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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 has had on road safety in Tunisia. The result of such experiment is important because many European countries decided to eliminate their bonus-malus scheme during the last decade. Results indicate that the bonus-malus system reduced the probability of accident for good risks but had no effect on that of bad risks. This finding is explained by the fact that bad risks can switch to another insurer so to escape the incentive effect imposed by the new rating policy. Many control variables are significant in explaining the number of accidents: the vehicle's horsepower, the policyholder's place of residence, entries and exists in the insurer portfolio, and the coverages for which policyholders are underwritten. The coefficients of the entry and exit variables are positive and indicate that those who switch company are bad risks.

Key words: Road safety, automobile insurance rating, bonus-malus, Tunisia, road accidents, panel data, probit, negative binomial distribution, Poisson distribution, random effects.

JEL numbers: D81, G22.

Résumé

L'objet de cette étude est d'évaluer empiriquement l'impact sur la sécurité routière de l'introduction du système bonus-malus dans la tarification de l'assurance automobile en Tunisie. Les résultats de ce type d'expérimentation sont importants, puisque plusieurs pays européens ont décidé d'éliminer leur système bonus-malus durant les dix dernières années. Nos résultats indiquent que le système bonus-malus réduit la probabilité des bons risques d'être responsable d'un accident mais ne réduit pas celles des mauvais risques. Ceci s'explique par le fait que les mauvais risques contournent les effets incitatifs de la loi en changeant d'assureur. De plus, nous vérifions que plusieurs variables sont significatives pour expliquer la fréquence d'accident : la marque de la voiture, la puissance du véhicule, la région de résidence de l'assuré et les garanties auxquelles il souscrit.

Mots clés : Sécurité routière, tarification de l'assurance automobile, bonus-malus, Tunisie, accidents de la route, données de Panel, Probit, Binomiale négative, effets aléatoires.

Classification JEL : D81, G22.

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Introduction

The objective of this study is to asses 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 company which claims a large fraction of the Tunisian market. The company in question ranks in the first five among the thirteen companies now operating on the Tunisian market. This data bank covers five years (in the 1990-1994 period) and is composed of 46,337 observations. It allowed us to estimate the relative importance of factors explaining the number of accidents occurring in the period studied and to see whether the bonus-malus system was optimal in reducing the frequency of accidents when the periods before and after the change in rating are compared. This serves as a unique laboratory experiment, for the Tunisian private market had no bonus-malus system before 1992. The result of such experiment is important because many European countries decided to eliminate their bonus-malus scheme during the last decade.

Bonus-malus schemes were introduced in the economic literature when multi-period insurance contracts appeared on the scene. These contracts are usually justified by the presence of asymmetrical 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 accidents (Lemaire, 1995; Dionne and Vanasse, 1989, 1992) 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 classes can still be heterogeneous even after an *a priori* rating (Crocker and Snow, 2000). The bonus-malus system makes it possible to use information disclosed on past accidents 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 all that counts is the frequency of the accidents observed over time, the objective being to evaluate as faithfully as possible the true distribution of accidents related to unchanging characteristics. Linked to moral hazard, the second role implies that the distribution of 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.

Justification of the use of a bonus-malus system is also associated with the equity of insurance pricing which consists in having policyholders pay premiums corresponding to their level of risk. (Lemaire, 1995; Dionne and Vanasse, 1992).

In this respect, our first task will consist in isolating those available characteristics of individuals and vehicles which can affect the frequency of accidents. In the next step, using models compatible with panel data (Hausman et al., 1984; Hsiao, 1986), we shall evaluate the impact that introduction of a bonus-malus system makes on the number of accidents, which amounts to measuring the incentive conveyed by the new rating.

Our article is organized as follows: In the first section, we shall present briefly the Tunisian bonus-malus system. In the next two sections, we shall describe the data and the models used in our research and present the empirical results. Finally, we shall conclude our study with interpretations emerging in the light of our results.

1. Description of the Tunisian bonus-malus system

On the 1st of January 1992, Tunisia introduced a bonus-malus system for rating automobile insurance which, on the 1st of January 1993, translated into changes in premiums, in accordance with Circular 3/91 issued by the Minister of Finance. The recording of accidents was begun in 1992 and the bonus-malus plan introduced applies only to vehicles destined for private use. The insurance premium is adjusted each time the contract comes up for renewal. The premium is calculated by multiplying the basic premium for civil 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 1.

(Table 1, about here)

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 caused no accident during one insurance year benefits from a 5% premium discount (bonus). The premium then drops 5% for each accident-free year. The accumulated discounts cannot, however, exceed 40% of the basic premium.

- The policyholder's premium is raised if he is responsible for one or more accidents during the insurance year. This increase is 10% for one accident, 30% for two accidents and 100% for three accidents or more during the insurance year so the system should increase incentives for road safety.

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 can provide no proof of prior insurance coverage for a vehicle in use, he is automatically placed in class 14 which carries with it a coefficient of 130. This particular aspect of the plan will be very important when interpreting the findings.

Table 2 shows the civil liability premiums for privately operated vehicles, according to their bonus-malus class and in Tunisian dinars (TD: 1 TD = US$ 0.67).

(Table 2, about here)

Prior to 1993, the civil-liability premium was that corresponding to class 9, meaning that it was based essentially on the automobile's use and horsepower, plus a discount for certain professional categories.

2. Description of data, variables and econometric models

2.1 Data

Our data base comes from the "automobile production and 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 (civil liability, theft, fire, damages);

- The date of accidents for the following years: 1990, 1991, 1992, 1993, 1994;
- The policyholder's liability in the accident.

In order to get around the problem of missing data, we weeded out all the policies with doubtful information regarding the policyholder's sex or place of residence; and the brand of his car or the dates of his 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. However, 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 the individual policyholders in the data bank stay with the same insurance company only two years and nine months, on average. These movements can be partially explained by the normal mobility of clients among insurance companies, but they may also be explained by the bonus-malus system. 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 indicative variables for entries and exits, while also accounting for the selection-bias problem encountered when panel data are used.

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 number of accidents for the first group is 6.16% and that for the second group is 7.29%. 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 civil 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 an automobile accident, taking no account of its seriousness but factoring in the policyholder's liability (the Tunisian bonus-malus system is based on civil liability). The variable that we try to explain is the following dependent variable: number of yearly accidents with civil liability. Usually not exceeding four, this count variable has non-negative values, so the Poisson family is a natural way to do the analysis.

2.2 Description of explanatory variables and of econometric specifications

2.2.1 *Explanatory variables*

The explanatory variables are described below:

<u>Horsepower</u>:	Seven dichotomous categories describing the vehicle's horsepower
4horsepower :	1 if the car has 4 HP or less (reference group), otherwise 0
5horsepower :	1, if the car has 5 HP; otherwise 0
6horsepower :	1, if the car has 6 HP; otherwise 0
7horsepower :	1, if the car has 7 HP; otherwise 0
8horsepower :	1, if the car has 8 HP; otherwise 0
9horsepower :	1, if the car has 9 HP; otherwise 0
10horsepower :	1, if the car has 10 HP or more; otherwise 0

<u>Sex</u>:	Two dichotomous categories
SexM :	Male group (reference group)
SexF :	Female group

<u>City code</u>:	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 rate 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.
Ccode1 :	Tunis territory (reference group); otherwise 0
Ccode2 :	1 if policyholder lives in the Sfax region; otherwise 0
Ccode3 :	1 if policyholder lives in the Sousse region; otherwise 0
Ccode4 :	1 if policyholder lives in the Nabeul region; otherwise 0
Ccode5 :	1 if policyholder lives in the Bizerte region; otherwise 0
Ccode6 :	1 if policyholder lives in the Ariana region; otherwise 0
Ccode7 :	1 if policyholder lives in the Ben Arous region; otherwise 0

Ccode8 : 1 if policyholder lives in the Monastir region; otherwise 0

Ccode9 : 1 if policyholder lives in the Médenine or Béjà region; otherwise 0

Ccode10 : 1 if policyholder lives in the Mehdia region; otherwise 0

Ccode11 : 1 if policyholder lives in the Gabès, Zaghouan or Tozeur region; otherwise 0

Ccode12 : 1 if policyholder lives in the Jendouba, Kasserine or Sidi Bouzid region; otherwise 0

Ccode13 : 1 if policyholder lives in the Kairouan, Kef or Siliana region; otherwise 0

Ccode14 : 1 if policyholder lives in the Tataouine or Kébili region; otherwise 0

<u>Country of car</u>: Seven dichotomous categories that capture the car's country-of-origin effect

France : 1 if the car is French (reference group); otherwise 0

Italy : 1 if the car is Italian; otherwise 0

Germany : 1 if the car is German; otherwise 0

England : 1 if the car is English; otherwise 0

Asia : 1 if the car is Asian; otherwise 0

Eastern Europe : 1 if the car is from former Eastern Europe (Poland, Russia, etc.); otherwise 0

Difbrands : 1 if the car is other than those from the countries mentioned above; otherwise 0

<u>Coverage</u>: 3 dichotomous variables that capture the effect of the different coverages underwritten

Fire : 1 if the policyholder's car is protected against fire; otherwise 0

Theft : 1 if the policyholder's car is protected against theft; otherwise 0

Damage : 1 if the policyholder's car is protected against collision; otherwise 0

Other exogenous, indicative variables have been introduced as needed for our estimations:

Period: Continuous variable providing information on the number of days during which the individual is insured per year; this is an exposure-to-risk variable.

Year: Five dichotomous variables; these variables assume the value of 1 if the individual is present during the year concerned; otherwise 0.

The two preceding variables were in fact created to construct the "PeriodYear" variable.

PeriodYear: Five continuous variables indicating the number of days for which the contract is valid for each of the five years. These variables represent an interaction between the "Period" and "Year" variables; they control for the effects related to time and individual exposure to risk.

Reform92: Indicative variable assuming the value of 1 for the years when the reform was in effect (years 92,93,94: post-reform period); otherwise 0 (90-91; pre-reform period). The years 90 and 91 have been chosen as a 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 accident. 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.

We also constructed two dichotomous variables in order to take into account any interplay effect between pre- and post-reform years not accounted for by other variables used. This means that, as constructed, the Reform92 variable could mask annual effects on the probability of accident that would have emerged without introduction of the pre- and post-reform variables.

Preref: is equal to 1, if we are in the second year of the pre-reform period, that is to say 1991; and it is equal to zero for 1990, the first year of the pre-reform period.

Postref: is equal to 1 if we are in the second part of the post-reform period, that is to say 1993 to 1994; and it is equal to zero for the first part of the post-reform period.

If the coefficients estimated for these last two variables are negative and significant, we have a sign that the policyholders present during the second parts of the pre-and post-reform periods are less at risk that those who are there during the corresponding first parts.

Entry: Assumes the value of 1 where the individual takes out a new insurance policy with the company; otherwise 0

Exit: Assumes the value of 1 for the year the insurance policy is cancelled with the insurance company; otherwise 0

These two variables must normally have estimated coefficients that are positive and significant, if we accept the hypothesis that those who move from one company to another are usually bad risks. This being so, we do not here consider the entries and exists as purely random.

2.2.2 *Econometric specifications*

Four types of random-effect regressions 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 effects were estimated in order to analyze the stability of the results.

Regression 1: A 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 and those linked to the characteristics of the file, plus the indicative variables Reform92, Preref, Postref.

Regression 2: A 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 regression with those who change company and with the introduction of variables Period90, Period91, Period92, Period93, and Period94 to capture the effects linked to time and individual exposure to risk because of the entry and exit possibilities.

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

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

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

All the probit-model regressions were performed with Limdep software, whereas the count-data regressions were done with SAS software.

To our knowledge, few studies have used panel data to evaluate the effect of a change in regulation. 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 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 accidents. 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 on the presence of information problems in insurance markets. Though some of the reviewed econometric models are very powerful and the results obtained interesting, none of these studies takes into account the entries and exists of individuals to and from the insurers; these movements are considered random. It is not clear, however, that they are completely random.

2.3 Models justification and estimations

Our estimations are based on random-effects probit, Poisson and negative binomial models (Gouriéroux and Montfort, 1984; Hsiao, 1986; Lechner, 1995; Winkelmann, 1994; Cameron and Trivedi, 1998; see Pinquet, 2000, for a survey).

Choice of the probit model is justified, in a first step, by the fact that only 0.5% of the individuals in the sample have more than one accident for the period under study (Table 3).

(Table 3, about here)

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

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).

The vector of explanatory variables is here formed with individual characteristics such as sex, residence classes, and characteristics of the car. It is known and generally accepted that these variables have a strong explanatory power with regard to individual accidents. Their omission in characterizing the distribution of automobile accidents would bring about a serious specification error and could bias the test for isolating the effect of the reform on individual accident rates. That is why the following results are based on random-effect models. These models, with their fixed but non- specific individual variables, can be called mixed.

2.4 Statistical tests

Once the regressions have been done, it is a matter of checking to see whether the coefficients of the independent variables are significant or not. We apply the Student test, that is the fact that:

$$t = \frac{\hat{\beta}}{\sigma_{\hat{\beta}}}$$

when correction for dependence between the independent variables due to the nature of the data is appropriately taken into account.

The maximum-likelihood ratio (Hsiao, 1986) is used to compare the different regressions when certain explanatory variables are withdrawn from one of the models. The test consists in not rejecting the unconstrained model (NC) when:

$$-2(LL_C-LL_{NC}) > X^2_{(\text{nber of constraints})}$$

Finally, the "no random effect in the panel data" test (Lechner, 1995) is carried out with the Wald test (W) for the hypothesis:

$$H_0 : \rho = 0 \text{ versus } H_1 : \rho \neq 0$$

where ρ is a measure of dependence between the independent variables; ρ has to be estimated.

The decision rule is to reject H_0 when:

$$W = \frac{\hat{\rho}^2}{V(\hat{\rho})} > X^2(1)$$

which can be approximated by using the Student test on $\hat{\rho}$ when the number of observations is large enough.

3. Econometric results

3.1 Econometric results linked to explanatory variables

The coefficient estimated for the SexF variable is negative and significant for regressions 2 and 3 when only individuals who change company are considered (see Tables 5 and 6). Among the latter, women have a lower probability of accidents than do men, but this is not the case when only the good risks are considered (those with company loyalty: regression 1, Table 4) or when all risks are lumped together (Table 7).

All the regions of residence have negative and significant coefficients, except for the Ariana (Ccode6) and Ben Arous (Ccode7: only significant for the first regression) regions, which corresponds to our predictions. In fact, as we mentioned previously, these two regions are very close to Tunis, Tunisia's most populous city and the one used as reference group.

(Table 4, about here)

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

The coefficient for the Fire protection variable is only significant for the first regression (Table 4); we note that 85.8% of the policyholders who stick with the company take out fire insurance; this is the case for 85.22% of those who are not always present. Logically, this variable should not really explain the probability of accident, since car fires are not necessarily linked to the driving behavior of policyholders. It may, however, represent some indirect measure of risk aversion.

(Table 5, about here)

The Damage and Theft variables, which are not significant for the first regression, have coefficients that are positive and very significant for the three estimations containing individuals who switch insurance company. We do however note that 0.8% of loyal policyholders take out the Damage coverage, while 2% of the switchers do so as well. The Damage coverage is less popular than Fire and Theft (81.1% of loyal policyholders, 73.85% of those who switch, respectively).

PeriodYear: These variables, representing an interaction between period and year, were introduced into the model to take into account the effects of time on the distribution of accidents and the level of individual exposure to risk. They have positive and very significant coefficients. Introducing them into the model is thus very important for individuals who switch from their insurer to another insurer. However, these variables were not introduced in the first regression because all insureds are present during all days over all years.

(Table 6, about here)

The Preref and Postref variables show no significance for any of the regressions. This means that there are neither more nor fewer accidents in 1991 than in 1990 and neither more nor fewer accidents for the second post-reform period (1993,1994) than in 1992.

The origin of the car does not seem to have any impact on the probability of accident. In effect, these variables show no significance for any of the regressions.

Entry and Exit, introduced into the model in regressions 4, 5, and 6 have positive and often significant coefficients. In other words, those who enter and exit (particularly those who exit) are, on average, more likely to have accidents than those who do not switch company.

3.2 Econometric results linked to bonus-malus rating

As for the Reform92 variable, its coefficient is negative and significant for the first regression (at the 90% threshold, Table 4) and moderately significant for the second regression (90%, Table 5). However, the coefficient is no longer significant when the PeriodYear variables capturing the risk exposure effect are introduced into the model (Table 6). The related coefficients are positive and significant. This result may be explained by the flaw in the class-14 clause.

Regressions 4, 5, and 6, which contain all the portfolio's risks over the entire 5 years, confirm that the reform has had no significant effect. Indeed, bad risks skirt the law's incentive effects by switching company. The significant Entry and Exit variables obtained for these regressions confirm this interpretation of the results.

(Table 7, about here)

3.3 Econometric results linked to modeling

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 1% level, meaning that there is a significant effect linked to time and individual risk exposure and that we do not have enough variables to improve the specification and control for this effect (Dionne, Gagné, Vanasse, 1998). 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 1%, confirming the fact that there is not enough variables to correct the time and individual effects in the regression.

Given that individuals are not all insured by contracts of the same length, as in Regression 1, we were able to construct PeriodYear variables to improve the specification and eliminate the effects associated with time and individual risk exposure. Regression 3 shows clearly 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 accident. However, introducing these variables makes us lose the significance of the Reform92 variable. A maximum-likelihood ratio test between the third and the second regressions leads us to reject the second regression. Indeed:

$$-2(LL_{reg2}-LL_{reg3}) = -2(-9179{,}238+9157{,}324) = 43{,}828 > X^2_{(5)}$$

The fourth regression, in addition to containing observations for all the individuals, also contains two extra indicative variables related to the preceding regression for entries and exists (Entry, Exit). The ρ of this regression is not significant.

Besides, the Entry and Exit variables are both significant with a positive sign, which also proves that there is a bias upon entry and exit which must be taken into account by the model. The fact that the sign of the coefficients linked to these variables is positive means that those who switch company are bad risks.

The fifth and sixth regressions give us results like those of the fourth regression (except for the Entry variable). Interpretation of the statistics associated with the explanatory variables gives results identical to those from the probit model, confirming that the new rating system did not reduce the number of accidents.

Using these models enlarges our field of study; they allow us to calculate for each individual the probability of incurring 0, 1, 2 … accidents. Each coefficient obtained with the negative binomial (with random effects) can be interpreted as the impact of the explanatory variable on the average number of accidents estimated. When the coefficients are negative and significant, this means a decrease in the risk of accident linked to the character profile. These coefficients are to be interpreted as marginal risks associated with the explanatory variable.

The random-effects Poisson models and the random-effects negative binomial are not directly comparable with the same models without random effects (not presented here): We cannot compare the different models using the maximum-likelihood ratio test. We have, however, noticed that the likelihoods associated with the random-effects models are higher that those for the models without random effects, which leads us to prefer the former.

Conclusion

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

We distinguished two groups of individuals in the company: those who are loyal (8%) and those who switch company (92%). Our results indicate that the new bonus-malus rating system introduced in 1992 did reduce the probability that good risks would be involved in an accident (Regression 1), but did not reduce that probability for bad risks (Regression 3). When we consider all risks together (Regressions 4,5,6), 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 company. The very significant Entry and Exit variables in these regressions confirm this interpretation of the results. Thus, the bonus-malus rating system has not effectively reduced the average number of accidents.

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 accidents.

This study presented powerful econometric models suitable for application in estimating the probability of accident based on an incomplete panel where specific-effects problems linked to individuals and time may arise. These models are: the probit, Poisson, and negative binomial models with random effects and indicative variables representing entries and exits and time effects.

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Table 1

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

Table 2

Civil liability premium for private use according to bonus-malus class in TD, 1993

Class	Coef. of premium	1-2HP	3-4HP	5-6HP	7-10HP	11-14HP	>=15HP
17	200%	101.400	118.800	150.600	168.000	217.400	260.800
16	160%	81.120	95.040	120.480	134.400	173.920	208.640
15	140%	70.980	83.160	105.420	117.600	152.180	182.560
14	130%	65.910	77.220	97.890	109.200	141.310	169.520
13	120%	60.840	71.280	90.360	100.800	130.440	156.480
12	115%	58.305	68.310	86.595	96.600	125.005	149.960
11	110%	55.770	65.340	82.830	92.400	119.570	143.440
10	105%	53.235	62.370	79.065	88.200	114.135	136.920
09	**100%**	**50.700**	**59.400**	**75.300**	**84.000**	**108.700**	**130.400**
08	95%	48.165	56.430	71.535	79.800	103.265	123.880
07	90%	45.630	53.460	67.770	75.600	97.830	117.360
06	85%	43.095	50.490	64.005	71.400	92.395	110.840
05	80%	40.560	47.520	60.240	67.200	86.960	104.320
04	75%	38.025	44.550	56.475	63.000	81.525	97.800
03	70%	35.490	41.580	52.710	58.800	76.090	91.280
02	65%	32.955	38.610	48.945	54.600	70.655	84.760
01	60%	30.420	35.640	45.180	50.400	65.220	78.240

Table 3

Frequency of individuals with k accidents

Number of accidents (k)	Frequency	Percentage	Accumulated frequency	Accumulated percentage
0	43073	93.0	43073	93.0
1	3029	6.5	46102	99.5
2	211	0.5	46313	99.9
3	21	0.0	46334	100.0
4	3	0.0	46337	100.0

Table 4

Regression 1 - Maximum likelihood – Random-effects probit: regressions including only individuals who stay with the insurance company for the full five years

Variable	Coefficient	t Statistic
Constant	-1.6946	-14.604
SexF	0.74864E-01	1.142
Ccode2	-0.32607	-3.783
Ccode3	-0.14704	-1.451
Ccode4	-0.47079	-3.620
Ccode5	-0.33840	-2.281
Ccode6	0.34664E-01	0.357
Ccode7	-0.18061	-1.845
Ccode8	-0.57369	-3.524
Ccode9	-0.81318	-6.076
Ccode10	-0.74067	-2.462
Ccode11	-0.58892	-4.140
Ccode12	-1.1842	-2.773
Ccode13	-0.52158	-2.659
Ccode14	-0.65862	-2.629
5Horsepower	0.18201E-01	0.245
6Horsepower	-0.67937E-01	-0.712
7Horsepower	0.10474	1.228
8Horsepower	0.17925E-01	0.186
9Horsepower	-0.12236E-01	-0.094
10Horsepower	0.21450E-01	0.147
Fire	0.23047	1.913
Damage	-0.89003E-01	-0.324
Theft	0.71111E-01	0.613
Italy	-0.51974E-02	-0.051
Germany	0.60845E-01	1.085
England	-0.73804E-01	-0.251

Asia	0.76329E-01	0.310
Eastern Europe	0.42334	1.511
Difbrands	-3.4037	-0.001
Reform92	-0.21060	-2.984
Postref	0.82627E-01	1.312
Preref	-0.19356E-01	-0.292
ρ	0.15986	3.436
Log-Likelihood	-2206.093	
Number of individuals	2,010	
Number of observations	10,050	

Table 5

Regression 2 - Maximum likelihood – Random-effects probit: regressions including only individuals who switch insurance company during the period under study

Variable	Coefficient	t Statistic
Constant	-1.4707	-26.582
SexF	-0.47218E-01	-1.658
Ccode2	-0.16398	-5.074
Ccode3	-0.20102	-3.954
Ccode4	-0.36897	-5.573
Ccode5	-0.24698	-3 .361
Ccode6	-0.26367E-01	-0.543
Ccode7	-0.3224E-01	-0.672
Ccode8	-0.42649	-6.444
Ccode9	-0.61634	-11.124
Ccode10	-0.33341	-3.300
Ccode11	-0.31612	-5.411
Ccode12	-0.59167	-5.210
Ccode13	-0.40258	-6.030
Ccode14	-0.76314	-7.487
5Horsepower	0.18503E-01	0.560
6Horsepower	0.122003	3.052
7Horsepower	0.97208E-01	2.620
8Horsepower	0.23035	5.512
9Horsepower	0.11844	2.369
10Horsepower	0.16812	2.903
Fire	-0.24058E-01	-0.536
Damage	0.55725	10.098
Theft	0.10134	2.338
Italy	-0.10508E-01	-0.239
Germany	0.18895E-01	0.741
England	0.46991E-01	0.407

Asia	0.72929E-01	0.949
Eastern Europe	0.80882E-01	0.548
Difbrands	0.13212	1.333
Reform92	-0.62517E-01	-1.785
Postref	-0.12275E-01	-0.440
Preref	-0.44344E-01	-1.192
ρ	0.99559E-01	2.493
Log-Likelihood	-9179.238	
Number of individuals	23,356	
Number of observations	36,287	

Table 6

Regression 3 - Maximum likelihood – Random-effects probit: regressions including only individuals who switch insurance company during the period under study, with introduction of period variables to capture the effects specifically linked to time and individual exposure to risk

Variable	Coefficient	Statistique t
Constant	-2.0733	-9.523
SexF	-0.5018E-01	-1.851
Ccode2	-0.15619	-5.048
Ccode3	-0.19230	-3.944
Ccode4	-0.35028	-5.570
Ccode5	-0.24211	-3.448
Ccode6	-0.2857-E01	-0.620
Ccode7	-0.30379E-01	-0.665
Ccode8	-0.40081	-6.331
Ccode9	-0.58400	-10.938
Ccode10	-0.32213	-3.299
Ccode11	-0.29851	-5.307
Ccode12	-0.56073	-5.110
Ccode13	-0.37270	-5.791
Ccode14	-0.69260	-6.967
5Horsepower	0.17245E-01	0.547
6Horsepower	0.11766	3.133
7Horsepower	0.93265E-01	2.632
8Horsepower	0.22182	5.560
9Horsepower	0.11475	2.405
10Horsepower	0.16530	2.988
Fire	-0.25150E-01	-0.580
Damage	0.53488	10.335
Theft	0.94515E-01	2.259
Italy	-0.51001E-02	-0.122

Germany	0.18750E-01	0.770
England	0.50719E-01	0.457
Asia	0.68681E-01	0.940
Eastern Europe	0.68169E-01	0.487
Difbrands	0.12864	1.365
Period90	0.18498E-02	3.111
Period91	0.20043E-02	3.121
Period92	0.84076E-03	1.836
Period93	0.11380-E02	3.256
Period94	0.10545E-02	2.989
Reform92	0.29725	1.116
Postref	-0.10337	-0.512
Preref	-0.94719E-01	-0.304
ρ	0.43062E-01	0.988
Log-Likelihood	-9157.324	
Number of individuals	23,356	
Number of observations	36,287	

Table 7

Regressions 4,5,6 - Maximum likelihood – regression with all individuals and all explanatory variables from regression 3, plus two indicative variables for entries and exists (Entry and Exit)

Variable	Random-effects probit Regression 4		Random-effects Poisson Regression 5		Random-effects, negative binomial Regression 6	
	Coefficient	**t Statistic**	**Coefficient**	**t Statistic**	**Coefficient**	**t Statistic**
Alpha			1.973	71.546		
A					157.653	2.3029
B					2.569	4.147
Constant	-2.255	-10.251	-4.371	-9.380	-0.237	-0.327
SexF	-0.21819E-01	-0.909	-0.051	-1.135	-0.050	-1.035
Ccode2	-0.183	-6.448	-0.380	-6.954	-0.378	-6.459
Ccode3	-0.184	-4.390	-0.310	-4.119	-0.308	-3.786
Ccode4	-0.368	-6.749	-0.748	-6.637	0.758	-6.289
Ccode5	-0.257	-4.263	-0.485	-4.142	-0.490	-3.889
Ccode6	-0.52496-E02	-0.133	-0.062	-0.822	-0.064	-0.795
Ccode7	-0.62839-E01	-1.593	-0.054	-0.761	-0.058	-0.751
Ccode8	-0.433	-7.543	-0.883	-7.058	-0.884	-6.708
Ccode9	-0.623	-12.927	-1.295	-11.567	-1.288	-11.114
Ccode10	-0.393	-4.366	-0.845	-4.358	-0.853	-4.158
Ccode11	-0.351	-7.026	-0.675	-6.728	0.674	-6.343
Ccode12	-0.626	-6.066	-1.333	-5.518	-1.339	-5.329
Ccode13	-0.401	-6.740	-0.784	-6.139	-0.785	-5.833
Ccode14	-0.682	-7.564	-1.346	-6.463	-1.398	-6.227
5Horsepower	0.17685E-05	0.634	0.058	1.097	0.056	0.985
6Horsepower	0.82972E-01	2.466	0.192	2.980	0.194	2.827
7Horsepower	0.88825E-01	2.833	0.221	3.660	0.219	3.390
8Horsepower	0.17434	4.933	0.367	5.364	0.366	4.984
9Horsepower	0.83289E-01	1.921	0.196	2.346	0.199	2.218
10Horsepower	0.13072	2.626	0.350	3.847	0.351	3.549
Fire	0.25962E-01	0.660	-0.009	-.1060	0.001	0.016
Damage	0.490	9.979	0.913	12.109	0.904	10.454
Theft	0.105	2.759	0.243	3.031	0.246	2.911

Italy	-0.40821E-02	-0.109	-0.012	-0.1670	-0.007	-0.092
Germany	0.28292E-01	1.334	0.050	1.221	0.049	1.131
England	0.26564E-01	0.261	-0.016	-0.083	-0.009	-0.046
Asia	0.79360E-01	1.159	0.007	0.054	0.001	0.009
Eastern Europe	0.162	1.430	0.348	1.739	0.348	1.596
Difbrands	0.6264E-01	0.701	0.004	0.021	-0.001	-0.003
Reform92	0.310	1.165	0.839	1.565	0.808	1.469
Entry	0.54969E-01	2.545	0.081	1.686	0.079	1.554
Exit	0.100	4.223	0.198	4.414	0.197	4.182
Period90	0.21190E-02	3.548	0.005	3.933	0.005	3.773
Period91	0.22982E-02	3.563	0.005	4.177	0.005	4.047
Period92	0.91478E-03	1.997	0.002	2.428	0.002	2.336
Period93	0.14296E-02	3.947	0.002	2.937	0.002	2.837
Period94	0.14977E-02	4.027	0.003	3.232	0.003	3.117
Postref	-0.172	-0.853	-0.130	-0.322	-0.137	-0.324
Preref	-0.127	-0.408	-0.219	-0.343	-0.229	-0.352
ρ	0.43062E-01	1.427				
Log-Likelihood	-11,402.92		-10,830.499		-10,828.391	
Number of individuals	25,366		25,366		25,366	
Number of observations	46,337		46,337		46,337	