Journal of Business and Economics, ISSN 2155-7950, USA
June 2019, Volume 10, No. 6, pp. 517-530
DOI: 10.15341/jbe(2155-7950)/06.10.2019/003

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Automobile Insurance: Analysis of the Impact of a Premium Change on the Behavior of Insured at the Time of Subscription and Termination

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Abstract: the subscription of an insurance contract allows an individual to take precautions against the repercussions of hazards and fortuitous events affecting their person or property. In return for this insurance policy, the insured pays a contribution at the beginning of the coverage period, while the insurer may have to provide a service if a certain type of damage occurs during the period in question. While the insurance market acts both on the insured by being able to induce him to terminate his insurance contract, in the case of excessive prices to those of other insurers, and on the insurer by forcing him to a certain extent to make his insurance premiums tolerable. It therefore appears that the insurance premium risk threatens the competitiveness of insurers on the insurance market and the termination of policyholders at the end of the contract term.

By choosing to work on automobile insurance market, which is becoming increasingly competitive, as precise premium pricing is a major challenge for each insurer. The aim of this work is to study the sensitivity of insured persons to positives changes in automobile insurance premiums at the end of the contract.

Key words: automobile insurance; customer behavior; generalized linear model; logistic regression probability of termination; sensitivity to insurance premium variations

JEL: M310

1. Introduction

The act of subscribing to an insurance contract allows an individual to take precautions against the repercussions of hazards and fortuitous events affecting their person or property. In return for this insurance policy, the insured pays a contribution at the beginning of the coverage period, while the insurer may have to provide a service if a certain type of damage occurs during the period in question. Therefore, the insurance contract is an agreement in which a part guarantees a risk in exchange for the payment of a premium. Besides these two elements of the insurance contract, there is a third impersonal component, which is the market. The market acts both on the insured and the insurer, by being able to induce the former to terminate his insurance contract, in the case of excessive prices compared to those of other insurers, and on the insurer by forcing him to a certain extent to bring down his insurance premiums to a reasonable proportion. It therefore appears that the insurance premium risk threatens the competitiveness of insurers on the insurance market and the termination of policyholders at the

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end of the period.

Competitiveness in the insurance market is a barrier for insurers to charge high prices for insurance coverage. Indeed, the insurance premium is calculated according to the specific characteristics of the insured and the insurable property. While the insured is tempted to terminate his insurance contract with the initial insurer if he can negotiate a cheaper contract elsewhere with equivalent coverage.

Very little work has been done on why and when exchange relationships end (Tähtinen & Havila, 2004). In some services, when customers terminate a relationship, the company can incur high costs. Keaveney (1995) reveals that when companies lose a customer, not only they lose future receipts but they also incur costs to find new subscribers. He also announces that customer loyalty makes him less price-sensitive and less expensive. Keaveney and Parthasarathy (2001) find that consumer's changing behavior in service markets can be particularly serious in the case of continuous service, such as insurance. A premature end of the relationship would mean that customers end up costing the company more than they contribute. Customers become intolerant of incoherence or mediocrity and can dissolve the relationship as soon as a problem arises, when they can access information and make the best choices (Roos, 2002).

Two aptitudes can also be distinguished in terms of how consumers perceive the price of a product or service. The first argues that a high price is a good quality argument and vice versa (Dodds et al., 1991; Teas & Agarwal, 2000), while the second suggests that a low-price level can be seen as a sign of good value for money (Kirmani & Rao, 2000). Also, a low price can be perceived as a synonym for poor quality, or high price is considered abusive. When the price is felt to be unfair, the consumer tends to change his supplier (Campbell, 1999; Homburg et al., 2005). According to Keaveney (1995), consumers willingly change their suppliers when they are dissatisfied with the prices paid. Athanassopoulos (2000) and Bansal et al. (2005) agree with Keaveney (1995), and suggest that one of the reasons consumers may change their supplier is excessive pricing. (Wathne et al., 2001), argue that being informed by market opportunities, and the possibility of savings, can become a reason for an immediate replacement of supplier.

The work of Bland et al. (1997), and Kelsey et al. (1998) shows that the termination rate decreases over time. This means that the longer the insured remains in the portfolio, the lower the probability of termination. Termination depends largely on the insured's price flexibility. This price sensitivity depends on the psychological nature of the prices in the first place. In this context, Weber-Fechner's psychophysical law specifies that sensation varies as does the logarithm of excitation. Its transcription in terms of price sensitivity leads us to believe that a successive price increase leads to fewer terminations than a sudden and single price increase. Otherwise, a successive price decrease should encourage the renewal of contracts rather than a single price decrease.

By choosing to work on non-life insurance, the large collection of insurance premiums in this branch is mainly due to the strong presence of automobile insurance, which will be the subject of our study concerning the Rabat-Sale-Kenitra region. The automobile insurance sector has the lion's share and amounts to a turnover of approximately 10,527 million dirhams in 2017, with a growth rate of 5.8% compared to 2016, which reached 9,953.8 million dirhams, and has become the leading market with a 48.40% contribution in the non-life insurance sector, and a 27% contribution to overall insurance turnover in Morocco, as evidenced by the figures of the Moroccan Federation of Insurance and Reinsurance Companies.

Table 1 Total Revenues in Million Dirhams and the Evolution of the Non-life Insurance Branch

	2015	2016	2017	2016/2017
Non-life insurance	19862.9	20806.1	21981.5	5.6%
Physical accidents	3359.5	3652.8	3922.5	7.4%
Work accidents	2090.9	2174.1	2223.0	2.2%
Automobile	**9514.2**	**9953.8**	**10527.0**	**5.8%**
General civil responsibility	544.4	550.2	549.0	-0.2%
Fire	1312.1	1318.4	1331.7	1.0%
Technical risk	393.7	329.4	242.3	-26.4%
Transport	552.3	578.0	604.9	4.7%
Other non-life operations	701.2	734.5	979.4	33.3%
Assistance-Credit-Guarantee	1183.2	1331.1	1415.1	6.3%
Non-life acceptances	211.5	183.8	186.5	1.5%

Source: Moroccan Federation of Insurance and Reinsurance Companies.

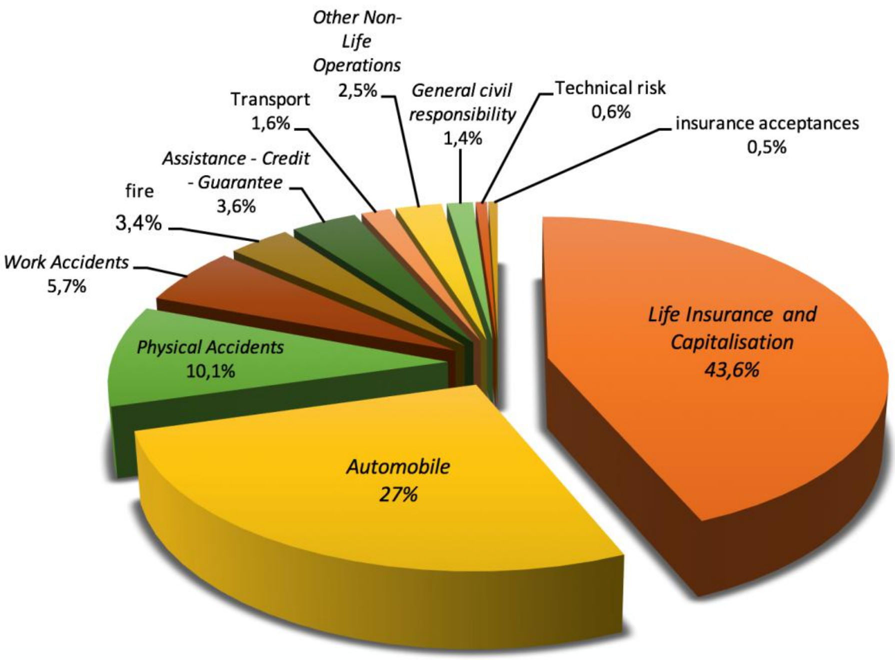

Figure 1 Structure of the Turnover of the Moroccan Insurance Sector in 2017

Source: Moroccan Federation of Insurance and Reinsurance Companies.

The automobile insurance market is becoming increasingly competitive, and accurate premium pricing is a major issue for every insurer. Despite the importance of this market, it is as competitive as it is not easy for an insurer to develop and attract customers while keeping its original policyholders. In this economic context, the price sensitivity of policyholders seems to be a decisive information for an insurance company in order to adjust its rates as effectively as possible. A price that is too high compared to the competition will be an obstacle to subscription or an incentive to terminate it. Consumer's behavior is more difficult to predict because it varies from one individual to another owing to many criteria.

Price sensitivity, which varies greatly from one policyholder to another, has an impact on the subscription and termination rates of contracts as well as on the profitability of the insurance portfolio. The objective of this work is to study the sensitivity of insured persons to changes in automobile insurance premiums. In other words, how important is it for the insured to take the market premium increase into account when deciding whether or not to renew his insurance contract with his current insurer? The aim is therefore to model the impact of premium variations on the insured's behavior at the end of the contract. This study will try to answer the following hypothesis: Changes in insurance premiums have a positive impact on policyholders' intentions to terminate their automobile insurance contracts.

Termination models are based on statistical regression models, the most well-known of which is the logistic model, which is part of the large class of generalized linear models introduced by John Nelder and Robert Wedderburn (1972). Logistic Regression is a modeling technique that, in its most frequent version, aims to predict and explain the values of a binary or dichotomous categorical variable (such as the presence or absence of an event) yi (variable to predict, explained variable, dependent variable, class attribute, endogenous variable) from a collection of continuous or binary X variables (predictive variables, explanatory variables, independent variables, descriptors, exogenous variables). Logistic regression has therefore become an increasingly useful statistical tool, especially over the last two decades, as evidenced by the work of Oommen, Baise and Vogel (2011), although its originals can be dated to the 19th century (Cramer, 2002). It is widely considered to be the statistic of situations in which the occurrence of a binary (dichotomous) result must be predicted (Hosmer & Lemeshow, 2000; King & Zeng, 2001).

2. The Proposed Method

Assume that we have a sample of n independent observations of yi, i = 1, 2..., n. Where yi is a column vector yi = (y1, y2,...,yn) representing the value of a dichotomous outcome variable which means that the result variable yi can take two values 0 or 1, representing the absence or the presence of the studied characteristic respectively. We consider a collection of p independent variables denoted by the matrix X = (X1, X2,...,Xp) where X1, X2,..., Xp are column vectors. And we put β = (β0, β1,..., βp) is a column vector of regression coefficients. In this article, we try to analyze the impact of the positive premium variations on the automobile insured's behavior at the end of the contract term (termination or renewal of the contract). We consider yi (response variable) as a realization of a random variable yi that can take the values 1 in the case of the automobile insurance contract termination or 0 in the case of the automobile insurance contract renovation with probabilities π and 1 − π, respectively. The distribution of yi is called a Bernoulli distribution with parameter π. And we can note yi ~ B (1, π). Let the conditional probability that the outcome is present be denoted by P(yi = 1|X) = π, where X is the matrix of explanatory variables with p column vectors. In our case, with only one explanatory variable (p = 1), the vector X1 represents the positive premium variations, and β = (β0, β1) the vector of regression coefficients. The modeling of response variables that have only two possible outcomes, which are "success" and "failure", is generally done with logistic regression (Agresti, 1996). Termination models are based on statistical regression models, the most well-known of which is the logistic model, which is part of the large class of generalized linear models introduced by John Nelder and Robert Wedderburn (1972). The logit of the logistic regression model is given by the equation:

$$\log it(\pi) = \ln\left(\frac{\pi}{1-\pi}\right) = \sum_{k=0}^{p} \beta_k x_{ik}\text{, where } i = 1, 2, \ldots, n \tag{1}$$

By logit transformation, we have from Equation (1) that:

$$\frac{\pi}{1-\pi} = \exp(\sum_{k=0}^{p} \beta_k x_{ik}) \quad (2)$$

We evaluate Equation (2) to obtain π and 1 − π as:

$$\pi = \exp(\sum_{k=0}^{p} \beta_k x_{ik}) - \pi \exp(\sum_{k=0}^{p} \beta_k x_{ik}) \quad (3)$$

$$\pi + \pi \exp(\sum_{k=0}^{p} \beta_k x_{ik}) = \exp(\sum_{k=0}^{p} \beta_k x_{ik}) \quad (4)$$

$$\pi \left(1 + \exp(\sum_{k=0}^{p} \beta_k x_{ik}) \right) = \exp(\sum_{k=0}^{p} \beta_k x_{ik}) \quad (5)$$

$$\pi = \frac{\exp(\sum_{k=0}^{p} \beta_k x_{ik})}{1 + \exp(\sum_{k=0}^{p} \beta_k x_{ik})} \quad (6)$$

$$\pi = \frac{1}{1 + \exp(-\sum_{k=0}^{p} \beta_k x_{ik})} \quad (7)$$

Similarly,

$$1 - \pi = 1 - \frac{1}{1 + \exp(-\sum_{k=0}^{p} \beta_k x_{ik})} = \frac{1}{1 + \exp(\sum_{k=0}^{p} \beta_k x_{ik})} = \frac{\exp(-\sum_{k=0}^{p} \beta_k x_{ik})}{1 + \exp(-\sum_{k=0}^{p} \beta_k x_{ik})} \quad (8)$$

3. Obtained Parameters β of Non-Linear Equations from Bernoulli Distribution Using Maximum Likelihood Estimation (MLE)

If yi is coded as 0 or 1 then the expression for π given in equation (7) provides the conditional probability that yi is equal to 1 given X and, this will be denoted as P(yi = 1|X). And the quantity 1- π gives the conditional probability that yi is equal to 0 given X, and this will be expressed as P(yi = 0|X). Thus, for yi = 1, the contribution to the likelihood function is π, and for those pairs where yi = 0, the contribution to the likelihood function is 1 − π. A convenient way to express the contribution to the likelihood function in the following way:

$$\pi^{y_i} (1-\pi)^{1-y_i}$$

Here, we estimated the (P+1) unknown parameters β using MLE as:

$$L\left(y_{1,}y_{2,}...,y_n,\pi\right) = \prod_{i=1}^{n} \pi^{y_i}(1-\pi)^{1-y_i}$$

Maximum likelihood is one of the most widely used estimation methods to determine the values of unknown β parameters that maximize the probability of obtaining an observed data set. In other words, the maximum likelihood function explains the probability of the observed data based on unknown β parameters. This method was developed by the english statistician Sir Ronald A. Fisher (1890-1962) in 1920. The goal of the maximum likelihood method is to find β estimates of (P) expressive variable as to make maximum the probability of yi variable observing.

$$L\left(y_{1,}y_{2,}...,y_n,\pi\right) = \prod_{i=1}^{n} \pi^{y_i}(1-\pi)^{1-y_i} = \prod_{i=1}^{n}\left(\frac{\pi}{1-\pi}\right)^{y_i}(1-\pi)$$

Substituting equation (2) for the first term and equation (8) for the second term, to obtain:

$$L\left(y_1,y_2,...,y_n,\beta_0,\beta_1,...\beta_p\right) = \prod_{i=1}^{n}\left(\exp(\sum_{k=0}^{p}x_{ik}\beta_k)\right)^{y_i}\left(1-\frac{\exp(\sum_{k=0}^{p}x_{ik}\beta_k)}{1+(\sum_{k=0}^{p}x_{ik}\beta_k)}\right)$$

But:

$$\frac{\pi}{1-\pi} = \exp(\sum_{k=0}^{p}x_{ik}\beta_k) \text{ and } 1-\pi = 1-\frac{\exp(\sum_{k=0}^{p}x_{ik}\beta_k)}{1+\exp(\sum_{k=0}^{p}x_{ik}\beta_k)}$$

$$L\left(y_1,y_2,...,y_n,\beta_0,\beta_1,...\beta_p\right) = \prod_{i=1}^{n}\left(\exp(y_i\sum_{k=0}^{p}x_k\beta_k)\right)\left(1+\exp(\sum_{k=0}^{p}x_k\beta_k)\right)^{-1}$$

We here simplify the above equation further by taking its Neperian logarithm. Since the logarithm is a monotonic function, any maximum of the likelihood function will also be a maximum of the log likelihood function and vice versa. Thus, taking the natural logarithm of the equation yields the log likelihood function (ι):

$$Ln\left(L\left(y_1,y_2,...,y_n,\beta_0,\beta_1,...\beta_p\right)\right) = Ln\left(\prod_{i=1}^{n}\left(\exp(y_i\sum_{k=0}^{p}x_k\beta_k)\right)\left(1+\exp(\sum_{k=0}^{p}x_k\beta_k)\right)^{-1}\right)$$

$$l\left(y_1, y_2, ..., y_n, \beta_0, \beta_1, ...\beta_p\right) = \sum_{i=1}^{n} y_i \left(\sum_{k=0}^{p} x_{ik}\beta_k\right) - \ln\left(1 + \exp\sum_{i=0}^{p} x_{ik}\beta_k\right)$$

In differentiating the last equation, note that:

$$\frac{\partial}{\partial \beta_k}\sum_{k=0}^{p} x_{ik}\beta_k = x_{ik}$$

$$\frac{\partial l(\beta)}{\partial \beta_k} = \sum_{i=1}^{n} y_i x_{ik} - \frac{1}{1+\exp(\sum_{k=0}^{p} x_{ik}\beta_k)} \cdot \frac{\partial}{\partial \beta_k}\left(1 + \exp\left(\sum_{k=0}^{p} x_{ik}\beta_k\right)\right) \quad (9)$$

$$= \sum_{i=1}^{n} y_i x_{ik} - \frac{1}{1+\exp(\sum_{k=0}^{p} x_{ik}\beta_k)} \cdot \exp\left(\sum_{k=0}^{p} x_{ik}\beta_k\right) \cdot \frac{\partial}{\partial \beta_k}\sum_{k=0}^{p} x_{ik}\beta_k \quad (10)$$

$$= \sum_{i=1}^{n} y_i x_{ik} - \frac{x_{ik}}{1+\exp(\sum_{k=0}^{p} x_{ik}\beta_k)} \cdot \exp\left(\sum_{k=0}^{p} x_{ik}\beta_k\right) \quad (11)$$

$$\text{Since } \pi = \frac{\exp(\sum_{k=0}^{p} x_{ik}\beta_k)}{1+\exp(\sum_{k=0}^{p} x_{ik}\beta_k)} \text{ and } \frac{\partial l(\beta)}{\partial \beta_k} = l'_{\beta_k} = \sum_{i=1}^{n} y_i x_{ik} - \pi . x_{ik} \quad (12)$$

Therefore, the estimation of the $\hat{\beta} = (\hat{\beta}0, \hat{\beta}1, \ldots, \hat{\beta}p)$ parameters that maximize the log likelihood function (ι) can be found by setting each of the P + 1 equations in equation (12) equal to zero and solving for each βk.

Each such solution, if any exists, specifies a critical point either a maximum or a minimum. The critical point will be a maximum if the matrix of second partial derivatives (Hessian matrix) is negative definite, that is, if every element on the diagonal of the matrix is less than zero (Glub & Van, 1996). The Hessian matrix results from taking the second derivative of equation (12). The general form of the matrix of second partial derivatives (Hessian matrix) is:

$$\frac{\partial^2 l(\beta)}{\partial \beta_k \partial \beta_{k'}} = \frac{\partial}{\partial \beta_{k'}}\sum_{i=1}^{n} y_i x_{ik} - x_{ik}\pi \quad (13)$$

$$= \frac{\partial}{\partial \beta_{k'}}(-x_{ik}\pi) \quad (14)$$

$$= -x_{ik}\frac{\partial}{\partial \beta_{k'}}\left(\frac{\exp(\sum_{k=0}^{p} x_{ik}\beta_k)}{1+\exp(\sum_{k=0}^{p} x_{ik}\beta_k)}\right) \quad (15)$$

where:

$$\pi = \frac{\exp(\sum_{k=0}^{p} x_{ik}\beta_k)}{1+\exp(\sum_{k=0}^{p} x_{ik}\beta_k)} = \frac{1}{1+\exp-(\sum_{k=0}^{p} x_{ik}\beta_k)}$$

To solve this Equation (13) we will make use for exponential functions and the rule for quotient of two functions so as to obtain:

$$\frac{d}{dx}\frac{e^{u(x)}}{1+e^{u(x)}} = \frac{(1+e^{u(x)}).e^{u(x)}\frac{d}{dx}u(x) - e^{u(x)}.e^{u(x)}\frac{d}{dx}u(x)}{(1+e^{u(x)})^2} \quad (16)$$

$$= \frac{e^{u(x)}\frac{d}{dx}u(x) + \left(e^{u(x)}\right)^2\frac{d}{dx}u(x) - \left(e^{u(x)}\right)^2\frac{d}{dx}u(x)}{(1+e^{u(x)})^2} \quad (17)$$

$$= \frac{e^{u(x)}\frac{d}{dx}u(x)}{(1+e^{u(x)})^2} \quad (18)$$

$$= \frac{e^{u(x)}}{(1+e^{u(x)})^2}\frac{d}{dx}u(x) = \frac{e^{u(x)}}{1+e^{u(x)}}.\frac{1}{1+e^{u(x)}}.\frac{d}{dx}u(x) \quad (19)$$

Since:

$$\frac{du(x)}{dx} = \frac{d}{dx}\sum_{k=0}^{p} x_{ik}\beta_k = x_{ik'}$$

While π and 1 − π are clearly defined. Thus, Equation (13) can now be written as:

$$l''_{\beta_k\beta'_k} = -x_{ik}.\pi(1-\pi)x_{ik'} \quad (20)$$

4. Result and Discussion

Every vehicle owner is obliged to take out motor insurance with an insurance company approved by the Minister of Finance. This obligation applies only to the guarantee of civil liability. While the other guarantees are optional. Should we expect an increase in insurance premiums for our motor vehicles? This is a question that insurance companies are currently asking themselves in a context of a continuous rise in claims rates and a decline in profitability. In this context, this work will attempt to examine the reaction and behaviour of policyholders towards a likely increase in insurance premiums. For this reason, it was decided to develop an online Survey, addressing the issue of increasing insurance premiums in order to discover the behaviour of policyholders and analyze their sensitivity to this likely change.

The literature indicates that online surveys have many operational benefits. Their costs of use are low (Deutskens et al., 2004; Wang et al., 2013; Ganassali, 2008; Bethlehem, 2008; Stepheson & Crête, 2011; Bigot et al., 2010), and they allow for rapid data collection (Deutskens et al., 2004; Ganassali, 2008; Bethlehem, 2008; Stephenson & Crête, 2011; Bigot et al., 2010). Reminder sending is facilitated by the use of e-mail (Deutskens et al., 2004, p. 21), and Web mode eliminates the risk of data entry errors (Stephenson & Crête, 2011).

Unlike surveys that require the physical presence of respondents, online surveys also have the advantage of allowing respondents to initiate questionnaires at a time and place of their choice, and to complete them within a time frame that is convenient for them (Lindhjem Navrud, 2011; Bigot et al., 2010). In addition, they generally provide a simple and accessible method of data collection for researchers (Bigot et al., 2010). Through email, this type of data collection method also allows for a broader geographical coverage of respondents (Wang et al., 2013; Bethlehem, 2008; Bigot et al., 2010).

The questionnaire used is inspired by the scale developed by Lichtenstein, Ridgway and Netemeyer (1993) dealing with the notion of price perception in its negative and positive role. In this study, we have only used the part that deals with the negative role of price since we are only interested by the price as an indicator of sacrifice. In this scale, the negative role of price is represented through five dimensions, we have retained just two of them which are: Price consciousness representing the degree of consumer interest in low prices, and value consciousness, this dimension is characterized by an interest in the price/quality ratio.

After choosing to work with the online survey as a data collection method, we collected the responses of n = 3390 policyholders in the Rabat-Sale-Kenitra region in 2017 concerning our departure issue which focuses on the sensitivity of policyholders to increases in insurance premiums and their decisions towards these changes at the end of the policy period. This data analysis will be realized by the SPSS software.

Table 2 The Study Datasets

Premium variations	Terminations		Terminations Frequency	Cumulative Frequency
	Yes	No		
[00%-10%[	1870	1520	0,5516	0,5516
[10%-20%[	3190	200	0,3893	0,9409
[20%-30%[	3280	110	0,0265	0,9674
[30%-40%[	3340	50	0,0176	0,9850
[40%-50%[	3390	0	0,0147	0,9998 $\simeq$ 1
Total	$n = 3390$		F $\simeq$ 1	-

We notice that the majority of policyholders terminate their insurance contracts as from an increase of between 10% and 20% in the automobile insurance premium. To analyze the insured's decision regarding positive changes in automobile insurance premiums at the end of the contract term, we consider yi as a realization of a random variable yi that can take the values one and zero with probabilities π and 1 − π, respectively. The distribution of yi is called a Bernoulli distribution with parameter π. And we can note yi ∼ B (1, π).

$$y_i = \begin{cases} 1 & \text{Termination of the automobile insurance contract} \\ 0 & \text{Renewal of the automobile insurance contract} \end{cases}$$

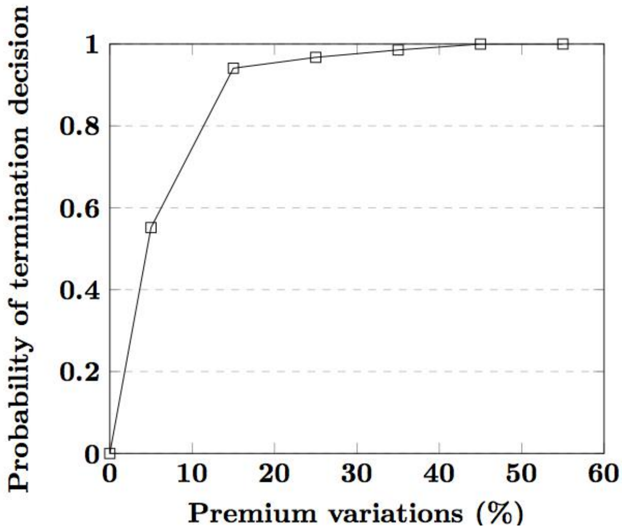

Figure 2 Termination Decision by Premium Variations

We notice that the probability of termination of automobile insurance contracts at the end of their term increases as the insurance premium increases. The curve is joined to 1 (probability of termination decision) as soon as the variation in the premium exceeds 10%. This explains the high sensitivity of the insured sample to the increase in the insurance premium.

Table 3 Variables in the Equation (step: 0).

Premium variations	$\hat{\beta}_0$	E.S.	Wald	df	Sig.	Exp(β_0)
[00%-10%[	,207	,109	3,601	1	,058	1,230
[10%-20%[	2,769	,231	144,348	1	0,000	15,950
[20%-30%[	3,395	,307	122,681	1	0,000	29,818
[30%-40%[	4,202	,451	86,97	1	0,000	66,800
[40%-50%[	5,127	,709	52,261	1	0,000	168,500

The Variables in the Equation table shows us the coefficient for the constant $\hat{\beta}0$not particularly important but we've highlighted the significance level to illustrate a cautionary tale. According to this table the model with just the constant is a statistically significant predictor of the outcome when the $p < 0.001$. However it is only significant starting from the second item (10%-20%) until the last premium variation (40%-50%) where p = 0,000. The reason we can be so confident that our baseline model has some predictive power.

Table 4 Omnibus Tests of Coefficients and Model Summary

		Chi-square	df	Sig
[00%-10%[	Step	23,878	1	0,000
	Bloc	23,878	1	0,000
	Model	23,878	1	0,000
[10%-20%[	Step	162,470	1	0,000
	Bloc	162,470	1	0,000
	Model	162,470	1	0,000
[20%-30%[	Step	228,859	1	0,000
	Bloc	228,859	1	0,000
	Model	228,859	1	0,000
[30%-40%[	Step	309,643	1	0,000
	Bloc	309,643	1	0,000
	Model	309,643	1	0,000
[40%-50%[	Step	379,704	1	0,000
	Bloc	379,704	1	0,000
	Model	379,704	1	0,000

The Omnibus Tests of Model Coefficients is used to check that the new model (with explanatory variables included) is an improvement over the baseline model. It uses chi-square tests to see if there is a significant difference between the Log-Likelihoods of the baseline model and the new model. If the new model has a significantly reduced -2LL compared to the baseline then it suggests that the new model is explaining more of the variance in the outcome and is an improvement. In our case, the second item for example, the chi-square is highly significant (chi-square = 162,470, p = 0,000 < 0,001) so our new model is significantly better.

To make things clear, there are three different versions; Step, Block and Model. The Model row always compares the new model to the baseline. The Step and Block rows are only important if we are adding the explanatory variables to the model in a stepwise or hierarchical manner. If we were building the model up in stages then these rows would compare the -2LLs of the newest model with the previous version to ascertain whether or not each new set of explanatory variables were causing improvements. In our case, we added a single explanatory variable in a single block. This means that the chi-square values are the same for the step, block and model. For all cases, p = 0.000 < 0.001, indicating that the model accuracy improves when we add our explanatory variables.

Table 5 Model Summary

Premium variations	-2LL	Cox & Snell R-Square	Nagelkerke R-Square	-2LL initial
[00%-10%[	446,076	0,068	0,091	469,954
[10%-20%[	307,484	0,381	0,508	469,954
[20%-30%[	241,094	0,491	0,655	469,954
[30%-40%[	160,311	0,599	0,798	469,954
[40%-50%[	90,249	0,674	0,898	469,954

The Model Summary provides the -2LL and pseudo-R2 values for the full model. For example, the -2LL value for the second item in this model (307,484) is compared to the -2LL for the previous null model (469,95) in the "omnibus test of model coefficients" which told us there was a significant decrease in the -2LL, i.e., that our new model (with explanatory variable) is significantly better fit than the null model.

The R2 values tell us approximately how much variation in the outcome is explained by the model (like in linear regression analysis). We prefer to use the Nagelkerke's R2, which suggests that the model explains for example, roughly 50.8% of the variation in the outcome as we see in the second item. We notice that the two versions (Cox Snell and Nagelkerke) are different, this proves that these R2 values are approximations and should not be overemphasized.

Table 6 Variables in the Equation (Step 1).

Premium variations	$\hat{\beta}_0$	$\hat{\beta}_1$	Wald	df	Sig.	Exp($\hat{\beta}_1$)	C.I 95% pour Exp($\hat{\beta}_1$)	
							inf.	**sup.**
[00%-10%[	0,207	-0,318	21,882	1	0,000	0,728	0,637	0,831
[10%-20%[	2,769	1,059	102,417	1	0,000	2,884	2,349	3,541
[20%-30%[	3,395	1,428	117,848	1	0,000	4,169	3,222	5,395
[30%-40%[	4,202	2,004	116,711	1	0,000	7,418	5,157	10,671
[40%-50%[	5,127	2,775	95,39	1	0,000	16,044	9,193	28,003

This table provides the regression coefficient ($\hat{\beta}0$), ($\hat{\beta}1$), the Wald statistic (to test the statistical significance), the all-important Odds Ratio (Exp ($\hat{\beta}1$)) for each variable category, and their confidence intervals (CI). Looking first at the results in "The table of the variable in the equations (step 1)", there is a highly significant overall effect for all the items according to the Wald test, (p = 0.000). The $\hat{\beta}1$coefficients for all items, are significant and positive except the first one which is negative $\hat{\beta}1$ = - 0.318, indicates that the increase in the insurance premium directly influences the decision of termination automobile insurance contracts at the end of their term.

The Exp ($\hat{\beta}1$) column (the odds ratio) indicates that insureds are for example, four (4.169) times more likely to terminate their automobile insurance contract, in the event of an increase in insurance premiums between [20%-30%]. According to our study, we realize that the more the variation in the insurance premium increases, the more the insureds terminates their contract, for example, an increase between [30%-40%] of the premium will generate seven (7.418) times the possibility of termination than to renew their insurance contract, while a decrease in the premium will result in a decrease in the termination rate.

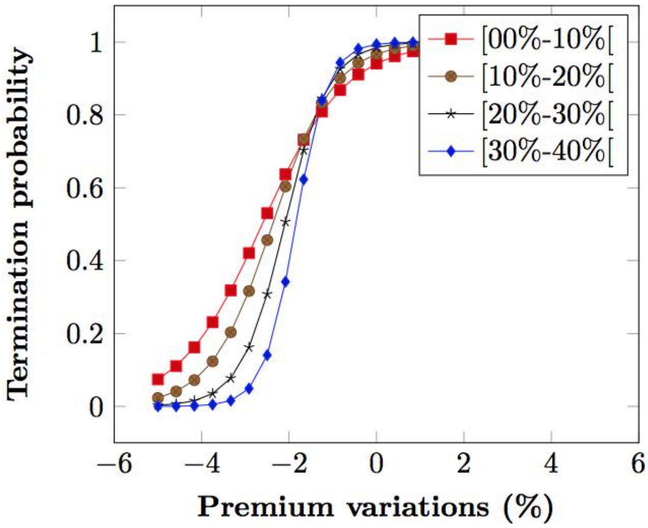

Figure 3 Logistic Fonctions

The logistic function is written as the probability of a success. The response value of 1 on the y-axis represents a success. The plot shows that the probability of a success increases as the insurance premium increases. When the variation in the automobile insurance premium exceeds 10%, the function is joined to 1 (probability of termination decision), which explains the very high sensitivity of the insured sample to the increase in the insurance premium, while the reduction in the insurance premium will generate a logistical function that tends towards 0, which means a high probability of renewal of the insurance contract.

5. Conclusion

Although research on client retention has improved our understanding of the interrelation- ships between customers and their service providers, another version of the dissolution and termination research was also conducted (Bansal & Taylor, 1999; Keaveney, 1995). Our work shows how positive fluctuations in automobile insurance premiums cause a change of insurer at the end of the contract. In our proposed model, we anticipate that positive fluctuations in automobile insurance premiums could determine the intention of insureds to change insurers.

In a context of a sharp increase in the claims ratio and a continuous decline in the profitability of insurance companies, the question that arises today is based on the possibility of increasing the insurance premium, while our work has tried to answer the insured's tolerance level for this increase. In other words, how sensitive policyholders are to positive premium fluctuations. For this reason, it has been proposed to analyze the behaviour of policyholders towards five different and increasing positive changes in motor insurance premiums ([0%-10%], [10%-20%], [20%-30%], [30%-40%], [40%-50%]), as shown in Table 2, to clarify the impact of each variation on the final insured's decision.

The statistical regression model proposed for this study is the logistic model, which is part of the large class of generalized linear models presented by John Nelder and Robert Wedderburn (1972). This analysis was realized by the SPSS software. The results of these studies show the influence of positive changes in the automobile insurance premium in the insured's final decision to continue or terminate his contractual relationship with his insurer. In our case study, we find that policyholders are very sensitive to increases in insurance premiums, especially when the premium increase exceeds 10% of the initial premium paid. In other words, most policyholders tend to terminate their insurance contract once their insurer has decided to increase the initial premium beyond 10%, which shows the low tolerance of policyholders for premium increases.

In the following work, we will attempt to study other factors that may encourage clients to terminate their automobile insurance contract with their current insurer and to measure their impact on their final decision.

Conflict of interest: The authors have no conflicts of interest.

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