# Testing for moral hazard on dynamic insurance data: theory and econometric tests*

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**Abstract**

Although several tests of asymmetric information using static insurance data have been recently performed, the distinction between moral hazard and adverse selection in such a context is difficult, and the introduction of the past history of the relationship raises complex econometric problems. In this paper, we show how dynamic data allow to overcome these difficulties. The key insight is that under a proportional experience rating scheme, moral hazard generates a *negative contagion* phenomenon on the accident process: conditional on the agent's characteristics (whether observed or unobserved), the occurrence of an accident increases the marginal cost of future accidents, hence increases incentives and reduces accident probability. We first show that this phenomenon is general, and only requires intertemporal separability and risk aversion. We then show how this negative contagion effect can be disentangled from the positive contagion induced by unobserved heterogeneity. In particular, we show that if the distribution of unobserved heterogeneity (conditional on observables) is constant across cohorts, then this distinction is possible even when the dates of occurrence

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of the accidents are unknown, and only the length of the observation period and the number of accidents over the period are known.

## 1. Introduction

Empirical tests of contract theory using insurance data have recently attracted much attention. Several papers test for the existence and estimate the magnitude of asymmetric information effects in competitive insurance markets. Pueltz and Snow (1994), Dionne and Vanasse (1992), Chiappori and Salanié (1996, 2000), Dionne, Gouriéroux and Vanasse (1997) and Richaudeau (1999), among others, analyze automobile insurance contracts, while Holly et al. (1998), Chiappori, Durand and Geoffard (1998), Chiappori, Geoffard and Kyriadizou (1998), Cardon and Hendel (1998) and Hendel and Lizzeri (1999) use health or life insurance data, and Poterba and Finkelstein (2001) consider annuity contracts.

**The 'conditional correlation' approach** One popular strategy used to provide evidence of asymmetric information phenomena investigates the existence, conditional on observables, of a correlation between the choice of a contract and the occurrence of an accident. Under adverse selection, for instance, agents know if their accident probability exceeds the average of their class of risk (as defined from the information available to the company). Should this be the case, they are, everything equal, more likely to choose a contract with more complete coverage, as well as to suffer from an accident. It follows that, conditional on observables, the choice of full insurance should be positively correlated with the accident rate - a property that can be tested using relevant parametric or non parametric techniques.

The conditional correlation approach has several advantages. It is simple and very robust, as argued by Chiappori and Salanié (2000) and Chiappori et al. (2002). Furthermore, it can be used on static, cross-sectional data that are (relatively) easier to obtain. However, these qualities come at a cost. The effect of the past history of the relationship on the current contract is difficult both to model and to estimate. Still, it can take a crucial importance, especially in a context when experience rating plays a role. Secondly, the conditional correlation approach may not allow to identify the type of information asymmetry involved (if any). Under adverse selection, risky agents choose to buy more insurance. Moral hazard, on the other hand, suggests the opposite causality : agents who, for any reason, buy more insurance become more risky since the extensive coverage has a negative impact on incentives and discourages cautious behavior. To the extent that static data only allow to identify correlations (instead of causalities), these two opposite stories can be very hard to distinguish.

**Adverse selection versus moral hazard** Several articles try to empirically disentangle adverse selection and moral hazard. Holly et al. (1998) estimates a structural model of health insurance, where the existence of a complete coverage, described by a dummy variable, is allowed to impact health expenditures in addition to a possible correlation between error terms[1]. Holly estimates a parametric version of the model, and suggests that the former effect can be interpreted as moral hazard, whereas the second represents adverse selection. However, the robustness of the qualitative results with respect to changes in the parametric assumptions (and in particular the form of the distribution) is a difficult issue in this context.

In a related but different approach, Cardon and Hendel (1998) exploit an interesting feature of employer-provided health insurance contracts : while workers may, in any particular firm, be proposed one or several contractual options, the menus offered widely differ across companies. Assuming that the choice of an employer is not primarily driven by the characteristics of the associated health insurance plan, Cardon and Hendel argue that these data provide a 'quasi-natural experiment', in the sense that similar agents turn out to be facing different (menus of) contracts for exogenous reasons. Then the existence of adverse selection can be tested using the self-selection of agents among the various contracts of a given menu, whereas the estimation of moral hazard relies on the differences between the menus proposed by different firms. Again, although the estimation idea is in principle non parametric, they construct and estimate a fully parametric model.

Another brand of the literature exploits some 'natural experiments' that provide an exogenous change in the agent's incentive schemes. An ideal situation for testing moral hazard is indeed when a given set of agents experiences a sudden and exogenous change in the incentive structure they are facing. A typical example is provided by the changes in automobile insurance regulation in Québec, where a "no fault" system was introduced in 19$$, then deeply modified in 19$$. Dionne and Vanasse recently provided a careful investigation of the effects of these changes. They show that the new system provides strong incentives to increase prevention, and that, as a result, the average accident frequency dropped significantly during the years that followed its introduction. They conclude that changes in agents' behavior, as triggered by new incentives, did have a significant effect

[1] Technically, one equation describes the choice of a contract, while the second models health expenditures. A dummy representing the coverage is introduced in the second equation; in addition, the model allows for general correlation between the two error terms. The equations are estimated simultaneously.

on accident probabilities.

A limitation of such studies is that, strictly speaking, they establish a simultaneity rather than a causality. They show that, on a given period, accident probabilities were modified in a given direction, while, in the same time, some structural changes did occur. But, of course, the two phenomena might stem from simultaneous and independent causes. Such a 'coincidence' may be more or less plausible. In the study of Dionne et Vanasse, for instance, the incentive explanation remains by far the more convincing one, given both the magnitude of the drop in accident rate and the absence of other major changes that could account for it during the period under consideration. It nevertheless remains that an ideal experiment would involve a 'reference' sample that is not affected by the change, so that the effects can be estimated in differences rather than in absolute values. In two recent papers, Chiappori, Durand and Geoffard (1998) and Chiappori, Geoffard and Kyriadizou (1998) use data on health insurance that display such features. Following a change in regulation, health insurance companies modified the coverage offered by their contracts in a non uniform way : some of them increased the level of deductible, while other did not. The tests use a panel of clients belonging to different companies, whose expenditures are observed before and after the change in regulation, and compare the evolution of expenditures for the 'control' group (whose incentives remained unchanged) and of the 'test' group (who faced the new deductible)[2].

**The dynamics of asymmetric information** One may however argue (Chiappori (2000)) that the easiest manner to distinguish between adverse selection and moral hazard is to analyze the dynamic aspects of the relationship. Two arguments suggest that this approach may reveal particularly fruitful. First, the qualitative characteristics of optimal contracts differ considerably in the two cases. For instance, while optimal contracts usually exhibit history dependence in both cases, adverse selection typically requires contracts with 'flat' memory, in the sense that past performances should be given an equal weight. Although the case of moral hazard is more complex, memory is likely to be 'shorter' and more concen-

[2] The ideal example of an investigation based upon exogenous changes in incentives remains the celebrated Rand study (see ). Generally speaking, such experiments, albeit expensive, can considerably improve our understanding of moral hazard. In particular, it is surprising that many insurance companies do not use such random changes in the proposed menus to extract information about their consumers.

trated on recent events[3]. This suggests that a careful empirical investigation of the qualitative properties of the contracts at stake may provide useful insights on the type of problem they are designed to address. Secondly, most 'real life' insurance contract exhibit some form of experience rating (although not necessarily that predicted by the theory). Under moral hazard, experience rating has a very interesting property. Any accident has an impact upon the next premium, and, if memory is long, on the whole schedule of future premia. This modifies not only the expected wealth of the agent and the expected average cost of insurance, but also, and more importantly, *the discounted marginal cost of a (future) accident.* The cost of the next accident (in terms, say, of expected future premia, or of the corresponding certainty equivalent) indeed depends on the current premium, hence on past history. It follows that *the occurrence of an accident changes the incentives faced by a driver* - hence, under moral hazard, the future accident probability. In other words, under moral hazard, any (possibly suboptimal) pricing schedule where current premium is related to past behavior will de facto introduce a complex autocorrelation in the accident process. Analyzing the corresponding dynamics can then allow to identify the moral hazard component (if any)[4].

**Optimal versus suboptimal contracts** The two strategies just described have their own advantages and disadvantages. The first approach should in principle be very robust, to the extent that it relies on simple, qualitative characteristics of optimal contracts. However, the qualitative characteristics of optimal dynamic contracts under asymmetric information are in general very difficult to derive, except for very specific cases , and can hardly be considered as particularly simple. Also, they typically involve complex schemes, such as randomized contracts or sophisticated revelation mechanisms[5]. These schemes are hardly observed in real life. In most models, moreover, optimal contracts are derived within a simplified setting (linear technologies, no loading or transaction costs, etc.). The robustness of the corresponding conclusions in a more realistic, hence way more complex setting is not guaranteed. Finally, even casual empiricism suggests that actual

[3] See Fudenberg, Holmstrom and Milgrom () and Chiappori et al. ()

[4] For a similar approach on labor data in a learning framework, see Chiappori, Salanié and Valentin ().

[5] Under moral hazard, for instance, Chiappori et al. () show that, except for the case of monetary cost of effort and CARA preferences, implementing any effort level above the minimum requires randomized contracts, at least when savings are not observable. For a general equilibrium analysis under moral hazard and non separable preferences, see Bennardo and Chiappori ().

insurance contracts are not always optimal (to say the least). For instance, theory strongly indicates that the characteristics of an optimal experience rating scheme should be specific to each class of risk; that individuals, at least in the presence of adverse selection, should be offered a menu of various experience rating schemes; and that not only the premium, but also the deductible (and more generally the whole (non linear) reimbursement profile) should depend on past experience. These features, however, are rarely observed in real life[6].

**The analysis of actual contracts** In this paper, we follow the alternative route, and take as given the existing (and possibly suboptimal) experience rating schemes. Then we study the induced dynamics of effort and accident probabilities, in order to find testable restrictions due to moral hazard. We consider the specific scheme used by French insurance companies, the so-called 'bonus-malus' mechanism. This choice has several advantages. One is that the French market is regulated, and all companies must by law adopt the same scheme. One can thus avoid the selection problems that would arise if agents could opt between different schemes. Also, the mechanism is both simple and explicit, which considerably simplifies the empirical investigation. The premium at any period $t$ is defined as a product of two components. One is a so-called 'base premium', that is computed at the beginning of the relationship. It can be defined freely, but can only depend on observables, excluding past experience, and must be uniform over agents with identical characteristics; it cannot be modified during the relationship unless some observable characteristic changes, and only in a predefined way. Experience rating, on the other hand, only operates through the second component, the 'bonus/malus' coefficient, on which we shall particularly concentrate in the paper. The evolution of the coefficient is by law identical across companies. Each year without an accident decreases the coefficient by some fixed factor $\delta < 1$ (currently .95); each year with an accident increases it by a factor $\gamma > 1$ (currently 1.25)[7]. It follows that any accident shifts the whole distribution of future (contingent) premia upwards, by a factor $\gamma$. In particular, the 'cost' of the $(n+1)$-th accident is $\gamma$ times larger than that of the $n$-th.

[6] From a more technical point of view, the optimality assumption also leads to difficult endogeneity issues. For instance, it is not possible, in general, to compare the performances of the different schemes that coexist on the market without taking into account the inherent selection bias : since each schedule is assumed optimal, the coexistence of different schemes must reflect differences in the corresponding populations. Such bias can be very difficult to correct.

[7] In addition, there exists a cap and a floor of the bonus/malus coefficient (currently, 3.5 and .5).

These features, in turn, must impact the optimal effort profile. A natural conjecture is that the increased marginal cost results in more cautious behavior and smaller accident probabilities. This intuition, however, deserves more careful scrutiny, because of the complex nature of the problem. Several effects are at stake here. For instance, the upward shift in the premium schedule decreases the agent's expected wealth, and the resulting wealth effect can modify risk aversion in potentially different directions. Also, the 'future cost' alluded to above is in fact a random variable. Its distribution depends not only on the risk characteristics of the agent, but also of the future effort profile; conversely, the latter will respond to (the consequences of) current behavior. In other terms, the determination of the optimal effort level at each period requires the resolution of an optimal control problem.

In the next section, we careful investigate this problem. We show that, under mild convexity assumptions on preferences and the prevention technology, the intuition is correct: everything equal (i.e., controlling for both observed and unobserved heterogeneity), the optimal effort level should increase with the premium. This implies that, conditionally on the driver's characteristics, the dynamics of accident should exhibit a 'negative contagion' property : the occurrence of an accident decreases the probability of future accidents. Obviously, this conclusion only holds conditionally. As it is well known, the existence of unobserved heterogeneity introduces an opposite, 'positive contagion' effect, since good drivers, who pay lower premia, tend to have both a smaller number of past accidents and a smaller probability of future accidents. The empirical techniques will thus have to disentangle unobserved heterogeneity from the 'state dependence' effect due to moral hazard.

The structure of the paper is as follows.

# 2. Dynamic moral hazard under experience rating : theory

## 2.1. The model

We consider a dynamic version of an insurance model a la Mossin (1968). Consider an agent $i$, who lives for $T_i$ periods. At each period $t$, the agent receives some fixed income, normalized to one.[8] With probability $1-p_t^i$ the agent has an accident and

[8]This normalization makes perfect sense for the short period studied in the empirical part. In theory, however, it assumes away life cycle growth in income, which may have an impact on accident dynamics. Two remarks can however be made. First, the comparative static conclusion

incurs a fixed monetary loss $L^i$. He is covered by an insurance contract involving a fixed deductible $D^i$ and a premium $Q_t^i$. Hence, his consumption in each period is $1 - Q_t^i$ without an accident and $1 - Q_t^i - D^i$ if an accident occurs.

The premium $Q_t^i$ depends on past experience. Specifically, the evolution of $Q_t^i$ is governed by the following "bonus-malus" system: for $t \geq 1$

$$Q_{t+1}^i = \begin{cases} \delta Q_t^i & \text{if no accident occurred at period } t \\ \gamma Q_t^i & \text{if an accident occurred at period } t \end{cases}, \tag{BM}$$

for some $0 < \delta < 1 < \gamma$ and some initial premium $Q_1^i > 0$.

Accidents may or may not be caused by the agent's behavior. Accidents that are not caused by the agent are fully covered by the insurance contract and have no impact on future premia; they can thus be disregarded in our context. Accidents in which the agent is (at least in part) responsible are subject to moral hazard. According to standard models, we assume that at each time $t$ the agent chooses the no accident probability $p_t^i \geq 0$ and incurs an utility cost $\Gamma\left(p_t^i\right)$, where the function $\Gamma$ is twice differentiable, increasing and convex in $p_t^i$.[9] The cost of effort is assumed to be separable, i.e. the agent attaches utility $u^i(x) - \Gamma(p)$ to a (fixed) income $x$ if he chooses probability $p$. Thus, the agent's expected time $t$ utility is

$$v^i(p_t^i, Q_t^i) = p_t^i u^i(1 - Q_t^i) + \left(1 - p_t^i\right) u^i(1 - Q_t^i - D^i) - \Gamma\left(p_t^i\right).$$

We assume that $u^i$ is increasing and strictly concave, so that the agent is risk-averse. The agent chooses effort levels $e_1^i, e_2^i, \ldots$ as to maximize expected discounted utility, with discount factor $0 < \rho^i < 1$. In other words, the agent solves the program

$$\max_{e_1^i,\ldots} \sum_{t=1}^{T_i} \left(\rho^i\right)^t v^i(p_t^i, Q_t^i) \quad \text{where } Q_t^i \text{ satisfies (BM).} \tag{P}$$

remains valid: *everything equal*, the occurence of an accident increases incentives; for any given age and wealth, a driver who faces a higher bonus should thus exert a higher effort of prevention. Secondly, life cycle effects are often ambiguous in insurance: they simultaneously increase the background wealth and the size of the potential loss, possibly in similar proportions. Under approximately constant relative risk aversion, these two effects may compensate each other.

[9] It should be noted that since $p_t^i$ is fully chosen by the agent, it depends on the history of the accident process only through the current incentives faced by the agent. We thus assume away any learning process whereby the driver's "quality" increases with experience in general, and the number of past accidents in particular; the empirical relevance of this assumption is discussed at the beginning of the empirical section.

It should be stressed that the characteristics at stake (preferences and technologies) are fully individual-specific. In particular, the model is compatible with any type of unobserved heterogeneity.

### 2.2. General results

We first derive results that are valid for all possible specifications of preferences and technologies. For notational simplicity, we drop the index $i$; it should be clear, however, that all results are valid at the individual level, irrespective of the form and degree of unobserved heterogeneity.

A first result is that past experience affects the current decision only through the current level of the premium. For future reference, we state this as

**Lemma 1.** *At each time $t$ the optimal no accident probability $p_t$ only depends on the past history through the current premium $Q_t$.*

Lemma 1 states, in essence, that past accidents only affect current behavior through their impact on the incentive scheme faced by the agent; the current premium level is a sufficient statistic for this impact. As mentioned above, we disregard alternative influences, such as learning, fear or cautionary reaction to an accident.

Then (P) is a standard optimum-control program, with a one-dimensional state variable $Q_t$. Let $V_t$ denote the value function of this program at date $t$. At that date, the agent chooses a no accident probability $p(Q_t)$, with two possible outcomes:

1. if no accident occurs and current utility is $u(1-Q_t)-\Gamma(p(Q_t))$. The agent starts the next period with a premium $\delta Q_t$, which generates an expected discounted future utility of $\rho V_{t+1}(\delta Q_t)$.
2. With probability $1-p(Q)$ the agent is involved in an accident and current utility is $u(1-D-Q_t)-\Gamma(p(Q_t))$. Now, next period's premium is $\gamma Q_t$ and the expected discounted future utility is $\rho V_{t+1}(\gamma Q_t)$.

Hence $V_t$ satisfies the following Bellman equation

$$V_t(Q) = \max_p \{(1-p)[u(1-Q-D)+\rho V_{t+1}(\gamma Q)] + p[u(1-Q)+\rho V_{t+1}(\delta Q)] - \Gamma(p)\}. \tag{B}$$

The value function can be derived for each $t$ by backward induction, starting from

$$V_T(Q) = \max_p (1-p)\, u(1-Q-D) + pu(1-Q) - \Gamma(p) \qquad (2.1)$$

We are however interested in the *qualitative* properties of both the value function and the optimal effort. In particular, we investigate whether optimal effort increases with the level of the premium. A first result is given by the following Lemma:

**Lemma 2.** *The value function $V_t$ is decreasing in $Q$ for all $t$.*

**Proof.** See Appendix **??**. ■Starting with (2.1), we first remark that for any $Q' < Q$, if $p'$ and $p$ denote the respective, optimal no accident probabilities:

$$\begin{aligned} V_T(Q') &\geq (1-p)\, u(1-Q'-D) + pu(1-Q') - \Gamma(p) \\ &\geq (1-p)\, u(1-Q-D) + pu(1-Q) - \Gamma(p) = V_T(Q) \end{aligned}$$

The proposition is then proved by backward induction. Assume that $V_{t+1}(Q)$ is decreasing; for any $Q' < Q$

$$\begin{aligned} V_t(Q') &\geq (1-p)\left(u(1-Q'-D) + \rho V_{t+1}(\gamma Q')\right) \\ &\quad + p\left(u(1-Q') + \rho V_{t+1}(\delta Q')\right) - \Gamma(p) \\ &\geq (1-p)\left(u(1-Q-D) + \rho V_{t+1}(\gamma Q)\right) \\ &\quad + p\left(u(1-Q) + \rho V_{t+1}(\delta Q)\right) - \Gamma(p) \\ &= V_t(Q) \end{aligned}$$

and $V_t(Q)$ is also decreasing, QED.

We now concentrate on the impact of the current premium, $Q$, on the optimal no accident probability $p$. Note, first, that the agent's behavior for 'large' premium levels is highly specific. In principle, if the number of accidents is large enough, the premium could exceed income. This situation, however, is unlikely to take place, because the agent can always choose $p = 1$, say by giving up driving (presumably at a high cost). Then the accident probability is zero, and becomes totally inelastic to the premium.

Here, however, we are primarily interested here in situations where the premium $Q$ is 'small' with respect to income.[10] The following result states that for

[10] Premia in our sample are a few hundred dollars, way less than the median income in the population uder consideration.

such 'small' values of the premium, effort is increasing in the premium, at intuition suggests.

**Proposition** *Assume the value function $V_t(Q)$ is differentiable in a neighbourhood of $Q = 0$ for all $t$ and $Q$. For small enough values of $Q$, the optimal no accident probability $p_t(Q)$ decreases with $Q$ for all $t$.*

**Proof** The Bellman equation can be rewritten as

$$\begin{aligned} V_t(Q) = \max_p \{ & -\Gamma(p) + u(1 - Q - D) + \rho V_{t+1}(\gamma Q) \\ & + p[u(1-Q) - u(1 - Q - D) + \rho V_{t+1}(\delta Q) - \rho V_{t+1}(\gamma Q)]\}. \end{aligned} \tag{B}$$

Since $V_{t+1}$ is decreasing, the last bracket is positive and the maximand is concave in $p_t$. This allows us to use the first order approach. Assuming an internal solution, the optimal probability $p_t(Q)$ at a premium $Q$ satisfies the first order condition

$$\Gamma'(p_t(Q)) = u(1-Q) - u(1-Q-D) + \rho V_{t+1}(\delta Q) - \rho V_{t+1}(\gamma Q)$$

It follows that whenever the value function is differentiable, one gets

$$\Gamma''(p_t(Q)) . p_t'(Q) = -u'(1-Q) + u'(1-Q-D) + \rho\delta V_{t+1}'(\delta Q) - \rho\gamma V_{t+1}'(\gamma Q)$$

Now, assume that $Q$ is small; first order approximation of this equation gives

$$p_t' \sim \frac{1}{\Gamma''(p_t)} \left( u'(1-D) - u'(1) - \rho(\gamma - \delta) V_{t+1}'(0) \right) > 0$$

QED.

Proposition 2.2 provides a simple testable implication of moral hazard under experience rating. For any agent the effort choices and the resulting accident probabilities are totally driven by the premium dynamics (BM). In particular, the main comparative static result is that for 'small' levels of premium, a higher premium increases incentives to take care, hence reduces accident probability. From a dynamic perspective, the occurence of an accident results in a discontinuous jump in the premium, hence in incentives. The resulting accident probability should then decrease, provided that the pure time effect (i.e., the difference between $V_t(Q)$ and $V_{t+1}(Q)$) is controlled for. Our empirical strategy will precisely distinguish between the general time effect and the specific impact of an accident. The theoretical prediction is that this specific impact should exhibit negative state dependence; i.e., the accident probability should decrease once an accident has occured.

It is important to note at this point that the previous analysis operates at the individual level (for some given agent $i$). In particular, the prediction is orthogonal to any issue related to unobserved heterogeneity: for any given agent the dynamics of accidents should exhibit the state dependence just described whatever the distribution of individual risks and preferences. In principle, the prediction is testable at the individual level. In practice, however, accidents are scarce, and panel data are not available for a sufficiently long period to allow such a test.[11] Empirical investigations are thus bound to exploit inter-individual comparisons, and unobserved heterogeneity then becomes a critical issue.

The theoretical model provides a simplified representation of actual experience-rating schemes and the agent's behavior under these schemes. One aspect, already mentioned, is that we ignore the non monetary consequences of an accident. On a more technical side, experience rating systems often entail ceilings and floors on the premium. In France, for instance, the bonus-malus coefficient cannot fall below 0.5 or increase above 3.5.[12] Our view is that the previous model nevertheless provides a useful approximation of actual behavior.[13]

[11] Moreover, the basic underlying assumptions (such as a constant baseline hazard) would probably not hold for a longer period).

[12] Given the actual values of $\gamma$ (1.25) and $\delta$ (0.95), however, the 0.5 level cannot be reached within 13 years. The 3.5 coefficient can be reached more quickly, but requires at least 6 accidents (and more if the agent receives bonuses for claim-free years before having 6 accidents). Therefore, given that drivers have on average one accident in every 7 years, reaching the ceiling quickly is a very rare event.

[13] To provide a simple benchmark, take a French driver aged less than 45. She faces an horizon of (possibly much) more than 20 years. Also, assume she is an average driver, so that her annual accident probability is around 12% (assume she either has one accident or no accident each year), she is paying the average premium in the population, $\bar{Q}$, and this amount represents only a small fraction of her income. The probability that she will reach a premium equal to $2\bar{Q}$ within 13 years is about 1%. And with a discount factor equal to 0.95, the present value of a premium $2\bar{Q}$ 13 years from now is exactly $\bar{Q}$. Similarly, the probability that she will reach a premium equal to $3\bar{Q}$— still an acceptable amount— within 20 years is about 0.2%.

## 3. Econometric specification and tests

We now come to the key question of the paper : what are the testable implications of the model above? And how is it possible to distinguish the moral hazard framework from adverse selection, or more generally unobserved heterogeneity?

The key insight is provided by Corollary 1 above : controlling for individual characteristics (including unobserved heterogeneity), the accident hazard should steadily increase during any period without an accident, then drop after an accident has occurred. Testing for this property, however, requires specific technics, the nature of which primarily depends on the type of data available.

### 3.1. Which data are available?

As in most empirical studies in insurance, a lot of information is available from the company's file. Many relevant characteristics of the driver (age, gender, place of residence, seniority, type of job, ...) and the car (brand, model, year, color, power, ...) are used by companies for pricing purposes; all these are available for the econometrician as well. The same is true for the characteristics of the contract (type of coverage, premium, deductible,...). Finally, each accident - or more precisely each claim - is recorded with all relevant information.

The main differences, however, are in the way past history is recorded in the available files. Existing situations can be gathered in three broad cases:

- In the most favorable situation, the exact date of each accident is recorded. Then the occurrence of an accident can be modelled in continuous time, using duration models.
- Most of the time, only the number of accidents per year is recorded. For any agent $i$, observed for $t$ periods, data indicate not only the number of accidents but also the year of occurrence.. In other words, each agent is identified to a length $t$ sequence of 0s and 1s from which the dynamics can be analyzed.
- Finally, the minimum information that is needed to implement the regulatory bonus/malus scheme is even poorer. Given the symmetric treatment of past accidents, whatever their exact date, the computation of a bonus/malus coefficient only requires the knowledge of the total number of accidents during the relevant period. An agent who has been driving during $t$ periods

and had $n$ accident will be charged a coefficient equal to $\gamma^n \delta^{t-n}$, whatever the exact timing[14].

In each case, the dynamics of accidents can be used to test for the presence of moral hazard, against the null that the accident probability does not depend on the agent's incentives, and only evolves according to some predetermined law (possibly depending on observables, such as age of the driver, age of the car, and others). In the first case, the essence of the test is clear. Under moral hazard, the hazard rate of an accident, conditional on observable and unobservable heterogeneity, should be steadily increasing throughout any period without an accident, then drop discontinuously when an accident occurs; whereas under the null, the hazard rate should not change after an accident. Note that this can be tested both in a parametric and non parametric way.

In what follows, we concentrate upon the other two tests. Before that, one point is worth being stressed. The null, in our framework, is consistent with the presence of unobserved heterogeneity, whatever its type. Such heterogeneity may reflect the impact of any information that is *not* available to the insurance company, but may or may not be known by the insuree himself. In other words, we do not, under the null, distinguish between *adverse selection* and symmetrically imperfect information. It is important to note, however, that testing for adverse selection is certainly possible in this context, and can lead to very interesting insight on the nature of learning processes. The idea would be to analyze the changes in insurance contract initiated by the driver, and the subsequent impact on the accident hazard[15]. This is left for future work.

[14] This claim should be qualified, at least in the French case, for two reasons. One is that the existence of a cap and a floor on the bonus/malus coefficient introduces some kind of asymmetry in the process; after a certain number of years, old accidents are de facto 'forgotten', provided that no 'new' accident occured in the meantime. Secondly, an additional regulation requires that after two years without an accident, the bonus/malus coefficient of an agent cannot exceed 1 (i.e., the base premium), whatever her past history may be. However, only a tiny minority of drivers are actually concerned by the latter rule.

[15] Salanie and Chiappori (forthcoming) find no evidence of adverse selection on a sample of 'young' (i.e., recent) drivers. They remark, however, that adverse selection may also arise during the relationship, due to asymmetries in learning between the firm and the client (e.g., such an informative event as a near-miss is typically observed by the driver only). For a theoretical investigation, see Garidel ().

### 3.2. Testing for moral hazard from sequences of accidents

We introduce an additional assumption, namely that, throughout the observation period, an agent's accident probability remains constant[16]. The basic idea of the test comes from Heckman () and Heckman and Honore (). To get the intuition, consider several agents for whom the corresponding sequences have same length and same average accident frequencies, but in different orders. Under the null, these sequences should have identical probabilities. This, however, is not the case under moral hazard, because at each period the accident probability changes, in a way that is moreover related to the occurrence (or not) of an accident during the period.

To give a simple illustration, consider the case of a 'no bonus' system, where the premium can only increase after an accident or remain constant (as argued above, this is a pretty satisfactory description of the French system). Assume, as in the example of subsection 2.5, that each accident multiplies the future accident probability by some factor $g < 1$. Consider a sequence of length $t$, with exactly one accident at period $s$. Its likelihood is:

$$\Lambda(s) = (1-q)^{s-1}\, q\, (1-gq)^{t-s}$$

where $q = 1 - p$ is the initial accident probability. This expression decreases exponentially in $s$. The intuition is that a year without an accident is more likely to occur *after* the accident has taken place (since the accident probability is smaller then). So a sequence like $(1, 0, ..., 0)$, where 1 (resp 0) stands for one year with (resp. without) accident, is more likely than any other; generally, such sequences can be ranked, likelihood being larger for earlier occurrence of the accident.

In the more general case of a bonus/malus schedule, where each year without an accident also multiplies the accident probability by some $d > 1$ , the likelihood of the previous sequence becomes

$$\Lambda'(s) = \prod_{n=1}^{s-1}\left(1 - d^{n-1}q\right) q \prod_{m=1}^{t-s}\left(1 - gd^{m-1}q\right)$$

As a function of $s$, $\Lambda'(s)$ is no longer monotonic, but typically exhibits an inverted U shape, with a maximum for some intermediate $s$. The intuition is that long sequences without an accident are unlikely, before as well as after the accident, because of the increasing accident probability.

[16] In principle, we should require constant risk only conditionally on observables. For instance, learning is possible, provided it is a given function of age or seniority only.

### 3.3. Testing for moral hazard from total number of accidents only

Surprisingly enough, even in the case where information is minimal - i.e., only the number of accident during a given period is known - it is still possible to test the moral hazard model against its null. One additional assumption is required; namely, that the distribution of unobserved heterogeneity in the population is identical across cohorts. That is, conditionally on observables, the no accident probability $p$ is distributed among the drivers of any given seniority according to some distribution $\mu$, that is identical for all seniorities.[17]

#### 3.3.1. Restrictions under the null

Assume, first, that there is no moral hazard, so that all observed behavior results from the distribution of unobserved heterogeneity. Although the latter distribution $\mu$ is unknown, its moments can readily be recovered from simple statistics on the population. Indeed, consider the population of drivers with seniority $t$. The probability of having no accident throughout the observation period, for any driver with individual no accident probability $p$, is $p^t$. Hence the proportion of drivers with no accident throughout the period is, under the null, exactly equal to

$$m_t = \int p^t d\mu(p)$$

i.e., to the $t$-th moment of the distribution.

This remarks immediately leads to a first series of tests. Indeed, the numbers $m_1, m_2, ...$ must, under the null, be the successive moments of the same distribution. A first consequence is that

$$m_1 \geq m_2 \geq ... \geq m_T$$

where $T$ is the maximum seniority in the population.

More generally, there exists necessary conditions for a given set of numbers to be the moments of a distribution. The corresponding restrictions, as derived by Akhiezer, are

$$\begin{vmatrix} 1 & m_1 \\ m_1 & m_2 \end{vmatrix} > 0, \begin{vmatrix} 1 & m_1 & m_2 \\ m_1 & m_2 & m_3 \\ m_2 & m_3 & m_4 \end{vmatrix} > 0, ...$$

Again, these conditions must be fulfilled by the observed statistics.

[17] The starting point for this analysis is an initial contribution by Heckman (1978).

Still another set of restrictions obtains when considering, among agents with seniority $t$, those with exactly one accident over the period. For any $p$, this event occurs with probability $p^{t-1}(1-p)$. It follows that, under the null, the proportion of these agents within the subpopulation of seniority $t$ is

$$\begin{aligned} m_t^1 &= \int t\, p^{t-1}(1-p)\, d\mu(p) \\ &= t\ (m_{t-1} - m_t) \end{aligned}$$

This result is interesting, since it provides a set of simple, linear restrictions involving three statistics, namely $m_{t-1}, m_t$ and $m_t^1$. Furthermore, these statistics are computed from *disjoint* subpopulations.

Finally, the previous remark generalizes easily. The probability of having $n \leq t$ accidents during $t$ periods is $\binom{t}{n} p^{t-n}(1-p)^n$, and the corresponding proportion is

$$\begin{aligned} m_t^n &= \int \binom{t}{n} p^{t-n}(1-p)^n\, d\mu(p) \\ &= \sum_{k=0}^{n} (-1)^k \frac{t!}{k!\,(n-k)!\,(t-n)!} m_{t-n+k} \end{aligned}$$

Again, we have a set of simple, linear conditions on $m_t^n$ and the $m_i$.

### 3.3.2. Moral hazard

Assume, now, there is moral hazard. Under the particular approximation described in Section 2.5, it is still possible to derive testable restrictions over the statistics at stake.

We begin by the simple case of a 'no bonus' scheme. Then each accident decreases the accident probability for the next period by a factor $d < 1$. In what follows, $q = 1 - p$ denotes the accident probability; $\nu$ denotes the distribution of $q$, and $n_t$ its $t$-th moment. Using the same approach as before, we note that:

- the probability of no accident during $t$ periods is

$$
\begin{aligned}
m_t &= \int (1-q)^t \, d\nu(q) \\
&= \int \sum_{k=0}^{t} (-1)^k \frac{t!}{k!\,(t-k)!} q^k d\nu(q) \\
&= \sum_{k=0}^{t} (-1)^k \frac{t!}{k!\,(t-k)!} \, n_k
\end{aligned}
$$

Note that this system is triangular, hence invertible in the $n_i$. Then

- the conditional probability of exactly one accident, occurring at period $\tau$, is

$$
\pi_t^{1,\tau} = (1-q)^{\tau-1} \, q \, (1-dq)^{t-\tau}
$$

Since the moment of occurrence is unobserved, on has to sum over all possible dates to get the conditional probability of exactly one accident

$$
\begin{aligned}
\pi_t^1 &= \sum_{\tau} (1-q)^{\tau-1} \, q \, (1-dq)^{t-\tau} \\
&= \sum_{l=0}^{t} q^{l+1} \left( \sum_{k=0}^{\min(l,\tau-1)} (-1)^l \frac{(\tau-1)!\,(t-\tau)!}{(l-k)!\,(\tau-l-k-1)!k!\,(t-\tau-k)!} d^k \right)
\end{aligned}
$$

Integrating out the unobserved probability gives the unconditional probability of exactly one accident

$$
\begin{aligned}
n_t^1 &= \sum_{\tau} \int (1-q)^{\tau-1} \, q \, (1-dq)^{t-\tau} \, d\nu(q) \\
&= \sum_{l=0}^{t} n_{l+1} \sum_{\tau} \left( \sum_{k=0}^{\min(l,\tau-1)} (-1)^l \frac{(\tau-1)!\,(t-\tau)!}{(l-k)!\,(\tau-l-k-1)!k!\,(t-\tau-k)!} d^k \right) \\
&= F[n_1, ..., n_t, d]
\end{aligned}
$$

Here, $F_t^1[n_1, ..., n_t, d]$ is a polynomial in $d$, of degree $t-1$, the coefficient of which are linear in the $n_i$. For $t = 2, ..., T$, the system above is overidentified; it provides an estimation of $d$ and the moments, plus $T-2$ overidentifying restrictions.

- Finally, similar computations can be made for $2, ...$ accidents, which provides additional testable restrictions.

### 3.3.3. Example : $t = 3$

As an illustration, we present the computations for the case $t = 3$. Here:

$$m_1 = \int (1-q)\, d\nu(q)\,,\ m_2 = \int (1-q)^2\, d\nu(q)\,,\ m_3 = \int (1-q)^3\, d\nu(q)$$

hence

$$m_1 = 1 - n_1,\ m_2 = 1 - 2n_1 + n_2,\ m_3 = 1 - 3n_1 + 3n_2 - n_3$$

which immediately gives the symmetric outcome

$$n_1 = 1 - m_1,\ n_2 = 1 - 2m_1 + m_2,\ n_3 = 1 - 3m_1 + 3m_2 - m_3$$

Then

- the conditional probabilities of exactly one accident is

$$\begin{aligned} \pi_2^1 &= -(d+1)\, q^2 + 2q \\ \pi_3^1 &= \left(d + d^2 + 1\right) q^3 + (-3d - 3)\, q^2 + 3q \end{aligned}$$

- the unconditional probabilities of exactly one accident is

$$\begin{aligned} n_2^1 &= -(d+1)\, n_2 + 2n_1 \\ n_3^1 &= \left(d + d^2 + 1\right) n_3 + (-3d - 3)\, n_2 + 3n_1 \end{aligned} \tag{C1}$$

- similarly, the unconditional probability of exactly two accident

$$n_3^2 = -d\,(1 + 2d)\, n_3 + 3dn_2 \tag{C2}$$

The statistics $n_1, n_2, n_3, n_2^1, n_3^1, n_3^2$ must satisfy (C1) and (C2) for some $d$, which identifies $d$ and provides two overidentifying restrictions.

### 3.3.4. The general case of a bonus/malus system

Again, we use the log linear approximation of section 2.5. We thus assume that

- after one period without accident, the accident probability $q = 1 - p$ is increased by a factor $c > 1$
- after one period with an accident, $q$ is decreased by a factor $d < 1$

For simplicity, we give the computations for the case $t = 3$. First,

$$
\begin{aligned}
m_1 &= \int (1-q)\, d\nu(q), \\
m_2 &= \int (1-q)(1-cq)\, d\nu(q) \\
&\text{and} \\
m_3 &= \int (1-q)(1-cq)\left(1-c^2 q\right) d\nu(q)
\end{aligned}
$$

hence

$$
\begin{aligned}
m_1 &= 1 - n_1 \\
m_2 &= 1 - (c+1)\, n_1 + c n_2, \\
&\text{and} \\
m_3 &= 1 - \left(c^2 + c + 1\right) n_1 + \left(c^3 + c^2 + c\right) n_2 - c^3 n_3
\end{aligned}
$$

Again, this system is triangular, hence invertible in the $n_i$. Then

- the conditional probabilities of exactly one accident is

$$
\begin{aligned}
\pi_2^1 &= -(d+c)\, q^2 + (c+1)\, q \\
\pi_3^1 &= \left(c^2 d + d^2 c + c^3\right) q^3 - \left(1 + c^2 + c\right)(c+d)\, q^2 + \left(1 + c^2 + c\right) q
\end{aligned}
$$

- the unconditional probabilities of exactly one accident is

$$
\begin{aligned}
n_2^1 &= -(d+c)\, n_2 + (c+1)\, n_1 && (3.1) \\
n_3^1 &= c\left(d^2 + c^2 + dc\right) n_3 - \left(1 + c^2 + c\right)(c+d)\, n_2 + \left(1 + c^2 + c\right) n_1 && (3.2)
\end{aligned}
$$

- similarly, the unconditional probability of exactly two accident

$$n_3^2 = -d\left(d^2 + c^2 + dc\right) n_3 + d\left(1 + c^2 + c\right) n_2 \qquad \text{(C'2)}$$

Again, the statistics $n_1, n_2, n_3, n_2^1, n_3^1, n_3^2$ must satisfy (C'1) and (C'2) for some $c$ and $d$, which identifies $c$ and $d$ and provides one overidentifying restriction.

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