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Abstract

Insurance fraud is now recognized as a significant resource allocation problem in many markets. One explanation is the non-optimality of traditional insurance contracts. The object of this study is to verify how straight deductible contracts may affect the falsification behavior of an insured. This type of contract is observed in many markets, even if it is not optimal under costly state falsification. Consequently, a higher deductible may create incentives to fraud or cheat, particularly when the insured anticipates that the claim has a small probability of being audited or when the probability of detecting fraud during an audit is small. To verify this proposition, we estimate a loss equation for which one of the determinants is the amount of the deductible, using a data set of claims filed for damages following an automobile accident with 20 insurance companies in Quebec in 1992. Since we only have access to reported losses, a higher deductible also implies a lower probability of reporting small losses. In order to isolate the fraud effect related to the presence of a deductible in the contract, we jointly estimate a loss equation and a threshold equation. The threshold is the amount over which an insured decides to report a given loss. It can be interpreted as a personal deductible and it is not observable. Therefore, we use the method of censored dependent variable developed by Nelson (1977) and extended to the truncation case by Maddala (1983). Our results indicate, among other things, that with an appropriate correction for selectivity, the amount of the deductible is a significant determinant of the reported loss, at least when no other vehicle is involved in the accident; in other words, when the presence of witnesses is less likely.

Key words: insurance fraud, deductible, econometric model, truncated dependent variable.

JEL numbers: D81, C20, G22.

Résumé

La fraude à l'assurance est devenue un problème important dans plusieurs marchés. Une cause potentielle de ce phénomène est la non optimalité des contrats traditionnels. L'objectif de cette recherche est de vérifier comment un contrat d'assurance standard avec franchise peut inciter les assurés à falsifier leurs réclamations. Ce type de contrat est observé dans plusieurs marchés, même s'il n'est pas optimal en présence de falsification potentielle. Ainsi, une franchise plus grande peut entraîner de la fraude, particulièrement lorsque les assurés anticipent que leur réclamation a une faible probabilité d'être vérifiée. Pour tester cette proposition, nous estimons une fonction de perte dont un des déterminants est la franchise. Étant donné que nous avons accès aux seules réclamations, une franchise plus élevée implique aussi une plus faible probabilité de déclarer un sinistre de moindre importance. Pour éliminer ce biais de sélection, nous avons estimé conjointement la fonction de perte avec une fonction de seuil. Ce seuil peut être interprété comme une franchise personnelle, non observable. Conséquemment, nous avons utilisé une méthode de variable dépendante tronquée (Nelson, 1977). Nos résultats indiquent, entre autres, qu'après correction pour le biais de sélection, le montant de la franchise est un facteur déterminant de la perte déclarée, du moins lorsqu'il n'y a pas d'autre véhicule impliqué dans l'accident; c'est-à-dire lorsque la présence de témoins est moins probable.

Mots clés : fraude à l'assurance, franchise, modèle économétrique, variable dépendante tronquée.

Codes JEL : D81, C20, G22.

Introduction

Since the significant contribution of Townsend (1979), an insurance contract with a deductible is described as an optimal contract in the presence of costly state verification problems. In order to minimize auditing costs and guarantee insurance protection against large losses to risk- averse policy-holders, this optimal contract reimburses the total reported loss less the deductible when the reported loss is above the deductible and pays nothing otherwise. Also, the contract specifies that the insurer commits itself to audit all claims with probability one. Consequently, we should not observe any fraud, notably in the form of build-up, in markets with deductible contracts, since the benefits of such activity are nil. This form of contract is often observed in automobile insurance markets for property damages.

Different extensions have been proposed in the recent literature on security design to take into account different issues regarding the deductible contract (Townsend, 1988; Lacker and Weinberg, 1989; Mookherjee and Png, 1989; Crocker and Morgan, 1997; Bond and Crocker, 1997; Crocker and Tennyson, 1996; Picard, 1996). Three main issues related to our empirical model are discussed in this literature. First, the deductible model implies that the principal fully commits to the contract in the sense that it will always audit all claims even if the perceived probability of lying is nil. It is clear that this contract is not renegotiation proof: at least for small losses above the deductible, the insurer has an incentive not to audit the claim and save the auditing cost. However, if the client anticipates such a behavior from the insurer, he or she will not necessarily tell the truth when filing the claim!

One extension to the basic model was to suggest that random audits are more appropriate to reduce auditing costs (Mookherjee and Png, 1989 and Townsend, 1988). However, the optimal insurance contract is no longer a deductible contract and the above commitment issue remains relevant. The same conclusion applies with random efficiency when auditing. Another extension is to suggest that costly state falsification is more pertinent than costly state verification for insurance contracting with ex-post moral hazard. The optimal contract under costly state falsification leads to insurance overpayments for small losses and under-compensation for severe accidents (Lacker and Weinberg, 1989; Crocker and Tennyson, 1996; Crocker and Morgan, 1997). We do not observe yet such contracts for property damages in automobile insurance markets, although they seem to be present for bodily injuries in some states or provinces (Crocker and Tennyson, 1996).

The object of this study is to verify how the presence of a deductible may affect the optimal falsification behavior of an insured. This is an important test, since it is now documented that about 10% of the claims in the studied market contain some fraud (Caron and Dionne, 1997). From the above literature, we already know that a straight deductible is not optimal under costly state falsification. However, we observe this type of contract in many markets such as the one we study. This presence can be explained by costly verification problems as well as by other information problems such as ex-ante moral hazard (Holmstrom, 1979; Shavell, 1979; Winter, 1992) or adverse selection (Rothschild and Stiglitz, 1976; Puelz and Snow, 1994; see, however, Chiappori and Salanié, 1996, 1997 and Dionne, Gouriéroux and Vanasse, 1997). We will show that this type of insurance contract can indeed introduce perverse effects when falsification behavior is potentially present: a higher deductible may create incentives to fraud or cheat, particularly when the insured anticipates that the claim has a small probability of being audited or when the probability of detecting fraud during an audit is small.

Our empirical hypothesis is as follows: when the success probability of defraud is sufficiently high, the observed loss following an accident is higher when the deductible of the insurance contract is higher. Under full commitment, the observed loss should not be affected by fraud activities and, consequently, by the level of the deductible. Moreover, under pure adverse selection or pure ex-ante moral hazard, the average loss should be *lower* when the deductible is higher, since good risks choose high deductibles, and a higher deductible also introduces more ex-ante incentives to reduce accident costs. Therefore, the presence of fraud, which in the present case is also known as *build-up* (see Weisberg and Derrig, 1993 for different definitions of fraud), is necessary to verify our hypothesis. Now the question is how to isolate the fraud or *build-up* effect from the data?

Since we only have access to reported losses, a higher deductible also implies a lower probability of reporting small losses to the insurer. In order to isolate the fraud effect related to the presence of a deductible in the contract, we must therefore introduce some corrections in the data to eliminate potential bias explained by incomplete information. We will use the method of censored dependent variable developed by Nelson (1977) and extended to the truncation case by Maddala (1983). Our econometric model considers jointly a loss equation and a threshold equation. The threshold is the amount over which an insured decides to report a loss to the insurance company. This threshold is a personal deductible. The threshold is not observable, because it is assumed that the personal deductible is not the same as the ex-ante (observable) deductible stipulated in the contract. Both loss and threshold variables are assumed to be log-normally distributed. The complete model (loss and threshold) is estimated by maximum likelihood.

The paper is organized as follows. In the next section, we show how the presence of a deductible in an insurance contract may affect the optimal falsification behavior. Again, our objective is not to derive the optimal insurance contract under costly state falsification, but to show how the parameters of an observed given contract with a deductible may affect the incentives for falsification. In section 3, we present the econometric model developed to take into account potential bias in the data explained by the fact that we do not have access to all accidents of the insured, but only to their claims made to insurance firms. Section 4 describes the data and variables used in the various specifications considered. Results in section 5 indicate, among other things, that with an appropriate correction for selectivity, the amount of the deductible remains a significant determinant of the reported loss, at least when no other vehicles are involved in the accident or when the success probability of defraud is sufficiently high. Section 6 concludes the paper.

Theoretical Model

Consider a risk-averse individual who is making the marginal decision of falsifying his true accident cost *(A>0)*. As already discussed in the introduction, our objective is to analyze the effect of a deductible on this decision. Consequently, we suppose that the agent has already signed a deductible contract for property damages. Ex-post, his decision is to choose the level of falsification in order to maximize:

$$pU(W-D+L-c(L))+(1-p)U(W-A-c(L)),$$

(1)

where $U(\cdot)$ is the standard von Neuman-Morgenstern utility function with $U'(\cdot)>0,\ U''(\cdot)<0$; D is the amount of the deductible; L is the level of falsification; p is the success probability of falsification; *c(L)* is the total cost function of falsification with $c'(L)>0$ and $c''(L)=0$; W is the level of wealth not contingent: this is the initial wealth W_o minus P the insurance premium.

We assume here that, without falsification, the individual's wealth determined by nature (or after his accident) is $W-D\equiv W_o-A-P+(A-D)$, where $(A-D)$ is the insurance coverage of the accident cost. We assume that A is sufficiently high $(A>D)$ to have access to insurance coverage. However, the analysis can also be extended to the case where $(A\leq D)$ and where falsification is made to reach the threshold that gives access to insurance coverage (see Derrig and Weinsberg, 1997). This latter type of behavior will be considered in the empirical section as well as the one described in (1) on which we now focus our attention.

Falsification is costly in two respects. There is a direct cost of falsification (*c(L)*) and there is a random penalty cost (*A*-*D*) when the activity is discovered with probability (*1*-*p*) by the insurer. In other words, we assume that there is no insurance coverage when falsification is discovered by the insurer. However, the important behavioral assumption in (1) is that falsification is not found with probability one, as implicitly suggested in standard contracts with a deductible (Townsend, 1979). The probability *1-p* is lower than one for at least two reasons: either the insurer does not audit the file (absence of full commitment or random auditing) or, it audits, but does not find any evidence of fraud even when there is fraud (see Dionne and Belhadji, 1997 and Caron and Dionne, 1997 for detailed analyses of claim auditing in the Quebec automobile insurance market).

Before considering the optimal level of falsification (L^*), let us analyze the decision to defraud. An individual will defraud if and only if

$$pU(W - D + L - c(L)) + (1 - p)U(W - A - c(L)) \geq U(W - D),$$

(2)

that is, if the expected utility of taking a fraud gamble is greater than the utility of not taking this gamble and supporting the deductible D (on fraud gamble, see also Cummins and Tennyson, 1994). We observe directly that the net benefit of fraud (*NB*) for all L such that (2) is solved, is a function of both p and D. In fact, writing *NB* as:

$$pU(W - D + L - c(L)) + (1 - p)U(W - A - c(L)) - U(W - D)$$

we obtain

$$\frac{dNB}{dp} = U(W - D + L - c(L)) - U(W - A - c(L)) > 0,$$

if $L+A>D$, which is always the case for all $L \geq 0$ since $A > D$ by assumption, and

$$\frac{dNB}{dD} = U'(W - D) - pU'(W - D + L - c(L)) > 0\,,$$

since $W - D + L - c(L) > W - D$ to solve (2).

Consequently, we already observe that higher deductibles and higher probabilities of success increase the probability that an individual will defraud for all *L*. This conclusion is important for the empirical part of the paper. Indeed, we observe only the total loss resulting from a claim which is the sum *A+L*. This total loss may contain fraud ($L > 0$) or it may not, and we will test its relationship with *p* and *D*.

Let us now consider the optimal level of falsification (L^*) . Maximizing (1) with respect to *L* yields

$$(1-p)U'(NS)(-c'(L)) + pU'(S)(1-c'(L)) = 0,$$

(3)

where $S \equiv W - D + L - c(L)$ is the level of wealth when fraud is not detected (success) and $NS \equiv W - A - c(L)$ is the level of wealth when fraud is detected. An interior solution to (3) implies that $(1-c'(L)) > 0$. The second-order condition is always verified under risk aversion and can be written as

$$H \equiv (1-p)U''(NS)\,(-c'(L))^2 + pU''(S)\,(1-c'(L))^2 < 0.$$

Again, for our empirical analysis, a result of interest concerns the relationship between the optimal level of fraud *L** and *D*. This relationship can be derived by taking the total differentiation of (3) with respect to *L* and *D*. This yields

$$\frac{dL}{dD} = \frac{\left[pU''(S)(1-c'(L))\right]}{H} > 0$$

under risk aversion. We can also easily verify that

$$\frac{dL}{dp} = -\frac{\left[U'(S)(1-c'(L)) - U'(NS)(-c'(L))\right]}{H} > 0.$$

These results support those obtained above on the decision to defraud for all *L*.

Another interesting result for the empirical model concerns the effect of p on dL/dD or, conversely, the effect of D on dL/dp. In the appendix, we verify that two sufficient conditions to obtain

$$\frac{d^2 L}{dDdp} = 2\frac{d(dL/dD)}{dp} > 0$$

(4)

are constant absolute risk aversion and $\frac{c'(L)}{(1-c'(L))} \geq \frac{(1-p)}{p}$. Consequently, p must be sufficiently high in order to obtain the desired result. As we will see in the next section, a test of (4) will be important to measure the effect of D on fraud, because the direct use of dL/dD may not be convincing when a potential bias is present in the data.

Econometric Model

The consistent estimation of a loss equation using insurer claim data requires that losses be reported regardless of their size. Without experience rating, it may be the case that nearly all losses are the object of a claim to the insurance company. However, with experience rating, it may not be in the insured's interests to declare certain losses to the insurance company. For instance, reporting a loss, no matter what its size, may raise future insurance premiums. When different deductibles are applicable to the losses, the under-reporting behavior is accentuated: a higher deductible implies a lower probability of reporting smaller losses to the insurance company. Therefore, without any appropriate correction, the parameter associated with the deductible in a loss equation is upward biased.

The decision by an insured to report a loss is not solely a function of the deductible or experience rating. Other aspects of the contractual relationship between the insurance company and its client may also influence the decision to report a given loss. For instance, the insured may hesitate to report a small loss because it implies transaction and labor costs that are not covered. Therefore, the threshold above which an insured reports a loss may not be simply a fixed proportion of the deductible. Furthermore, this threshold is specific to each individual and should be considered as a personal deductible. However, the latter is not observable for a particular individual and is considered as a random variable in our econometric model.

The objective is to estimate the parameters of the model

$$ln(L_i) = b_1^{'} X_{1i} + u_{1i} , if \ L_i \geq S_i , \quad (5)$$

$ln(L_i)$ is not observed otherwise,

where L_i is the total loss resulting from an accident (collision with or without another vehicle and upset) for individual i, b_1 is a k_1x1 vector of parameters, X_{1i} is a k_1x1 vector of regressors, S_i is an unobservable threshold and u_{1i} is a disturbance in our setup. Consequently, in relation with the theoretical model, S_i is the personal deductible and L_i is the sum of the claim ($L+A$) and the deductible. Non-negativity of the left-hand side of (5) is imposed by taking the log of the total loss. Hence, assuming that u_{1i} follows a normal distribution, equation (5) implies that L_i is log-normally distributed. A claim is made to the insurance company when L_i is greater than the unobservable threshold S_i, otherwise L_i is not observed by the insurance company. Our model is therefore related to the censored dependent variable model of Nelson (1977), except that he considered the case where $L_i = 0$ when $L_i < S_i$. An extension of this model to truncation is discussed in Maddala (1983). The unobserved threshold may be expressed as

$$ln(S_i) = b_2^{'} X_{2i} + u_{2i} , \quad (6)$$

where b_2 is a k_2x1 vector of parameters, X_{2i} is a k_2x1 vector of regressors and u_{2i} is a disturbance. We assume that the disturbances u_{1i} and u_{2i} follow a bivariate normal distribution with $E(u_{1i}) = E(u_{2i}) = 0$ and $Var(u_{1i}) = \sigma_1^2$, $Var(u_{2i}) = \sigma_2^2$ and $cov(u_{1i},u_{2i}) = \sigma_{12}$.

Two major drawbacks preclude the estimation of equation (5) by ordinary least squares (OLS). The truncation of L_i above S_i implies also the truncation of u_{1i}. Since $E(u_{1i} \mid L_i$ ³ $S_i)$ ¹ 0, estimates based on OLS are biased. Furthermore, OLS residuals obtained with the truncated sample may be correlated with X_{1i} (Nelson, 1977). Estimation by maximum likelihood (ML) is preferable.
For individual i, the likelihood of the model is given by

$$p_i = \frac{pr(u_{1i} = ln(L_i) - b_1^{'} X_{1i}, u_{2i} \leq ln(L_i) - b_2^{'} X_{2i})}{pr(b_1^{'} X_{1i} + u_{1i} \geq b_2^{'} X_{2i} + u_{2i})}. \tag{7}$$

Since the sample includes data only for the cases where L_i ³ S_i, the numerator in (7), which is the joint probability of observing a given loss and that this loss is reported, is weighted by the probability that a loss is reported. The joint density of u_{1i} and u_{2i} is $f(u_{1i}, u_{2i})$, which can be written as $f(u_{1i}) \times f(u_{2i}|u_{1i})$. Therefore, the numerator in (7) may be rewritten as

$$f(ln(L_i) - b_1^{'} X_{1i}) \cdot F(Z_i), \tag{8}$$

where F is the cumulative distribution function of the unit normal distribution and

$$Z_i = \frac{1}{\left(s_2^2 - s_{12}^2 / s_1^2\right)} \left[ln(L_i) - b_2^{'} X_{2i} - \frac{s_{12}}{s_1^2} \left(ln(L_i) - b_1^{'} X_{1i} \right) \right]. \tag{9}$$

Analogously, the denominator in (7) can be replaced by $F(Z_{2i})$, with

$$Z_{2i} = \left(\frac{b_1^{'} X_{1i} - b_2^{'} X_{2i}}{s} \right), \tag{10}$$

where $s^2 = \sigma_1^2 + \sigma_2^2 - 2\sigma_{12}$. Finally, using (8), (9) and (10), the log-likelihood function for a sample of n observations is given by

$$ln(P) = -n\,ln(s_1) - \frac{1}{2s_1^2}\sum_{i=1}^{n}(ln(L_i) - b_1^{'}X_{1i}) + \sum_{i=1}^{n} ln(F(Z_{1i})) - \sum_{i=1}^{n} ln(F(Z_{2i})), \qquad (11)$$

where $P = \prod_{i=1}^{n} p_i$. The maximization of (11) with respect to parameters b_1, b_2, s_1^2, s_2^2 and s_{12} will allow us to determine if reported losses are really a function of the deductible (beyond any statistical link due to selectivity), since the joint estimation of the loss and threshold equations leads to an unbiased estimate of the parameter associated with the deductible.

Finally, the identification of the parameters requires some restrictions. If the same variables appear in both equations, at least one restriction must be placed on the variance-covariance terms. For instance, Nelson (1977) sets $s_{12} = 0$. However, if at least one variable included in the loss equation is not in the threshold equation, all the parameters, including all variance-covariance terms, are identified. In our application, one of the specifications allows for the identification of all parameters, otherwise s_{12} is set to 0.

Data and Variables

Our data set includes a sample of 15,861 claims for collision or upset. Only private passenger automobiles are considered. Other vehicles, such as trucks, buses or motorcycles and automobiles used for commercial activities, such as taxis, are excluded. All the accidents occurred in 1992. The claims were filed with 20 insurance companies in the province of Quebec. These companies are amongst the largest in the Quebec automobile insurance market, holding a cumulative market share of approximately 75%.

Only the claims for which the insured has been held responsible for 100% of the damages to the automobile have been retained for the empirical analysis. Therefore, there is no deductible sharing and the ex-ante (prior to accident) deductible is the same as the observed one. Furthermore, we only retained the claims for which the deductible is $250.00 or $500.00. These claims account for nearly 98% of the total claims for which a deductible is applicable. All data have been provided by the statistical agency of the "Groupement des assureurs automobiles du Quebec", an association of automobile insurance companies in Quebec.

The only types of damages which are considered are damages to the automobile and its content. Bodily injuries are covered by a separate state-owned insurance firm, the "Société d’assurance automobile du Quebec". For bodily injuries in Quebec, there is a pure no-fault system that pays 90% of the revenue losses up to a maximum (Boyer and Dionne, 1987; Devlin, 1992). Hospital care and other medical expenses are covered by the public health-care system.

The following variables are used in the analysis (the subscript i is omitted):

L: the total loss (claim + deductible) in Canadian dollars.

INS1-INS19: a set of dummy variables with *INS(j)=1* if the claim was filed with insurance firm *j*; *INS(j)=0*, otherwise.

R1-R6: a set of dummy variables with *R(j)=1* if the automobile is mainly used in region *j*; *R(j)=0*, otherwise. The Montreal region is omitted.

NDRIV: a dummy variable with *NDRIV=1* if the principal driver of the automobile has held a first valid driver's license for less than five years; *NDRIV=0*, otherwise.

YMALE: a dummy variable with *YMALE=1* if the principal driver is a male under 25 years of age; *YMALE=0*, otherwise.

YFEMALE: a dummy variable with *YFEMALE=1* if the principal driver is a female under 25 years of age; *YFEMALE=0*, otherwise.

DRC: the principal driver's record, measured as the number of years without a claim (maximum 6 years).

AGE: the age of the automobile in years, computed as 92-model year.

GN1-GN5: a set of dummy variables with *GN(j)=1*, if year and automobile model belong to the rating group *j*; *GN(j)=0*, otherwise. Rating groups are used to set insurance premiums. They reflect the repair and replacement costs of the automobile (including normal depreciation).

COLL: a dummy variable with *COLL=1* if at least one other vehicle is involved in the accident; *COLL=0*, otherwise.

HITR: a dummy variable with *HITR=1* if the accident is a collision with another vehicle whose owner is not identified (hit-and-run); *HITR=0*, otherwise.

REPC: a dummy variable with *REPC=1* if a replacement cost endorsement is applicable to the claim; *REPC=0*, otherwise. This endorsement to the insurance policy is granted for 24 months following the delivery of a new vehicle. During that period, no depreciation is considered for claim settlement.

D500: a dummy variable with *D500=1*, if a $500.00 deductible is applicable to the loss; *D500=0*, otherwise. Claims with a $250.00 deductible is the omitted category.

Table 1 presents the descriptive statistics of the continuous variables and Table 2 gives the frequencies of the dummy variables, except for *INS1-INS19* which are available from the authors upon request. All the above variables are included in both loss and threshold equations.

Table 1
Descriptive Statistics of the Continuous Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
L	2552,65	2416,01	251,00	34 179,00
AGE	3,40	2,53	0	11
DRC	5,05	1,10	0	6

Table 2
Frequency of the Dummy Variables (in %)

Variable	Frequency	Variable	Frequency	Variable	Frequency
R1	13,5	*NDRIV*	6,1	*GN4*	19,3
R2	19,0	*YMALE*	6,1	*GN5*	14,1
R3	8,1	*YFEMALE*	4,7	*COLL*	69,1
R4	2,8	*GN1*	29,5	*HITR*	14,4
R5	18,4	*GN2*	20,0	*REPC*	13,0
R6	7,8	*GN3*	22,9	*D500*	9,4

The dummy variables *INS1-INS19* are included to capture firm-specific effects. In the loss equation, the dummy variables control for firm-specific practices in claim settlement which may, in turn, have an impact on the amount admissible for the claim. Recall that we observed the amount of the claim and we deducted from it the total reported loss (claim+deductible). Firm effects may also control for risk specificity. Furthermore, in the province of Quebec, even if there is a standard automobile insurance contract, most insurance companies offer extended protection. Insurance firms may tend to specialize in a certain type of protection, and this specialization is reflected in a firm-specific "standard" contract. Therefore, since the decision to report a loss may depend on the nature of the contract between the insurance company and the insured, firm dummy variables are also included in the threshold equation.

Region-specific variables *(R1-R6)* are used mainly to take into account regional differences in the behavior of drivers and in their driving environment. These regional differences are well known to the insurance companies, which take them into account in when setting premiums. This region-specific treatment by the insurance companies could induce regional differences in the loss-reporting behavior of the insured and, therefore, in the personal deductible (threshold). Also, the type and mix of roads (urban, rural, freeways) is specific to each region and may influence the amount of the loss if it has an effect on speed and traffic density. In that sense, *R1-R6* are also considered as risk-exposure variables in the loss equation.

In the loss equation, *NDRIV* measures the ability (or inability) of inexperienced drivers to minimize the damages, given that there is an accident. In the threshold equation, two different interpretations can be given to *NDRIV*. It can capture the lack of experience of new drivers in claim settlement, which may increase the probability of filing a claim or, with experience rating, it may decrease the probability of filing a claim because doing so will increase already high insurance premiums of inexperienced drivers.

YMALE and *YFEMALE* are introduced as behavioral variables in the loss equation. It is well known that young drivers, particularly young males, have riskier behavior due to immaturity: they drive faster and take more risks. This results in more severe accidents with more damages to the vehicles involved. With experience rating, young drivers may also be more reluctant to report their losses to the insurance company, because they are already paying high insurance premiums. It is therefore expected that *YMALE* and *YFEMALE* have a positive effect on the threshold.

The principal driver record *(DRC)* is a measure of the ability to drive. Drivers with a good past record are more likely to behave properly in the event of an accident and, therefore, to limit the amount of loss. However, good drivers are defined as drivers who rarely file claims with the insurance company. Consequently, *DRC* may imperfectly measure the ability to drive if the drivers apply a self-selection rule, particularly for small losses. This would imply that *DRC* is, in a sense, truncated from below or upward biased. But, even in this case, the effect on the amount of the claim is still negative. In the threshold equation, *DRC* may have opposite effects. If *DRC* is truly an unbiased measure of experience and ability, it should reduce the threshold, since good drivers are not heavily penalized by experience rating in the event of an accident (in some cases, the first claim over a certain period of time has no impact on future premiums). On the other hand, drivers with a clean record may be more reluctant to report smaller losses in order to keep their good record with the insurance company. If *DRC* is a biased measure of ability, the self-selection rule applied by the driver in the past indicates a higher actual threshold. In that case, the effect of *DRC* on the unobserved threshold is positive.

The age of the automobile *(AGE)* is included in the loss equation because new automobiles are more costly to repair. It is, in conjunction with *GN1-GN5*, a variable which takes into account the type of automobile and, therefore, its value. The rating groups *GN1-GN5* reflect the cost of repairing or replacing an automobile. Therefore, *AGE* should reduce the amount of loss, while the coefficients associated with *GN1-GN5* should be positive and increasing. It is also expected that owners of older and cheaper automobiles are more reluctant to report a loss, in particular small losses, because the payoff in such cases is small. Thus, the effects of *AGE* and *GN1-GN5* on the threshold are the opposite of their effects on the amount of loss.

Collision with at least one other vehicle *(COLL)* is an indicator of the type of accident. Presumably, when other vehicles are involved in the accident, the damages to the automobile are not of the same nature as those experienced in an accident where no other vehicles are involved. The sign of the effect is, however, undetermined. *COLL* can also be interpreted as a fraud indicator. When *COLL=1*, an accident report and witnesses are more likely and build-up is more difficult. In that case, reported losses may be smaller. Unfortunately, it is not possible to separate the two effects of *COLL* on total losses and, thus, to infer any fraudulent behavior from *COLL* alone. The inclusion of *COLL* in the threshold equation is also supported by several interpretations. For instance, it may be the case that the presence of witnesses on the accident site (the other vehicle's driver) and the existence of a written report on the accident (for instance a police report or a "Joint Report of Automobile Accident"[1]) is an incentive to report the loss to the insurance company. In that case, the threshold would be lower. However, uncertainty about the degree of responsibility of the driver in the accident may discourage filing in some cases. This type of uncertainty occurs only when other vehicles are involved, otherwise the driver is automatically held responsible for 100% of the damages. The net effect of *DRC* on the unobserved threshold is therefore ambiguous.

In the loss equation, *HITR* plays a role similar to *COLL*. The fact that the other vehicle(s) involved were able to leave the site of the accident is an indicator of the severity of the accident; hit-and-run accidents should imply less damages. Also, to be labeled hit-and-run, the driver (or automobile owner) must provide a police accident report. This obligation may have a negative effect on the amount of loss and a positive effect on the threshold. Also, the victim of a hit-and-run is automatically held responsible for 100% of his or her damages and a full deductible applies. Therefore, in a hit-and-run situation, the victim may be more reluctant to make a claim to the insurance company. Thus, both interpretations lead to the same result: a hit-and-run accident should imply a higher threshold.

When a no-deprecation replacement cost endorsement *(REPC)* is applicable to the claim, it means that new parts are used for the repairs or, in the event of a major crash, that the automobile is replaced by a new one at the current market value. Claims are thus higher under that endorsement. Since that endorsement can increase the pre-accident value of the automobile, it is also an incentive to report the loss. Hence, it is expected that *REPC* decreases the threshold.

In the absence of build-up and with appropriate correction for selection bias, the deductible should not have any effect on the amount of loss. Therefore, the presence of *D500* in the loss equation provides a test for build-up. In addition, the inclusion of *D500* in the threshold

[1] The form of this report was designed by the "Groupement des assureurs automobiles du Quebec". It can be used when there are no bodily injuries. The parties involved in an accident fill out the form together and each party sends a copy to its insurance company.

equation will allow us to evaluate if the personal deductible (unobserved threshold) is proportional to the observed deductible. Finally, to test (4), an interaction term between *COLL* and *D500* is included in the loss equation.

Empirical Results

General Results

The results of the estimation using different specifications and estimation methods are presented in Table 3. In addition, estimations of firm effects are given in Table A1 in appendix. We first ran *OLS* regressions on the loss equation with two different specifications: with and without an interaction term between the deductible variable *(D500)* and *COLL* (columns *OLS1* and *OLS2*). We also estimated three different versions of the joint loss-threshold model. The first one (*ML1*) does not include an interaction term between *D500* and *COLL*, while the second one (*ML2*) is specified with this interaction term. Also, since the inclusion of this interaction term in the loss equation alone makes all the parameters of the model identifiable, we also estimated a model where *cov(u1i,u2i)* is not constrained at 0, but estimated as a free parameter (*ML3*). In addition to parameter estimates and standard errors, Table 3 also reports R^2 for *OLS* regressions and log-likelihood for maximum likelihood (*ML*) estimates. Different starting values have been used in the case of *ML* estimates to check for the existence of local maximum, and the results always converged to the same point. The Newton method with analytical first derivatives was used for the optimization of the likelihood functions.

Table 3
Estimation Results

Variable	*OLS 1*	*OLS 2*	*ML1*		*ML2*		*ML3*	
	Loss	Loss	Loss	Threshold	Loss	Threshold	Loss	Threshold
INTERCEPT	0.3570*	0.3495*	-0.9420**	0,7559	-0.7835**	0,4949	-0.8198**	-0,1454
	(0.063)	(0.063)	(0.389)	(0.581)	(0.369)	(0.577)	(0.383)	(0.257)
R1	0.0420**	0.0419**	0.1480*	-0,1752	0.1487*	-0,1800	0.1465*	-0,0123
	(0.020)	(0.020)	(0.055)	(0.105)	(0.054)	(0.105)	(0.054)	(0.066)
R2	0.0582*	0.0588*	0.2346*	-0.3343*	0.2361*	-0.3409*	0.2324*	-0,0457
	(0.019)	(0.019)	(0.051)	(0.100)	(0.051)	(0.100)	(0.051)	(0.105)
R3	-0.0689*	-0.0692*	0,0004	-0,1929	0,0001	-0,1928	-0,0018	-0,0945
	(0.024)	(0.024)	(0.067)	(0.129)	(0.067)	(0.129)	(0.066)	(0.050)
R4	-0,0664	-0,0666	0,0170	-0,2470	0,0269	-0,2745	0,0143	-0,1130
	(0.038)	(0.038)	(0.098)	(0.198)	(0.095)	(0.197)	(0.096)	(0.081)
R5	0.1170*	0.1172*	0.3839*	-0.5432*	0.3851*	-0.5600*	0.3792*	-0,0747
	(0.019)	(0.019)	(0.053)	(0.110)	(0.053)	(0.110)	(0.052)	(0.169)
R6	0,0167	0,0161	0.2382*	-0.5201*	0.2407*	-0.5376*	0.2352*	-0,1378
	(0.025)	(0.025)	(0.062)	(0.132)	(0.061)	(0.131)	(0.061)	(0.144)
NDRIV	0,0267	0,0261	0,0126	0,0517	0,0232	0,0224	0,0250	0,0214
	(0.029)	(0.029)	(0.072)	(0.155)	(0.070)	(0.155)	(0.070)	(0.051)
YMALE	0.1145*	0.1123*	0.1759*	-0,0921	0.1750*	-0,1012	0.1709*	0,0430
	(0.027)	(0.027)	(0.061)	(0.149)	(0.060)	(0.149)	(0.060)	(0.072)
YFEMALE	0,0419	0,0427	0,0038	0,1317	0,0043	0,1333	-0,0006	0,0716
	(0.031)	(0.031)	(0.077)	(0.162)	(0.076)	(0.161)	(0.077)	(0.057)
DRC	-0.2026*	-0.2028*	-0.4953*	0,5284	-0.4959*	0,5443	-0.4880*	0,0098
	(0.065)	(0.065)	(0.152)	(0.332)	(0.150)	(0.330)	(0.149)	(0.215)
AGE	-0,0018	-0,0019	-0,0066	0,0086	-0,0083	0,0127	-0,0086	0,0022
	(0.005)	(0.005)	(0.014)	(0.028)	(0.014)	(0.028)	(0.014)	(0.009)

Parameter Estimates (standard errors in parentheses)

Table 3 (continued)
Estimation Results

Parameter Estimates (standard errors in parentheses)

Variable	*OLS 1*	*OLS 2*	*ML1*		*ML2*		*ML3*	
	Loss	Loss	Loss	Threshold	Loss	Threshold	Loss	Threshold
GN1	0.2667*	0.2661*	0.8702*	-0,5613	0.7853*	-0,4770	0.8042*	0,1701
	(0.031)	(0.031)	(0.265)	(0.328)	(0.243)	(0.307)	(0.255)	(0.235)
GN2	0.3193*	0.3186*	1.2340*	-1.0902*	1.1040*	-0.9439**	1.1378*	0,0999
	(0.037)	(0.037)	(0.317)	(0.402)	(0.293)	(0.380)	(0.307)	(0.377)
GN3	0.3788*	0.3782*	1.4831*	-1.5203*	1.3351*	-1.3373*	1.3704*	0,0225
	(0.042)	(0.042)	(0.343)	(0.447)	(0.319)	(0.424)	(0.334)	(0.486)
GN4	0.3916*	0.3906*	1.5757*	-1.7773*	1.4226*	-1.5790*	1.4545*	-0,0489
	(0.046)	(0.046)	(0.351)	(0.466)	(0.328)	(0.443)	(0.342)	(0.544)
GN5	0.4334*	0.4318*	1.6288*	-1.7638*	1.4731*	-1.5535*	1.5066*	-0,0132
	(0.048)	(0.048)	(0.356)	(0.481)	(0.333)	(0.458)	(0.347)	(0.549)
COLL	-0.0483*	-0.0362*	-0.2169*	0.4928*	-0.2059*	0.5397*	-0.1921*	0,1431
	(0.014)	(0.014)	(0.042)	(0.120)	(0.042)	(0.127)	(0.042)	(0.143)
HITR	-0.6724*	-0.6734*	-2.0742*	1.4508*	-2.1794*	1.5739*	-2.0848*	-0,3450
	(0.018)	(0.018)	(0.232)	(0.298)	(0.233)	(0.307)	(0.231)	(0.625)
REPC	0,0027	0,0029	0,0816	-0.2506**	0,0764	-0.2371**	0,0767	-0,0799
	(0.021)	(0.021)	(0.044)	(0.108)	(0.043)	(0.106)	(0.043)	(0.067)
D500	0.2615*	0.3483*	0.1547*	0.5474*	0.2198*	0.7284*	0.2759*	0.3780*
	(0.022)	(0.038)	(0.055)	(0.116)	(0.062)	(0.135)	(0.075)	(0.140)
*COLL*D500*	-	-0.1260*	-	-	-0.2116*		-0.3057*	-
	-	(0.044)	-	-	(0.071)		(0.116)	-
s_1^2	0,5721	0,5718	0.7902* (0.030)	-	0.7856* (0.030)	-	0.7844* (0.031)	-
s_2^2	-	-	-	0.7359* (0.046)	-	0.7312* (0.046)	-	0.3794* (0.021)

Table 3 (continued)
Estimation Results

Parameter Estimates (standard errors in parentheses)											
Variable	*OLS 1*	*OLS 2*		*ML1*			*ML2*			*ML3*	
	Loss	Loss		Loss	Threshold		Loss	Threshold		Loss	Threshold
s_{12}^2	-	-		-			-			0.4010* (0,138)	
R^2 adjusted (*OLS*)	0,14	0,14		-	-		-	-		-	-
ln (*P*) (*ML*)	-	-		-17786,7			-17782,0			-17781,4	

* (**) Denotes statistical significance at the 1% (5%) confidence level.

In terms of sign and statistical significance, the results are quite robust across the different estimated models for the loss equations. However, the magnitudes of the parameters are very different between *OLS* and *ML*. Generally, parameter estimates are much larger in the *ML* cases.

Several parameters associated with the region where the automobile is principally used are significant, indicating that there are regional differences in the behavior of the drivers, in their driving environment and/or in the claim settlement behavior of the insurance firms.

When considering the personal characteristics of the drivers, it seems that the only two variables that matter in the explanation of the amount of loss are *YMALE* and *DRC*; young male drivers and drivers with a poor past record have bigger crashes than the others. It is well known that these two types of drivers, particularly young males, are more risky (in terms of claim frequency), and our results show that their driving behavior also has a significant influence on severity. In the case of young males, we may conjecture that they tend to drive faster, while in the case of drivers with a poor past record, it seems that their overall ability to drive not only limits their capacity to avoid accidents, but also their capacity to avoid severe accidents.

The type of automobile is measured using the age (*AGE*) and the rating groups (*GN1*-*GN5*). Possibly because it is used in conjunction with the rating groups, the age of the automobile is not a significant characteristic in the explanation of the amount of loss. However, the rating groups are all positive, increasing and statistically significant in all models considered. This result is consistent with the fact that the rating groups essentially reflect the cost of repairing or replacing an automobile.

The particular circumstances of the accident are taken into account with *COLL* and *HITR*. The expected sign of *COLL* was undetermined, since it may reflect the specific nature of the damages when other vehicles are involved as well as a significant amount of build-up, since when *COLL=0*, the presence of witnesses is less likely on the site of the accident. In all models considered, the parameter associated with *COLL* is negative and statistically significant. Our results indicate that when CO*LL=1*, the amount of losses reported is 5 to 20% smaller. Similarly, the effect of *HITR* is negative and statistically significant in all cases. This result, along with the result on *COLL*, tends to confirm that when other vehicles are implicated in the accident, the severity is of less importance. However, whether this result is the consequence of the particular nature of the accident or the consequence of build-up remains an unanswered question at this stage.

The presence of a replacement cost endorsement in the insurance contract (*REPC*) does not have any effect on the amount of loss reported. Thus, even if this endorsement stipulates that the automobile should be repaired with new parts or should be replaced by a new one at the current market value, the amount of loss reported is not (significantly) different. It may be the case that this effect is adequately taken into account by the rating groups and that no residual effect persists beyond, particularly since this endorsement is only valid in the first two years following the purchase of a new automobile.

Results Associated with the Deductible

In all estimated models, the increase of the deductible from $250 to $500 has a significant effect on the reported losses. Without an interaction term between D500 and *COLL*, the increase in the amount of loss following a $250 increase of the deductible is 29.8% ($761) with *OLS1* and 16.7% ($426) with *ML1*. Of course, *OLS* results are biased upward since, without an appropriate correction for selection bias, the parameter associated with *D500* not only measures the true effect of *D500* but also the selection effect. These results indicate that in our data set, the selection bias is quite important, and that a correction for the selection bias is essential in order to infer the proper effects.

The inclusion of an interaction term between *D500* and *COLL* is interesting for two reasons (see Dionne and St-Michel, 1991 for a similar methodology). First, with such an interaction term, we can separate the effect of *D500* on the amount of loss between two effects, that is when *COLL=0* and when *COLL=1*. Also, the inclusion of an additional variable in the loss equation allows for the identification of the covariance between the residuals of the loss and threshold equations, and therefore the estimation of a totally unconstrained model. The *OLS* estimates of the specification with the interaction between *D500* and *COLL* (*OLS2*) show that the effect of the deductible is closely related to *COLL*. For *COLL=0*, a $250 increase of the deductible is followed by a 41.7% increase of the amount of loss reported (or $1064), while with *COLL=1* the corresponding increase is 24.9% ($636). These results are, of course, biased upward. With an appropriate correction for selection (*ML2*), the increase in the amount of loss is 24.6% ($628) when no other vehicle is implicated in the accident, while no statistically significant increase is found when at least one other vehicle is implicated in the accident. The model labeled *ML3* reports the results with the constraint on the covariance between the residuals of the loss and threshold equations relaxed. The estimated covariance term is statistically significant (at a 1% confidence level) and positive, indicating a positive relationship between loss and threshold. The increase in the amount of loss reported following an increase of the deductible is 31.8% or $812 when *COLL=0*, and the corresponding increase when *COLL=1* is not statistically different from 0.[2] This result confirms the one obtained with *ML2*. Here, however, the increase in the amount of loss reported when *COLL=0* is larger than, but not statistically different from, the increase estimated with *ML2*.[3]

This result is quite significant. It implies that when there are no witnesses (other than the driver and his or her passengers) on the site of the accident, the losses reported to the insurance companies are somewhere between 24.6% and 31.8% higher for those insured with a $500 deductible relatively to those with a $250 deductible. Furthermore, we are confident that this increase corresponds to build-up, since our result is closely related to the presence of witnesses. Since the mean loss reported in our sample is $2552.65, these

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2 The parameter associated with *D500* when *COLL=1* is computed as 0.2759-.3057=-0.0298 with a standard error of 0.094. Therefore, this parameter is not statistically different from 0 at any reasonable confidence level.

3 The difference between the two coefficients is 0.2759-0.2198=0.0561 with a standard error of 0.097.

increases correspond to increases of the reported losses from $628 to $812, which is far more than the difference between the two deductibles ($250). Thus, it seems than when an insured decides to fraud, not only does he or she try to recover the deductible, but also to increase his or her net wealth (for instance, by increasing the net value of the automobile).

The results obtained for the threshold equation also call for some short comments. On the one hand, when the covariance between the residuals of the loss and threshold equations is set to 0 (*ML1* and *ML2*), several parameters are statistically significant in the threshold equation. In addition to *D500*, which is positive and significant in all estimated threshold equations, it seems that the threshold over which an insured reports a loss may be a function of his or her personal characteristics, as well as of the characteristics of the automobile (notably the rating groups). In most cases, the results obtained are intuitively justifiable.

On the other hand, when the constraint on the covariance is relaxed, no parameter in the threshold equation is statistically significant, with the exception of the parameter associated with *D500* and two firm effects (see Table A1 in appendix). This result indicates that the threshold over which an insured decides to report a loss (therefore, his or her ex-post personal deductible) is a sole function of the ex-ante deductible. On a sample average basis, the threshold is 45.9% or $437 higher when the deductible is $500 rather than $250. The average predicted threshold is $950 for observations with a $250 deductible and $1427 for observations with a $500 deductible. Thus, even if the threshold is a sole function of the deductible, the relationship between the two variables is not linear.

Conclusions

The object of this paper was to measure the effect of deductible contracts on fraudulent claims. We verified that a higher deductible is a determinant of the reported loss, particularly when no other vehicle is involved in the accident and, therefore, when the presence of witnesses is less likely. Hence, a higher deductible increases fraudulent activities when the probability of fraud success is high enough as documented by (4) in the theoretical model. The main cause of such result is the absence of commitment to the implicit monitoring policy of deductible contracts.

The results were obtained from an econometric model that makes corrections for the selection bias due to the fact that we observed only reported losses. Indeed, we show that ordinary least squares results are biased. The coefficient associated with the deductible in that model measures both the true (fraud) effect of the deductible and the selection effect. Our model separates the two effects, which yields a proper interpretation of the effect of the deductible.

Recent contributions (Crocker and Morgan, 1997; Crocker and Tennyson, 1996) tend to show that other types of contracts are more effective than deductible contracts in reducing this type of ex-post moral hazard when falsification activities are potentially present. The time has come for the insurance industry (in many countries) to consider seriously the problem of insurance fraud. One way is to introduce for automobile insurance other types of contracts than the standard deductible contract. However, insurance fraud is an industry problem and it is difficult for a single firm to be a leader against fraud, since such activity generates externalities for the whole industry. This suggests that some form of collective action between firms may be desirable (see Picard, 1996 for a similar conclusion).

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Appendix

We have to show that

$$\frac{d^2 L}{dDdp} > 0.$$

This expression can be obtained by totally differentiating two times the first-order condition (3) with respect to L, D and p. We first obtain that

$$HdL + BdD + Cdp = 0,$$

(A1)

where $B \equiv -pU''(S)(1-c'(L)) > 0$ and $C \equiv U'(S)(1-c'(L)) - U'(NS)(-c'(L)) > 0$. From (A1), we verify that

$$dL = -\frac{B}{H}dD - \frac{C}{H}dp$$

or

$$dL = \frac{\partial L}{\partial D}dD + \frac{\partial L}{\partial p}dp.$$

By differentiation, we have

$$d^2 L = \frac{\partial\left(\partial L/\partial D\right)}{\partial D}dD^2 + \frac{\partial\left(\partial L/\partial D\right)}{\partial p}dDdp + \frac{\partial\left(\partial L/\partial p\right)}{\partial D}dpdD + \frac{\partial\left(\partial L/\partial p\right)}{\partial p}dp^2.$$

By symmetry

$$\frac{\partial\left(\partial L/\partial D\right)}{\partial p} \equiv \frac{\partial\left(\partial L/\partial p\right)}{\partial D},$$

and consequently

$$\frac{d^2 L}{dDdp} = 2\left(\frac{\partial\left(\partial L/\partial D\right)}{\partial p}\right).$$

We then only have to analyze the sign of $\partial\left(\partial L/\partial D\right)/\partial p$ to obtain the desired result. The differentiation of $\partial L/\partial D$ with respect to p can be written as

$$\frac{\partial}{\partial p}\left(\frac{pU''(S)(1-c'(L))}{H}\right)$$

where H is defined in the text. By differentiating the above expression we obtain

$$\frac{U''(S)(1-c'(L))}{H} - \frac{pU''(S)(1-c'(L))}{H^2}\left(U''(S)(1-c'(L))^2 - U''(NS)(-c'(L))^2\right).$$

The first term is strictly positive under risk aversion since $H<0$. Using the first-order condition we obtain for the second term

$$\frac{-\,pU''(S)(1-c'(L))}{H^2}\left[\frac{U''(S)(1-c'(L))}{U'(S)p} - \frac{U''(NS)c'(L)}{U'(NS)(1-p)}\right],$$

which can be rewritten under constant risk aversion as

$$\frac{-\,pU''(S)(1-c'(L))}{H^2}\left(-\frac{U''(S)}{U'(S)}\right)\left[\frac{c'(L)}{(1-p)} - \frac{(1-c'(L))}{p}\right].$$

Multiplying each term by $(1-p)^2 \big/ p(1-c'(L)) > 0$ does not affect the sign and yields

$$\frac{-pU''(S)(1-c'(L))}{H^2}\left(-\frac{U''(S)}{U'(S)}\right)\left[\frac{(1-p)c'(L)}{p(1-c'(L))}-\frac{(1-p)^2}{p^2}\right].$$

The first term in the scarred bracket is strictly less than 1 from the first-order condition since, under risk-aversion, the expected marginal monetary benefit of fraud $(p(1-c'(L)))$ has to be greater than the expected monetary marginal cost $((1-p)c'(L))$. Consequently, the above expression is positive if the sum of the two terms in the scarred bracket is greater than 0, which is the case when $\frac{1-p}{p} \leq \frac{c'(L)}{(1-c'(L))}$ or when the probability of success is high enough which, as we will see in the empirical section of the paper, is the case when the presence of witnesses is less likely.

Table A1
Estimation Results of Firm Effects

Variable	*OLS 1*	*OLS 2*	*ML1*		*ML2*		*ML3*	
	Loss	Loss	Loss	Threshold	Loss	Threshold	Loss	Threshold
INS1	0.2738*	0.2738*	0.3414*	0,1382	0.3323*	0,1512	0.3348*	0.2412*
	(0.042)	(0.042)	(0.115)	(0.229)	(0.114)	(0.229)	(0.112)	(0.076)
INS2	0.2086*	0.2081*	0.4064*	-0,2881	0.4009*	-0,2897	0.3963*	0,0658
	(0.046)	(0.046)	(0.107)	(0.234)	(0.105)	(0.233)	(0.105)	(0.147)
INS3	0.2827*	0.2831*	0.4200*	-0,0096	0.4120*	0,0020	0.4084*	0.2125**
	(0.037)	(0.037)	(0.100)	(0.197)	(0.098)	(0.196)	(0.098)	(0.093)
INS4	0,0319	0,0321	0.2418*	-0.4909*	0.2313*	-0.4761*	0.2310*	-0,1165
	(0.027)	(0.027)	(0.074)	(0.139)	(0.073)	(0.139)	(0.073)	(0.132)
INS5	0.1607*	0.1613*	0.3325*	-0.2532**	0.3294*	-0.2575**	0.3261*	0,0442
	(0.022)	(0.022)	(0.063)	(0.118)	(0.062)	(0.117)	(0.061)	(0.110)
INS6	0,0077	0,0071	0,1300	-0,2821	0,1197	-0,2653	0,1189	-0,0689
	(0.034)	(0.034)	(0.089)	(0.170)	(0.088)	(0.169)	(0.087)	(0.085)
INS7	0.1307*	0.1308*	0.3016*	-0,2691	0.2959*	-0,2640	0.2917*	0,0234
	(0.030)	(0.030)	(0.083)	(0.154)	(0.082)	(0.153)	(0.081)	(0.107)
INS8	0.0812**	0.0815**	0.2894*	-0.4006**	0.2869*	-0.4091**	0.2809*	-0,0499
	(0.038)	(0.038)	(0.097)	(0.193)	(0.095)	(0.192)	(0.095)	(0.138)
INS9	-0,0436	-0,0429	-0,0520	-0,0327	-0,0549	-0,0275	-0,0525	-0,0426
	(0.039)	(0.039)	(0.114)	(0.207)	(0.112)	(0.205)	(0.111)	(0.058)
INS10	0.0649**	0.0652**	0.2536*	-0.3815**	0.2431*	-0.3656**	0.2423*	-0,0553
	(0.031)	(0.031)	(0.083)	(0.158)	(0.082)	(0.157)	(0.081)	(0.117)
INS11	0.0983*	0.0990*	0.2266**	-0,1911	0.2147**	-0,1683	0.2141**	0,0283
	(0.033)	(0.033)	(0.092)	(0.177)	(0.091)	(0.177)	(0.091)	(0.086)
INS12	0,0578	0,0584	0,1590	-0,1718	0,1628	-0,1842	0,1617	-0,0064
	(0.035)	(0.035)	(0.097)	(0.183)	(0.094)	(0.182)	(0.094)	(0.083)

Parameter Estimates (standard errors in parentheses)

Table A1 (continued)
Estimation Results of Firm Effects

Variable	Parameter Estimates (standard errors in parentheses)							
	OLS 1	*OLS 2*	*ML1*		*ML2*		*ML3*	
	Loss	Loss	Loss	Threshold	Loss	Threshold	Loss	Threshold
INS13	0,0326 (0.040)	0,0339 (0.040)	-0,0737 (0.124)	0,2422 (0.210)	-0,0744 (0.122)	0,2497 (0.210)	-0,0659 (0.121)	0,0801 (0.080)
INS14	-0,0433 (0.037)	-0,0427 (0.037)	-0,0231 (0.097)	-0,0759 (0.183)	-0,0188 (0.094)	-0,0860 (0.180)	-0,0207 (0.095)	-0,0504 (0.056)
INS15	0.1420* (0.044)	0.1433* (0.044)	0.3082* (0.111)	-0,2338 (0.242)	0.3141* (0.109)	-0,2537 (0.243)	0.3090* (0.109)	0,0395 (0.129)
INS16	0.2029* (0.029)	0.2033* (0.029)	0.3556* (0.077)	-0,1373 (0.148)	0.3450* (0.076)	-0,1196 (0.147)	0.3415* (0.076)	0,1187 (0.093)
INS17	0.3141* (0.052)	0.3134* (0.052)	0.4847* (0.116)	-0,1264 (0.249)	0.4818* (0.114)	-0,1366 (0.246)	0.4763* (0.114)	0,1838 (0.139)
INS18	0.1197* (0.036)	0.1205* (0.036)	0.2606* (0.094)	-0,2242 (0.179)	0.2567* (0.093)	-0,2300 (0.177)	0.2485* (0.092)	0,0224 (0.101)
INS19	-0,0069 (0.030)	-0,0066 (0.029)	0,0632 (0.080)	-0,1430 (0.166)	0,0506 (0.079)	-0,1137 (0.167)	0,0502 (0.079)	-0,0305 (0.059)

* (**) Denotes statistical significance at the 1% (5%) confidence level.