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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 results of the Tunisian experiment are now of particular importance since, during the last decade, many European countries decided to eliminate their bonus-malus scheme. These results indicate that the bonus-malus system reduced the probability of reported accident for good risks but had no effect on that of bad risks. Moreover, the overall effect of the reform on reported accidents rates is not statistically significant. This finding is explained by the fact that bad risks can switch to another insurer so as to escape the incentive effect imposed by the new rating policy. Many control variables are statistically significant in explaining the number of reported accidents: the vehicle's horsepower, the policyholder's place of residence, exits from the insurer portfolio, and the coverages for which policyholders are underwritten. The coefficient of the predicted exit variable is positive in explaining the number of accidents. This indicates that policyholders who switch company are higher risks. The final results were obtained by introducing random individual-specific effects to make joint estimates of the accident and selection equations.

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

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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. 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 five 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. We used the data to estimate the relative importance of factors explaining the number of accidents occurring in the period studied and to see whether, upon comparison of the pre- and post- reform periods, the bonus-malus system proved optimal in reducing the frequency of 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 accidents. Its introduction would serve as a unique laboratory experiment, since the Tunisian private market had no bonus-malus system 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 bonus-malus scheme. In 1994, the European Union decreed that all its member countries must drop their bonus-malus systems, claiming that such systems reduced competition between insurers from different countries. Since that date, Belgium, for example, has dropped its system. However, the French system is, to date (2004), still operating. French insurers are trying to convince the European Community that their bonus-malus system is transparent and competitive (see Dionne, 2001, for more details on different countries in Europe).

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; 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 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 only the frequency of accidents observed over time comes into play, the objective being to evaluate as faithfully as possible the true distribution of accidents related to unchanging characteristics. The second role is linked to moral hazard and 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.

Use of a bonus-malus system is also justified by the call for equity in insurance pricing which would consist in having policyholders pay premiums that correspond to their level of risk. (Lemaire, 1995; Dionne and Vanasse, 1989, 1992).

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 accidents. The next step will involve using models compatible with panel data (Hausman et al., 1984; Hsiao, 1986; Dionne et al., 1998), to evaluate what impact a bonus-malus system might have 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 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 automobile insurance market

The overall insurance market

In 2002, insurance products accounted for only 1.8% of Tunisia's G.D.P. (share that the industry's total real-term sales represent in the country's Gross Domestic Product), as compared to 6.7% 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) amounted to a 14.33% growth rate, as compared to 5.73% in 2001 and 11.60% 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, 3 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% in 2000, as compared to 38.9% for the public sector and 14.4% for the mutual and cooperative sector.

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

In 2002, the transportation, diverse risks, automobile, and life branches experienced the highest growth rates, with 26.53%, 24.72%, 15.97%, and 13.87%, respectively. In 2002, claims settled for automobile and group health insurance represented 77.14% of all settlements, as compared to 64.5% in 1992. The premiums collected for these two branches represented 60.80% in 2002.

In 2002, automobile insurance premiums represented 43% of total sales, as compared to 32.72% in 1992. For the automobile branch, the ratio of claims to paid-up premiums (not counting management fees) increased from 94.92% in 2001 to 116.32% in 2002, whereas it was 130.95% in 1993.

The automobile insurance market

The rating system used for automobiles in Tunisia is essentially based on horsepower plus a bonus-malus system 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 deficit of 42 million Tunisian dinars (TD: 1 TD = US$ 0.67), 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 for bodily injuries and 50 billion for material damages. These figures naturally appear rather high for a country numbering only nine million inhabitants, especially when compared with data from other countries (see Table 1). Our calculations place Tunisia eighth on the list of risky countries (see Smith, 2004, for a recent comparison between different countries).

(Table 1, about here)

The seriousness of accidents has remained at a more or less constant level (Table 2), despite the efforts made (building and repairing roads, improving emergency response services, surveillance, safe driving campaigns) by public authorities to lower this level. The National Traffic Observatory explains this as 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 accidents (33.69%), followed by motorcyclists and pedestrians. We do, however, observe a decline in deaths per capita. The Observatory has also found that accidents involving drivers between the ages of 20 and 30 accounted for 30% of all accidents in 1993, compared with 27% for those in the 31 to 40 age range and 11% for those over 51. Again in 1993, women were involved in only 3.31% of accidents while they represented about 15% of drivers.

(Table 2, about here)

As concerns the geographical distribution (Table 3) of accidents, we note 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 accident.

(Table 3 about here)

The 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 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 4. It is interesting to observe that the bonus-malus scheme is very close to the former (1971) Belgian system (Lemaire, 1985).

(Table 4, 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. 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 accident-free years.

- 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 therefore 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 accidents with third-party responsibility. For policyholders who stay with their insurer, the maximum class is 17.

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. A policyholder having accidents at fault each year can stay in class 14 for his life as long he changes insurer each year! This particular aspect of the plan will be very important when interpreting the findings. To our knowledge, there are no transition rules such that an accident does not matter after two claim-free years as it was in Belgium. There is a similar rule in the current French system.

Table 5 shows the third-party liability premiums for privately operated vehicles, according to their bonus-malus class and in Tunisian dinars.

(Table 5, about here)

Several aspects of the bonus-malus system 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 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). These experts also call attention to the excessively long waits for claim settlements. For their part, insurers complain that the bonus-malus system applies to only one category of vehicles, representing only a third 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 bonus-malus system introduces the appropriate incentives.

2. Description of data, variables and econometric models

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 (third-party 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 variables for entries and exits, while also accounting for the selection-bias problem encountered when panel data are used. One model will consider jointly the 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 accidents at fault 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 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 an automobile accident, taking no account of its seriousness but factoring in the policyholder's liability (the Tunisian bonus-malus system is based on third-party liability). The variable that we try to explain is the following dependent variable: number of yearly claims with third-party liability for each policyholder. Usually not exceeding four, this count variable has non-negative 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 6: (for more details, see Dionne and Ghali, 2003).

The variables Entry and Exit were estimated, for each year, by using the probit model. They must normally have estimated coefficients in the accidents model 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 exits as purely random.

(Table 6, about here)

Four types of random individual-specific effects regressions for 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 estimation of accident and selection models was made to verify how potential selectivity bias might affect 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 estimated entries and exits variables—Entry and Exit.

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

Regression 7: Joint estimates of 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 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 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 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, 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 7).

(Table 7, about here)

Independence between the different observations is a necessary condition when using the maximum-likelihood method to make estimation 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).

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 individual-specific effects models.

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

3. Econometric results

Descriptive statistics

Table A, in Appendix, presents the main statistics of our data set. The first line gives the average number of accidents with third-party liability while the second shows the frequency of having more than one accident. The two statistics and their standard deviation are very similar. The annual accident rates at-fault in the portfolio from 1990 to 1994 are respectively: 0.084, 0.082, 0.071, 0.074, 0.073.

The third line indicates the average presence of an individual in the data set over the five 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 over the five years are 39% and 38%. The exits and entries are particularly high after 1992. For example, in 1991, 32% of subjects were new clients while 37% subjects left at the end of the contract-year. In 1993, the numbers are respectively 49% and 43%. 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 accidents. Fifteen percent of the policyholders are from the city of Tunis (Ccode2), 29% of the insured cars are in the category 5horsepower and only 2% of drivers are insured for property damages. Twenty-eight percent of the vehicles come from Germany, and the average duration of contracts is 350 days. Sixty-eight percent of the observations were made after the reform and the repartition of the days are quite evenly distributed over the years, although we do observe more days per period after 1992.[3] Finally, the probability of entry for the average individual (at the mean of all explanatory variables in the probit model) is 44% whereas that of exit is 41%.

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 8 and 9). 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 8) or when all risks are lumped together (Table 9).

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, these two regions are very close to Tunis, Tunisia's most populous city and the one used as reference group.

[3] These numbers per year are much lower than 365 days because the variable is from an interaction between Contract duration and Year (see PeriodYear in Table 6).

(Table 8, 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 8); 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.

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).

The variables PeriodYear, representing an interaction between contract duration 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.

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.

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

Econometric results linked to bonus-malus rating

As for the Reform92 variable, its coefficient is negative and significant for the first regression (at the 95% threshold, Table 8) and moderately significant for the second regression (90%, Table 8). However, the coefficient is no longer significant when the PeriodYear variables capturing the risk exposure effect are introduced into the model (Table B in Appendix). This result may be explained by the flaw in the class-14 clause of the bonus-malus scheme.

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 Exit variable obtained for these regressions confirm this interpretation of the results.

(Table 9, about here)

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 99% 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 99%, 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 (Appendix B) 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 exits (Entry, Exit). The ρ of this regression is not significant.

Besides, the Exit variable is significant with a positive sign, which also proves that there is a bias upon exit which must be taken into account by the model. The fact that the sign of the coefficient linked to this variable 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. 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 last two 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.

From Table 9, we observe that, whereas the predicted entry variable is not significant, the predicted exit variable is significant. To complete the analysis, we propose, in Table 10, a joint estimation of two probit models—one for exit and one for accidents—which can account even more explicitly for the panel aspect of the data. This estimation is in the spirit of Dionne et al. (1998). The period-by-period estimated variables included in Table 9 already test for the presence of any entry and exit bias. We could also have used dummy variables. 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 is 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 9 was also estimated with 34,890 observations. The results are not presented here but are mainly identical to those in Table 9.

(Table 10, about here)

The statistical results in Table 10 are similar to those of Table 9 regarding the 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 Tunis exit more often; subscribers to fire and theft insurance as well as owners of German made cars exit less often. 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 was assumed that, as usual in the literature, the random and disturbance effects would not be correlated. It seems that the potential exit bias of the previous regression (Table 9) is not strong enough to affect the conclusion concerning effect of the new bonus-malus scheme on accidents since the estimated coefficients for the reform are almost the same between the two probit accident regressions of Tables 9 and 10.

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, whereas the new bonus-malus rating system introduced in 1992 did reduce the probability that good risks would be involved in an accident (Regression 1), it did not reduce that probability for bad risks (Regression 3). When we consider all risks together (Regressions 4,5,6,7), 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 company. The very significant Exit variable in regressions 4, 5, and 6 confirms 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. 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 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 individual-specific effects and indicative variables representing entries and exits and time effects. We also estimated jointly the accident and selection equations with random individual-specific effects to control for potential bias on the results explained by the fact that some determinants of the selection equations (observed or not) may have affected the effects of the determinants of the accident equation. The results indicate that the potential bias were not strong enough to affect our conclusion concerning the effect of the 1992 bonus-malus scheme on accidents.

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Appendix

Table A
Descriptive statistics

Variable	Mean	Std Dev	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	0.385	0.486	0	1.000
Exit	0.384	0.486	0	1.000
Contract period	350.259	50.563	6.000	365.000
Reform92	0.676	0.468	0	1.000
Year90	0.163	0.369	0	1.000
Year91	0.161	0.368	0	1.000
Year92	0.208	0.406	0	1.000
Year93	0.221	0.415	0	1.000
Year94	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
Preref	0.161	0.368	0	1.000
Postref	0.468	0.499	0	1.000
prob_entry	0.436	0.156	0.045	0.893
prob_exit	0.406	0.208	0.027	0.944
Number of observations	46,337			

Table B

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	t-Statistic
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 1
Traffic 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

Table 2
Evolution of number of accidents and of their victims during the 1989-2000 period

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

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

Table 3
Number of accidents and victims according to government districts in 1995

Government district	Number of accidents	Number of deaths	Number of injured
Sfax	1,115	130	1,365
Tunis	1,030	137	1,387
Nabeul	919	132	1,234
Sousse	912	96	1,168
Ariana	720	64	835
Bizerte	705	96	95
Ben Arous	560	73	805
Monastir	505	50	617
Médenine	431	90	540
Mahdia	425	59	555
Gabès	369	48	461
Kairouan	357	45	422
Béja	314	54	491
Gafsa	295	36	361
Sidi Bouzid	266	46	382
Jendouba	263	33	333
Kasserine	206	34	253
Kef	193	26	236
Siliana	179	20	240
Zaghouan	107	20	156
Tataouine	103	9	143
Kébili	70	15	81
Tozeur	69	5	73
Total	**10,113**	**1,318**	**13,089**

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

Table 4
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 5
Third-party 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 6
Explanatory variables

Variable	Definition
Horsepower:	Seven dichotomous categories describing the vehicle's horsepower. The group 4horsepower 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:	3 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 five years. These variables represent an interaction between the "Contract duration" 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.
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.
Entry:	Estimates the probability that the individual takes out a new insurance policy with the company (probit model).
Exit:	Estimates the probability that the policy is cancelled with the insurance company (probit model).

Table 7
Frequency of individuals with k accidents at-fault over the four-year period

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 8

Regressions 1 and 2 - Maximum likelihood – Random-effects probit: regressions separating individuals who stay with the insurance company for the full five years from those who switch from one insurer to another during the same period.

Variable	Individuals who stay		Individuals who switch	
	Coefficient	t-Statistic	Coefficient	t-Statistic
Constant	-1.6946	-14.604	-1.4707	-26.582
SexF	0.74864E-01	1.142	-0.47218E-01	-1.658
Ccode2	-0.32607	-3.783	-0.16398	-5.074
Ccode3	-0.14704	-1.451	-0.20102	-3.954
Ccode4	-0.47079	-3.620	-0.36897	-5.573
Ccode5	-0.33840	-2.281	-0.24698	-3.361
Ccode6	0.34664E-01	0.357	-0.26367E-01	-0.543
Ccode7	-0.18061	-1.845	-0.3224E-01	-0.672
Ccode8	-0.57369	-3.524	-0.42649	-6.444
Ccode9	-0.81318	-6.076	-0.61634	-11.124
Ccode10	-0.74067	-2.462	-0.33341	-3.300
Ccode11	-0.58892	-4.140	-0.31612	-5.411
Ccode12	-1.1842	-2.773	-0.59167	-5.210
Ccode13	-0.52158	-2.659	-0.40258	-6.030
Ccode14	-0.65862	-2.629	-0.76314	-7.487
5Horsepower	0.18201E-01	0.245	0.18503E-01	0.560
6Horsepower	-0.67937E-01	-0.712	0.122003	3.052
7Horsepower	0.10474	1.228	0.97208E-01	2.620
8Horsepower	0.17925E-01	0.186	0.23035	5.512
9Horsepower	-0.12236E-01	-0.094	0.11844	2.369
10Horsepower	0.21450E-01	0.147	0.16812	2.903
Fire	0.23047	1.913	-0.24058E-01	-0.536
Damage	-0.89003E-01	-0.324	0.55725	10.098
Theft	0.71111E-01	0.613	0.10134	2.338
Italy	-0.51974E-02	-0.051	-0.10508E-01	-0.239
Germany	0.60845E-01	1.085	0.18895E-01	0.741

England	-0.73804E-01	-0.251	0.46991E-01	0.407
Asia	0.76329E-01	0.310	0.72929E-01	0.949
Eastern Europe	0.42334	1.511	0.80882E-01	0.548
Difbrands	-3.4037	-0.001	0.13212	1.333
Reform92	-0.21060	-2.984	-0.62517E-01	-1.785
Postref	0.82627E-01	1.312	-0.12275E-01	-0.440
Preref	-0.19356E-01	-0.292	-0.44344E-01	-1.192
ρ	0.15986	3.436	0.99559E-01	2.493
Log-Likelihood	-2206.093		-9179.238	
Number of individuals	2,010		23,356	
Number of observations	10,050		36,287	

Table 9

Regressions 4,5,6 – Maximum likelihood – regression with all individuals and all explanatory variables from regression 3, plus two indicative variables for entries and exits (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			1.581	72.863		
A					244.285	1.156
B					1.736	6.843
Constant	-2.146	-9.664	-4.063	-8.880	0.889	0.848
SexF	-0.155E-01	-0.643	-0.046	-1.126	-0.046	-0.977
Ccode2	-0.182	-5.551	-0.348	-6.019	-0.348	-5.484
Ccode3	-0.192	-4.601	-0.384	-5.343	-0.384	-4.716
Ccode4	-0.371	-6.721	-0.728	-6.914	-0.734	-6.310
Ccode5	-0.274	-4.492	-0.489	-4.464	-0.494	-4.036
Ccode6	-0.866E-02	-0.219	-0.007	-0.109	-0.009	-0.112
Ccode7	-0.677E-01	-1.712	-0.090	-1.365	-0.093	-1.224
Ccode8	-0.442	-7.509	-0.890	-7.644	-0.891	-7.091
Ccode9	-0.633	-12.908	-1.369	-13.095	-1.365	-12.429
Ccode10	-0.408	-4.492	-0.800	-4.658	-0.800	-4.332
Ccode11	-0.363	-7.201	-0.742	-7.741	-0.742	-7.133
Ccode12	-0.645	-6.252	-1.312	-5.930	-1.315	-5.645
Ccode13	-0.418	-6.496	-0.833	-6.759	-0.835	-6.335
Ccode14	-0.692	-7.600	-1.411	-7.438	-1.438	-7.073
5Horsepower	0.163E-01	0.584	0.043	0.893	0.042	0.766
6Horsepower	0.841E-01	2.448	0.154	2.577	0.155	2.294
7Horsepower	0.857E-01	2.721	0.179	3.207	0.178	2.819
8Horsepower	0.167	4.663	0.337	5.387	0.336	4.721
9Horsepower	0.713E-01	1.632	0.154	2.020	0.155	1.780
10Horsepower	0.126	2.510	0.264	3.183	0.264	2.740
Fire	0.398E-01	0.993	0.038	0.524	0.044	0.550
Damage	0.479	9.344	0.936	13.222	0.933	10.572
Theft	0.108	2.529	0.206	2.687	0.207	2.483
Italy	-0.767E-02	-0.204	-0.039	-0.590	-0.037	-0.500

Germany	0.378E-01	1.752	0.076	2.024	0.075	1.751
England	0.357E-01	0.352	0.052	0.322	0.055	0.297
Asia	0.947E-01	1.375	0.157	1.351	0.155	1.152
Eastern Europe	0.163	1.421	0.254	1.314	0.256	1.112
Difbrands	0.584E-01	0.649	0.113	0.718	0.113	0.621
Reform92	0.303	1.137	0.764	1.449	0.751	1.379
Entry	-0.117	-0.902	-0.285	-1.234	-0.290	-1.191
Exit	0.268	4.300	0.540	4.861	0.541	4.470
Period90	0.174E-02	2.948	0.004	3.358	0.004	3.236
Period91	0.192E-02	3.015	0.005	3.646	0.004	3.533
Period92	0.620E-03	1.370	0.001	1.797	0.001	1.721
Period93	0.104E-02	3.004	0.002	3.745	0.002	3.589
Period94	0.102E-02	2.925	0.002	3.719	0.002	3.558
Postref	-0.136	-0.678	-0.284	-0.786	-0.283	-0.749
Preref	-0.121	-0.389	-0.256	-0.407	-0.258	-0.401
ρ	0.431E-01	1.421				
Log-Likelihood	-11,409.16		-12,299.17		-12,298.53	
Number of individuals	25,366		25,366		25,366	
Number of observations	46,337		46,337		46,337	

Table 10

Regression 7 – Simultaneous analysis of accident probability and exit decision with panel modelization

	Accident probability		**Exit decision**	
Parameter	**Estimate**	**t-Statistic**	**Estimate**	**t-Statistic**
Constant	-2.715	-10.490	0.163	5.386
SexF	-0.417	-1.183	-0.131	-5.635
Ccode2	-0.227	-5.499	0.408	16.420
Ccode3	-0.186	-3.118	0.175	4.686
Ccode4	-0.455	-5.837	-0.198	-4.043
Ccode5	-0.337	-3.873	0.136	2.546
Ccode6	-0.059	-0.999	-0.558	-1.300
Ccode7	-0.012	-0.209	0.036	0.907
Ccode8	-0.509	-6.066	0.403	9.234
Ccode9	-0.667	-10.059	0.369	12.020
Ccode10	-0.492	-3.858	0.462	7.792
Ccode11	-0.387	-5.506	0.167	4.517
Ccode12	-0.726	-5.224	0.381	5.946
Ccode13	-0.407	-4.954	0.760	17.435
Ccode14	-0.782	-6.197	0.368	6.398
5Horsepower	0.067	1.655	0.526	2.150
6Horsepower	0.179	3.655	0.154	5.049
7Horsepower	0.158	3.435	0.179	6.650
8Horsepower	0.278	5.446	0.234	7.594
9Horsepower	0.152	2.431	0.328	8.946
10Horsepower	0.235	3.197	0.220	4.687
Fire	-0.000	-0.002	-0.259	-8.520
Damage	0.580	7.587	0.396	5.791
Theft	0.124	2.227	-0.448	-15.697
Italy	-0.001	-0.015	0.015	0.442
Germany	0.011	0.355	-0.233	-11.665
England	-0.025	-0.158	-0.120	-1.359
Asia	0.041	0.396	-0.100	-1.359
Eastern Europe	0.294	1.901	-0.349	-2.891
Difbrands	0.005	0.041	0.128	1.310
Reform92	0.461	1.457		

Entry	-0.020	-0.552		
Period90	0.003	3.850		
Period91	0.003	3.765		
Period92	0.001	2.259		
Period93	0.002	3.139		
Preref	-0.073	-0.198		
Postref	-0.343	-1.085		
Number of observations	34,890			
Correlation	Coefficient		t-Statistic	
ρ_μ	-0.083		-0.677	
ρ_ε	0.415		4.572	