deductible choice and no cross-subsidization between the classes was measured.

In this paper we focus our attention on such an empirical test. We will first present in Section 1 a theoretical discussion on adverse selection in insurance markets by introducing different issues related to transaction costs, accident costs and moral hazard. In Section 2, we discuss in detail the article of Puelz and Snow (1994). Particularly we analyze one important issue related to their empirical findings : we question their methodology of using the accident variable to measure the presence of residual adverse selection in risk classes. In Section 3, we present an econometric modeling based on latent variables and its relationship with the structural equations which may be useful to analyze the presence of adverse selection in the portfolio of an insurer. Finally, we present our results derived from a new data set. We replicate on this data set the analysis of Puelz and Snow, and then propose some extensions about the methodology used. We show that their conclusion is not robust and that residual adverse selection is not present when appropriate risk classification is made.

[1] But we know that the data may contain effects from long-term behavior.

1. Adverse selection and optimal choice of insurance

1.1 All accidents have the same cost

Let us first consider the economy described by Rosthschild and Stiglitz (1976) (see Akerlof, 1970, for an earlier contribution). There are two types of individuals (i = H,L) representing different probabilities of accidents with $p^H > p^L$. We assume that at most one accident may arrive during the period. Without insurance their level of welfare is given by :

$$V(p^i) = (1 - p^i)\, U(W) + p^i\, U(W - C), \tag{1}$$

where :

- p^i is the accident probability of individual type i, i = H,L
- W is initial wealth
- C is the cost of an accident
- U is the von Neumann-Morgenstern utility function ($U'(\bullet) > 0$, $U''(\bullet) \leq 0$) assumed, for the moment, to be the same for the two risk categories (same risk aversion).

Under public information about the probabilities of accident, a competitive insurer will offer full insurance coverage to each type if there is no proportional transaction cost in the economy. In presence of proportional transaction costs the premium can be of the form $P = (1 + k)p^iI^i$ where I^i is insurance coverage and k is loading factor. With $k > 0$, less than full insurance is optimal. However an increase in the probability of accident does not necessarily imply a lower deductible if we restrict the form of the optimal contracts to deductibles for reasons that will become evident later on. In fact we can show :

<u>Proposition 1</u> : In presence of a loading factor ($k > 0$), sufficient conditions to obtain that the optimal level of deductible decreases when the probability of accident increases are constant risk aversion and $p^i < ½\,(1 + k)$.

The sufficient condition is quite natural in automobile insurance since p^i is lower than 10% while k is higher than 10%. This means that individuals with high probabilities of accidents do not necessarily choose a low deductible under full information and non actuarial insurance. However, in general, different risk types have different insurance coverage even under perfect information. Under private information, many strategies have being studied in the literature (Dionne and Doherty, 1992, Hellwig, 1987 and Fombaron, 1997). The nature of equilibrium is function of the insurers' anticipations of the behavior of rivals. Rothschild and Stiglitz (1976) assume that each insurer follows a Cournot-Nash strategy. Under this assumption, it can be shown that a separating equilibrium exists if the proportion of high risk individuals in the market is sufficiently high. Otherwise there is no equilibrium. The optimal contract is obtained by maximizing the expected utility of the low risk individual under a zero-profit constraint for the insurer and a binding self-selection constraint for the high risk individual who receive full insurance.

If we restrict our analysis to contracts with a deductible, the optimal solution for the low-risk individual is obtained by maximizing V (p^L) with respect to D^L under a zero profit constraint and a self-selection constraint :

$$\begin{aligned} &\underset{D^L}{\text{Max}} \quad p^L U(W - D^L - P^L) + (1 - p^L) U(W - P^L) \\ &\text{s.t.} \quad P^L = p^L (C - D^L)(1 + k) \qquad (2) \\ &U(W - p^H C) = p^H U(W - D^L - P^L) + (1 - p^H) U(W - P^L), \end{aligned}$$

where P^L is the insurance premium of the L type. The solution of this problem yields $D^{L*} > 0$ while $D^{H*} = 0$ when the loading factor (k) is nul.

If now we introduce a positive loading fee (k > 0) proportional to the net premium, the total premium for each risk type becomes $P^i = (1 + k)\, p^i\, (C – D^i)$ and we obtain, from the above problem with the appropriate definitions, that $D^{L*} > D^{H*} > 0$ which implies that $p^H (C – D^{H*}) > p^L (C – D^{L*})$ or that $P^{H*} > P^{L*}$.

We then have as second result :

Proposition 2 : When we introduce a proportional loading factor ($k > 0$) to the basic Rothschild-Stiglitz model, the optimal separating contracts have the following form : $0 < D^{H*} < D^{L}$.

This result indicates that the traditional prediction of Rothschild-Stiglitz is not affected when the same proportional loading factor applies to the different classes of risk.

1.2 Introduction of different accident costs

If now we take into account different accident costs in the basic Rothschild and Stiglitz model, the optimal choice of deductible may be affected by the distributions of costs conditional to the risk classes (or types). Fluet (1994) and Fluet and Pannequin (1994) obtained that a constant deductible will be optimal only when the conditional likelihood ratio $\frac{f^{H}(C)}{f^{L}(C)}$ is constant for all C, where f^{i} (C) is the density of costs for type i which implies that the two conditional distributions are identical and the observed amounts of loss do not provide any information to the insurer. By a constant (or a straight) deductible it is mean that the deductible is not function of the accident costs.

We can show that the results of Fluet and Pannequin (1994) are robust to the introduction of a proportional loading factor. We consider two costs levels C_1,C_2 and we denote p_1^i, p_2^i the distribution of the cost conditional to the occurrence of an accident in class i. In other words, the conditional expected cost of accident for individual i is equal to :

$$E^{i}(C) = p_1^{i}C_1 + p_2^{i}C_2. \tag{3}$$

We also assume that $p^H > p^L$ and p^H $(E^H(C)) > p^L$ $(E^L(C))$. Under the assumption that $C_1 > D_1^i$ and $C_2 > D_2^i$, (i = H,L) it can be shown that $D_1^{L*} \gtreqless D_2^{L*}$ as $\frac{p_2^H}{p_2^L} \gtreqless \frac{p_1^H}{p_1^L}$.

When $k > 0$, $D_1^{H*} = D_2^{H*} = D^{H*} > 0$ whatever C_j and the same relative results are obtained for the low risk individual. In other words :

Proposition 3 : Let $\frac{p_j^H}{p_j^L}$ be conditional likelihood ratio for accident costs of type H relative to type L and let D^{H^*} be the optimal deductibles of type H in the presence of a proportional loading factor k ≥ 0, then the optimal deductibles of individual L have the following property :

$$D_j^{L^*} > D^{H^*} \geq 0 \quad \text{for } j = 1, 2 \tag{4}$$

$$\text{and } D_1^{L^*} \overset{>}{\underset{<}{=}} D_2^{L^*} \quad \text{as } \frac{p_2^H}{p_2^L} \overset{>}{\underset{<}{=}} \frac{p_1^H}{p_1^L}. \tag{5}$$

The intuition of the result is the following one. The optimal contract of the low risk individual will be a straight or constant deductible if the observed amount of loss does not provide information to the insurer. Otherwise, the level of coverage vary with the size of the loss. In the extreme case where the observed loss reveals all the information, both risk types will buy the same deductible when k = 0 (Doherty and Jung, 1993). Since in the above analysis it was assumed that both costs distributions have the same support, all the information cannot be revealed by the observation of an accident. For the analysis of other definitions of likelihood ratios see Fluet (1994).

1.3 Adverse selection with moral hazard

The research on adverse selection with moral hazard is starting (see however Dionne and Lasserre 1988). We know that a constant deductible may be optimal under moral hazard if the individual can modify the occurrence of accidents but not the severity (Winter, 1992). Here to keep matters simple we assume that an insured can affect his probability of accident with action a^i but not the severity. Moreover, $\frac{p_j^H}{p_j^L}$ is independent of the cost level j and k = 0. Under these assumptions, Chassagnon and Chiappori (1996) have shown that some particularities of the basic Rothschild-Stiglitz model are preserved. Particularly, a higher premium is always associated to better coverage and individuals with a lower deductible are more likely to have an accident, which permits to test the association between deductible and accident occurrence. However, the presence of moral hazard may reduce differences between accident probabilities.

1.4 Cross-subsidization between different risk types

One difficulty with the pure Cournot-Nash strategy lies in the fact that a pooling equilibrium is not possible. Wilson (1977) proposed the anticipatory equilibrium concept that always results in an equilibrium (pooling or separation). When the proportion of high risk individuals is sufficiently high, a Wilson equilibrium coincides with a Rothschild-Stiglitz equilibrium.

Moreover, welfare of both risk classes can be increased by allowing subsidization : low risk individuals can buy more insurance coverage by subsidizing the high risks (see Crocker and Snow, 1985 and Fombaron, 1997, for more details).

1.5 Different risk aversions

The possibility that different risk types may also differ in risk aversion was considered in detail by Villeneuve (1996). It is then necessary to control for risk aversion when we test for the presence of residual adverse selection. We will see that the risk classification variables do, indeed, capture some information on risk aversion. In other words, we can also test for the presence of residual risk aversion in risk classes.

1.6 Risk categorization

In many insurance markets, insurers use observable characteristics to categorize individual risks. It was shown by Crocker and Snow (1986) that such categorization is welfare improving if its cost is not too high and if observable characteristics are correlated with hidden knowledge. The effect of risk categorization is to reduce the gap between the different risk types and to decrease the possibilities of separation by the choice of different deductibles.

This result suggests that a test for the presence of adverse selection should be applied inside different risk classes or by introducing categorization variables in the model. It is known that the presence of adverse selection is sufficient to justify risk classification when risk classification variables are costless to observe. Now the empirical question becomes :

Empirical question : Given that an efficient risk classification is used in the market, should there remain residual adverse selection in the data ?

Another result of Crocker and Snow is to show that, with appropriate taxes and subsidies on contracts, no insureds loose as a result of risk categorization. This result can be obtained for many types of equilibrium and particularly for both Rothschild-Stiglitz and Wilson (or Wilson-Miyazaki-Spence) equilibria.

Since risk categorization facilitates risk separation within the classes, it may reduce the need of cross-subsidization between risk types of a given class. However, there should be subsidization between the risk classes according to the theory.

2. Empirical measure of adverse selection : some comments on the current literature

Different tests can be used to verify the presence of adverse selection in a given market and their nature is function of the available data. If we have access to individual data from the portfolio of an insurer and want to test that high risk individuals in a given class of risk choose the lower deductible, the test will be function of the different risk classes used by the insurer, and consequently of the explanatory variables introduced in the model. Intuitively, when the list of explanatory variables is large and the classification is appropriate, the probability to find residual adverse selection in a portfolio is low.

Very few articles have analyzed the significance of residual adverse selection in insurance markets. Dahlby (1983, 1992) reported evidence of some adverse selection in Canadian automobile insurance markets and suggested that his empirical results were in accordance with the Wilson-Miyazaki-Spence model that allows for cross-subsidization between individuals in each segment defined by a categorization variable. His analysis was done with aggregate data. Until recently, the only detailed study with individual data was that of Puelz and Snow (1994) (see Chiappori, 1998, for an overview of the recent papers and Richaudeau, 1997, for a thesis on the subject).

In their analysis they considered four different adverse selection models. They found evidence of adverse selection with market signaling and no-cross-subsidization between the contracts of different risk classes. In other words, they found evidence of separation in the choice of deductible with non-linear insurance pricing and no-cross-subsidization.

To obtain their results they estimated two structural equations : a demand equation for a deductible and a premium function that relates different tarification variables to the observed premia.

The demand equation can be derived from the low risk individual maximization problem in a pure adverse selection model with a positive loading factor. This yields $D^{L*} > D^{H*} > 0$ with two types of risk in a given class (Proposition 2). Unfortunately, it cannot be obtained from the first order condition (4) in Puelz and Snow which corresponds to the first order condition of the result presented in Proposition 1 above.

Another criticism concerns the relationship on non-linear insurance pricing and Rothschild-Stiglitz model. In fact from the discussion above, the separation result is due to the introduction of a self-selection constraint in the low-risk individual problem and not from the fact that insurance pricing is non-linear. The two problems yield different empirical tests. From Proposition 2, we do not need the non-linearity of the premium schedule to verify that a separating contract is chosen.

In Rothschild-Stiglitz model this is the self-selection constraint that separates the risk types. Therefore what we need to test is the fact that different risk types choose different deductibles in the controlled classes of risk and that the self-selection constraint of the high risk individuals is binding. In that perspective, the estimation of both equations (6) and (7) in Puelz and Snow (1994) remain useful if we do not have access to the tarification book of the company. Otherwise, the estimation of (6) is not useful. For discussion we reproduce here their equations (6) and (7) :

$$\begin{aligned} P = {} & \beta_0 + \beta_1 \times D_1 + \beta_2 \times D_2 + \beta_3 \times A + \beta_4 \times A \times D_1 + \beta_5 \times A \times D_2 + \beta_6 \times MR \\ & + \sum_{i=7}^{10} \beta_{1i} \times SYM_i + \sum_{i=11}^{14} \beta_{2i} \times T_i + \sum_{i=7}^{10} \beta_{3i} \times SYM_i \times D_1 + \sum_{i=7}^{10} \beta_{4i} \times SYM_i \times D_2 \\ & + \sum_{i=11}^{14} \beta_{5i} \times T_i \times D_1 + \sum_{i=11}^{14} \beta_{6i} \times T_i \times D_2 + \beta_7 \times MALE + \beta_8 \times PERAGE + \varepsilon_1 \end{aligned} \qquad (6)$$

$$\begin{aligned} \overline{D} = {} & \alpha_0 + \alpha_1 \times RT + \alpha_2 \times \hat{g}_d + \alpha_3 \times W_1 + \alpha_4 \times W_2 + \alpha_5 \times W_3 + \alpha_6 \times MALE \\ & + \alpha_7 \times PERAGE + \varepsilon_2, \end{aligned} \qquad (7)$$

where A is the age of the automobile; MR = 1 for a multirisk contract and 0 otherwise; SYM is the symbol of the automobile; T is the territory; $\overline{D}$ = 0 for D = \$100, $\overline{D}$ = 1 for D = \$200, and $\overline{D}$ = 2 for D = \$250; W_1, W_2, W_3 = wealth dummy variables; MALE = 1 for a male and 0 for a female; PERAGE is the age of the individual; RT is for risk type measured by the number of accidents; and $\hat{g}_d$ is the deductible price on which we will come back.

The dependent variable of equation (6) is the gross premium paid by the insured and both D_1 and D_2 are dummy variables for deductible choice. Puelz and Snow used equation (6) to generate a marginal price variable and to test for the non-linearity of the premium equation. Equation (6) yields the values of deductible prices and equation (7) indicates if different risks choose different deductibles given that we have controlled for the different prices and other characteristics that may influence that choice. They also estimated a price equation to determine their price variable $\hat{g}_d$ in the demand equation for a deductible (7) and used the number of accidents (RT) at the end of the current period to approximate the individual risks. Both variables have significant parameters with right signs. But it is not clear that they had to estimate $\hat{g}_d$. It would have been easier to use directly the values obtained from equation (6). Finally, very few variables are used in (7): the age and the symbol of the automobile are not present.

3. A new evaluation of adverse selection in automobile insurance

In this section we present an econometric model and empirical results on the presence of adverse selection in an automobile insurance market. The data come from a large private insurer in Canada and concern collision insurance since the insured has the choice for a deductible for that type of insurance only. There is no bodily injuries in the data and liability insurance for property damages is compulsory. In that respect we are close to Puelz and Snow (1994).

3.1 Latent model

3.1.1 *Pure adverse selection model*

In order to perform carefully the analysis of adverse selection in this portfolio from a structural model, it is important to design a basic latent model. The discussion presupposes that two deductibles $D_1 < D_2$ are available.

The latent variables of interest are for the individual i :

– the tarification variables from the insurer :
  P_{1i} the premium for the contract with the deductible D_1
  P_{2i} the premium for the contract with the deductible D_2.

Since $D_1 < D_2$, it is clear that $P_{1i} > P_{2i}$.

– the individual risk variables :
  This risk can be measured by accident occurrences and costs. For the moment, we limit the number of potential accidents in a given period to one :

$$Y_i = \begin{cases} 1, \text{ if individual i has an accident,} \\ 0, \text{ otherwise;} \end{cases}$$

C_i = potential cost of accident for individual i.

– the deductible choice variable :

Finally, we must analyze the deductible choice by individual i. Since we have only two possible choices, this yields a binary variable :

$$Z_i = \begin{cases} 1, \text{ if the individual chooses deductible } D_1, \\ 0, \text{ otherwise.} \end{cases}$$

A latent model may correspond to :

$$p_{1i} = \log P_{1i} = g_1(x_i,\theta) + \varepsilon_{1i},$$

$$p_{2i} = \log P_{2i} = g_2(x_i,\theta) + \varepsilon_{2i},$$

$$Y_i = 1_{Y_i^* > 0}, \text{with } Y_i^* = g_3(x_i,\theta) + \varepsilon_{3i},$$

$$c_i = \log C_i = g_4(x_i,\theta) + \varepsilon_{4i}$$

$$Z_i = 1_{Z_i^* > 0}, \text{with } Z_i^* = g_5(x_i,\theta) + \varepsilon_{5i},$$

where 1 denotes the indicator function.

The latent model would be very simplified if the different error terms are uncorrelated $\varepsilon_i = (\varepsilon_{1i}, \varepsilon_{2i}, \varepsilon_{3i}, \varepsilon_{4i}, \varepsilon_{5i}) \sim N(0,\Omega)$. However these correlations may be different from zero and have to be analyzed. In fact, they will become very important in the discussion of the test for the presence of adverse selection in the insurer portfolio.

Moreover, the above dependent variables are not necessarily observable. At least two dependent sources of bias have to be considered :

1) Accident declarations

The insurer observes only the accidents for which a payment has to be made, that is only the accidents that generate a cost higher than the chosen deductible. Moreover, the insured may also take into account of the intertemporal variation of his premia when he files a claim and declares only the accidents that will not increase to much his future premia. For example, in our data set, we observe very few reimbursements below $250 for the insured individuals with a deductible of $250 which means that they do not file claims between $250 and $500 systematically. The same remark applies for those who choose the $500 deductible.

Therefore, limiting ourselves to a static scheme, the observed accidents are the claims filed :

$$\hat{Y}_{1i} = \begin{cases} 1, \text{if individual } i \text{ with deductible } D_1 \text{ had an accident and filed a claim,} \\ 0, \text{otherwise;} \end{cases}$$

$$\hat{Y}_{2i} = \begin{cases} 1, \text{if individual } i \text{ with deductible } D_2 \text{ had an accident and filed a claim,} \\ 0, \text{otherwise.} \end{cases}$$

Similarly, accident costs faced by the insurer correspond to their true values C_{1i}, C_{2i} only when $\hat{Y}_{1i} = 1$ and $\hat{Y}_{2i} = 1$ respectively. Therefore, when appropriate precautions are not taken, we should obtain an undervaluation of the accident probabilities and an overvaluation of the accident costs.

2) Available premia

When the tarification book of the insurer is available, all premia P_{1i}, P_{2i} considered by each individual are observable for the determination of the two functions $g_1(x_1,\theta)$ and $g_2(x_2,\theta)$. In practice, we may often be limited to the chosen premium $\hat{P}_i \begin{cases} P_{1i}, \text{if } Z_i = 1, \\ P_{2i}, \text{if } Z_i = 0. \end{cases}$

3.1.2 *Introducing moral hazard*

Under moral hazard, the agent effort is not observable. The insurer can introduce incentive schemes to reduce the negative moral hazard effects on accident and costs distributions, but does not eliminate all of them in general. This is the standard trade-off between insurance coverage and effort efficiency. This means that there may remain a residual moral hazard effect in the data that is not taken into account even by an extended latent model with moral hazard.

Residual moral hazard can affect accident occurrences and costs jointly with deductible choice : non observable low effort levels imply high accident probabilities and high accident costs. Moreover, residual moral hazard can explain why, for example, predicted low risk individuals in an adverse selection model with moral hazard may choose the lowest deductible D_1, when they anticipate low effort activities in the contract period.

In order to take into account of the moral hazard effect, we extend the above model by introducing a non observable variable a_i that summarizes all the efforts of individual i not already taken into account explicitly. This variable can be affected by non observable costs and incentive schemes. But some of them are observable. Particularly, the bonus-malus scheme of the insurer may influence the premia, both accidents numbers and effort costs distributions and deductible choice. An insured that is not well classified according to his past accidents record (high malus) at the beginning of the period, may want to improve his record by increasing his safety activities (less speed, no alcohol while driving, …) during the current period. These activities should reduce accident occurrences and accident costs. They may also influence the deductible choice if the anticipated actions affect particularly low cost accidents.

The explicit introduction of moral hazard goes as follows : let a_i a continuous variable measuring non observable individual's i action be a function of a vector of different observable explanatory variables $\tilde{x}_i$ and of non observable variables. The former are called explicit moral hazard variables while the second take into account of the residual moral hazard. One can extend the latent model in the following way : premium functions are naturally affected by the observable explanatory variables for the explicit moral hazard while the two distributions for cost and accidents and the deductible choice are function of two ingredients: the explicit and the residual moral hazard. Introducing the relation $a_i = \tilde{x}_i\delta + \varepsilon_i$, the three relationships can be rewritten as follows :

$$Y_i = 1_{Y_i^* > 0,} \text{ with } Y_i^* = g_3(x_i, \theta) + \gamma_3 \tilde{x}_i \delta + \varepsilon_{3i} + \gamma_3 \varepsilon_i,$$

$$c_i = g_4(x_i\theta) + \gamma_4 \tilde{x}_i \delta + \varepsilon_{4i} + \gamma_4 \varepsilon_i,$$

$$Z_i = \mathbb{1}_{Z_i^* > 0,} \text{ with } Z_i^* = g_5(x_i, \theta) + \gamma_5 \tilde{x}_i \delta + \varepsilon_{5i} + \gamma_5 \varepsilon_i.$$

For the premium function we just have to introduce the $\tilde{x}_i$ variables in the regression component. We must say that this form of moral hazard may introduce some autocorrelation between the different equations (same ε_i) and some link between the parameters ($\gamma_3\delta$, $\gamma_4\delta$, $\gamma_5\delta$).

3.2 Some specification tests

Comparison of the observed and the theoretical premia

The observed premia P_{1i} and P_{2i} can be compared to the individual underlying risks, for instance through the pure premia. The pure premia may be taken equal to the expected claims, contract by contract, i.e. deductible by deductible.

For the contract with deductible D_1 the corresponding pure premium is given by :

$$\Pi_{1i} = E\left(Y_i (C_i - D_i)\, \mathbb{1}_{C_i > D_1} / Z_i = 1\right).$$

Equivalently, we have :

$$\Pi_{2i} = E\left(Y_i (C_i - D_2)\, \mathbb{1}_{C_i > D_2} / Z_i = 0\right).$$

If we assume that there is no correlation between Z_i, Y_i and C_i when the explanatory variables are taken into account, we obtain :

$$\Pi_{1i} = P(Y_i = 1) E\left((C_i - D_1)\, \mathbb{1}_{C_i > D_1}\right).$$

$$\Pi_{2i} = P(Y_i = 1) E\left((C_i - D_2)\, \mathbb{1}_{C_i > D_2}\right).$$

Then using the cost equation we deduce :

$$E\left((C-D)\,\mathbb{1}_{C>D}\right)=E\left((\exp(g_4+\sigma_4 u)-D)\,\mathbb{1}_{\exp(g_4+\sigma_4 u)>D}\right),$$

where u is a normal variable N(0,1). We then have :

$$\begin{aligned}
E\left((C-D)\,\mathbb{1}_{C>D}\right) &= E\left((\exp g_4\ \exp \sigma_4 u - D)\,\mathbb{1}_{u>\frac{\log D-g_4}{\sigma_4}}\right)\\
&= \int_{\frac{\log D-g_4}{\sigma_4}}^{\infty} (\exp g_4\ \exp \sigma_4 u - D)\,\varphi(u)\,du\\
&= \exp g_4 \int_{\frac{\log D-g_4}{\sigma_4}}^{\infty} \exp(\sigma_4 u)\,\varphi(u)\,du - D\int_{\frac{\log D-g_4}{\sigma_4}}^{\infty} \varphi(u)\,du\\
&= \exp\left(g_4+\frac{\sigma_4^2}{2}\right)\int_{\frac{\log D-g_4}{\sigma_4}}^{\infty} \varphi(u-\sigma_4)\,du - D\int_{\frac{\log D-g_4}{\sigma_4}} \varphi(u)\,du\\
&= \exp\left(g_4+\frac{\sigma_4^2}{2}\right)\phi\left(\frac{g_4+\sigma_4^2-\log D}{\sigma_4}\right)-D\,\phi\left(\frac{g_4-\log D}{\sigma_4}\right).
\end{aligned}$$

This last expression is like a Black-Scholes price equation for an European call option. In fact, we obtain $E\left((C-D)\,\mathbb{1}_{C>D}\right)=E\,(C-D)^{+}$. This is an option on the reimbursement cost (C) where the deductible (D) is the exercise price. For the insured, the contract valuation includes a private option of non declaration.

From the above expression and the corresponding expression P (Y_i = 1) we obtain :

$$\Pi_{1i}(\theta)=\phi\left(\frac{g_3(x_i\theta)}{\sigma_3}\right)\mathrm{x}\left\{\exp\left(g_4(x_i,\theta)+\frac{\sigma_4^2}{2}\right)\phi\left(\frac{g_4(x_i,\theta)+\sigma_4^2-\log D_1}{\sigma_4}\right)-D_1\phi\left(\frac{g_4(x_i,\theta)-\log D_1}{\sigma_4}\right)\right\}$$

and a corresponding expression $\Pi_{2i}(\theta)$ by replacing D_1 by D_2.

After the estimation of the different parameters of the model, pure and observed premia can be compared by using a regression model of the type $g_k\left(x_i,\hat{\theta}\right)=\alpha_k\Pi_{ki}\left(\hat{\theta}\right)+\beta_k$ which will measure the links between premia and individual risks and the estimated coefficients will provide information on marginal profits or fix costs. We can also compare marginal profits for different deductibles by comparing (α_1, β_1) to (α_2, β_2). We may also verify whether the insurance tarification is set mainly from accident frequencies or if the pure premia is significant by doing a regression of $g_1(x,\theta)$ on $\phi\left(\frac{g_3(x_i,\theta)}{\sigma_3}\right)$ and then testing the significance of the effect on average cost. Finally, we may also consider some aspects related to the risk aversion by considering if $V(C - D)^+$ influences also the premium.

Comparison of the observed and theoretical deductible choices

Another important structural aspect is the individual choice of deductible. Suppose there are only two possibilities $D_1 < D_2$ and let us assume risk neutrality for the moment. When individual i chooses the premium k, his payments are equal to :

$$P_{ki} + Y_i \left(C_i \mathbb{1}_{C_i < D_k} \; D_k \mathbb{1}_{C_i > D_k}\right) = P_{ki} + Y_i C_i - Y_i \left(C_i - D_k\right) \mathbb{1}_{C_i > D_k}$$

In expected value we obtain :

$$P_{ki} + E\left(Y_i C_i / x_i\right) - E\left(Y_i (C_i - D_k)^+ / x_i\right).$$

D_1 is prefered to D_2 by individual i if :

$$\begin{aligned}
&P_{1i} - E\left(Y_i (C_i - D_1)^+ / x_i\right) < P_{2i} - E\left(Y_i (C_i - D_2)^+ / x_i\right) \\
&\Leftrightarrow \\
&P_{2i} - P_{1i} - E\left(Y_i (C_i - D_2)^+ / x_i\right) + E\left(Y_i (C_i - D_1)^+ / x_i\right) > 0.
\end{aligned}$$

Therefore it is possible to check this kind of behavior by comparing the observed choices Z_i to the one $Z_1^* = \mathbb{1}_{P_{2i} - P_{1i} - E\left(Y_i (C_i - D_2)^+ / x_i\right) + E\left(Y_i (C_i - D_1)^+ / x_i\right) > 0}$ corresponding to this modeling (as soon as P_{1i} and P_{2i} are known).

It is clear that, if the tarification is based on pure premia only, the insured would be indifferent between the two deductibles. It becomes also evident that we must study jointly the two structural aspects related to the insurance tarification and the deductibles choice to verify the presence of some adverse selection effects. This is the topic of the next section.

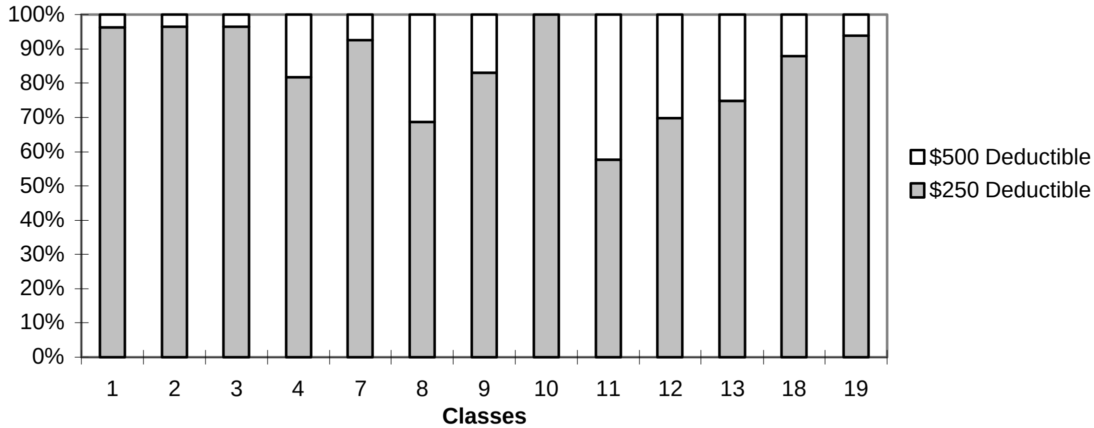
3.3 Econometric results

We now present econometric results from two structural equations like those proposed in Puelz and Snow and different extensions. At this point we have not yet analyzed the accident costs and not taken into account moral hazard explicitly. However, we will use some tarification variables of the insurers that take into account accident costs indirectly and moral hazard. These variables are: 1) the tarification group variable for different automobile characteristics; 2) the age of the car; and 3) the bonus-malus variables.

Different contracts corresponding to various levels for a straight deductible are proposed by the insurer. From the data, we observe that the deductible choice does matter for only two deductible levels $250 and $500 and in fact the choice of $500 is done only by about 4% of the overall portfolio, while it is made by nearly 18% of the young drivers.

The next figure shows how the choice of the $500 does matter for risk classes higher than 3. We will then concentrate our analysis to these classes. (See Appendix I for formal definitions of classification variables.)

Figure 1
Observed Deductible Choices According to Classes



A preliminary analysis of the data showed that the choice of the $500 deductible was significant only for groups of vehicles 8 to 15 and for drivers in driving classes 4 to 19 or for 4,772 policy holders of the entire portfolio : in these classes, 13.5% of potential permit holders choose the $500 deductible while 86.5% choose the $250 deductible. The corresponding accident frequencies are 0.081 for the $500 deductible and 0.098 for the $250 deductible.

Many factors can explain these observations. The most important one is the type of car. We will control for this pattern by using the "group of vehicle" variable. Another factor may be risk aversion. As in Puelz and Snow (1994), we use the "chosen limit of liability insurance" variable to approximate individuals' wealth. The rebate associated to a larger deductible can also influence the choices since this is a price variable. This marginal price variable will also be considered and the information comes from the tariff book of the insurer. It is important to notice here that since we do have access to this price variable directly, we do not have to estimate (as in Puelz and Snow, 1994) this price information. However, for matter of comparison, we will compare results obtained from both methods. The whole list of variables is presented in Appendix 1.

Let us first consider the choice of the deductible. As discussed in the previous section, if we want to test the prediction of Rothschild and Stiglitz (1976) that low residual risk individuals choose the higher deductible, we must use a measure of individual's risk. That measure of individual risk has to represent some asymmetrical information between the insurer and the insured in the sense that, at the date of contract choice, the insured has more information than the insurer about his individual (residual) risk during the contractual period. A first risk variable is the expected number of accidents. Since we have access to all claims we can estimate the ex-ante probability of accident the insured knew at the beginning of the period. In that sense we may have more information than the insurer but probably less than the insured since we have access to only part of his private information. However, since the estimated probability of accident is obtained by using observable characteristics, its value does not contain asymmetrical information. We may also use the number of accidents as in Puelz and Snow (1994), but precautions have to be made on its interpretation.

To obtain the individual probabilities of accident we estimated the regression coefficients for the equations associated with the individual's risks in the latent model and we used the prediction of this regression to construct the individual expected number of accidents. In this section we do not take into account of the accident costs but we allow for more than one accident during the period. Results are presented in Table 1. They come from the estimation of an Ordered Probit Model where the dependent variable considers three categories : no accident (with a claim higher than $500) during the period, one accident and 2 and more accidents (see Appendix 2 for a description). Since only one individual had three accidents, this last category was grouped with that of two accidents. (See Dionne et al, 1997, for results with the Negative binomial model. The results are identical.) Claims between $250 and $500 were not used to eliminate potential selection biais associated to the fact that these claims are not observable for those who have the $500 deductible.

Table 1
Ordered Probit on Claims
(0, 1, 2 and more)

Variable	Coefficient	T-ratio
Intercept	–1.0661	–(7.201)
Intercept μ	1.1440	(17.230)
SEXF	–0.1365	–(2.218)
MARRIED	0.0692	(1.082)
AGE	–0.0028	–(0.885)
NEW	0.1719	(2.964)
Group of vehicles		
G9	–0.0119	–(0.189)
G10	0.0228	(0.280)

G11	0.0732	(0.484)
G12	0.1797	(0.984)
G13	0.4049	(2.040)
G14	0.0003	(0.001)
G15	0.0769	(0.185)
Territory		
T2	–0.2749	–(0.958)
T3	–0.1509	–(0.963)
T4	–0.4247	–(2.555)
T5	–0.0694	–(0.499)
T6	–0.2981	–(1.509)
T7	–0.2194	–(1.912)
T8	–0.4901	–(2.040)
T9	–0.1359	–(0.787)
T10	–0.0059	–(0.026)
T11	–0.4585	–(3.333)
T12	–0.3850	–(1.534)
T13	–0.0998	–(0.549)
T14	–0.3203	–(2.490)
T15	0.1225	(0.504)
T16	–0.5180	–(1.577)
T17	0.2480	(0.712)
T18	–0.3416	–(1.859)
T19	–0.5231	–(3.256)
T20	–0.5287	–(2.887)
T21	–0.2689	–(1.837)
T22	–0.2703	–(2.016)
Number of observations	4,772	
Log-Likelihood	–1,509.0790	
Observed Frequencies	0 1 2 3	4,350 390 31 1

In order to introduce a price in the deductible equation, we used two different approaches. The first one was to calculate the premia variations from the insurer's book of premia for different deductibles where the risk classes are identified by the control variables in the regression. This yielded the GD variable. In the second approach we estimate a premium equation and calculate the premia variations by using the deductible coefficient which yielded the $\hat{G}D$ variable. We have to emphasize here that the $\hat{G}D$ variable in the deductible equation is different from the $\hat{g}_D$ variable in Puelz and Snow. Their $\hat{g}_D$ variable was obtained from a regression, where a $\hat{G}D$ variable like ours was the dependent variable ! The estimation results are given in Tables 2 and 3 for GD while those for $\hat{G}D$ are in Tables A1 and A2 in the Appendix.

Our results for the frequencies of accidents goes in the expected direction. The observed statistics indicated that the individuals who choose the larger deductible have an average frequency of accident (0.081) lower than the average one (0.098) of those who choose the smaller deductible. In fact, from Table 2, we observe in Model 2 that the predicted probability of accident E(acc) (which should be the right variable to measure the individual observable risk if we do not take care of the accident costs) is significant and has a negative coefficient (–5.30) to explain the choice of the higher deductible. However, this variable may take into account of some non-linearities that are not modelized yet.

Table 2
Probit on Deductible Choice with GD
(Z = 1 if $500 deductible)

Variable	Model 1 Conditional on the number of claims		Model 2 Conditional on the expected number of claims		Model 3 Conditional on the number of claims and expected number of claims	
	Coefficient	**T-ratio**	**Coefficient**	**T-ratio**	**Coefficient**	**T-ratio**
Intercept	–0.75045	–(5.006)	–0.49080	–(3.123)	–0.48891	–(3.111)
Acc	–0.15791	–(1.983)			–0.11662	–(1.457)
E(acc)			–5.30850	–(6.417)	–5.21290	–(6.278)
GD	–0.00985	–(5.275)	–0.01449	–(7.123)	–0.01452	–(7.132)
SEXF	–0.50974	–(8.296)	–0.59015	–(9.334)	–0.59041	–(9.338)
AGE	–0.02508	–(7.975)	–0.02440	–(7.784)	–0.02445	–(7.792)
Liability limit						
W2	–0.01330	–(0.177)	–0.03525	–(0.465)	–0.03695	–(0.487)
W3	–0.20162	–(1.872)	–0.20000	–(1.848)	–0.20139	–(1.860)
W4	0.01147	(0.172)	0.04013	(0.597)	0.03929	(0.584)
W5	–0.23370	–(2.990)	–0.17042	–(2.156)	–0.17123	–(2.166)
Group of vehicles						
G9	0.14844	(2.683)	0.13889	(2.494)	0.13897	(2.494)
G10	0.24281	(3.359)	0.26775	(3.685)	0.26877	(3.698)
G11	0.42420	(3.267)	0.49196	(3.769)	0.49244	(3.770)
G12	0.69343	(4.346)	0.85845	(5.262)	0.85981	(5.270)
G13	0.79738	(4.485)	1.34750	(6.802)	1.34670	(6.783)
G14	1.14240	(4.937)	1.10390	(4.795)	1.10690	(4.813)
G15	1.05820	(3.541)	1.10420	(3.667)	1.10700	(3.680)
YMALE	0.11269	(0.734)	0.06126	(0.401)	0.06569	(0.429)
Number of observations	4,772		4,772		4,772	
Log-likelihood	–1,735.406		–1,716.054		–1,714.961	

For comparison we did also estimate the same equation by using the numbers of accidents as in Puelz and Snow (RT). The variable "accident" (Acc) yielded a similar result but its coefficient is less important in absolute value (–0.16) than that of E(acc) in Model 2. However, if we compare the log likelihood values of the two regressions (–1735.4 compared to –1716.0), any test will choose the regression with the expected number of claims. Another possibility is to include both variables in the same equation which is a natural method for introducing a correction for misspecification problems (see Dionne et al, 1997, for more details). As shown in Table 2, only the E(acc) variable is significant when both variables are introduced in the same regression (Model 3).

This result is very important for our main purpose. It indicates that when we control for the individuals' observable risk by using the E(acc) variable, there is no residual adverse selection in the portfolio since the Acc variable is no more significant. It also indicates that a conclusion on the presence of residual adverse selection obtained from a regression without the E(acc) variable is misleading : the coefficient of the accident variable is significant because there is a misspecification problem. By introducing the E(acc) variable, we introduce a natural correction to this problem (see Dionne, Gouriéroux, Vanasse, 1997, for more details).

Results in Table 3 introduce a further step by adding more risk classification variables in the model. We observe that when sufficient classification variables are present, both Acc and the E (acc) variables are not significant. In other words, an insurer that uses appropriate risk classification variables can eliminate the presence of residual adverse selection and can take into account the non linearities. Our results indicate clearly that there is no residual adverse selection in the portfolio studied.

Table 3
Probit on Deductible Choice with GD
and More Risk Classification Variables
(Z = 1 if $500 deductible)

Variable	**Model 1'** Conditional on the number of claims		**Model 2'** Conditional on the number of claims and expected number of claims	
	Coefficient	**T-ratio**	**Coefficient**	**T-ratio**
Intercept	–1.22120	–(4.547)	–1.30590	–(2.490)
Acc	–0.10517	–(1.276)	–0.10553	–(1.280)
E(acc)			0.58938	(0.188)
GD	–0.00201	–(0.545)	–0.00202	–(0.550)
W2	0.06887	(0.859)	0.06879	(0.858)
W3	–0.11428	–(1.001)	–0.11423	–(1.000)
W4	0.12576	(1.727)	0.12584	(1.728)
W5	–0.02418	–(0.277)	–0.02432	–(0.278)
G9	0.17841	(3.054)	0.17944	(3.058)
G10	0.30520	(4.021)	0.30279	(3.933)
G11	0.44785	(3.318)	0.43993	(3.112)
G12	0.68037	(4.144)	0.65893	(3.297)
G13	0.84015	(4.641)	0.78287	(2.209)
G14	1.11860	(4.763)	1.11900	(4.764)
G15	1.29860	(4.230)	1.28800	(4.128)
YMALE	0.25763	(1.588)	0.25703	(1.584)
Territory				
T2	–0.03209	–(0.105)	0.00336	(0.009)
T3	0.25254	(1.564)	0.27327	(1.398)
T4	0.20936	(1.271)	0.25921	(0.831)
T5	–0.16668	–(1.093)	–0.15676	–(0.971)
T6	–0.16993	–(0.798)	–0.13253	–(0.455)
T7	–0.42383	–(2.983)	–0.39531	–(1.902)
T8	0.04565	(0.215)	0.09895	(0.279)
T9	–0.77727	–(3.293)	–0.75859	–(2.962)
T10	–0.37822	–(1.364)	–0.37624	–(1.356)
T11	0.07027	(0.478)	0.12135	(0.393)
T12	0.00237	(0.011)	0.04693	(0.144)
T13	–0.07428	–(0.391)	–0.05999	–(0.293)
T14	–0.25654	–(1.697)	–0.21748	–(0.846)
T15	–0.59145	–(1.753)	–0.61204	–(1.725)
T16	–0.35069	–(1.157)	–0.29534	–(0.699)
T17	–0.55868	–(0.882)	–0.60648	–(0.886)
T18	–0.10787	–(0.569)	–0.06671	–(0.230)
T19	–0.03533	–(0.222)	0.01937	(0.058)
T20	–0.06699	–(0.373)	–0.01027	–(0.029)

T21	–0.17568	–(1.097)	–0.14160	–(0.586)
T22	0.28629	(2.054)	0.32019	(1.405)
Driver's class				
CL7	–0.61323	–(7.384)	–0.61280	–(7.376)
CL8	0.52957	(1.491)	0.52165	(1.458)
CL9	–0.08160	–(0.822)	–0.08974	–(0.829)
CL10	–3.20880	–(0.092)	–3.21030	–(0.092)
CL11	0.83600	(5.470)	0.83427	(5.450)
CL12	0.44447	(3.435)	0.44263	(3.412)
CL13	0.22995	(2.464)	0.22891	(2.449)
CL18	–0.24645	–(1.859)	–0.23576	–(1.634)
CL19	–0.64555	–(6.869)	–0.63486	–(5.782)
NEW	–0.25013	–(4.402)	–0.26935	–(2.304)
AGECAR	0.05673	(3.247)	0.05686	(3.252)
Number of observations	4,772		4,772	
Log-likelihood	–1,646.41		–1,646.392	

In Appendix, we reproduce similar results (Tables A1, A2) when $\hat{G}D$ (instead of GD) is used. Its value is obtained from the regression of the premium equation presented in Table A3. The same conclusions on the absence of residual adverse selection are obtained.

In the premium equation we verify that the average effect of having a $500 deductible (deductible variable and interactions with age, sex, marital status, use of the car, territories…) on the premia is negative and significant (–$24). This is the sum of the direct and interaction effects.

Table 4 summarizes the different results. Again we observe that the use of GD instead of $\hat{G}D$ does not affect the conclusions of the paper.

Table 4
Summary of econometric results

D^H = $ 250 $E_H(acc) = 0.098$	
D^L = $ 500 $E_L(acc) = 0.081$	
Coefficient of E(acc) in a regression of the deductible choice with GD (Table 2, Model 2)	–5.30
Coefficient of GD (in the same regression) taken from the insurer book (Table 2, Model 2)	–0.01
Coefficient of Acc in a regression of the deductible choice with GD (Table 2, Model 1)	–0.16
Coefficient of GD (in the same regression) taken from the insurer book (Table 2, Model 1)	–0.01
Coefficient of Acc in a regression on the deductible choice with GD and E(acc) (Table 2, Model 3) (no residual adverse selection)	Not significant
Coefficients of E(acc) and Acc in Table 3 (Models 1' and 3')	Not significant
Coefficient of E(acc) in the regression of the deductible choice with $\hat{G}D$ (Table A1, Model 5)	–3.80
Coefficient of $\hat{G}D$ (in the same regression) obtained from results in table A3 (Table A1, Model 5)	–0.006

Average effect of \$500 deductible on the premia (Sum of the interaction variables and deductible variable)	–\$24
Coefficient of Acc in the regressions of the deductible choice with $\hat{G}D$ (Table A1, Model 4)	–0.16
Coefficient of $\hat{G}D$ (in the same regression) obtained from results in Table A3 (Table A1, Model 4)	–0.006
Coefficient of Acc in a regression on the deductible choice with $\hat{G}D$ and E(acc) (Table A1, Model 6) (No residual adverse selection)	Not significant
Coefficients of E(acc) and Acc in Table A2 (Models 4' and 6')	Not significant

4. Conclusion

In this paper we have proposed a new empirical analysis on the presence of adverse selection in an insurance market. We have presented a theoretical discussion on how to test such presence in a market with transaction costs where moral hazard may be present and where accident costs may differ between the insurance policies. Our econometric results were derived, however, from a model without different accident costs. They show that individuals who choose the larger deductible have an average frequency of accident lower than the average one of those who choose the smaller one. However, since the expected numbers of accidents were obtained from observable variables, this result does not mean that there is adverse selection in the portfolio. Further analyses show that, in fact, there is no residual adverse selection in the portfolio studied. The insurer is able to control for adverse selection by using an appropriate risk classification procedure. In this portfolio, no other selfselection mechanism (as the choice of deductible) is necessary for adverse selection. Deductible choices may be explained by proportional transaction costs as suggested by Proposition 1.

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Appendix 1
Definition of variables

AGE :	Age of the principal driver.
SEXF :	Dummy variable equal to 1, if the principal driver is a female.
MARRIED :	Dummy variable equal to 1, if the principal driver of the car is married.
Z :	Dummy variable equal to 1, if the deductible is $500 [equal to 0 for a $250 deductible].
T1 to T22 :	Group of 22 dummy variables for territories. The reference territory T1 is the center of the Montreal island.
G8 to G15 :	Group of 8 dummy variables representing the tariff group of the insured car. The higher the actual market value of the car, the higher the group. G8 is the reference group.
CL4 to CL19 :	Driver's Class, according to age, sex, marital status, use of the car and annual mileage. The reference class is 4.
NEW :	Dummy variable equal to 1 for insured entering the insurer's portfolio.
YMALE :	Dummy variable equal to 1, if there is a declared occasional young male driver in the household.
AGECAR :	Age of the car in years.
N (acc) :	Observed number of claims [for accidents where the loss is greater than $500] (range 1 to 3).
E (acc) :	Expected number of accidents obtained from the ordered probit estimates.
GD :	Marginal price (rebate) for the passage from the $250 to the $500 deductible. This amount is negative and comes from the tariff book of the insurer.
W1 to W5 :	Chosen limit of liability insurance. W1 is the reference limit.
$\hat{G}D$:	Estimated marginal price obtained from the premium equation.
RECB1 to RECB6 :	Driving record (number of years without claims) for Chapter B (collision).
RECA1 to RECA6	Same as above for Chapter A (liability).
GOODA to GOODF	Bonus programs according to driving record of both Chapter A and B and seniority.
PROFESSIONAL REBATE GROUP	Dummy variable equal to one if the main driver is a member of one of the designated professions admissible to an additional rebate.

Table A1

Probit on Deductible Choice with $\hat{G}D$

(Z = 1 if \$500 deductible)

Variable	**Model 4** Conditional on the number of accidents and predicted GD		**Model 5** Conditional on the expected number of accidents and predicted GD		**Model 6** Conditional on the number of accidents and expected number of accidents and predicted GD	
	Coefficient	**T-ratio**	**Coefficient**	**T-ratio**	**Coefficient**	**T-ratio**
Intercept	–0.59938	–4.990	–0.24400	–1.722	–0.24439	–1.724
Acc.	–0.16361	–2.042			–0.12928	–1.606
E(Acc.)			–3.80580	–4.899	–3.69290	–4.733
$\hat{G}D$	–0.00583	–6.314	–0.00623	–6.677	–0.00629	–6.720
SEXF	–0.56096	–9.455	–0.64578	–10.379	–0.64603	–10.383
AGE	–0.02105	–6.449	–0.02186	–6.691	–0.02184	–6.681
Liability limit						
W2	–0.00431	–0.057	–0.02250	–0.297	–0.02429	–0.321
W3	–0.19344	–1.801	–0.18530	–1.724	–0.18693	–1.739
W4	0.03076	0.460	0.05540	0.824	0.05427	0.807
W5	–0.18271	–2.343	–0.12793	–1.622	–0.12906	–1.636
Groups of vehicles						
G9	0.19945	3.559	0.19517	3.470	0.19581	3.480
G10	0.11705	1.560	0.12420	1.652	0.12429	1.653
G11	0.54925	4.170	0.60081	4.542	0.60259	4.552
G12	0.72856	4.554	0.84384	5.179	0.84570	5.190
G13	0.60624	3.352	0.99577	5.033	0.99204	5.000
G14	1.23100	5.362	1.20330	5.258	1.20830	5.287
G15	–0.24092	–0.661	–0.30273	–0.823	–0.31143	–0.847
YMALE	0.18868	1.243	0.19079	1.263	0.19551	1.291
Number of observations	4,772		4,772		4,772	
Log-likelihood	–1,729.084		–1,718.887		–1,717.555	

Table A2

Probit on Deductible Choice with $\hat{G}D$
and More Risk Classification Variables
(Z = 1 if $500 deductible)

Variable	Model 4' Conditional on the number of accidents and predicted GD		Model 6' Conditional on the number of accidents and expected number of accidents and predicted GD	
	Coefficient	T-ratio	Coefficient	T-ratio
Intercept	–1.18420	–7.191	–1.35560	–2.783
Acc.	–0.10446	–1.268	–0.10522	–1.276
E(acc)			1.18280	0.374
$\hat{G}D$	–0.00249	–1.308	–0.00260	–1.349
W2	0.06937	0.866	0.06925	0.864
W3	–0.11466	–1.005	–0.11456	–1.004
W4	0.12695	1.744	0.12716	1.746
W5	–0.02300	–0.263	–0.02323	–0.266
G9	0.20576	3.315	0.20902	3.334
G10	0.25080	2.904	0.24361	2.754
G11	0.50262	3.548	0.48913	3.347
G12	0.69886	4.237	0.65661	3.285
G13	0.73866	3.742	0.61925	1.650
G14	1.16430	4.912	1.16720	4.922
G15	0.74599	1.423	0.70033	1.301
YMALE	0.26833	1.751	0.26680	1.740
Territory				
T2	–0.01498	–0.049	0.05648	0.157
T3	0.24189	1.603	0.28386	1.509
T4	0.20172	1.340	0.30241	0.980
T5	–0.15344	–1.010	–0.13324	–0.826
T6	–0.19533	–0.953	–0.12053	–0.421
T7	–0.42620	–3.373	–0.36811	–1.838
T8	0.03137	0.160	0.13891	0.399
T9	–0.77733	–3.526	–0.73862	–3.032
T10	–0.35369	–1.273	–0.34859	–1.254
T11	0.06260	0.479	0.16574	0.543
T12	–0.00809	–0.038	0.08189	0.254
T13	–0.08406	–0.460	–0.05501	–0.277
T14	–0.26498	–1.976	–0.18593	–0.743
T15	–0.56614	–1.677	–0.60689	–1.709
T16	–0.36035	–1.213	–0.24888	–0.591
T17	–0.55716	–0.889	–0.65308	–0.960
T18	–0.11687	–0.665	–0.03365	–0.119
T19	–0.04111	–0.285	0.06936	0.211
T20	–0.08157	–0.490	0.03258	0.094
T21	–0.18741	–1.239	–0.11875	–0.499

T22	0.27224	2.111	0.34042	1.524
Driver's class				
CL7	–0.59306	–7.362	–0.59073	–7.309
CL8	0.43937	1.314	0.42114	1.246
CL9	–0.13153	–1.286	–0.14982	–1.321
CL10	–3.43610	–0.099	–3.44830	–0.099
CL11	0.53978	1.896	0.52287	1.814
CL12	0.38650	3.002	0.37924	2.913
CL13	0.23058	2.656	0.22801	2.618
CL18	–0.23466	–1.811	–0.21309	–1.502
CL19	–0.69262	–7.811	–0.67270	–6.506
NEW	–0.24305	–4.268	–0.28135	–2.401
AGECAR	0.05788	3.311	0.05819	3.324
Number of observations	4,772		4,772	
Log-likelihood	–1,645.699		–1,645.629	

Table A3
Premium Equation
(Ordinary Least Squares)
Dependent Variable : Ln (Annual premium)

Variable	Coefficient	T-ratio
Intercept	7.084913	108.26
Deductible of $500 (dummy = 1 if $500)	–0.054733	–2.789
SEXF=1	–0.260412	–3.103
Driver's class		
Class 7	–0.38553	–5.333
Class 7 * SEXF	0.178657	2.118
Class 8	–0.06917	–0.283
Class 9	–0.157935	–1.276
Class 10	1.080943	9.382
Class 11	1.037563	5.157
Class 12	0.337937	3.636
Class 13	0.085396	0.915
Class 18	–0.017673	–0.144
Class 19	–0.087705	–0.768
Territory		
T2	0.049853	1.558
T3	–0.32234	–12.887
T4	–0.428307	–16.876
T5	–0.186941	–11.311
T6	–0.314625	–11.301
T7	–0.556104	–25.089
T8	–0.631718	–21.777
T9	–0.605816	–22.812
T10	–0.335885	–10.216
T11	–0.430645	–18.698
T12	–0.43563	–14.307
T13	–0.263681	–9.763
T14	–0.460916	–20.157
T15	–0.258951	–7.293
T16	–0.206303	–6.263
T17	–0.038313	–0.752
T18	–0.41909	–16.002
T19	–0.49535	–20.614
T20	–0.401352	–15.64
T21	–0.253889	–10.604
T22	–0.270222	–18.002
Group of vehicles (ref. = group 8)		
G9	0.192655	13.312
G10	0.416005	21.603
G11	0.478457	14.722
G12	0.609115	13.284
G13	0.617026	8.148
G14	0.955519	7.635
G15	1.058637	5.702

Driving record (Collision)		
RECB1	0.041914	0.21
RECB2	–0.134967	–1.194
RECB3	–0.228689	–2.774
RECB4	–0.293009	–3.881
RECB5	–0.317626	–1.585
RECB6	–0.696749	–11.102
Driving record (Liability)		
RECA1	–0.063876	–1.091
RECA2	–0.096978	–1.484
RECA3	–0.002518	–0.049
RECA4	–0.071683	–1.671
RECA5	–0.213864	–1.104
Bonus program		
GOODA	–0.083631	–6.423
GOODB	–0.119077	–5.14
GOODC	–0.174539	–16.196
GOODD	–0.194518	–9.845
GOODE	–0.070396	–1.809
GOODF	0.012065	0.53
YMALE	0.286499	15.985
Professional rebate group	0.045926	2.48
NEW	–0.049648	–1.314
YIELDED	–0.032502	–1.366
MARRIED	–0.071916	–6.804
Interactions of class and driving record		
Class 7 * RECB1	0.141226	0.698
Class 7 * RECB2	0.195843	1.588
Class 7 * RECB3	0.19459	2.113
Class 7 * RECB4	0.1854	2.167
Class 7 * RECB5	0.070982	0.968
Class 7 * RECB6	0.100558	1.405
Class 8 * RECB3	0.312208	1.152
Class 8 * RECB4	0.14898	0.578
Class 9 * RECB1	0.030102	0.122
Class 9 * RECB2	–0.253693	–1.449
Class 9 * RECB3	–0.036103	–0.261
Class 9 * RECB4	–0.106038	–0.793
Class 9 * RECB5	–0.066021	–0.525
Class 9 * RECB6	–0.060992	–0.492
Class 11 * RECB3	–0.432049	–2.133
Class 11 * RECB4	–0.382129	–1.888
Class 12 * RECB3	–0.08459	–0.795
Class 12 * RECB4	–0.069648	–0.678
Class 12 * RECB5	–0.047533	–0.496
Class 12 * RECB6	–0.03493	–0.37
Class 13 * RECB1	–0.052951	–0.233
Class 13 * RECB2	0.271941	1.822
Class 13 * RECB3	–0.062888	–0.553
Class 13 * RECB4	0.000224	0.002

Class 13 * RECB5	–0.007535	–0.078
Class 13 * RECB6	0.006852	0.073
Class 18 * RECB1	–0.026089	–0.107
Class 18 * RECB2	0.431126	1.947
Class 18 * RECB3	–0.06275	–0.636
Class 18 * RECB4	0.041668	0.426
Class 19 * RECB1	–0.141484	–0.687
Class 19 * RECB2	0.058235	0.267
Class 19 * RECB3	–0.144316	–1.611
Class 19 * RECB4	–0.066468	–0.758
Class 19 * RECB5	–0.091214	–1.144
Class 19 * RECB6	–0.055647	–0.712
Interactions of professional rebate group and vehicle group		
Prof * G9	0.0013	0.049
Prof * G10	0.007034	0.138
Prof * G11	–0.010439	–0.161
Prof * G12	–0.044153	–0.234
Prof * G13	–0.020836	–0.196
Prof * G14	–0.111709	–0.751
SEXF * professional rebate group	–0.048515	–2.084
Interactions of SEXF and vehicle group		
SEXF * G9	0.006607	0.239
SEXF * G10	0.023595	0.688
SEXF * G11	0.060012	0.836
SEXF * G12	0.143218	1.42
SEXF * G13	–0.000809	–0.01
SEXF * G14	–0.0437	–0.564
SEXF * G15	0.631914	3.014
Interactions of group of vehicle and driver's class		
G9 * Class 7	0.016709	0.906
G9 * Class 8	–0.161462	–1.292
G9 * Class 9	0.03871	1.456
G9 * Class 10	0.242653	1.139
G 9 * Class 11	–0.001598	–0.035
G9 * Class 12	0.034983	1.158
G9 * Class 13	0.024637	0.98
G9 * Class 18	0.035378	0.82
G9 * Class 19	0.022656	0.669
G10 * Class 7	–0.019087	–0.787
G10 * Class 8	–0.428632	–2.76
G10 * Class 9	–0.020901	–0.576
G10 * Class 10	–0.268559	–1.257
G10 * Class 11	–0.076604	–1.159
G10 * Class 12	–0.05897	–1.382
G10 * Class 13	–0.0222	–0.66
G10 * Class 18	0.009635	0.162
G10 * Class 19	–0.01693	–0.384
G11 * Class 7	0.039974	1.007
G11 * Class 8	–0.086491	–0.326

G11 * Class 9	0.143368	1.424
G11 * Class 11	–0.71324	–3.751
G11 * Class 12	0.112595	1.204
G11 * Class 13	0.062381	0.944
G11 * Class 18	–0.002747	–0.014
G11 * Class 19	0.052501	0.544
G12 * Class 7	0.011695	0.207
G12 * Class 9	–0.025601	–0.249
G12 * Class 11	0.152149	1.088
G12 * Class 12	–0.042248	–0.409
G12 * Class 13	0.005722	0.061
G12 * Class 18	–0.015306	–0.098
G12 * Class 19	0.006389	0.051
G13 * Class 7	0.128514	1.538
G13 * Class 9	0.197948	1.306
G13 * Class 12	0.075903	0.509
G13 * Class 13	0.2423	2.546
G13 * Class 18	0.290609	1.897
G13 * Class 19	0.212369	1.562
G14 * Class 7	–0.020646	–0.164
G14 * Class 13	–0.070231	–0.432
G14 * Class 19	0.189302	0.806
G15 * Class 7	0.069737	0.361
Interactions of $500 deductible and driver's class		
$500 deductible * (Class 7)	0.033987	1.261
$500 deductible * (Class 8)	–0.010424	–0.07
$500 deductible * (Class 9)	–0.063634	–2.013
$500 deductible * (Class 11)	–0.098077	–2.235
$500 deductible * (Class 12)	–0.049638	–1.586
$500 deductible * (Class 13)	–0.010831	–0.407
$500 deductible * (Class 18)	0.003292	0.025
$500 deductible * (Class 19)	–0.045019	–0.352
Interactions of $500 deductible and group of vehicle		
$500 deductible * G9	0.03751	1.92
$500 deductible * G10	–0.019147	–0.767
$500 deductible * G11	0.06299	1.353
$500 deductible * G12	0.041928	0.814
$500 deductible * G13	–0.027005	–0.451
$500 deductible * G14	0.058139	0.79
$500 deductible * G15	–0.26241	–2.583
Urban territory * $500 deductible	–0.001154	–0.061
SEXF * $500 deductible	–0.003106	–0.025
SEXF * Class 7 * $500 deductible	–0.044678	–0.332
Professional rebate group* $500 deductible	–0.055141	–1.401
YMALE * $500 deductible	–0.005919	–0.11
NEW * $500 deductible	0.005266	0.288
Number of observations	4,772	
R^2	0.8318	
Adjusted R^2	0.8253	

Appendix 2
Ordered Probit Model

Let Y_i^* be the individual i risk. As usual, Y_i^* is unobservable. What we do observe is Y_i, the number of claims of individual i.

If

$$Y_i^* = X_i\beta + \varepsilon_i,$$

then

$$\begin{aligned} Y_i &= 0, \text{ if } Y_i^* \leq 0, \\ &= 1, \text{ if } 0 < Y_i^* \leq \mu, \\ &= 2, \text{ if } \mu \leq Y_i^*, \text{ where the threshold } \mu > 0 \end{aligned}$$

If ε is normally distributed across observations and if we normalize the mean and variance of ε respectively to zero and one, we obtain:

$$\begin{aligned} P(Y = 0) &= \Phi(x_i\beta), \\ P(Y = 1) &= \Phi(\mu - x_i\beta) - \Phi(-x_i\beta), \\ P(Y = 2) &= 1 - \Phi(\mu - x_i\beta), \end{aligned}$$

where $\Phi(\bullet)$ is the cumulative distribution function of the normal distribution, x_i is a vector of exogenous variables, β is a vector of parameters of appropriate dimension to be estimated along with μ the threshold parameter.