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SEPARATING MORAL HAZARD FROM ADVERSE SELECTION IN AUTOMOBILE INSURANCE: LONGITUDINAL EVIDENCE FROM FRANCE

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Separating Moral Hazard from Adverse Selection in Automobile Insurance: Longitudinal Evidence from France*

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Abstract

This paper uses longitudinal data to perform tests of asymmetric information in the French automobile insurance market for the 1995-1997 period. This market is characterized by the presence of a regulated experience-rating scheme (bonus-malus). We demonstrate that the result of the test depends crucially on how the dynamic process between insurance claims and contract choice is modelled. We apply a Granger causality test controlling for the unobservables. We find evidence of moral hazard which we distinguish from adverse selection using a multivariate dynamic panel data model. Experience rating appears to lead high risk policyholders to choose contracts that involve less coverage over time. These policyholders respond to contract changes by increasing their unobservable efforts to reduce claims.

JEL CODES: D80, G22, C23, L51.

KEYWORDS: Automobile insurance, road safety, asymmetric information, experience rating, moral hazard, adverse selection, dynamic panel data models, Granger causality test.

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1 Introduction

In France, automobile insurance pricing is based on two elements. The first is a so-called *a priori* pricing system which consists in constructing classes of homogeneous risks based on the characteristics of policyholders. The second is an *a posteriori* pricing mechanism or experience-rating scheme called bonus-malus, where past at-fault accidents are used to adjust the premium in the next periods.

The insurance industry is fully committed to the application of the bonus-malus scheme and this commitment is in fact enforced by a law stipulating that each insurer must apply the same bonus-malus formula for similar driving histories according to rules that cannot be renegotiated. Over the last decade, regimes of this sort have come under criticism from the European Commission, on several grounds (Council of European Communities, 1992; Picard, 2000). One specific criticism is that such pricing schemes reduce competition among insurers. In its analysis, the Commission did not, however, take into account the value of the scheme's commitment to enforcing optimal incentive contracts in the presence of asymmetric information.

Experience rating works at two levels. Since past accidents implicitly reflect unobservable characteristics of drivers (e.g. their driving skills) and introduce safe-driving incentives, experience rating can help in responding directly to the problems of adverse selection and moral hazard which often disturb the insurance market's allocation of risk. (Dionne, 2001). To confirm the need for such a multi-period scheme, we must prove the existence of residual asymmetric information in single-period contracting. Puelz and Snow (1994) tested for the presence of adverse selection in the portfolio of an American insurer. Their idea was to take a risk profile observable by the insurer and look for a positive correlation between insurance claims and levels of insurance coverage. The seminal theories of Rothschild and Stiglitz (1976) and Wilson (1997) do strongly predict that such a correlation should be observed in the data. Puelz and Snow (1994) concluded that there was adverse selection in the contractual relationships they looked at. But the same correlation between insurance coverage and claims can also be explained by moral hazard or even heterogeneous risk aversion (Chiappori et al., 2004).

Dionne, Gouriéroux, and Vanasse (2001) have shown that the Puelz-Snow results (1994) were probably derived from incomplete specification of the econometric model. These authors found no evidence of residual asymmetric information when testing for non-linearities in insurance pricing with a model based on similar data from a Canadian insurer. They also pointed out that heterogeneous risk aversion was captured by a number of observable classification variables. Chiappori and Salanié (2000) came to the same conclusion concerning residual asymmetric information when looking at data collected from French insurers on the claims policyholders filed in 1990. Needless to say, this lack of evidence for the presence of residual asymmetric information in the automobile insurance market is somewhat puzzling. And especially it is so, seeing that the insurance industry seems of the common opinion that the additional use of experience rating for insurance pricing is crucial in responding to information problems. However, it could be that moral hazard and adverse selection work in opposite directions when no means are found to control for certain unobservable factors. Single-period data on contracts may not provide sufficient instruments to separate the two problems.

Studies by Chiappori (2000) and Chiappori and Salanié (2000) have clearly shown that tests using the Puelz-Snow methodology (1994) fail to distinguish between adverse selection and moral hazard. Such tests give only a global view of the presence of asymmetric information. Experience rating, by contrast, not only provides additional information on risk classification but may also play an important role in the dynamic relationship between policyholders' insurance claims and contract choice (Dionne, 2001). The theoretical literature clearly indicates that these features may help overcome problems of moral hazard when risks known to the policyholder (endogenous) are unobservable by the insurer (Winter, 2000).

In France, contract choice is influenced by the evolution of the premium which, by law, is itself closely linked to the policyholder's driving record. Since increased insurance coverage tends to lower the expected costs of accidents, incentives for safe driving is weakened for all risks. Under experience rating, the subsequent rise in accidents increases the marginal costs of future accidents. Hence, experience rating may help in correcting the disincentive effect created by single-period insurance coverage. Since results obtained by Chiappori and Salanié (2000) can be interpreted as evidence that there is no residual asymmetric information problem in the French automobile insurance market, the benefits of experience rating mitigating moral hazard can also be called into question. However, these tests were conducted in a static framework which fails to recognize the dynamics that experience rating and semi-commitment introduce into contractual relationships.

Abbring et al. (2003a) have made a recent attempt to apply this multi-period incentive mechanism, by focusing on the dynamics of claims but not on the dynamics of contract choice (because of data limitations). Applying specific assumptions about the wealth effects of accidents to policyholders who differ only in their claims record (thus their experience rating), their model predicts that subjects with the worst claims records should try harder to drive safely and thereby, *ceteris paribus*, file fewer claims. Yet, their data do not support the presence of moral hazard. After all, the puzzle identified by Chiappori and Salanié (2000) and Dionne, Gouriéroux, and Vanasse (2001) remains unsolved. Does no residual asymmetric information mean no residual moral hazard **and** no residual adverse selection?

In this paper, we shall show that failure to detect residual asymmetric information and, more specifically, moral hazard in insurance data and, potentially, in other data sets, is due to the failure of previous econometric approaches to model adequately the dynamic relationship between contract choice **and** claims when looking at experience rating. Using a unique longitudinal survey of policyholders from France, we show that, as anticipated by Chiappori and Salanié (2000), omission of the experience-rating variable most plausibly explains the failure to detect asymmetric information in tests similar to the one they applied. The bonus-malus coefficient is, indeed, negatively related to the level of insurance coverage (through fluctuations in the premium) and positively correlated to claims (potentially through unobserved heterogeneity). The coefficient thus appears to hide the link between claims and contract choice which is exactly what Chiappori and Salanié (2000) had in mind. This is apparent in traditional cross-sectional tests as well as in extrapolations using longitudinal data models that simply pool repeated observations or permit the correlation of unobserved independent factors with each contract observed over time. For our data set, these factors essentially improve the power of the test to detect asymmetric information.

This paper also proposes a methodology to disentangle the historical pathways which lead asymmetric information to a conditional correlation between claims and levels of coverage. Within a longitudinal data framework controlling for unobservables (Chamberlain, 1984), we show how Granger causality (Granger, 1969) can be used to disentangle moral hazard from adverse selection. We argue that this test is the most appropriate in insurance markets characterized by semi-commitment, where full anticipation of long-run behavior is not optimal.

We find evidence of Granger causality linking insurance coverage with accident rates in following years and this points to the presence of moral hazard. After filing at-fault claims or receiving premium increases, policyholders reduce their level of coverage and try harder to substantially reduce their likelihood of filing any future claims. In our data set, a switch from all-risk coverage (costs covered for both parties) to limited coverage (only third-party costs) is associated with a substantial 6% decline in the probability a claim will be filed.

We also find that there is no presence of residual contemporaneous asymmetric information in the data. From our results, it appears that a priori classification can account for the unobservable risk characteristics of policyholders if insurers have access to experience rating as an additional source of information in assessing the risk profiles of their clients. Indeed, we find that the change in contract is most often triggered by a rising experience rating coefficient.

The paper is organized as follows. In section 2, we present key features of the French automobile insurance market and discuss important issues regarding the regulatory context within which tests of asymmetric information are made. In section 3, we present the data used in our analysis and examine their main features. In section 4, we replicate methodologies similar to those of Chiappori and Salanié (2000) and Dionne et al. (2001) for each cross-section but also for the panel data examining the effect of omitted variables, (especially experience rating) on test conclusions. In section 5, we perform Granger causality test for moral hazard and adverse selection. Section 6 concludes.

2 The French Automobile Insurance Market

To understand how one can study empirically asymmetric information in the French automobile insurance market, it is important to start with a description of the institutional setting peculiar to France.[1]

Exclusivity and Semi-commitment — There is no clause in insurance contracts "forcing" drivers to stay with the same insurance company once the contractual period is over or even during a contractual period. However, there is some exclusivity written into insurance contracts, in that a policyholder cannot have contracts with different insurers to insure the same risk in a given period. Hence, only semi-commitment is possible in this market. It is not optimal for a policyholder to commit to multiperiod arrangements with one insurer, since there is the possibility of renegotiating contracts and switching insurer. This is common to many insurance markets. (On the notion of commitment, see Dionne and Doherty, 1994, and Hendel and Lizzeri, 2003).

Experience Rating Law — According to the regulations in force in France (Article A 121-1 - Automobile insurance - Reduction-Increase clause of the French Insurance Code and its appendix), the premium charged to the policyholder is necessarily determined by multiplying the amount of the a priori premium by a so-called reduction-increase coefficient.[2] The base coefficient is 1. After each year of accident-free insurance coverage, the coefficient applied is that of the preceding contract period minus 5%. Each at-fault accident occurring within the insurance year will increase the coefficient by 25%. The clause also stipulates that there will be no increase for the first accident occurring after a period of at least three years during which the bonus-malus coefficient was equal to 0.50.

Public Information on Accidents — At-fault claims filed by drivers fall into the domain of public information to which rival companies have free access. Bonus-malus information must be reported when the subscriber purchases a new insurance contract.

[1] See Richaudeau (1998), Picard (2000), Dionne (2001), and Fombaron (2002) for a detailed description of the automobile insurance market in France and Pinquet (1999) for an analysis of the experience rating.

[2] Throughout this paper, this coefficient will be referred to as the bonus-malus coefficient, meaning that it counts as a bonus when less than 1 but as a malus when more than 1.

Moreover, since experience rating is enforced by law, the industry is fully committed to application of the bonus-malus scheme.

This commitment on the part of insurers is crucial. Theoretical studies have shown that, failing commitment on the insurer's part, the bonus-malus scheme will provide no incentive whatsoever (Chiappori et al., 1994). Similarly, any benefits from the bonus-malus will be eliminated if a particular insurance company acquires an informational edge from access to private data on its clients' accidents. Drivers will then choose another insurer when the malus increases (Kunreuther and Pauly, 1985; Dionne and Doherty, 1994; Fombaron, 1997). Finally, evidence seems to show that there is full competition among insurers regarding the a priori pricing of insurance.

Types of Insurance Coverage — Two types of insurance coverage predominate: all-risk insurance (tous risques) and third-party liability (responsabilité civile). The former insures against losses incurred by both the policyholder and the third-party, whereas the latter, as its name indicates, insures only against third-party losses. At minimum, the law prescribes that a policyholder must have a limited third-party insurance policy. Chiappori and Salanié (2000) report an average annual premium of 3000 Francs (1986 Francs) for this coverage, whereas the premium for all-risk insurance coverage costs twice as much and increases with the value of the vehicle. Hence, the choice of insurance coverage is an important decision for policyholders.

To summarize, the institutional setting of the French automobile insurance market corresponds to dynamic models characterized by renegotiation and semi-commitment. As already argued, this setting introduces testable predictions of the effects of asymmetric information on contractual relationships. In such a setting, where insurers are committed and the policyholder's driving record is public information, the experience rating scheme can be expected to promote safe driving and to serve as a useful tool in classifying the riskiness of drivers.

3 The SOFRES Longitudinal Survey

The SOFRES longitudinal survey covers a representative sample of French drivers from 1995 to 1997 (3 years).[3] The information available in the database is composed of three elements. The first concerns information on driver characteristics (sex, age, number of accidents). The second covers the vehicles (year, group, etc.). The third and most important element for the problem we are studying relates to insurance contracts. It provides the bonus-malus coefficient and the type of insurance coverage. These two variables represent a very good proxy for actual insurance contract characteristics. Unfortunately,

[3] See chapter 6 of Dahchour (2002) for a detailed description of the database.

information on other characteristics of the contract is very limited, containing nothing about insurance premiums or deductibles, let alone anything about the identity of the insurer from year to year. Though ideally, one would prefer to have such information, the choice between "all-risk" insurance or "third-party" is likely to be the most important decision for the policyholder. In fact, the level of deductible seems mainly related to the value of the vehicle.

Our final sample is thus a three-year incomplete panel (1995-1997). We define an observational unit as a policyholder along with a vehicle defined by the first 4 digits of its license number plus the year the car was manufactured.[4] A policyholder is not necessarily present in each year. Indeed, many contracts are observed for less than three years. Table 1 gives the structure of the panel, with its entries and exits.

[Table 1 about here]

Using surveys based on policyholder records has two main advantages. The first is that, since attrition is presumably much less problematic than with insurers' portfolios, the representability of the panel might be expected to remain constant over time. In the case of data provided by insurers, the reason prompting a policyholder to switch insurers might well be the changing terms of his contract, which is precisely the subject under investigation in this literature. In our case, although we cannot observe the identity of the insurer, we do not lose track of contracts that are switched so long as the policyholder keeps the same vehicle. Therefore, no observational unit need be censored because drivers change insurers. However, if the decision to change a vehicle is correlated with changes in contract parameters, then there might still be an attrition bias. (We look into that possibility in Section 4 but fail to confirm that suspicion.) Furthermore, we use entrants in 1996 and 1997 to maintain the representability of the sample, thus limiting any loss in efficiency as the yearly sample sizes decrease.

The second advantage relates to the observability of both claimed and unclaimed accidents, one which provides a window for the analysis of reporting behavior. Since the contract party reporting accidents is the policyholder, both unclaimed and claimed accidents involving material damage and injuries are reported. Although this is not the primary concern of the present investigation, the availability of such information is precious, because it leads to a better interpretation of the results, making it possible to separate a drop in accidents from the underreporting of claims.

[4] In constructing the panel we had to match vehicles with policyholders drawn from different files for each year. We merged policyholder IDs with a car identifier consisting of the first 4 digits of the automobile identification number plus the year in which it was manufactured. This produced a match quality which minimized the possibility of matching errors while allowing us to trace contracts across years. In what follows, we use the term contract to denote an observational unit.

3.1 Contract Characteristics

The SOFRES survey provides relatively rich source of information to classify policyholders and their vehicle. This is highly important for the empirical investigation of asymmetric information, because the econometrician must try to replicate what the insurer can know about the policyholder's risk in order to price insurance. A subset of the contract characteristics that we use are described in Table 2 for 1995. These have been documented elsewhere to be fairly representative of the risk classification variables that insurers use for *a priori* classification (see Dahchour, 2002 chap. 2).

[Table 2 about here]

It should be noted that the panel is generally representative of French drivers although young drivers are underepresented. This can be explained by the fact that young drivers are often included on their parents' insurance policies, as occasional drivers. Indeed, 45.2% of 1995 contracts feature the presence of occasional users. Policyholders have, on average, 25 years of experience and relatively few have less than 2 years of experience. Regional and socio-economic status (SES) is fairly representative of the population. Policyholders mostly use city and highway networks, although a small proportion use rural networks. More than half of the respondents have more than one vehicle; one-third of the vehicles being less than three years old. Yet, a sizeable proportion of vehicles are older than five years.

3.2 Bonus-Malus, Accidents and Insurance Coverage

The evolution of the key variables used to study the dynamics in insurance contract choices and accidents is given in Table 3.

[Table 3 about here]

The percentage of policyholders reporting at least one claim in a given year is 12.6% in 1995. Undeclared accidents are much less frequent. An estimated 7.8% of policyholders did not report an accident in 1995 and this relative frequency decreases to 5% in 1997.

The bonus-malus is the coefficient applicable at the beginning of the contractual year. Therefore, it does not take into account claims in the current year. Nearly two-thirds of policyholders have a maximal bonus (or minimal bonus-malus) coefficient while very few have one in excess of 1. Indeed, the law prescribes that a policyholder cannot have a bonus-malus in excess of unity after three years without at-fault claims.

The mean exposure to risk, measured by the number of kilometers the vehicle was used, does not change over the period. On average policyholders report driving their vehicle about 13,700 km per year, while three quarters of policyholders use their vehicle less than 18,000 km per year. Finally, more than two-thirds (69%) of the contracts observed are all-risk insurance contracts.

Before proceeding with tests for residual asymmetric information in this insurance market, we first document correlation and dependence patterns among the main variables of interest. In Table 4, we look at how the distribution of claims varies by type of insurance coverage.

[Table 4 about here]

A first observation is that there are very few contracts which feature multiple claims within a year. The relative frequencies show that types of contracts and claims do not appear to be unconditionally independent of the number of claims (Chi-square = 79.2, p-value<0.001). Those with all-risk coverage tend to file more claims. All-risk policyholders have a 4.6% higher claim incidence than do those with third-party coverage.

We should stress that this is not an indication of asymmetric information in contractual relationships as Dionne, Gouriéroux, and Vanasse (2001) noted. Insurers gather information on policyholders so as to price their policies differentially, with an actuarial fairness that restores an efficient allocation of risk. Therefore, one must look within a risk class, as defined by the characteristics insurers can observe in policyholders (for example those in Table 2), to see whether or not there is any correlation between contract choice and claims (Crocker and Snow, 1986). We shall perform such an exercise in the next section.

To get a better understanding of how contract choices, experience rating, exposure to risk (mileage), and the decision to file a claim interact, we can look at rough correlations among these variables. In Table 5, bivariate correlations are reported.

[Table 5 about here]

These correlations and the information in Table 4 tend to illustrate the three main points made about the bonus-malus by many observers. (See Picard (2000) for an analysis of deregulation in Europe).

First, it is believed that experience-rating schemes lead to inflation of *a priori* premiums for drivers with a limited or poor driving history. Some insurers may indeed take advantage of the experience rating regulation to manipulate *a priori* pricing based on the evolution of the bonus-malus.[5] In Table 5, the correlation between the bonus-malus and

[5]Some evidence is provided in an experiment performed by the magazine *Que Choisir* (November, 1998). For identical individuals who only differed in their bonus-malus coefficient, there was considerable heterogeneity in the premium offered across insurance companies, over and above what is mandated by *a posteriori* pricing, suggesting that the bonus malus may also be used in *a priori* pricing.

contract choice (coverage where 1 is for all-risk coverage) is negative and strongly significant. However, the bonus-malus is positively correlated to claims, plausibly through non-observable heterogeneity.

Second, one of the common characteristic of these schemes is that they penalize less than reward, resulting in some sort of "forced" risk pooling at the lowest-end of the experience-rating distribution. From Table 4, we see that more than two-thirds of policyholders are at the lower end of the distribution. Very few policyholders have a bonus-malus above 1. It is thus difficult, for low risks with the best records, to separate themselves from high risks with similar experience-rating coefficients. Over and above what is prescribed by law, some insurers may even use specific rebates that reduce the "effective" bonus-malus coefficient to its lowest limit of 0.5.[6]

Third, since the penalty for a claim where the driver is at fault does not take into account of the size of the claim, small claims that would otherwise be reported may not be under experience rating and this adds to the possibility of cross-subsidization. We get a glimpse of this from Table 5 if we take the correlation between undeclared accidents and the bonus-malus. The correlation is positive and statistically significant indicating that those with a higher bonus-malus may tend to refrain from filing a claim.

In summary, all these stylized observations tend to suggest that experience-rating schemes introduce dynamic mechanisms, where contract choice and claims depend on the evolution of experience-rating coefficients which in turn depend on the past decisions of the contractual parties. There appears to be a somewhat "dangerous" triangular correlation between claims, contract choice, and the experience-rating coefficient. This can confuse the correlation between claims and contract choice within risk profiles, a correlation which is crucial for testing asymmetric information, as we shall see in the next section.

4 Presence of Asymmetric Information

4.1 Cross-Sectional Data Test

Based on a traditional conditional independence test, one can use a cross-section of policyholders along with their characteristics to test whether those with high unobservable risk have more coverage. If there is asymmetric information in a contractual relationship then, within a risk class summarized by a vector of the policyholder's characteristics which are observable to both parties, $\mathbf{x}_i$, the residual unobserved variation in risk and contract choice should be correlated. This is a robust prediction from the adverse se-

[6] Some analysts even argue that the effective coefficient might be below 0.5.

lection and/or moral hazard literature, as applicable to the setting described in the introduction. As already discussed, such single period tests are designed to detect the presence of residual asymmetric information, since they cannot disentangle moral hazard from adverse selection.

Denote by d_i the contract choice of policyholder i and n_i the number of claims. Then, conditional independence holds under

$$H_0 : F(d_i|\mathbf{x}_i, n_i; \theta_d) = F(d_i|\mathbf{x}_i; \theta_d) \tag{1}$$

given θ_d is some finite-dimensional parameters vector and F is the cumulative distribution function (cdf) of d_i conditional on $\mathbf{x}_i$. Relation (1) means that the number of claims does not give information on the distribution of contract choice (Dionne et al., 2001). In other words, under the null, there is no residual asymmetric information within a risk class and contract choice does not correlate with claims. If, however, high-risk policyholders would choose more coverage than low risk policyholders under adverse selection or if individuals with more insurance coverage would be less motivated to drive carefully under moral hazard, then a positive correlation should be observed.

A non-parametric test will handle the dreaded dimensionality problem. The vector $\mathbf{x}_i$ must be rich enough to represent the insurer's information set and the data requirements for generating fixed power to reject the null of conditional independence will grow exponentially. In this paper, we opt for a parametric form of the test where

$$d_i = I(\mathbf{x}_i'\beta_d + \pi_n n_i + u_{di} > 0). \tag{2}$$

The error term u_{di} follows a distribution that we will assume to be normal but which could also be logistic with some rescaling.[7] $I(.)$ is the indicator function ($I(a) = 1$ if a is true, 0 otherwise) that denotes the choice of a certain insurance coverage (1 is for all-risk coverage). This could be extended to other types of discrete or continuous choice sets but available data will generally force a particular choice. In our case, we only observe a binary variable for insurance contracts, so we consider a class of binary-choice models.

A test for asymmetric information using this parametric model is given by $\pi_n = 0$ under the null hypothesis of conditional independence and is implemented by estimating (2) on a cross section of N contracts $\{d_i, n_i, \mathbf{x}_i\}_{i=1}^N$.

Implicit in (1) is that the model is correctly specified. But, as Dionne, Gouriéroux, and Vanasse (2001) emphasize, care must be given to the specification of the index $\mathbf{x}_i'\beta_d$. Indeed, it must reflect the insurer's knowledge of the driver's situation at the time where the contract is negotiated. We use combinations of dummy variables (age, socio-economic status, income, region, road network used, car type, fuel type, number of active

[7]We investigate the possibility of faulty specification of such a distribution in the next section.

drivers) in addition to continuous variables such as the car's manufacture date and the driver's experience. For these variables, we use spline functions with nodes at natural points, given the distribution of the data.[8] So, these constitute flexible approximations to non-linear functions. This is highly important as Chiappori and Salanié (2000) show; even for very simple utility functions, the optimal pricing policy can be quite non-linear.[9] Note that, for now, we make no room for using the bonus-malus coefficient in *a priori* pricing. Hence, we assume that insurers will follow regulations and not use experience rating to classify policyholders ex-ante.

The database also contains data on mileage for the current year. However, the use of such a variable is problematic: no assumption can be made concerning its evolution during the contract year nor can it be observed by the insurer when the contract is negotiated. Clearly, claims can affect kilometers in the current year. The potential bias resulting from a correlation between the unobservables of contract choice and mileage can affect the claim coefficient being tested. Insurers use some proxy for kilometers in their risk classification. For now, we shall report results with and without mileage.

Based on the three years of data, Table 6 reports the results for each year with and without mileage spline variables. Most of the risk-classification controls in the table take the anticipated signs (see Appendix A for complete results), while the pseudo R-square varies between 0.35 to 0.38. Results for 1995 and 1997 suggest that we should not reject conditional independence at the 5% level ($t_{0.05}$=1.96) and hence conclude for the absence of asymmetric information for both specifications with and without mileage. For 1996, the conclusion depends on the inclusion of the mileage variable. Without this variable there seems to be enough evidence to reject the null. However, once the mileage variable is introduced, there seems to be less evidence against the absence of asymmetric information. The mileage variable is informative about contract choices. This can be seen from comparisons of the likelihoods. For 1996 and 1997, we can reject the restrictions that the four mileage splines included do not provide information about contract choice ($\chi^2(4)$ =19.6 (21.8) for 1996 (1997)) . The causality's direction is however uncertain. Usage can change as a result of contract change or change in planned usage can encourage the policyholder to modify insurance coverage. Furthermore, a simultaneity bias can lead to a bias in the claim coefficient. This variable obviously does not belong in the insurer's information set when negotiation takes place. Since conclusions across years are ambiguous, we perform some robustness checks to see if a

[8]For a continuous variable z, the m spline denoted z_m with lower node at ψ_{m-1} and ψ_m will be given by $z_m = \max(\min(z - \psi_{m-1}, \psi_m - \psi_{m-1}), 0)$. In a linear regression of y on $z_1, ..., z_M$, the slope for z_m measures the local slope on the segment (ψ_{m-1}, ψ_m). We also experimented with combinations of splines and binary indicators which did not change results (available upon request).

[9]We experimented with limited interactions among variables to the extent that the data provides enough variation (involving additional variation in contract choice) to identify their effect.

more stable pattern could emerge.

[Table 6 about here]

4.2 Robustness Tests

4.2.1 False specification of Functional Form

The first check is designed to verify if the rejection of the hypothesis for 1996 is robust to false specification of the functional form of the conditional mean whose general form can be written as $E(d_i|\mathbf{x}_i, n_i) = F(h(\mathbf{x}, n_i))$. The first object that can be incorrectly specified is the index $h(\mathbf{x}_i, n_i)$ inside the distribution function. As proposed by Dionne, Gouriéroux, and Vanasse (2001), we can include best predictor insurers' of drivers' claims in the conditional mean of (2) to see whether any non-linearities and interactions have escaped the specification used in Table 6.

To do so, we estimate, in a first-step, the negative binomial model for the number of claims in each year, using the same set of risk factors as in the test (since there are no plausible exclusion restrictions).[10] We then use estimated parameters to generate a prediction for each year. This prediction is included along with actual claims in the index of (2). The identification of this effect will come entirely through the exponential structure of the prediction. Table 7 reports results for 1995-1997 where we do not include the mileage variable.[11]

[Table 7 about here]

Contrary to the findings of Dionne, Gouriéroux, and Vanasse, the conclusion of the test does not appear to depend on the functional form of the index. For 1995, the inclusion of this variable actually helps into increasing the estimate of the parameter on the claim coefficient but does not affect the conclusion. The conclusion of the test for 1996 and 1997 does not change also. One explanation of this negative result may be that our data set is limited; we do not have access to all insurers' contract variables as did Dionne, Gouriéroux, and Vanasse (2001) for a single insurer.

[10] Denote by $\mu_{it} = \exp(x_i'\pi)$ the conditional mean of a Poisson distribution of n_i. Then it holds true that $Var(n_i|x_i) = E(n_i|x_i)$ which is usually rejected by the data, the so-called equivariance property. One can assume that μ_{it}^* is given by $\exp(x_i'\pi + \nu_i)$ and assume that ν_i follows a gamma distribution with parameters (δ, δ). This relaxes the equivariance property, since the mixing distribution yields a negative binomial distribution for n (Gouriéroux, Monfort, Trognon, 1984).

[11] In results not reported here, the inclusion of the mileage variable does not change the qualitative results of this robustness check. Results available upon request.

Since the incorrect specification of $F(\cdot)$ is as problematic as that of $h(\cdot)$, we also test for normality using the test proposed by Chesher and Irish (1987).[12] Interestingly, we cannot reject normality at conventional levels for all the three years (χ^2= 1995:10.8, 1996:19.8, 1997:24.1 ;$\chi^2_{46,0.95}$=31.4). We also experimented with exponential forms of heteroscedasticity by modelling $Var(u_{di}|\mathbf{z}_i) = \exp(\mathbf{z}_i'\phi)$ for some vector of characteristics $\mathbf{z}_i$, but this did not alter the results. All standard errors calculated in Table 6 and 7 are robust to unknown forms of heteroscedasticity.

Therefore, we conclude that the rejection for 1996 does not appear to come from a faulty specification of the functional form.

4.2.2 Omitted Variables

A second check is made to see whether there is not an omitted variable which hides the link between claims and contract choice. Indeed, Chiappori and Salanié (2000) note after finding that drivers with a maximal bonus (0.5) tend to buy more comprehensive coverage:

> "*In fact, as our final result on the effect of the bonus coefficient clearly suggests, it may be the case that some variable that is observed by the insurers but somehow is not recorded in our data influences contract choice and riskiness in opposite directions, and that it cancels out a conditional dependence in our estimates.*" (p.72)

What the correlations in Table 5 suggest is that the bonus-malus coefficient itself meets this criterion exactly: correlated negatively with contract choice and positively correlated with claims. Table 8 presents the same tests as in Table 7 where we add as a regressor a dummy for whether the driver has a minimum coefficient of 0.5 plus the coefficient itself to measure the correlation when the coefficient is above 0.5. This can capture the effect of specific rules embodied in the bonus-malus regulation or specific pricing techniques that can be used to attract low risks.

[12] Denote by $\lambda(z_i'\widehat{\theta})$ the hazard of the standard normal distribution at $z_i'\widehat{\theta}$, $\phi(z_i'\widehat{\theta})/(1-\Phi(z_i'\widehat{\theta}))$. ϕ and Φ are the standard normal pdf and cdf and z contains all k regressors used in Table 7 while $\widehat{\theta}$ is the corresponding maximum likelihood estimator of the parameter vector under the null of normality. Then, a conditional moment test is given by $LM = \iota' R(R'R)^{-1}R'\iota$. R is the matrix of scores, a $N \times (K+3)$ matrix, with row i (for contract i) evaluated under the null hypothesis of normality $R_i = (\widehat{e}_i^1 z_i', \widehat{e}_i^2, \widehat{e}_i^3, \widehat{e}_i^4)$. The scores are given by $\widehat{e}_i^1 = -(1-d_i)\ \lambda(z_i'\widehat{\theta}) + d_i\lambda(-z_i'\widehat{\theta})$, $\widehat{e}_i^2 = -(z_i'\widehat{\theta})\widehat{e}_i^1$ (dropped if z contains a constant), $\widehat{e}_i^r = (r + (z_i'\widehat{\theta})^r)\widehat{e}_i^1$ for $r = 3, 4$. This is distributed as $\chi^2(k+3)$ under the null of normality (Chesher and Irish, 1987).

[Table 8 about here]

Indeed, the parameter for the number of claims increases significantly for all three years while the precision of the estimates remain constant. We now reject the absence of asymmetric information for 1995 at a level higher than 10% and furthermore, even with a smaller number of observations in comparison to 1996 and 1995, the coefficient for 1997 jumped. The bonus-malus parameters are quite informative about contract choice (Chi-square (2) = 41.8 (1995), 50.4 (1996), 39.8 (1997)). Although it is still too soon to speak of causal effects at this point, the strong association between the bonus-malus and contract choice does form a stronger correlation between claims and contract choices. Since longitudinal data are available, we now extend these tests in that direction.

4.3 Longitudinal Data Tests

The risk classification parameters remain relatively stable across years. A Chi-square test for the restriction that parameters should remain stable across years in a pooled probit with errors clustered at the contract level yields a value of 104.2 and a p-value of 0.182. We can therefore impose this parametric restriction and pursue a panel data analysis with invariant parameters. As pointed out in Arulampalam (1999), the parameters in pooled and error component probits (random effect) have a direct correspondence but the error component probit allows us to identify the share of unobserved heterogeneity in the total variance of the error term.[13] If there exist contract-specific attributes that are constant over time but independent of observable risk classification, this will lead to serial correlation across years. Enforcing parameter restrictions across time and also allowing for serial correlation in this way can improve the efficiency of the estimator. We perform the Dionne, Gouriéroux, and Vanasse (2001) first-step estimate using a negative binomial model with beta random effects in the dispersion parameter[14] (Hausman et al., 1984). We also make predictions from the cross-sectional negative binomial estimates. Table 9 reports the pooled probit estimates for the Dionne, Gouriéroux, and Vanasse test (including the bonus-malus coefficient), along with the share of unobserved heterogeneity in contract choice from the error component probit.

[Table 9 about here]

[13]Define $u_{dit} = \alpha_{di} + \varepsilon_{dit}$ such that if α_{di} and ε_{dit} are independent of each other and normally distributed with variances σ_ε^2 and σ_α^2, we will obtain that the pooled probit estimates of π_n will be $\pi_n/\sqrt{(\sigma_\varepsilon^2+\sigma_\alpha^2)}$ while the error component probit estimate will be π_n/σ_ε. Therefore, one must multiply the error component probit estimate by $\sqrt{(1-\rho)}$ where $\rho = \sigma_\alpha^2/(\sigma_\varepsilon^2+\sigma_\alpha^2)$ in order to get pooled probit estimates.

[14]The negative binomial random effect model allows δ, the overdispersion parameter, to vary across contracts by assuming that it follows a beta distribution.

We obtain a sufficient increase in precision, with no significant variation in the size of parameters. We can easily reject the conditional independence assumption and conclude for some evidence of residual asymmetric information. However, we do not know the source of this correlation, whether it is adverse selection or moral hazard.

Since the attrition rate in the panel is high, we first verify if those leaving have a different conditional relationship between claims and contract choice. Those leaving the panel in a particular year may possibly be those who are faced with increasing premiums. In this case, these should be the contracts most probably scheduled for revision of terms in the last observed year. Consequently, there should be a stronger association between claims and contract choice for these contracts than for those remaining in the panel. We test this idea by comparing estimates from the unbalanced sample containing those who leave and remain and the balanced sample containing only those who remain. Under the null of attrition that does not bias the inference supporting the relationship between contract choice and claims, the estimator $\widehat{\theta}_u$, for the unbalanced sample, should be asymptotically efficient while $\widehat{\theta}_b$, the balanced sample estimator, should not be efficient for all parameters in the conditional independence test (see Nijman and Verbeek, 1996): $Var(\widehat{\theta}_b - \widehat{\theta}_u) = Var(\widehat{\theta}_b) - Var(\widehat{\theta}_u)$. We can use the Durbin-Wu-Hausman test (see Hausman, 1978) that should be Chi-square distributed with degrees of freedom $\dim(\theta)$ under the null of $H_0 : \widehat{\theta}_b - \widehat{\theta}_u = 0$.[15] Under non-random attrition these estimates should differ considerably. The test applied to the specification in column 1 of Table 9 yields a value of 44.78 which has a p-value of 0.644. It thus finds no evidence of an attrition bias. Note that, as this test may not be powerful enough, we also rely on another test proposed by Fitzgerald et al. (2000) to check for the possibility of a bias due to attrition. If the probability of attrition depends on past accidents and past contract choices, then whether or not a contract exits or remains in the panel should be correlated with initial contract choice and initial claims. We can estimate the following model

$$d_{i1} = I(\mathbf{x}_{i1}'\beta_d + \pi_n n_{i1} + \pi_a a_i + \pi_n^a n_{i1} a_i + u_{di1} > 0)$$

where $a_i = I(T_i < 3)$ and T_i is the number of years in which a contract is observed. The null hypothesis should therefore be that where both π_n^a and π_a are zero. This test performed on the specification used in the first column of Table 9 yields the following relationship (t-values in brackets):

$$\begin{aligned} d_{i1} &= I(... + \underset{[1.45]}{0.196} n_{i1} - \underset{[-0.93]}{0.055} a_i - \underset{[0.30]}{0.042} n_{i1} a_i + u_{di1} > 0) \\ N &= 11,808;\ \chi^2(2) = 1.26 \end{aligned}$$

This test leads to a conclusion similar to that of the Durbin-Wu-Hausman test. There appears to be no evidence of an attrition bias. Indeed, with a survey of policyholders,

[15] The test statistic is $W = (\widehat{\theta}_b - \widehat{\theta}_u)' Var(\widehat{\theta}_b - \widehat{\theta}_u)^{-1} (\widehat{\theta}_b - \widehat{\theta}_u)$.

attrition is presumably much less problematic than when using data from insurers where a change in contract parameters may lead policyholders to switch insurer. Furthermore, with the conditional independence test which controls for a long list of characteristics we are less likely to face the risk of retention based on unobservables.

4.4 Summary of Conditional Independence Tests

Results from this section can be summarized as follows: Experience rating plays a confounding role in our attempts to study the conditional correlation between contract choice and claims. Once we focus on the bonus-malus coefficient, a clearer positive correlation emerges, pointing to the presence of asymmetric information. The rejection of conditional independence is not due to false specification of the conditional mean of the risk classification equation. Longitudinal data are of considerable help in improving the precision of the estimates. Finally, we find no evidence of any attrition bias.

We now investigate the dynamic link between contract choice and claims, taking into account experience rating, in order to design a test that will distinguish between adverse selection and moral hazard.

5 Adverse Selection and Moral Hazard

Let us start with the conditional independence test in (1)

$$H_0 : F(d_i|\mathbf{x}_i, n_i; \theta_d) = F(d_i|\mathbf{x}_i; \theta_d).$$

Using the law of joint probabilities $F(d_i|\mathbf{x}_i; \theta_d) = \frac{F(d_i,n_i|\mathbf{x}_i;\theta)}{F(n_i|\mathbf{x}_i;\theta_n)}$, we can write H_0 in an equivalent form

$$H_0 : F(d_i, n_i|\mathbf{x}_i; \theta) = F(d_i|\mathbf{x}_i; \theta_d)F(n_i|\mathbf{x}_i; \theta_n)$$

where θ, θ_n and θ_d are some finite-dimensional parameter vectors.

Indeed, as Chiappori and Salanié (2000) note, we can perform such a test by formulating a bivariate probit of the form

$$\begin{aligned} n_i &= I(\mathbf{x}_i'\beta_n + u_{ni} > 0) \\ d_i &= I(\mathbf{x}_i'\beta_d + u_{di} > 0). \end{aligned} \tag{3}$$

The test focuses on the correlation between u_{ni} and u_{di} denoted by ρ_u. The test for conditional independence becomes $H_0 : \rho_u = 0$. Now, let us consider the case where we have T_i repeated observations on a contract (assume $T_i = T$ fixed for simplicity). We can decompose the error term of both equations in (3) into an error component structure

$$\begin{aligned} u_{ni} &= \alpha_{ni} + \varepsilon_{nit} \\ u_{di} &= \alpha_{di} + \varepsilon_{dit}. \end{aligned}$$

Assume, for a moment, that the econometrician and both contractual parties can observe the pair $\boldsymbol{\alpha}_i = (\alpha_{ni}, \alpha_{di})$ where α_{ni} may represent specific policyholder characteristics, while α_{di} could represent specific contract characteristics. The test for asymmetric information now takes the form

$$H_0 : F(d_{it}, n_{it}|\mathbf{x}_{it}, \boldsymbol{\alpha}_i; \theta) = F(d_{it}|\mathbf{x}_{it}, \boldsymbol{\alpha}_{it}; \theta_d)F(n_{it}|\mathbf{x}_{it}, \boldsymbol{\alpha}_{it}; \theta_n) \ \forall t.$$

Hence, if we again assume normality for $(\varepsilon_{dit}, \varepsilon_{nit})$ we still have a test for residual contemporary asymmetric information given by testing $\rho_\varepsilon = 0$. Now include the history of each of the decision variables in the conditioning set such that

$$\begin{aligned} &H_0 : F(d_{it}, n_{it}|\mathbf{x}_{it}, d_{it-1}, n_{it-1}, \boldsymbol{\alpha}_i; \theta) = \\ &\qquad F(d_{it}|\mathbf{x}_{it}, d_{it-1}, n_{it-1}, \boldsymbol{\alpha}_i; \theta_d)F(n_{it}|\mathbf{x}_{it}, d_{it-1}, n_{it-1}, \boldsymbol{\alpha}_i; \theta_n) \ \forall t > 1. \end{aligned}$$

This still yields a test for residual asymmetric information given by $\rho_\varepsilon = 0$. Looking at the marginals, we claim that the cross-sectional variation in contract choice d_{it-1}, holding $\boldsymbol{\alpha}_i$ and n_{it-1} constant, effectively identifies moral hazard if n_{it} responds positively to such a variation. Under pure adverse selection, such variation in contract choice will not lead to a subsequent change in the distribution of claims in the next period. Therefore, we propose to test for the presence of moral hazard by using Granger causality, crucially holding $\boldsymbol{\alpha}_i$ fixed (Chamberlain, 1984): Rejecting the following null hypothesis,

$$H_0 : F(n_{it}|\mathbf{x}_{it}, d_{it-1}, n_{it-1}, \boldsymbol{\alpha}_i; \theta_n) = F(n_{it}|\mathbf{x}_{it}, n_{it-1}, \boldsymbol{\alpha}_i; \theta_n) \ \forall t > 1 \tag{4}$$

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

One can distinguish moral hazard from adverse selection within this dynamic framework because changes in exogenous risk factors (adverse selection) are controlled over time. So access to longitudinal data is crucial. Since we do not observe $\boldsymbol{\alpha}_i$ and the cross-sectional variation in d_{it-1}, n_{it-1}, is, by construction, correlated with unobserved heterogeneity, one additional observation is therefore needed in order to have two pairs of (n_{it}, d_{it}) and (d_{it-1}, n_{it-1}) from which we can separate the effect of unobserved heterogeneity. This is analogous to the identification argument Heckman (1981) makes for a dynamic binary-choice model with an error-component structure. Two remarks should be made at this point.

First, we must address the possibility that d_{it} responds to n_{it+1} and, similarly, that n_{it} responds to d_{it+1} .This is a classical difficulty in applying Granger causality, as the test would reveal the wrong causal mechanisms.[16] If one variable responds to its lead instead of the other variable responding to the lag, then causality is reversed. However, we would argue that this concern does not apply for testing moral hazard in the presence of experience rating in France, because of the particular features of the long-term contractual relationship existing here.

Indeed, this market has been described as one which is characterized by semi-commitment, because it offers the possibility of renegotiation and switching insurer. The partial commitment from the part of the insureds implies that there is little incentive for them to choose contracts based on the evolution of future accident outcomes passed the date when the contract ends (one year) even if they have rational expectations about accidents. Since they are free to renegotiate the contract without cost the following year, we can claim that the choice of insurance coverage is not based on claims forecast two years in advance. We would therefore argue that the Granger causality test from d to n will indeed serve to detect moral hazard.

The second remark concerns the test for residual instantaneous asymmetric information. Even with our use of longitudinal data, the point Chiappori (2000) made concerning the impossibility of separating moral hazard and adverse selection instanteneously is still valid. It is indeed possible that contract change will, in the very short term, affect the probability of a claim such that there could be contemporaneous causality from contract choice to claims and vice versa. This is due to the discrete-time nature of the data we use. Time cannot serve as a "pseudo-instrument" to identify causality and one would need external instruments to distinguish one from the other, which may prove very difficult.[17] Therefore the contemporaneous test (ρ_ε) is still one for residual asymmetric information, although the dynamic moral hazard test does distinguish moral hazard from adverse selection.

5.1 Parametric Model and Initial Conditions

As we have seen in Table 4, very few annual contracts feature more than one claim. Therefore, with some abuse of notation, we will define n_{it} as the occurrence of at least one claim. We postulate the following parametric model for the evolution of claims and

[16] See Hamilton (1994, 306-309) for an example where the wrong conclusion about causality is drawn from a Granger causality test in the presence of rational expectations.

[17] Because of the discrete choice nature of both variables of interest, there would be an additional "coherency" problem if both simultaneous effects were present. Coherency is defined as the impossibility of finding a unique mapping from $(\varepsilon_{dit}, \varepsilon_{nit})$ to the data for any given value of the parameters. The simultaneous binary-choice model suffers from this problem as emphasized by Schmidt (1980).

contract choice:

$$
\begin{aligned}
d_{it} &= I(\mathbf{x}_{it}'\beta_d + \mathbf{w}_{it}'\gamma_d + \phi_{dd}d_{it-1} + \phi_{dn}n_{it-1} + \alpha_{di} + \varepsilon_{dit} > 0), \\
n_{it} &= I(\mathbf{x}_{it}'\beta_n + \mathbf{w}_{it}'\gamma_n + \phi_{nn}n_{it-1} + \phi_{nd}d_{it-1} + \alpha_{ni} + \varepsilon_{nit} > 0). \\
i &= 1, ..., N, \ t = 1, .., T_i.
\end{aligned} \tag{5}
$$

We define $\mathbf{w}_{it}$ to be a set of variables that are predetermined at t such that $E(\varepsilon_{dit}\mathbf{w}_{it+s}) = 0$ and $E(\varepsilon_{nit}\mathbf{w}_{it+s}) = 0$ are assumed to hold for $s = 0$ but may not necessarily hold for $s > 1$. This plausibly allows for feedback from accidents and contract choice to certain variables such as the bonus-malus and lags in the vehicle's mileage. The bonus-malus coefficient has proved to be of particular importance in the conditional independence tests. Therefore, $\mathbf{w}_{it}$ is of the same nature as lags of the dependent variables, given that $\mathbf{w}_{it}$ may also possibly be correlated with unobserved heterogeneity $(\alpha_{ni}, \alpha_{di})$.

The dynamic test for moral hazard is one for

$$
\begin{aligned}
H_0 &: \phi_{nd} \leq 0 \\
H_1 &: \phi_{nd} > 0
\end{aligned} \tag{6}
$$

while the contemporaneous test for residual asymmetric information (plausibly again moral hazard or adverse selection) is given by

$$
\begin{aligned}
H_0 &: \rho_\varepsilon \leq 0 \\
H_1 &: \rho_\varepsilon > 0
\end{aligned} \tag{7}
$$

For a small panel (small T), predetermining a dynamic binary choice with an error-component structure will lead to the initial condition problem (Heckman, 1981). Since $(\alpha_{ni}, \alpha_{di})$ are unobserved we must somehow integrate out unobserved heterogeneity from the conditional probabilities. Because contracts have a prior history which is hidden for the econometrician, we need to sort out the joint density of $(\alpha_{ni}, \alpha_{di})$ and the prior initial conditions, since d_{i0} and n_{i0} are missing. Indeed, we need to know how the different $(\alpha_{ni}, \alpha_{di})$ got sorted out in different outcomes, since it is unlikely to be random. We follow the solution proposed by Wooldridge (2000) and assume the mean of the distribution of $(\alpha_{ni}, \alpha_{di})$ to be a linear index $\mathbf{y}_{i1}'\boldsymbol{\zeta}_d$ and $\mathbf{y}_{i1}'\boldsymbol{\zeta}_n$ of endogenous variables and predetermined variables, $\mathbf{y}_{i1} = (d_{i1}, n_{i1}, \mathbf{w}_{i1})'$.[18] The parameters $\boldsymbol{\zeta}_n$ and $\boldsymbol{\zeta}_d$ do not capture causal effects and therefore cannot be used to test any of the relevant sources of asymmetric information. They capture both the correlation in unobserved heterogeneity and the effect of past causal mechanisms, such as the moral hazard prior

[18] Replacing unobserved heterogeneity by their conditional means yields the following equations re-

to the observation period. One can note that we do "lose" one observation in the process. This is a good illustration of the identification issue. Unobserved heterogeneity entails the use of two repeated observations, conditional on unobserved heterogeneity and recent history of the variables, in order to test for moral hazard.

5.2 Estimation

If the conditional expectations in (5) were linear in parameters, the two equations could be estimated separately using ordinary least square, as they contain the same conditioning variables. In essence, this is a reduced-form vector autoregression. However, since the two equations are non-linear because of the binary nature of the dependent variables, we estimate them jointly using a bivariate probit with correlated errors. Note that normality was not rejected in the conditional independence tests. Furthermore, we allow the errors $\varepsilon_{nit}, \varepsilon_{dit}$ to be clustered at the contract level. Finally, we use the same set of conditioning variables as in the conditional independence tests, as these are crucial for the contemporaneous test of asymmetric information. We replace $(\alpha_{ni}, \alpha_{di})$ by their conditional expectations to take account of initial conditions and take the bonus-malus and mileage to be the predetermined variables in $\mathbf{w}_{i1}$. Including mileage in lags did not provide any changes in the results and yielded statistically insignificant parameters.

Quite naturally, we use the unbalanced panel, although the identification of moral hazard will come primarily from the contracts observed over three years (1049). The addition of those exiting or entering during the three years (but remaining for 2 years) may improve the efficiency of the estimator. Trivially, those remaining in the panel for only one year will not be used because of the presence of lagged decisions in the two equations.

5.3 Results

Estimation results are presented in Table 10. (Complete results are in Appendix B.)

[Table 10 about here]

placing (5),

$$\begin{aligned} d_{it} &= I(\mathbf{x}'_{it}\beta_d + \mathbf{w}'_{it}\gamma_d + \phi_{dd}d_{it-1} + \phi_{dn}n_{it-1} + \mathbf{y}'_{i1}\boldsymbol{\zeta}_d + \varepsilon_{dit} > 0), \\ n_{it} &= I(\mathbf{x}'_{it}\beta_n + \mathbf{w}'_{it}\gamma_n + \phi_{nn}n_{it-1} + \phi_{nd}d_{it-1} + \mathbf{y}'_{i1}\boldsymbol{\zeta}_n + \varepsilon_{nit} > 0). \\ i &= 1,...,N,\ t = 2,..,T_i. \end{aligned} \tag{8}$$

We find evidence that the rejection of conditional independence is entirely derived from the presence of moral hazard in the contractual relationships that we observe. The hypothesis of no moral hazard is rejected at the 5% level (t-value=2.02).[19] Indeed, we find that those switching from all-risk coverage to third-party coverage tend to exhibit a 5.9 percentage point decrease in the probability that they will file a claim the next year. Therefore, these policyholders try harder to avoid claims when faced with higher prospective insurance premia.

This change of insurance coverage can itself be triggered by the rising expected cost of accidents under an all-risk insurance policy. Indeed, those moving from a maximal bonus of 0.5 because of an at-fault claim in the last year have a 5.8% higher probability of switching from all-risk coverage to third-party coverage. This effect is significant at a level of 10% (t-value = 1.73). This can be explained by rising premiums not only due to *a posteriori* pricing but potentially also due to *a priori* pricing, as many suspect. Initial conditions also reveal the sorting of contracts along bonus-malus coefficient lines in initial-year contracts. Those with high bonus-malus coefficients tend to opt for third-party insurance policies (t-value = 2.20) and also file fewer claims (not significant at 10%).

The second test we proposed is designed to capture residual contemporaneous asymmetric information. We do not find evidence of residual asymmetric information when looking at the correlation parameter between error terms. This coefficient is low (0.014) and imprecisely estimated (t-value = 0.25). It is very similar to the one found by Chiappori and Salanié (2000) who were careful to isolate adverse selection from moral hazard by selecting a sample of drivers who are less likely to be affected by moral hazard. The test we did in this paper effectively creates a similar setting by using longitudinal data to replicate conditions in which "moral hazard" stemming from past relationships among contractual relationships is taken into account.

One last interesting result is that we find evidence of a positive contagion effect (positive state-dependence) in the claim process, which we can distinguish from the contagion effect created by unobserved heterogeneity in claims. A policyholder filing a claim in a given year is 6.1% point more likely to file another claim in the next year as compared to another policyholder with a comparable risk profile (both observed and unobserved) who did not file a claim (t-value = 2.55). As suggested by Abbring et al. (2003a) not finding a net negative contagion effect does not necessarily imply that moral hazard is absent under experience rating. Note that, in testing for such an effect, we control for initial exposure to risk by including mileage among the initial conditions.

[19] Strictly speaking according to the test in (6), the one sided p-value is 0.021.

6 Conclusion

Testing for residual asymmetric information in different markets is becoming a significant research topic (Dionne and St-Michel, 1991; Fortin and Lanoie, 1992; Genesove, 1993; Hendel and Lizzeri, 1999; Crocker and Tennyson, 2002; and many others, Chiappori and Salanié, 2003). The main objective is to verify whether actual stylized contracts derived from the theory deal efficiently with different information problems. A more difficult task is to identify the nature of the different information asymmetries. Researchers usually face an identification problem because the same prediction or correlation may correspond to either ex-ante moral hazard, ex-post moral hazard, or adverse selection in single period contracting.[20]

To overcome this identification problem, Chiappori (2000) has suggested the use of multi-period data. Multi-period data seems to be a necessary but not sufficient condition. Indeed, focusing on claims dynamics, Abbring et al. (2003a, 2003b) were not able to identify any form of moral hazard in the data set obtained from a French insurer. In this research, we used a unique longitudinal survey of policyholders in France to take experience rating into account. Indeed, we had access to the dynamic claims as well as the dynamic contract choices of the policyholders. Having access to contract choices increased the number of instruments available to isolate moral hazard from adverse selection. We were able to apply the Granger causality test controlling for the unobservables (Chamberlain, 1984).

Our results indicate, first, that residual asymmetric information is present in our panel. They also isolate dynamic moral hazard: drivers faced with significant increases in their bonus-malus and premium switch from all-risk coverage to third-party coverage only (partial insurance) and, improving their safe-driving efforts, significantly reduce their chances of having an accident in the next period.

Our results also indicate that there is no residual contemporaneous asymmetrical information in the data, when the above dynamic behavior is isolated, confirming the results of Chiappori and Salanié (2000) and Dionne et al. (2001), who did not have access to multi-period contracts.

The presence of a bonus-malus scheme was crucial to the derivation of our results. But our results also justify this scheme existence by crediting its introduction for appropriate incentives for road safety. More research on its optimal form or on (improved) substitutes seems needed to respond to the criticisms directed against it over the last ten years. It is not clearly apparent also that the industry's actual form of commitment to the bonus-malus scheme in France reduces competition among insurers. This issue is im-

[20] For an analysis of ex-post moral hazard along with ex-ante moral hazard and adverse selection, see Dionne and Gagné (2002).

portant because, as shown by Chiappori et al. (2004), market power can itself partially explain contemporaneous residual correlation between claims and insurance coverage.

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Panel structure status	Number of driver-vehicles Year 1995	Year 1996	Year 1997
Enter	5443	3464	2901
Exit	3052	3796	-
Remain	2391	2059	-
Total	5443	5855	4960

Table 1: Composition of the SOFRES Survey: Number of contracts observed in each wave. Exit refers to contracts that will exit the panel at the end of the year while Enter refers to contracts which enter the panel (first observed) in a given year. 1049 observations remain in the panel for the full three years.

(% and mean)	Year 1995		Year 1995
Gender (male)	62.9	Region	
Age		Paris	33.4
18-24	5.2	North	9.2
25-34	22.3	East	9.8
35-44	21.7	South	35.2
45-54	16.5	West	12.4
55-64	14.7	Occ. drivers	45.2
65+	20.0	Network	
		Rural	13.3
SES Position		City	40.6
Retired	28.3	Road	46.6
Farmer/Artisan	4.3	Vehicle age	
Manager	8.0	Less 3 yrs	34.3
Professional	7.6	3-5 yrs	18.6
Teacher	19.4	5-10 yrs	33.4
Employee	29.1	More 10 yrs	13.7
Student	3.2	Experience (yrs)	
# vehicles		1st quartile	14
one	45.8	Median	24
two	45.6	3rd quartile	36
3 and more	8.5	Mean	25.2
# driver-vehicles	5443		

Table 2: Contract Characteristics for 1995.

	1995	1996	1997
Declared accident (%)	12.6	11.8	10.7
Undeclared accident (%)	7.8	5.5	5.0
Bonus-malus (b) (%)			
$= 0.5$	64.9	65.9	68.3
$0.5 < b \leq 1$	33.6	32.9	30.8
$1 < b \leq 1.25$	0.9	0.7	0.5
b>1.25	0.6	0.4	0.4
Kilometers ('000) mean	13.75	13.6	13.7
1st quartile	8	8	7
3rd quartile	18	17	18
All-risk insurance (%)	69.4	69.9	69.1
# driver-vehicles	5443	5855	4960

Table 3: Accidents, Contract Choice and Utilization of Vehicle over 1995-1997: Percentage with one claim or one undeclared accident given. The kilometers are reported in thousands.

	Claims				
Coverage	None	1	2	3	4
Third-party coverage	91.5	7.4	0.9	0.2	0.1
All-risk coverage	86.9	11.2	1.6	0.2	0
% of contracts	88.3	10.1	1.4	0.2	0.1
Chi-square test	79.2 (p-value<0.001)				

Table 4: Distribution of Claims across Different Types of Contracts 1995-1997: The tabulations (conditional relative frequencies) are made using all observations across all years. Similar results emerge for yearly tabulations. The Chi-square test measures the distance between estimated frequencies and expected cell frequencies under the null hypothesis of independence.

	Claims	Undeclared	Bonus-malus	Kilometers	Coverage
Claims	-				
Undeclared	-0.01	-			
Bonus-malus	0.08**	0.08**	-		
Kilometers	0.13**	0.05**	0.12**	-	
Coverage	0.06**	-0.01	-0.14**	0.18**	-

Table 5: Correlation Patterns among Variables: Bivariate correlations. ** indicates p-value<0.05, * p-value<0.10.

Point estimates probit (robust SE)	Coverage (d_i= 1 if all-risk) Year 1995	Year 1996	Year 1997
With mileage			
Claims (n_i)	0.080 [1.55]	0.107 [1.82]	0.061 [0.90]
	(0.052)	(0.058)	(0.068)
LogLike	-2123.6	-2258.9	-1919.2
Without mileage			
Claims (n_i)	0.089 [1.74]	0.118 [1.99]	0.072 [1.06]
	(0.051)	(0.054)	(0.068)
Loglike	-2126.7	-2268.7	-1930.1
$\chi^2(4)$ usage (km)	6.22	19.6**	21.8**
# driver-vehicles	5443	5855	4960

Table 6: Cross-Sectional Conditional Independence Tests: Point estimates along with robust asymptotic standard errors reported (in parenthesis) and t-values [in brackets]. Estimation by maximum likelihood probit. Controls for: age dummies (7), experience splines (4), no presence of occasional drivers, principal network used, number of active drivers, income bracket dummies (9), gender, socio-economic status dummies (8), region (4), age of vehicle splines (4), type of vehicle (5). Mileage is included as 4 splines in thousands of kilometers. The same set of controls is used in all estimations. Complete results in Appendix A.

Point estimates probit	Coverage ($d = 1$ if all-risk) Year 1995	Year 1996	Year 1997
Without mileage			
Claims (n)	0.084 [1.63]	0.119 [2.01]	0.071 [1.03]
	(0.052)	(0.059)	(0.068)
Predicted claims ($\widehat{n}$)	2.307	1.793	1.569
	(1.037)	(1.574)	(1.443)
LogLike	-2124.3	-2268.1	-1929.4
# driver-vehicles	5443	5855	4960

Table 7: Cross-Sectional Conditional Independence Tests of Dionne, Gouriéroux, and Vanasse (2001): Point estimates along with robust asymptotic standard errors reported. Estimation by maximum likelihood probit.

Point estimates probit	Coverage ($d = 1$ if all-risk) Year 1995	Year 1996	Year 1997
Without mileage			
Claims (n)	0.097 [1.86]	0.147 [2.49]	0.095 [1.40]
	(0.052)	(0.059)	(0.068)
Predicted claims ($\widehat{n}$)	2.509 [2.39]	1.934 [1.23]	1.913 [1.40]
	(1.052)	(1.583)	(1.426)
Bonus-malus = 0.5	0.123 [1.84]	0.277 [4.10]	0.246 [3.28]
	(0.067)	(0.067)	(0.075)
Bonus-malus	-0.806 [-4.33]	-0.422 [-1.94]	-0.514 [-1.98]
	(0.185)	(0.217)	(0.259)
LogLike	-2103.4	-2242.9	-1909.5
$\chi^2(2)$ bonus-malus	41.8	50.4	39.8
# driver-vehicles	5443	5855	4960

Table 8: Cross-Sectional Conditional Independence Tests for the Presence of Asymmetric Information with Control for the Bonus-Malus: Point estimates along with robust asymptotic standard errors reported. Estimation by maximum likelihood probit.

Point estimates without mileage	Coverage ($d = 1$ if all-risk) None	Panel Negbin	Cr-Sec Negbin
Claims (n)	0.119 [3.46]	0.116 [3.36]	0.114 [3.32]
	(0.034)	(0.035)	(0.035)
Predicted claims ($\widehat{n}$)	-	4.128 [3.81]	0.658 [1.81]
		(1.081)	(0.363)
Bonus-malus = 0.5	0.216 [4.70]	0.213 [4.61]	0.217 [4.72]
	(0.046)	(0.046)	(0.046)
Bonus-malus	-0.573 [-4.04]	-0.597 [-4.14]	-0.573 [-4.03]
	(0.142)	(0.144)	(0.142)
LogLike (pooled)	-6309.3	-6300.1	-6307.8
$\chi^2(2)$ bonus-malus	129.4		
ρ (% unobserved heterogeneity)	0.918	0.923	0.918
Attrition (bal. vs unb.) $\chi^2(49)$	44.78		
# driver-vehicles	11,808	11,808	11,808

Table 9: Panel Conditional Independence Tests: Point estimates along with robust (clustered at the contract level) asymptotic standard errors reported. Estimation by maximum likelihood probit. The rho estimate comes from an error-component probit model and represents the share of unobserved heterogeneity in the total variance of the error time. The second column and third column correspond to estimates using the Dionne-Gouriéroux-Vanasse (2001) predictor generated by a random effect negative binomial model (column2) and the pooling of cross-section negative binomial models (column3). Controls for risk classification included.

Point estimates (1996-97) t-value in brackets	Dependent variable Claims	Coverage
Coverage (d_{it-1})	0.409**	2.464**
	[2.02]	[10.57]
Claims (n_{it-1})	0.319**	-0.082
	[2.55]	[-0.51]
Bonus-malus = 0.5	-0.200**	0.202*
	[-2.34]	[1.73]
Bonus-malus (b_{it-1})	0.222	0.358
	[0.70]	[0.71]
Initial condition		
Accident out (n_{i1})	0.137	0.154
	[1.10]	[0.94]
Coverage (d_{i1})	-0.367*	0.576**
	[-1.81]	[2.43]
Bonus-malus (b_{i1})	-0.149	-0.703**
	[-0.53]	[2.20]
Kilometers ('000)	0.008**	0.002
	[2.30]	[0.42]
Correlation ρ_ε	0.014	
	[0.25]	
LogLike	-2222.8	
# driver-vehicles (1996-97)	4450	

Table 10: Test for Moral Hazard and Adverse Selection: Point estimates reported along with t-values in brackets. Critical level for alpha 0.05 is 1.96 for two-sided. ** denotes p-values of less than 5 pct, * less than 10 pct. Robust standard errors are clustered by contract. Controls for risk classification included in both equations. Complete results in Appendix B.

Appendix A: Complete results for Cross-Section Conditional Independence Tests

Definition of variables

Variable Name	Name
RE1	Experience spline 0-10 yrs
RE2	Experience spline 10-15 yrs
RE3	Experience spline 15-20 yrs
RE4	Experience spline 20-25 yrs
RE5	Experience spline 25+ yrs
RNR	Number of claims
RNT1	Car used on route
RNT2	Car used on city
RNT3	Car used on highway
RBM	Bonus-malus coefficient
RBM1	Bonus-malus minimum (0.5)
RD	Insurance Coverage (1=all-risk)
RKM1	Mileage spline 0-5000 km
RKM2	Mileage spline 5-10000 km
RKM3	Mileage spline 10-15000 km
RKM4	Mileage spline 15000+ km
RDR	Number of active drivers
RU	Presence of at least one occasional driver
RINC1-9	Income categories
RCAR	Number of cars owned
RASEXM	Gender of policyholder (1=male)
RAGE1	Age 18-24
RAGE2	Age 25-34
RAGE3	Age 35-44
RAGE4	Age 45-54
RAGE5	Age 55-64
RAGE6	Age 65+
RSES1	Retired
RSES2	Agriculture or Artisan
RSES3	Manager
RSES4	Professional
RSES5	Education
RSES6	Worker
RSES7	Student

RREG1	Paris region
RREG2	North region
RREG3	East region
RREG4	South region
RREG5	West region
RY1	Car age spline 0-5 yrs
RY2	Car age spline 5-10 yrs
RY3	Car age spline 10-15 yrs
RY4	Car age spline 15 yrs
RV1-5	Car group
RG1-5	Car type
RDIE	Car runs on diesel

Cross-Section Conditional Independence Tests (w/km = without kilometers, km = with, ** 5%, * 10%) (Table 6)

Variables	1995 w/km	1996 w/km	1997 w/km	1995 km	1996 km	1997 km
RAGE1	0.004	0.298*	0.522**	-0.012	0.276	0.485**
RAGE2	0.013	0.045	0.249**	0.005	0.037	0.231**
RAGE4	0.310**	0.131	-0.068	0.319**	0.144	-0.059
RAGE5	0.283**	0.104	0.120	0.304**	0.132	0.157
RAGE6	0.362**	0.267*	0.218	0.398**	0.323**	0.297*
RE1	-0.005	0.039*	0.057**	-0.006	0.037*	0.053**
RE2	0.079**	0.089**	0.079**	0.079**	0.088**	0.079**
RE3	0.036	0.027	0.070**	0.037	0.027	0.069**
RE4	-0.037	-0.005	0.031	-0.039	-0.007	0.032
RE5	-0.021**	-0.011*	-0.013**	-0.206**	-0.012**	-0.016**
RU	-0.030	-0.108**	-0.135**	-0.024	-0.106**	-0.129**
RNT1	0.389**	0.239**	0.150**	0.365**	0.198**	0.094
RNT2	0.022	0.017	0.024	0.017	0.012	0.017
RNT3	0.141**	0.123**	0.123**	0.119**	0.090**	0.088*
RDR	0.022	0.018	-0.053	0.019	0.010	-0.057
RINC1	-0.213*	-0.105	-0.024	-0.209*	-0.093	-0.035
RINC2	-0.012	0.221*	0.054	-0.007	0.219*	0.047
RINC3	-0.096	0.054	0.141	-0.099	0.054	0.122
RINC4	0.022	0.142**	0.048	0.023	0.142**	0.047
RINC6	0.199**	0.216**	0.266**	0.206**	0.217**	0.262**
RINC7	-0.012	0.163**	0.099	-0.011	0.163**	0.095
RINC8	0.114	0.294**	0.020	0.117	0.295**	0.027
RINC9	0.215**	0.314**	0.209	0.217**	0.312**	0.194
RASEXM	-0.176**	-0.173**	-0.215**	-0.192**	-0.194**	-0.234**
RSES2	-0.151	-0.202	-0.042	-0.144	-0.213	-0.041
RSES3	0.128	0.002	0.086	0.124	-0.009	0.062
RSES4	-0.463**	-0.163	-0.269**	-0.476**	-0.175	-0.282**
RSES5	-0.125	0.005	0.187	-0.137	-0.009	0.153
RSES6	-0.385**	-0.233**	-0.031	-0.397**	-0.252**	-0.054
RSES7	-0.156	-0.164	0.183	-0.163	-0.178	0.176

Variables	1995 w/km	1996 w/km	1997 w/km	1995 km	1996 km	1997 km
RREG2	0.169**	0.106	0.004	0.173**	0.097	0.009
RREG3	0.151*	0.027	0.009	0.152*	0.022	0.016
RREG4	-0.113**	-0.024	-0.089	-0.114**	-0.023	-0.089*
RREG5	0.009	0.065	0.059	0.003	0.051	0.041
RY1	-0.215**	-0.207**	-0.186**	-0.214**	-0.208**	-0.189**
RY2	-0.316**	-0.305**	-0.305**	-0.313**	-0.301**	-0.301**
RY3	-0.076**	-0.112**	-0.147**	-0.069**	-0.099**	-0.132**
RY4	-0.002	-0.002	0.021	-0.001	0.007	0.026
RV2	0.034	-0.200**	-0.011	0.035	-0.200**	0.012
RV3	0.067	0.122**	0.114	0.070	0.124**	0.119*
RV4	0.086	-0.044	0.193**	0.083	-0.046	0.174**
RV5	0.181**	0.027	0.207**	0.178**	0.034	0.183*
RNR	0.089*	0.118**	0.072	0.081	0.107*	0.061
RKM1	.	.	.	-0.004	0.042	-0.008
RKM2	.	.	.	0.018	0.043**	0.063**
RKM3	.	.	.	0.017	-0.003	0.005
RKM4	.	.	.	-0.004	-0.003	-0.004
constant	1.499**	0.957**	0.639**	1.471**	0.726**	0.583*

Appendix B: Complete results for dynamic model of contract and claim choices (Table 10), (5%, * 10%)**

Variables	Claims	Coverage
RAGE1	-0.008	0.388
RAGE2	-0.232	0.337
RAGE4	-0.028	0.092
RAGE5	0.038	-0.038
RAGE6	0.100	-0.011
RE1	0.052	-0.030
RE2	-0.020	0.133**
RE3	-0.015	-0.025
RE4	-0.029	0.056
RE5	0.005	-0.008
RU	-0.129**	-0.023
RNT1	0.081	0.154*
RNT2	0.107*	0.049
RNT3	0.058	-0.001
RDR	-0.021	-0.107*
RINC1	0.108	0.005
RINC2	0.069	0.073
RINC3	0.063	0.015
RINC4	0.053	0.013
RINC6	0.158	0.257**
RINC7	0.098	0.201
RINC8	0.219**	0.302**
RINC9	0.176	0.029
RASEXM	0.032	-0.147*
RSES2	0.231	-0.104
RSES3	0.193	0.007
RSES4	0.210	-0.282
RSES5	0.072	0.256
RSES6	0.097	0.051
RSES7	0.412	-0.262

Variables	Claims	Contract
RREG2	-0.038	-0.184
RREG3	0.076	-0.209*
RREG4	0.027	-0.041
RREG5	-0.142	0.172
RY1	0.013	-0.165**
RY2	-0.038*	-0.156**
RY3	-0.034	0.046
RY4	-0.126**	-0.051
RV2	0.013	0.091
RV3	-0.071	0.044
RV4	-0.072	0.018
RV5	-0.189*	0.009
1997		0.118
Predetermined		
Lag RD	0.409**	2.466**
Lag RNR	0.319**	-0.082
RBM1	-0.200**	0.202*
RBM	0.222	0.358
Initial conditions		
R1D (1995)	-0.367*	0.576**
R1BM (1995)	-0.149	-0.703**
R1NR (1995)	0.137	0.154
R1KM (1995)	0.008**	0.002
constant	-1.926**	-0.932
Rho	0.014	