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The (1992) Bonus-Malus System in Tunisia: An Empirical Evaluation

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Abstract

The objective of this study is to assess empirically what impact introduction of the bonus-malus system (BMS) has had on road safety in Tunisia. The results of the Tunisian experiment are of particular importance since, during the last decade, many European countries decided to eliminate their mandatory bonus-malus scheme. These results indicate that the BMS reduced the probability of reported accidents for good risks but had no effect on bad risks. Moreover, the reform's overall effect on reported accident rates is not statistically significant, but the exit variable is positive in explaining the number of reported accidents. To avoid any potential selectivity bias, we also made a joint estimate of the reported accident and selection equations. The reform has a positive effect on the exit variable but still does not affect the accidents reported. This indicates that policyholders who switch companies are those attempting to skirt the imposed incentive effects of the new rating policy. Some of the control variables are statistically significant in explaining the number of reported accidents: the vehicle's horsepower, the policyholder's place of residence, and the coverages for which policyholders are underwritten.

Introduction

The objective of this study is to assess empirically what impact introducing a bonus-malus automobile insurance rating system has had on road safety. The context for this assessment is Tunisia, where experience with the bonus-malus rating system dates back to 1992. We had at our disposal a data bank supplied by a private insurance

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company that claims a large fraction of the Tunisian market. This company is one of the top five of the thirteen companies now operating on the Tunisian automobile insurance market. The data bank in question covers 5 years (in the 1990–1994 period) and is composed of 46,337 observations. An observation is a policyholder-year providing information on different characteristics and accidents at fault reported to the insurer (reported accidents, hereafter). We used the data to estimate the relative importance of factors explaining the number of reported accidents occurring in the period studied and to see whether, upon comparison of the pre and postreform periods, the bonus-malus system (BMS) proved optimal in reducing the frequency of reported accidents. The optimality criterion corresponds to that of the principal–agent model under moral hazard (Winter, 2000).

Introducing the bonus-malus scheme could, in theory, be expected to create more incentives for safe driving, as it links individual premiums to past reported accidents. And its introduction would serve as a unique laboratory experiment, since the Tunisian private market had no BMS before 1992. The results of the Tunisian experiment are now of particular importance since, during the last decade, many European countries decided to eliminate their national bonus-malus scheme. In 1994, the European Union decreed that all its member countries must drop their mandatory BMSs, claiming that such systems reduced competition between insurers, whether domestic or foreign. Since that date, Belgium, for example, dropped its mandatory system in 2002, but companies still apply some form of private BMS. However, the mandatory French system is still operating[1] (see Dionne, 2001, for more details on different countries in Europe). The European Union was not concerned with road safety.

The BMS is nothing new in the insurance industry.[2] The United Kingdom and Scandinavia set up their first system in 1910, and Morocco, a country close to Tunisia, got its system in 1940. The first actuarial and technical studies of such systems were launched in the early 1960s, with the works of Bichsel (1960) and Delaporte (1962). Buhlmann (1970) and Lemaire (1977) made significant contributions in the 1970s. Economists started their analyses of BMS much later. In fact, bonus-malus schemes were introduced in the economic literature when multi-period insurance contracts appeared on the scene (Rubinstein and Yaari, 1983; Dionne and Lasserre, 1985; Cooper and Hayes, 1987). These contracts are usually justified by the presence of asymmetric information between policyholders and insurers (adverse selection and moral hazard). Bonus-malus is a mechanism for adjusting the parameters of insurance contracts according to the past record of policyholders. For example, the premium can be adjusted based on individuals' past record of reported accidents (Lemaire, 1995; Dionne and Vanasse, 1989; Besson and Partrat, 1992; Brouhns et al., 2003) or on the number of demerit points accumulated (Dionne et al., 2000). By adjusting the information underlying the criteria of risk classification, an *a posteriori* scheme can be used to revise the *a priori* rating. Experience actually shows that using observable variables to estimate a policyholder's risk may not always provide a sufficiently exact segmentation of the population. Risk

[1] In fact, a recent decision of the European Court of Justice (September 2004) established that both the French and the Luxembourg mandatory BMSs are not contrary to the freedom to set premium rates that is in line with the European legislation.

[2] We thank very much a referee for providing very useful information that significantly improved the content of this section.

classes can still be heterogeneous even after an *a priori* rating (Crocker and Snow, 2000). The BMS makes it possible to use information disclosed on past experience to improve the insurance rating and thus render risk classes more homogeneous. With this system, it is also possible to maintain incentives encouraging cautious behavior and to reduce the inefficiencies associated with moral hazard (Arnott, 1992; Henriet and Rochet, 1986; Bressand, 1993; Winter, 2000).

Henriet and Rochet (1986) have distinguished two roles played by the bonus-malus, showing that its two roles involve different rating structures. The first role deals with the problem of adverse selection where nothing counts but the frequency of reported accidents observed over time, since the objective is to evaluate as faithfully as possible the true distribution of reported accidents related to unchanging characteristics. The second role is linked to moral hazard and implies that the distribution of reported accidents over time must be taken into account in order to maintain the incentives for cautious behavior at an optimal level. This means that more weight must be given to recent information in order to maintain such incentives.

Use of a BMS is also justified by the need for equity in insurance pricing, meaning that policyholders should pay premiums corresponding to their level of risk (Lemaire, 1995; Dionne and Vanasse, 1989).

In this respect, our first task will consist in combining the available data to isolate the characteristics of individuals and vehicles which can affect the frequency of reported accidents. The next step will involve using models compatible with panel data (Hausman, Hall, and Griliches, 1984; Hsiao, 1986; Dionne, Gagne, and Vanasse, 1998) to evaluate what impact a BMS might have on the number of reported accidents, which amounts to measuring the incentive conveyed by the new rating.

Our article is organized as follows: In the first section, we will present the Tunisian automobile insurance market, with particular attention to the BMS. In the next two sections, we will describe the data and the models used in our research and present the empirical results. Finally, we will conclude our study with interpretations emerging in the light of our findings.

DESCRIPTION OF THE TUNISIAN AUTOMOBILE INSURANCE MARKET

The Overall Insurance Market

In 2002, insurance products accounted for only 1.8 percent of Tunisia's GDP (share that the industry's total real-term sales represent in the country's Gross Domestic Product), as compared to 6.7 percent in the United States. This shows that the enormous potential of Tunisia's insurance market has been only marginally developed. In 2002, total sales in the insurance sector (direct business and acceptances) posted a 14.33 percent growth rate, as compared to 5.73 percent in 2001 and 11.60 percent in 2000 (FTUSA, 2002).

There are 24 insurance companies operating in Tunisia: 17 of them are headquartered there and 7 are not. Among the resident companies, we find 11 multi-branch companies, three firms specialized in life insurance, two others specialized in export credit insurance, and one in reinsurance. The private sector has kept its lead, with a market share of 46.7 percent in 2000, as compared to 38.9 percent for the public sector and 14.4 percent for the mutual and cooperative sector.

The market structure has not changed since 1992. Automobile insurance leads in total sales, with 32.7 percent of the market in 1992 and 43 percent in 2002. It is followed by the group health insurance branch, which posted 17.80 percent in 2002, and 19.9 percent in 1992 (FTUSA, 1992, 1993, 1994).

In 2002, the transportation, diverse risks, automobile, and life branches experienced the highest growth rates, with 26.53 percent, 24.72 percent, 15.97 percent, and 13.87 percent, respectively. In 2002, claims settled for automobile and group health insurance represented 77.14 percent of all settlements, as compared to 64.5 percent in 1992. For the automobile branch, the ratio of claims to paid-up premiums (not counting management fees) increased from 94.92 percent in 2001 to 116.32 percent in 2002, whereas it was 130.95 percent in 1993.

The Automobile Insurance Market

The rating system used for automobiles in Tunisia is essentially based on horsepower plus a BMS introduced in 1992. In Tunisia, the main problem with automobile insurance is linked to the low premiums set by the authorities for the different categories of vehicles. Authorized increases in premiums have been too small to bear the rising costs of repairs and the large settlements awarded by courts (based on a sovereign power of appraisal) in cases of bodily injuries or death. In 2000, for example, this state of affairs produced a technical deficit (not including interest on investments) of 41.8 million Tunisian dinars (TD: 1 TD = US$ 0.67),[3] compared to a 22.6 million TD deficit in 1992 (FTUSA, 1998, 2002).

Highway safety has become a social issue in many countries and especially in Tunisia. In 1995 alone, there were 14,407 victims of traffic accidents (1,318 killed, 13,089 injured). And the financial cost estimated by the World Bank for the same year was 170 billion TD for bodily injuries and 50 billion TD for material damages. These figures naturally appear rather high for a country numbering only 9 million inhabitants, especially when compared with data from other countries (see Table 1). Our calculations place Tunisia eighth on the list of reported risky countries. It is well known that these comparisons do not measure driving skill and risk exposure but remain important for the measure of social cost related to road accidents in different countries (see Smith, 2004, for another recent comparison between different countries).

The numbers in Table 2 report that, on average, 12.7 persons are killed for each 100 reported accidents, which is very high. More than one person is injured for each reported accident. The average number of deaths per 100 vehicles is also very high but, after the reform, it decreased slightly. It is not clear, however, that the reform is the cause of this variation.

The seriousness of accidents has remained at a more or less constant level, despite the efforts public authorities have made to lower it (building and repairing roads, improving emergency response services, surveillance, safe driving campaigns). The

[3] The total insurance income is of 207,845,311 TD and the total charges for claim settlements and other insurance expenses are 249,611,937 TD, which yields a technical deficit of 41,766,626 TD.

TABLE 1
Traffic Reported Accidents: Number of Deaths per 100,000 Inhabitants (1998)

Country	Number of Victims	Deaths per 100,000 Inhabitants
Portugal	2,425	24.7
South Korea	10,416	22.8
Greece	2,226	21.2
Poland	7,080	18.3
United States	41,967	15.4
France	8,918	15.2
Spain	5,747	14.5
Tunisia	**1,330**	**14.25**
New Zealand	504	13.8
Hungary	1,371	13.7
Czech Republic	1,360	13.3
Ireland	462	13.0
Belgium	1,300	12.8
Austria	963	11.8
Italy	6,724	11.7
Australia	1,763	9.7
Germany	7,792	9.5
Canada	2,672	8.9
Denmark	454	8.7
Japan	10,805	8.6
Switzerland	597	8.2
Norway	352	8.1
Finland	397	7.7
Holland	1,066	6.8
United Kingdom	3,581	6.2
Sweden	540	6.1

National Traffic Observatory explains that this failure is one of the consequences of a constantly evolving population and vehicle pool. This applies particularly to drivers of compacts who lead in the number of reported accidents (33.69 percent), followed by motorcyclists and pedestrians.

The Observatory has also found that reported accidents involving drivers between the ages of 20 and 30 years accounted for 30 percent of all reported accidents in 1993, compared with 27 percent for those in the 31 to 40 age range and 11 percent for those over 51. Again in 1993, women were involved in only 3.31 percent of reported accidents while they represented about 15 percent of drivers.

As concerns the geographical distribution of reported accidents, we note from the data that they are more numerous in large cities with heavy economic, tourist, and industrial activity. Sfax tops the list followed by the city of Tunis. Place of residence is thus a potential explanatory factor for risk of reported accident.

TABLE 2
Evolution of Number of Reported Accidents and of Their Victims During the 1989–2000 Period

	Reported Accidents		Killed		Injured			
Year	Number	Rate of Evolution (%)	Number	Rate of Evolution (%)	Number	Rate of Evolution (%)	Number of Deaths per 100 Reported Accidents	Number of Deaths per 100 Vehicles
1989	8,817	4.11	1,180	8.1	11,589	8.2	13.4	2.40
1990	9,329	5.8	1,207	2.3	12,148	4.8	12.9	2.30
1991	9,411	0.9	1,259	4.3	12,127	−0.2	13.4	2.30
1992	10,192	8.3	1,336	6.1	12,926	6.6	13.1	2.35
1993	**9,730**	**−4.5**	**1,273**	**−4.7**	**12,549**	**−2.9**	**13.1**	**2.14**
1994	9,901	1.8	1,299	2.0	13,119	4.5	13.1	2.06
1995	10,133	3.1	1,318	1.5	13,089	−0.2	12.9	1.96
1996	10,209	0.1	1,297	−1.6	13,581	3.8	12.7	1.81
1997	10,759	5.4	1,307	0.8	14,569	7.3	12.1	1.76
1998	11,229	4.4	1,330	1.8	15,450	6.0	11.8	1.71
1999	12,345	10.0	1,444	8.6	16,861	9.1	11.7	1.76
2000	12,652	2.4	1,499	3.8	17,540	4.0	11.8	1.74
Average	10,664	3.2	1,336	2.3	14,181	3.8	12.7	2.03

Source: Ministère de l'Intérieur, Observatoire national de la circulation, sub-unit of studies and analyses and Annuaire Statistique de la Tunisie.

The Bonus-Malus System

On January 1, 1992, Tunisia introduced a BMS for rating automobile insurance which, on January 1, 1993, translated into changes in premiums, in accordance with Circular 3/91 issued by the Minister of Finance. The recording of reported accidents was begun in 1992 and the bonus-malus plan then introduced would apply only to vehicles destined for private use. The insurance premium is adjusted each time the contract comes up for renewal. It is calculated by multiplying the basic premium for third-party liability (set according to the car's horsepower in the Minister of Finance's Circular), before taxes, by a decreasing or increasing coefficient (%) as shown in Table 3. It is interesting to observe that the bonus-malus scheme is very close to the former (1971) Belgian system (Lemaire, 1995).

On the 1st of January 1992, all policyholders were placed at the class 9 level. Movement up or down the class scale is governed by the following mechanism:

- The policyholder who has reported no accident during one insurance year benefits from a 5 percent premium discount (bonus). The premium then drops 5 percent for each reported accident-free year. The accumulated discounts cannot, however, exceed 40 percent of the basic premium. If the policyholder moves to another insurer at the end of a period, he keeps the same class as long he is able to document his class with the previous insurer. Then, the same rule applies for all subsequent reported accident-free years.
- The policyholder's premium is raised if he is responsible for one or more reported accidents during the insurance year. This increase is 10% for one reported accident,

TABLE 3
Bonus-Malus Coefficients

Classes	Coefficients for Level of Premiums (%)
17	200
16	160
15	140
14	130
13	120
12	115
11	110
10	105
09	**100**
08	95
07	90
06	85
05	80
04	75
03	70
02	65
01	60

30% for two reported accidents, and 100% for three reported accidents or more during the insurance year, so the system should increase incentives for road safety.

- These adjustment and transition rules are repeated over the years without any specific or additional rule. The minimum class is 01 and drivers can stay in this class as long as they have no reported accident with third-party responsibility. For policyholders who stay with their insurer, the maximum class is 17.

When insureds do stay with the same insurer, the transition rules that determine the transfer from one class to another class over the years follow a Markov process. Memory is not used. Knowledge of the actual class and the number of accidents reported during the actual year determine the next year's class.

The decrease–increase coefficient acquired by the vehicle designated in the contract is automatically transferred when the vehicle is replaced or if the insurer is changed. If a policyholder cannot provide any proof of prior insurance coverage for a vehicle in use, he is automatically placed in class 14 that carries with it a coefficient of 130. A policyholder having reported at-fault accidents each year can stay in class 14 for life as long he changes insurer each year! This particular aspect of the plan will be very important when interpreting the findings of this study. To our knowledge, there are no other particular transition rules such that no policy can be in a class above 09 after four consecutive claim-free years, as observed in some European countries during the 1980s and early 1990s.

Several aspects of the BMS have been criticized by insurers and World Bank experts (Vitas, 1995). World Bank experts have taken particular exception to the low premiums and the regulatory nature of these premiums, as insurance companies are thereby deprived of any power to initiate private measures promoting safe driving. And, since rates are fixed, insurers are prevented from using the rate technique (i.e., setting the basic premium on driving records). But, as suggested by other experts, this is exactly what BMSs are supposed to achieve. The World Bank experts also call attention to the excessively long waits for claim settlements. For their part, insurers complain that the BMS applies to only one category of vehicles (vehicles for private use), representing only a fraction of those on the road.

In Tunisia, there is no central body where all insurers can have immediate access to actuarial information on each vehicle and driver. Besides that, bonus-malus statements are not issued quickly enough. In conclusion, it is not clear that the actual BMS introduces the appropriate incentives.

DESCRIPTION OF DATA, VARIABLES, AND ECONOMETRIC MODELS

Data

Our data base comes from the "automobile production and reported accidents" files of a large Tunisian insurance company which, in the 1990–1994 period, laid claim to a large fraction of the automobile insurance market in Tunisia. For each policyholder, we obtained the following information:

- The policyholder's sex;
- The policyholder's place of residence;
- The car's horsepower;
- The brand of the car;
- The coverages underwritten by the policy (third-party liability, theft, fire, damages);
- The date of reported accidents for the following years: 1990, 1991, 1992, 1993, 1994;
- The policyholder's liability in the reported accident.

In order to get around the problem of missing data, we weeded out all the policies with doubtful information regarding policyholders' sex or place of residence, the brand of their car or the dates of their insurance contracts.

Once the annual files were cleaned up, the number of observations retained for each year were as follows: 7,549 for 1990; 7,482 for 1991; 9,641 for 1992; 10,218 for 1993; and 11,447 for 1994. To carry out our study, we created a data bank based on this regrouping of the annual data. A panel was thus formed, covering the period from the 1st of January 1990 to December 31, 1994. The panel is composed of 46,337 observations and 25,366 individuals. Since the individuals are not all present in the sample for each of the periods, the panel is incomplete. Individuals enter and exit the panel. This entry–exit phenomenon had a significant effect on the insurer portfolio, since, on average, the individual policyholders in the data bank stay with the same insurance company only 2 years and 9 months. These movements can be partially explained by the normal mobility of clients among insurance companies, but they may also be explained by the BMS. Since private insurers have no access to centralized information on risk classes, clients whose bonus-malus rank is higher than class 14 can simply switch insurance company and thus contract a new policy as a new class-14 policyholder.

When modeling, this kind of behavior must be taken into account by introducing variables for entries and exits, while also accounting for the selection bias problem encountered when panel data are used. One analysis will consider jointly the reported accident and selection equations.

Our sample is composed of two groups of individuals—those with a long-term commitment to their company (2,010 individuals) and those who switch companies (23,356). The average annual number of reported at-fault accidents for the first group is 6.16 percent and that for the second group is 7.29 percent. These averages may seem low when compared to the bad record of death per capita presented in Table 2, but correspond to the average reported accident rate in the country which is about 5 percent for the period 1989–2000. It seems that accidents are underreported when there is no injury or death; it also seems that road accidents are really dangerous for people involved in accidents (both inside and outside the vehicle). This insurance company's pool of clients should be representative of the behavior of Tunisian drivers, seeing that it operates branches across Tunisia and that the rating criteria for third-party liability are the same for all companies. There is, moreover, no price competition, since prices are fixed by the Government.

We chose to model the risk of accident without taking its seriousness into account, but we did factor in the policyholder's liability (the Tunisian BMS is based on third-party liability). The variable that we try to explain is the following dependent variable: number of yearly reported accidents with third-party liability for each policyholder. Usually not exceeding four, this count variable has nonnegative values, so the Poisson family is a natural way to do the analysis.

Description of Explanatory Variables and of Econometric Specifications

The explanatory variables are described in Table 4 (for more details, see Dionne and Ghali, 2003). A time-trend variable is used to take into account any possible variations in the distribution of reported accidents that are not controlled by the model's variables.

We had to estimate the Entry and Exit variables for two periods because we observe neither the Entry in the first period nor the Exit in the last period. Entry was predicted for 1990, using a Probit model estimated with data from 1991. Otherwise, we used a 0–1 variable. Exit was predicted for the year 1994, using a Probit model estimated with data from the year 1993. Otherwise, we used a 0–1 variable. Results of estimation are presented in the Appendix. The Experience variable in the Exit equation is the number of years within the insurer portfolio.

The estimated coefficients for Entry and Exit in the reported accidents model should normally be positive and significant, if we accept the hypothesis that those who move from one company to another are usually higher risks. This being so, we do not here consider the entries and exits as purely random.

Four types of random individual-specific-effect regressions for reported accidents were performed using the Probit model. So as to highlight the effects of policy variables, we added observations and explanatory variables gradually. Two other regressions using count-data models capable of capturing random individual-specific effects were estimated in order to analyze the stability of the results. Finally, a joint

TABLE 4
Explanatory Variables

Variable	Definition
Horsepower	Seven dichotomous categories describing the vehicle's horsepower. The group 4 horsepower or less is the reference group.
Sex	Two dichotomous categories. SexM is the reference group.
City code	14 dichotomous variables that take into account the territory in which the policyholder lives (in reality, Tunisia is divided into 23 territories, but we group some of them together, given the low number of policyholders in certain regions). The criterion used in regrouping is the following ratio: the number of accidents in 1993/number of inhabitants in the region. Regions with similar ratios have been grouped together. Tunis territory is the reference group.
Country of car	Seven dichotomous categories that capture the car's country-of-origin effect. France is the reference group. Difbrands means the car is other than those from the countries mentioned.
Coverage	Three dichotomous variables that capture the effect of the different coverages underwritten: Fire, theft, and damage.
PeriodYear	Five continuous variables indicating the number of days for which the contract is valid for each of the 5 years. These variables represent an interaction between the contract duration during a year (Contract period) and Year dummy variables; they control for the effects related to individual exposure to risk.
Reform92	Indicative variable taking the value of 1 for the years when the reform was in effect (years 92,93,94: postreform period); otherwise 0 (90–91; prereform period). The years 90 and 91 have been chosen as the reference category. If the coefficient linked to category 92,93,94 is negative and significant, this is a sign that the reform reduced the probability of reported accident at fault. The variable 1992 has been considered a reform year, since this is the year in which accidents started to be calculated in view of applying the bonus-malus system, so the change in behavior should have started during that year.
Entry	Is the estimated probability that the individual takes a new insurance policy with the company (probit model) in 1990. Is equal to 1 if the individual enter in all other periods and 0 otherwise.
Exit	Is the estimated probability that the policy is cancelled with the insurance company (probit model) in 1994. Is equal to 1 if the individual cancel his policy in all other periods and 0 otherwise.
Time trend	Is equal to 1,2,3,4,5 for the years during the period 1990–1994, to take into account of time.

estimation of reported accident and selection models was made to verify how potential selectivity bias might affect the results. To sum up, we estimated, in a first step, three regressions (1 to 3) for reported accidents without Entry and Exit variables. We then estimated reported-accident regressions 4 to 6 with Entry and Exit variables. Finally, we estimated jointly reported accidents (regression 7) and selection equations.

Regression 1: A random-effects Probit regression using only the individuals who remained during the five full periods (2,010 individuals, 10,050 observations). To perform this regression, we included all the classification variables as well as those linked to the characteristics of the file, plus the indicative variable Reform92.

Regression 2: A random-effects Probit regression using only drivers who switch company in the period under study (36,287 observations, 23,356 individuals). For this regression, we maintained exactly the same variables as in the preceding regression.

Regression 3: A random-effects Probit regression with those who change company and with the introduction of variables Period90, Period91, Period92, Period93, and Period94 to capture the effects linked to individual exposure to risk because of the entry and exit possibilities.

Regression 4: A random-effects Probit regression with all individuals, keeping the same variables included in the third regression, plus the explicit entries and exits variables—Entry and Exit.

Regression 5: A random-effects Poisson regression with all individuals and the same variables as those in regression 4.

Regression 6: A random-effects negative binomial regression with all individuals and the same variables as those in regression 4.

Regression 7: Joint estimates of reported accidents and selection equations with random individual-specific effects to control for selectivity bias from the incomplete panel.

To our knowledge, few studies have used panel data from an insurer portfolio to evaluate the effect of a change in regulation in the insurance sector. Dionne et al. (2000) have done so (with estimations obtained from count-data models) to see how successful Quebec's change in automobile insurance rating was in reducing the number of traffic violations and reported accidents. They found that, in actuarial terms, this change introduced a more equitable rating of risks, by forcing more risky drivers to pay higher insurance premiums. Dionne et al. (2000) also showed that the 1992 reform in Quebec had had a positive effect on road safety, by reducing the number of reported accidents and traffic violations. These effects have been interpreted as showing decreased moral hazard in the market studied. Chiappori (2000) presented an original review of the literature on empirical verification models designed to detect the presence of information problems in insurance markets. Though some of the econometric models reviewed are very powerful and the results obtained are quite interesting, none of these studies takes into account the entries and exits of individuals to and from the insurers; these movements are considered random. It is not clear, however, that they are completely random.

Models: Justification and Estimations

Our estimations of reported-accident equations are based on random-effects Probit, Poisson, and negative binomial models (Gouriéroux, Monfort, and Trognon, 1984; Hsiao, 1986; Lechner, 1995; Winkelmann, 1994; Cameron and Trivedi, 1986, 1998; see Pinquet, 2000, for a survey).

TABLE 5
Frequency of Individuals With *k* Reported Accidents at Fault Over the 4-Year Period

Number of Reported Accidents (*k*)	Frequency	Percentage	Accumulated Frequency	Accumulated Percentage
0	43,073	93.0	43,073	93.0
1	3,029	6.5	46,102	99.5
2	211	0.5	46,313	99.9
3	21	0.0	46,334	100.0
4	3	0.0	46,337	100.0

Choice of the Probit model is justified, in a first step, by the fact that only 0.5 percent of the individuals in the sample have more than one reported accident for the period under study (Table 5).

Independence between the different observations is a necessary condition when using the maximum-likelihood method to make estimations with this kind of data. Because of potential effects linked either to time or to individuals, this hypothesis is often not respected when dealing with panel data.

In our case, the temporal effect can be modeled, since T (the number of periods) is small (five periods). We thus introduced variables for time. However, effects linked to individuals cannot be modeled explicitly because N (the number of individuals) is large (incidental parameter problem, Hsiao, 1986). That is why the following results are based on random individual-specific-effect models.

The vector of explanatory variables is here formed with individual characteristics such as sex and residence; and horsepower, and other characteristics of the car. It is known and generally accepted that these variables have a strong explanatory power with regard to individual reported accidents. Their omission in characterizing the distribution of reported automobile accidents would bring about a serious specification error and could bias the test for isolating the effect of the reform on individual reported-accident rates.

Finally, since we are working with an incomplete data set that contains endogenous entries and exits, the results may be somewhat biased by links between some of the entry–exit determinants and determinants in the reported-accident model (observed or unobserved). To handle this possibility, we make joint estimations of the reported accident and selection models (two Probit equations) with random individual-specific effects.

RESULTS

Descriptive Statistics

Table 6 presents the main statistics of our data set. The first line gives the average number of reported accidents with third-party liability while the second shows the frequency of having more than one reported accident with third-party liability. The two statistics and their standard deviation are very similar. The annual at-fault accident

TABLE 6
Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Nacc	0.076	0.288	0	4.000
Acc	0.070	0.256	0	1.000
Number of periods	2.725	1.577	1.000	5.000
SexF	0.184	0.387	0	1.000
Ccode2	0.151	0.358	0	1.000
Ccode3	0.056	0.230	0	1.000
Ccode4	0.038	0.191	0	1.000
Ccode5	0.026	0.159	0	1.000
Ccode6	0.048	0.213	0	1.000
Ccode7	0.053	0.223	0	1.000
Ccode8	0.034	0.182	0	1.000
Ccode9	0.093	0.290	0	1.000
Ccode10	0.015	0.121	0	1.000
Ccode11	0.058	0.234	0	1.000
Ccode12	0.014	0.119	0	1.000
Ccode13	0.035	0.184	0	1.000
Ccode14	0.024	0.153	0	1.000
5Horsepower	0.285	0.451	0	1.000
6Horsepower	0.127	0.333	0	1.000
7Horsepower	0.173	0.378	0	1.000
8Horsepower	0.110	0.313	0	1.000
9Horsepower	0.061	0.239	0	1.000
10Horsepower	0.038	0.192	0	1.000
Fire	0.875	0.330	0	1.000
Damage	0.019	0.136	0	1.000
Theft	0.797	0.402	0	1.000
Italy	0.070	0.255	0	1.000
Germany	0.276	0.447	0	1.000
England	0.009	0.094	0	1.000
Asia	0.015	0.121	0	1.000
Eastern Europe	0.005	0.068	0	1.000
Difbrands	0.008	0.089	0	1.000
Entry	0.434	0.461	0	1.000
Exit	0.403	0.441	0	1.000
Contract period	350.259	50.563	6.000	365.000
Reform92	0.676	0.468	0	1.000
Year = 90	0.163	0.369	0	1.000
Year = 91	0.161	0.368	0	1.000
Year = 92	0.208	0.406	0	1.000
Year = 93	0.221	0.415	0	1.000
Year = 94	0.247	0.431	0	1.000
Period90	57.292	131.347	0	365.000
Period91	56.680	130.727	0	365.000
Period92	72.439	143.452	0	365.000
Period93	77.739	147.735	0	365.000
Period94	86.109	152.622	0	365.000
Number of observations		46,337		

rates reported in the portfolio (Nacc) from 1990 to 1994 are respectively: 0.084, 0.082, 0.071, 0.074, and 0.073.

The third line indicates the average presence of an individual in the data set over the 5 years. The average is 2.73, clearly indicating that we are faced with an incomplete data set with many entries and exits. The table also indicates that the averages of these two variables (Entry and Exit) over the 5 years are 43 percent and 40 percent. The exits and entries are particularly high after 1992. For example, in 1991, 32 percent of subjects were new clients while 37 percent of subjects left at the end of the contract year. In 1993, the numbers are, respectively, 49 percent and 43 percent. This means that the movements between insurers increased significantly after the reform, an issue that will become important when analyzing the impact of the reform on reported accidents. Fifteen percent of the policyholders are from the city of Sfax (Ccode2), 29 percent of the insured cars are in the category 5Horsepower and only 2 percent of drivers are insured for property damages because the price of this coverage is very high. Twenty-eight percent of the vehicles come from Germany (63 percent from France, the omitted category), and the average duration of contracts (Contract period) is 350 days. Sixty-eight percent of the observations were made after the reform and the days per period are quite evenly distributed over the years, although we do observe more days per period after 1992.[4]

Econometric Results

Regressions 1, 2, and 3 are presented in Table 7. The first regression, which uses only individuals present during the whole period under study, allowed us to conclude that using panel data is the right approach for taking into account individual repetitions over time. The ρ estimated is in effect significant at the 99 percent level, meaning that there may be a significant effect linked to the individual-specific effect and that we do not have enough variables to improve the specification and control for this effect in that regression. This first regression is more of a traditional panel relation, since it deals only with individuals present for the whole period.

The second regression repeats the same specification as the first, but only with policyholders who change company during the period under study. We observe that coefficient ρ remains significant at 99 percent, confirming the fact that the individual-specific effect may still matter in the regression.

Given that individuals are not all insured by contracts of the same length, as in Regression 1, we were able to introduce PeriodYear variables to improve the specification. Regression 3 clearly shows that ρ is no longer significant when the PeriodYear variables are introduced. This regression also indicates that all the PeriodYear variables are very significant in explaining the probability of reported accident.

The coefficient estimated for the SexF variable is negative and significant for regressions 2 and 3 where only individuals who change company are considered. Among

[4] These numbers per year are much lower than 365 days because the variable PeriodYear is from an interaction between contract duration during a given year (Contract period) and a dummy for the year (Year) (see PeriodYear in Table 4).

TABLE 7
Regressions 1, 2, and 3—Maximum Likelihood—Random-Effects Probit: Regressions Separating Individuals Who Stay With the Insurance Company for the Full 5 Years From Those Who Switch From One Insurer to Another During the Same Period

	Individuals Who Stay Regression 1		Individuals Who Switch Regression 2		Individuals Who Switch Regression 3	
Variable	Coefficient	*t* Statistic	Coefficient	*t* Statistic	Coefficient	*t* Statistic
Constant	−1.7689	−14.546	−1.4664	−26.213	−2.1046	−9.539
SexF	0.75082×10^{-01}	1.145	-0.46846×10^{-01}	−1.647	-0.50139×10^{-01}	−1.849
Ccode2	−0.32614	−3.785	−0.16336	−5.057	−0.15598	−5.041
Ccode3	−0.14696	−1.452	−0.20071	−3.945	−0.19209	−3.943
Ccode4	−0.47029	−3.629	−0.36805	−5.559	−0.35030	−5.571
Ccode5	−0.33908	−2.285	−0.24690	−3.363	−0.24178	−3.445
Ccode6	0.35316×10^{-01}	0.364	-0.25739×10^{-01}	−0.530	-0.28258×10^{-01}	−0.613
Ccode7	−0.18091	−1.853	-0.32235×10^{-01}	−0.672	-0.30288×10^{-01}	−0.663
Ccode8	−0.57329	−3.525	−0.42611	−6.437	−0.40076	−6.331
Ccode9	−0.81216	−6.070	−0.61609	−11.105	−0.58385	−10.937
Ccode10	−0.73840	−2.466	−0.33280	−3.296	−0.32190	−3.298
Ccode11	−0.58504	−4.120	−0.31573	−5.403	−0.29793	−5.297
Ccode12	−1.1806	−2.785	−0.59154	−5.203	−0.56038	−5.108
Ccode13	−0.52173	−2.668	−0.40221	−6.016	−0.37212	−5.786
Ccode14	−0.65895	−2.633	−0.76151	−7.462	−0.69452	−6.996
5Horsepower	0.18956×10^{-01}	0.255	0.18194×10^{-01}	0.551	0.17354×10^{-01}	0.550
6Horsepower	-0.65736×10^{-01}	−0.689	0.12026	3.056	0.11796	3.143
7Horsepower	0.10697	1.255	0.97440×10^{-01}	2.625	0.93342×10^{-01}	2.634
8Horsepower	0.19133×10^{-01}	0.198	0.23104	5.529	0.22185	5.561
9Horsepower	-0.11464×10^{-01}	−0.088	0.11885	2.376	0.11489	2.407
10Horsepower	0.22174×10^{-01}	0.152	0.16878	2.912	0.16507	2.985
Fire	0.22605	1.877	-0.21535×10^{-01}	−0.479	-0.25952×10^{-01}	−0.598
Damage	-0.89138×10^{-01}	−0.325	0.55669	10.086	0.53487	10.340

(*continued*)

TABLE 7
(Continued)

	Individuals Who Stay Regression 1		Individuals Who Switch Regression 2		Individuals Who Switch Regression 3	
Variable	Coefficient	*t* Statistic	Coefficient	*t* Statistic	Coefficient	*t* Statistic
Theft	0.76739×10^{-01}	0.662	0.10049	2.318	0.94798×10^{-01}	2.267
Italy	-0.55773×10^{-02}	−0.054	-0.10314×10^{-01}	−0.235	-0.52102×10^{-02}	−0.124
Germany	0.60299×10^{-01}	1.076	0.19091×10^{-01}	0.748	0.18657×10^{-01}	0.766
England	-0.74982×10^{-01}	−0.255	0.47974×10^{-01}	0.415	0.50954×10^{-01}	0.459
Asia	0.77026×10^{-01}	0.312	0.73337×10^{-01}	0.954	0.68626×10^{-01}	0.939
Eastern Europe	0.42449	1.519	0.80389×10^{-01}	0.545	0.67567×10^{-01}	0.483
Difbrands	−3.4042	−0.001	0.13306	1.342	0.12846	1.364
Period90					0.19678×10^{-02}	4.309
Period91					0.18880×10^{-02}	4.041
Period92					0.99522×10^{-03}	2.393
Period93					0.10320×10^{-02}	3.673
Period94					0.97788×10^{-03}	2.467
Reform92	−0.25011	−2.647	-0.13743×10^{-02}	−0.031	0.30595	0.941
Time trend	0.41761×10^{-01}	1.311	-0.18798×10^{-01}	−1.286	-0.10704×10^{-01}	−0.104
ρ	0.15978	3.434	0.99880×10^{-01}	2.499	0.43062×10^{-01}	0.987
Log-likelihood	−2,206.059		−9,179.240		−9,157.527	
Number of individuals	2,010		23,356		23,356	
Number of observations	10,050		36,287		36,287	

the latter, women have a lower probability of reported accidents than do men, but this is not the case when only those with company loyalty (Regression 1) are considered.

All the regions of residence have negative and significant coefficients, except for the Ariana (Ccode6), Ben Arous (Ccode7: only significant for the first regression), and Sousse (Ccode3: not significant in the first regression) regions, which corresponds to our predictions. In fact, Ariana and Ben Arous are very close to Tunis, Tunisia's most populous city and the one used as a reference group.

As concerns the horsepower of the vehicles, the results are astonishing. Introducing individuals who switch companies renders the coefficients positive and significant (in comparison with the first regression), except for the 5 horsepower category.

The coefficient for the Fire Protection variable is only significant for the first regression; we note that 85.8 percent of the policyholders who stick with the company take out fire insurance; this is the case for 85.22 percent of those who are not always present. Logically, this variable should not really explain the probability of a reported accident, since car fires are not necessarily linked to the driving behavior of policyholders. It may, however, represent some indirect measure of risk aversion.

The damage and theft variables, which are not significant for the first regression, have coefficients that are positive and significant for the two estimations containing individuals who switch insurance companies. We do, however, note that 0.8 percent of loyal policyholders take out the damage coverage, while 2 percent of the switchers do so as well. The origin of the car does not seem to have any impact on the probability of reported accident. In effect, these variables show no significance for any of the regressions. The time–trend variable is not significant.

As for the Reform92 variable, its coefficient is negative and significant for the first regression (at the 95 percent threshold) and nonsignificant for the second regression. The coefficient remains nonsignificant when the PeriodYear variables are introduced into the model (Regression 3). This result may be explained by the flaw in the class-14 clause of the bonus-malus scheme. A maximum-likelihood ratio test between the third and the second regressions leads us to reject the second regression. Indeed:

$$-2(\mathrm{LL}_{\mathrm{reg2}} - \mathrm{LL}_{\mathrm{reg3}}) = -2(-9179.240 + 9157.527) = 43.426 > X^2_{(5)}.$$

So we must keep the PeriodYear variables in the analysis.

We now turn to regressions 4, 5, and 6 presented in Table 8. The fourth regression, in addition to containing observations for all the individuals, also contains two extra variables (Entry, Exit). The ρ of this regression remains non-significant. The fifth and sixth regressions give us results like those of the fourth regression. As indicated previously, these two additional regressions were made to verify the stability of the results. The Poisson model is a count model that weights differently than the Probit the numbers of reported accidents higher than one. Compared to the Poisson model, the negative binomial model has a supplementary parameter which is designed to take non-observable individual heterogeneity into account (Gouriéroux, Monfort, and Trognon, 1984; Cameron and Trivedi, 1998). The expected value is known for the Poisson model while it is not perfectly observed for the negative binomial model.

TABLE 8
Regressions 4, 5, 6—Maximum Likelihood—Regression With All Individuals and All Explanatory Variables From Regression 3, Plus Two Variables for Entries and Exits (Entry and Exit)

	Random-Effects Probit Regression 4		Random-Effects Poisson Regression 5		Random-Effects, Negative Binomial Regression 6	
Variable	Coefficient	t Statistic	Coefficient	t Statistic	Coefficient	t Statistic
Alpha			1.57103	72.79201		
A					211.17935	1.46126
B					1.75512	6.92598
Constant	−2.1235	−7.992	−4.04579	−7.70400	0.76405	0.82977
SexF	-0.26660×10^{-01}	−0.953	−0.06312	−1.27291	−0.06519	−1.16081
Ccode2	-0.55591×10^{-02}	−0.030	−0.07288	−0.20695	−0.04149	−0.10724
Ccode3	−0.14992	−2.657	−0.31334	−3.08087	−0.30676	−2.70383
Ccode4	−0.44428	−4.545	−0.83902	−4.44089	−0.85943	−4.12979
Ccode5	−0.44419	−2.572	−0.75941	−2.28440	−0.79399	−2.16958
Ccode6	-0.32235×10^{-01}	−0.745	−0.04601	−0.61725	−0.05083	−0.59105
Ccode7	−0.11015	−2.076	−0.15875	−1.68076	−0.16930	−1.58622
Ccode8	−0.33533	−2.520	−0.72563	−2.81739	−0.70651	−2.50615
Ccode9	−0.71274	−9.339	−1.50490	−9.70435	−1.51158	−9.05364
Ccode10	−0.39272	−4.032	−0.78136	−4.22513	−0.77614	−3.88636
Ccode11	−0.43930	−4.274	−0.85401	−4.33886	−0.86941	−4.03575
Ccode12	−0.63390	−6.032	−1.29433	−5.76672	−1.29461	−5.46607
Ccode13	−0.31945	−2.424	−0.68579	−2.70303	−0.66791	−2.40914
Ccode14	−0.79414	−6.514	−1.57890	−6.27165	−1.62480	−5.93416
5Horsepower	0.41637×10^{-01}	1.101	0.08397	1.22290	0.08707	1.13658
6Horsepower	0.11716	2.259	0.20277	2.11548	0.21086	1.98003
7Horsepower	0.10875	2.707	0.21476	2.91974	0.21784	2.65018
8Horsepower	0.13512	3.259	0.28419	3.79465	0.28014	3.31605

9Horsepower	0.30539×10^{-01}	0.580	0.08621	0.88597	0.08080	0.74092
10Horsepower	0.11433	2.291	0.24221	2.92311	0.24139	2.50930
Fire	0.22765	1.247	0.33898	0.96238	0.37692	0.97290
Damage	0.57752	4.469	1.08359	4.52792	1.10063	4.13662
Theft	0.13532	3.440	0.26380	3.66812	0.26567	3.37982
Italy	-0.52248×10^{-01}	−0.925	−0.11010	−1.04147	−0.11554	−0.98530
Germany	0.28335×10^{-01}	1.165	0.06020	1.39953	0.05755	1.17972
England	0.31835×10^{-01}	0.313	0.04404	0.27200	0.04576	0.24888
Asia	0.21558	1.567	0.34549	1.32801	0.36422	1.26266
Eastern Europe	0.96960×10^{-01}	0.727	0.15538	0.65712	0.14639	0.53352
Difbrands	0.73764×10^{-01}	0.789	0.13118	0.79630	0.13521	0.71351
Reform92	0.37379	1.156	0.97136	1.60510	0.95066	1.51281
Entry	−0.0728	−1.025	−1.71968	−0.85808	−1.90052	−0.86280
Exit	0.29079	4.196	0.55383	4.48998	0.55560	4.13946
Period90	0.17740×10^{-02}	3.921	0.00418	4.55996	0.00415	4.39541
Period91	0.18371×10^{-02}	3.977	0.00438	4.79138	0.00435	4.61893
Period92	0.76819×10^{-03}	1.869	0.00167	2.24273	0.001688	2.16123
Period93	0.90280×10^{-03}	3.251	0.00207	4.14057	0.00207	3.96105
Period94	0.94401×10^{-03}	2.459	0.00229	3.13462	0.00228	2.99235
Time trend	-0.28747×10^{-01}	−0.279	−0.08556	−0.44067	−0.08244	−0.40750
ρ	0.43062×10^{-01}	1.419				
Log-likelihood	−11,409.53		−12,300.60		−12,299.89	
Number of individuals	25,366		25,366		25,366	
Number of observations	46,337		46,337		46,337	

TABLE 9
Regression 7—Simultaneous Analysis of Reported Accident Probability and Exit Decision With Panel Modelization

	Reported Accident Probability		Exit Decision	
Parameter	Estimate	*t* Statistic	Estimate	*t* Statistic
Constant	−2.414	−5.990	−0.181	−4.251
SexF	−0.418	−1.186	−0.140	−6.105
Ccode2	−0.230	−5.559	0.397	16.184
Ccode3	−0.185	−3.110	0.200	5.494
Ccode4	−0.453	−5.813	−0.181	−3.798
Ccode5	−0.336	−3.859	0.149	2.808
Ccode6	−0.059	−0.992	−0.054	−1.277
Ccode7	−0.011	−0.201	0.040	1.007
Ccode8	−0.511	−6.088	0.409	9.518
Ccode9	−0.669	−10.091	0.359	11.681
Ccode10	−0.493	−3.867	0.471	7.957
Ccode11	−0.387	−5.501	0.193	5.275
Ccode12	−0.726	−5.221	0.409	6.528
Ccode13	−0.408	−4.967	0.766	17.754
Ccode14	−0.784	−6.208	0.360	6.324
5Horsepower	0.067	1.659	0.057	2.384
6Horsepower	0.178	3.637	0.145	4.809
7Horsepower	0.157	3.428	0.185	6.928
8Horsepower	0.278	5.445	0.244	7.987
9Horsepower	0.152	2.421	0.347	9.484
10Horsepower	0.234	3.186	0.229	4.930
Fire	0.001	0.009	−0.259	−8.459
Damage	0.579	7.572	0.393	5.903
Theft	0.127	2.281	−0.418	−14.634
Italy	−0.000	−0.004	0.017	0.522
Germany	0.011	0.362	−0.245	−12.423
England	−0.025	−0.156	−0.132	−1.505
Asia	0.040	0.386	−0.123	−1.700
Eastern Europe	0.296	1.913	−0.332	−2.788
Difbrands	0.004	0.032	0.123	1.268
Reform92	0.817	1.587	0.122	3.011
Entry	−0.009	−0.256		
Period90	0.003	4.081		
Period91	0.003	4.867		
Period92	0.001	2.680		
Period93	0.002	3.335		
Time trend	−0.236	−0.978	0.093	5.117
Number of observations		34,890		
Correlation	Coefficient		*t* Statistic	
ρ_μ	−0.080		−0.643	
ρ_ε	0.400		4.431	

Regressions 4, 5, and 6, which contain all the portfolio's risks over the entire 5 years, indicate that the reform has had no significant effect on reported accidents. Indeed, higher risks skirt the law's incentive effects by switching company. The significant Exit variable obtained for these regressions confirm this interpretation of the results. In other words, those who exit are, on average, more likely to have reported accidents than those who do not switch companies.

To complete the analysis, we propose, in Table 9, a joint estimation of two Probit models—one for exit and one for reported accidents—which can account even more explicitly for the panel aspect of the data. This estimation is in the spirit of Dionne, Gagne, and Vanasse (1998). The period-by-period variables included in Table 8 already test for the presence of any entry and exit bias. Since the coefficient of the entry variable is not statistically significant, there is no entry bias in the data set according to the test of Verbeek and Nijman (1992). However, the coefficient of the exit variable is statistically different from zero. So, for the joint estimation, entry can be considered exogenous by keeping an entry variable to track potential entry bias in the joint estimation. The data are now limited to the 1990–1993 period because the 1994 data must be used to identify firms exiting in 1993. The final sample is reduced to 34,890 observations. The Probit specification in Table 8 was also reestimated with 34,890 observations. The results are not presented here but are mainly identical to those in Table 8.

The statistical results in Table 9 are similar to those of Table 8 regarding the reported accident equation. Again, neither the reform nor the entry variable is statistically significant. From the exit equation, we observe the following: females exit less often than do males; people in Sfax (Ccode2) exit more often; subscribers to fire and theft insurance as well as owners of German and Eastern Europe made cars exit less often while those with damage insurance exit more often. Finally, we observe that Reform 92 has a positive and significant parameter, confirming our interpretation that the reform increased insureds mobility between insurers.[5] We also observe that the correlation between the two random effects (μ_i) is not significant while that between the residual disturbance (ε_{it}) of the two equations is significant. It seems that the potential exit bias of the previous regression (Table 8) is not strong enough to affect the conclusion concerning the effect of the new bonus-malus scheme on reported accidents, since the estimated coefficients for the reform are not significant in the two Probit reported-accident regressions of Tables 8 and 9.

CONCLUSION

The objective of this study was to assess empirically what impact introduction of the BMS has had on road safety in Tunisia.

We distinguished two groups of individuals in the company: those who are loyal (8 percent) and those who switch companies (92 percent). Our results indicate that, whereas the new bonus-malus rating system introduced in 1992 did reduce the probability that good risks would be involved in a reported accident (Regression 1), it did not reduce that probability for bad risks (Regressions 2 and 3). When we consider all

[5] We thank a referee for asking us to add the Reform 92 variable in the Exit equation. We were not able to use the PeriodYear variables in this regression because only those who exit have less than full year contracts.

risks together (Regressions 4, 5, 6, and 7), we obtain that the reform had no significant effect. This is explained by the fact that the bad risks get around the incentives built into the law by switching companies. The very significant Exit variable in regressions 4, 5, and 6 confirms this interpretation of the results. We also obtained that the reform had a positive effect on the Exit variable. Thus, the bonus-malus rating system has not effectively reduced the average number of reported accidents. One suggestion to improve the efficiency of the BMS would be to abolish the "class 14 rule" that permits bad risks to switch to another insurer without being penalized.

Another important finding is that besides the horsepower data actually used by insurers in the country, other variables, such as policyholders' place of residence and choice of coverage, can explain the number of reported accidents. So there is room to improve the *a priori* pricing of automobile insurance.

This study presented powerful econometric models suitable for application in estimating the probability of reported accident based on an incomplete panel with individual-specific effects. These models are: the Probit, Poisson, and negative binomial models with random individual-specific effects and variables representing the effects of entries and exits. We also estimated jointly the reported accident and selection equations with random individual-specific effects to control for any potential bias in the results possibly produced by the fact that some of the selection equation's unobserved or observed determinants may have affected the determinants of the reported- accident equation. The results indicate that the potential for bias was not strong enough to affect our conclusion concerning the effect of the 1992 bonus-malus scheme on reported accidents. They also indicate that the reform has a positive effect on policyholders' mobility.

APPENDIX

Entry and Exit Estimates

	Probit Entry (1991)		Probit Exit (1993)	
Parameter	Estimate	*t* Statistic	Estimate	*t* Statistic
Constant	−1.0597	−14.8003	0.6073	10.7869
SexF	−0.0386	−0.9369	−0.1150	−3.1856
Ccode2	0.4746	9.9289	0.1367	3.3753
Ccode3	0.0997	1.5505	0.1126	1.7649
Ccode4	−0.2364	−2.9042	−0.0976	−1.2594
Ccode5	−0.5238	−4.8999	0.2408	2.7178
Ccode6	−0.0498	−0.6985	0.0828	1.2661
Ccode7	−0.1010	−1.4553	0.1216	1.9241
Ccode8	0.3115	3.7942	0.3052	4.0052
Ccode9	−0.1924	−2.7252	0.3472	6.1670
Ccode10	0.1031	0.7746	0.4581	3.8987
Ccode11	−0.2760	−3.4074	0.0330	0.4911
Ccode12	0.0529	0.4126	0.3744	3.1810
Ccode13	0.3012	3.3729	0.4968	6.3126
Ccode14	−0.2743	−2.2157	0.2498	2.7572
5Horsepower	0.0715	1.6067	0.0403	1.0177

(*continued*)

APPENDIX
(Continued)

	Probit Entry (1991)		Probit Exit (1993)	
Parameter	Estimate	*t* Statistic	Estimate	*t* Statistic
6Horsepower	0.1147	1.9879	0.0841	1.7448
7Horsepower	0.0712	1.3666	0.0951	2.1086
8Horsepower	−0.0570	−0.9268	0.2177	4.0844
9Horsepower	−0.0934	−1.2289	0.2996	4.6306
10Horsepower	−0.0020	−0.0219	0.2148	2.7363
Fire	0.5809	7.2522	−0.2688	−5.3868
Damage	0.3073	3.0366	0.3566	3.8303
Theft	−0.0207	−0.3090	−0.3704	−7.9145
Italy	−0.1166	−1.8898	0.0363	0.6760
Germany	−0.0321	−0.8699	−0.1558	−4.8235
England	−0.0152	−0.0916	−0.1696	−1.1608
Asia	0.3239	2.5424	−0.1820	−1.6382
Eastern Europe	−0.2072	−0.9120	−0.0949	−0.4585
Difbrands	0.0650	0.3744	0.1192	0.8278
Experience			−0.3908	−35.2072
Log-likelihood	−4,482.202		−5,870.622	
Number of observations	7,482		10,218	

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