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Survival Analysis of a Household Portfolio of Insurance Policies: How Much Time Do You Have to Stop Total Customer Defection?

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Abstract

Customer-side influences on insurance have been relatively ignored in the literature. Using the household as the unit of analysis, this article focuses on the behavior of households having multiple policies of different types with the same insurance company, and who cancel their first policy. How long after the household's cancellation of the first policy does the insurer have to retain the customer and avoid customer defection on all policies to the competition? And, what customer characteristics are associated with customer loyalty? Using logistic regression and survival analysis techniques, an assessment is made of the probability of total customer withdrawal, and the length of time between first cancellation and subsequent customer withdrawal. Using a European database spanning 54 months of household multiple policyholder behavior, the results show that cancellation of one policy is a very strong indicator that other household policies will be canceled. Further, the insurer can have time to react to retain the customer after the first cancellation, however, this time is significantly dependent on the method used to

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contact the company, household demographics, and the nature of the household's insurance policy portfolio. Surprisingly, core customers having three or more policies in addition to the canceled policy are more vulnerable to total defection on all policies than noncore customers. Further, the potential customer repelling effects of premium increases seem to wear out after 12 months. Strategic implications of the results are presented.

INTRODUCTION

It has long been recognized that insurance operates in a marketplace. Yet, the focus of the vast majority of research has been supply-side, emphasizing study of financial and actuarial elements. Very little has been published concerning the dynamics behind customer demand for insurance products.[1] This article expands perspectives on the marketplace to the study of customer behavior.

The Importance of Customer-Side Analysis

A firm must generate sales to survive, and just as actuarial estimations and financial analyses are critical for an insurer's long-term business survival, so too are sales and customer relationship management. In this regard, the firm's sales are not only a function of new customer numbers, but are also of how many existing customers are retained. Managing customer growth and market share requires consideration of customer-side marketplace dynamics in order that customer relationships may be developed and matured.[2]

Persistency Studies and the Importance of the First Notification of Cancellation Signal

Persistency studies have been conducted in life and annuity markets to determine factors correlated with policy lapses (LIMRA International, 2001; Kuo, Tsai, and Chen, 2003; Drinkwater et al., 2002). Although these studies provide customer-side information in the form of sales operations, servicing operations, etc, they are generally conducted using a single policy as the unit of analysis. There has not been a tendency to conduct persistency studies in the property and casualty area, even for single policy units of analysis, although insurance companies do focus on both retention of existing customers and attraction of new customers (Cooley, 2002).

In spite of the lack of attention given to persistency in property and casualty, policy lapses are important there: first, because of the heavier load of expenses in the first

[1] Customer-side influences have been addressed, but to a lesser extent than have supply-side considerations. For example, topics studied are habit formation and the demand for insurance (e.g., Ben-Arab, Briys, and Schlesinger, 1996), consumer perceptions of service quality (Wells and Stafford, 1995; Stafford, Stafford, and Wells, 1998), individual portfolio decisions and demand (Mayers and Smith, 1983), household characteristics (Showers and Shotick, 1994), and demand in the presence of other risks (Doherty and Schlesinger, 1983; Schlesinger and Doherty, 1985; Gollier and Scharmure, 1994).

[2] Insurance has long focused on compensation and marketing techniques, including a comparison of distribution systems, to study methods for providing sales incentives and better customer relationship management (although not necessarily discussed in those terms). Examples of this type of research are Barrese, Doerpinghaus, and Nelson (1995) and Gravelle (1994).

years of a policy, and second, because in multipolicy households, policy cancellation can be a customer behavior that signals purchasing decisions in process or on the customer's decision-making horizon. Often a household will buy multiple policies from the same insurer, and consequently a lapse in one may be a signal of the beginning of the customer's defection to a competitor.

In most cases, lapses signal the customer's brand switching behavior: moving from one insurer/company to another indicates the customer's defection to the competitor in a customer-side market analysis.[3] Customer retention becomes increasingly important when the company sells multiple policies to the same person or household. Whether comprising one individual or several, the household is an appropriate unit of analysis, because insurance purchases are often made as a bundle of products serving multiple risk management needs of the household operating as a decision-making unit.

Focus and Purpose of the Research

This article focuses on customer-side dynamics by analyzing household customer behavior for a bundle of insurance products purchased from a single insurer. Specifically, we focus on households for whom at least one policy has lapsed and investigate the effects for the lapse rates of other policies owned by the same household. Multiple risks, such as are reflected in multiple policies, and household decision making have been shown to be important for understanding customer behaviors (cf. Bonato and Zweifel, 2002; Dionne, Gourieroux, and Vanasse, 2006).

By focusing on the household as the unit of analysis, and upon multiple policy households, we are able to provide useful managerial information on the response time from the first lapse signal to total customer defection (lapse of all policies purchased from the firm). This time frame is a window of opportunity for the firm to stop customer defection through customer relationship management techniques. From a pure financial perspective, it will be less costly for the firm to retain an existing customer, when possible, than it is to attract a new customer or win-back a customer who completed a total defection (cf. Griffin, 2003, 2004). Retention is particularly important because the most undesired consequence of losing a good customer is the possibility that they will be replaced by a not-so-good customer.

This article also provides information on the customer variables and experiences that relate to cancellation behavior. Specifically, we investigate customer demographics, customer history and firm experiences, the manner in which the cancellation is made, and household portfolio dynamics. Losing and gaining customers through brand switching is a major well-founded concern for insurance firms. For example, Schlesinger and Graf von der Schulenberg (1993) found that 30.1 percent of customers interviewed had switched automobile insurance carriers at some point in time. The persistency data analysis and corresponding predictive information presented herein allow the firm to segment the customer market on the basis of demographics (and

[3] Note that lapses are not always the consequence of switching to a competitor. In case of nonmandatory insurances, lapses may simply indicate that the insured has decided against insurance or no longer has the need.

other variables), to better predict the likely time until defection from the first cancellation, and to managerially target such consumer for customer retention techniques.

EMPIRICAL AND CONCEPTUAL FRAMEWORK

Policy Lapse Versus Changing Customer Needs

In the insurance setting, when a policy is terminated, two basic situations are possible: (1) the risk is going to be covered by another insurance company (e.g., an automobile insurance policy is taken out with another insurance company), or (2) the risk does not exist any more for the policyholder (e.g., a car being sold). Any empirical investigation into policy lapse must explicitly take the difference between these two situations into account. In keeping with the importance of making this distinction, this article does not view all terminations as cancellations or lapses. The rule that we have applied to determine whether a termination is regarded as a cancellation or lapse, and thus immediately relevant as a signal of impending customer defection for other policies purchased from the same firm, is whether the risk continues to exist at the time the contract is ended.

It is useful to note here differences that exist between the European processes of insurance contract renewal and that used in the United States. In Europe (the source of the longitudinal database used in this article), a policy will be automatically renewed via a bank account debit, unless the customer takes an explicit action to terminate it. Thus, a termination, because of a brand switch or lack of need, requires explicit action in Europe.[4]

This automatic renewal process makes the European database particularly relevant for study, even to gain insight into brand switch in any country. Customers in any country might notify their insurer of an intent to switch firms prior to nonpayment, but customers in Europe must notify the current insurer in order to switch brands. Thus, European insurers automatically have information of an impending brand switch without having to wait to realize a lost sale/customer.

Policy Coverage Data Versus Customer Notification Data

Our focus in this article centers on three types of insurance contracts: contents, house, and automobile. Contents insurance covers the items inside the house subject to loss, such as furniture, silver and gold, paintings, clothes, and audiovisual equipment. House insurance covers the building itself from damage generally caused by phenomena such as fire, storm, or water. Automobile insurance covers bodily injury and property liability.

All policies considered are 1-year contracts, and generally notifications of cancellation for house, contents, and automobile policies occur close to the renewal date. If a customer does not want to renew a particular policy, the notification must be made a minimum of 1 month before the renewal date. If the notification is made less than

[4] In the United States, on the other hand, the policy automatically lapses if not explicitly renewed by payment ahead of time. Thus, for European policies the default action is automatic renewal in the absence of intervention, and the United States the default action is automatic termination in the absence of intervention.

30 days before the renewal date, the policy will be canceled at the next renewal date—up to 13 months after the initial notification.[5]

Note that if several cancellation notices on several policies are made by the customer, depending upon the renewal dates, the first policy to actually lapse may not necessarily be the first policy the customer notified the insurer about canceling. The insurer may have reaction time after first notification to save the household portfolio of policies, and how much time (and how to predict it) is the subject of this study.

From the perspective of understanding the customer's intention and predicting the length of time the customer is likely to remain with an insurer after cancellation of a policy, the type of first notice of cancellation contains relevant information. Notification data properly reflect the customer point of view with respect to the insurance relationship, whereas, policy lapse date information only describes the risk being covered. Therefore, the customer's intent is properly established by the type and moment in time of the first notification of cancellation (not the first policy to actually lapse).

On the other hand, when the date of the first risk out of coverage is taken to define the beginning of the notification period there is a problem of misclassification of the temporal decision-making process. This distinction between lapse and notification is important, as the notification data define the customer-side characteristics, which are the source of the ultimate lapse. This issue only arises for multiple policies underwritten by the same insurer, as is considered here. The brand switch signal must be taken from the time of the first cancellation notification (and not the time of the first lapse in coverage).

This article measures lapse from the time of first policy cancellation notification to the insurer. Thus, we capture the brand switch signal so as to be able to analyze the response time available to the insurer before the customer is lost, as well as the probability that the customer household will subsequently cancel additional policies.

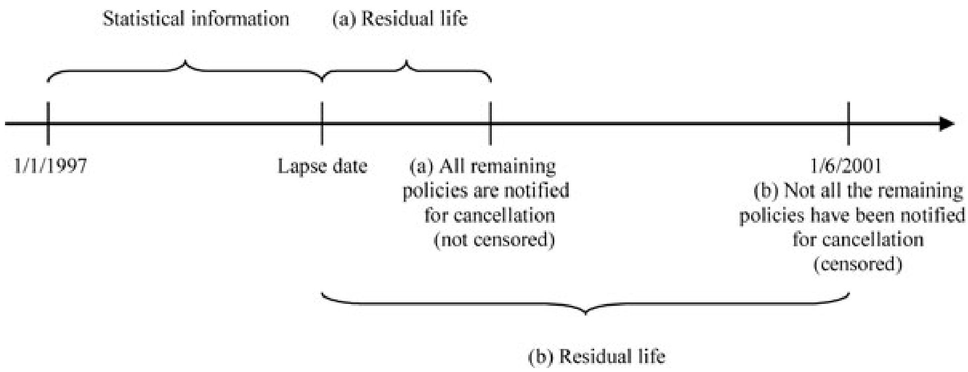
THE HOUSEHOLD DATA SET

The data set used in this article consists of 151,290 Danish households possessing multiple insurance policies, who sent cancellation notice for their first policy to a particular major Danish insurer between January 1, 1997 and June 1, 2001. Among the policies considered here, only the third-party liability motor insurance is compulsory. The information was collected according to the time frame shown in Figure 1.

Some of the household covariates refer to the occurrence of an event (a claim, a premium increase, or a change of address) from January 1, 1997 until the date of the

[5] When the insurer is notified of the cancellation less than 1 month in advance, there is always the possibility that the customer could reject the bank processing the automatic payment of the premium and the policy be thereby canceled. Hence, the recorded notification period can conceivably be different than 30 days for some individuals. For our analytic results the exact number of days of notification is used in the models.

FIGURE 1
Time Frame



first notification of cancellation while other covariates are measured at the time of first policy cancellation (e.g., the tenure or the age of the policyholder). Once the first policy cancellation occurs, the residual household customer lifetime is measured by the number of days until all remaining policies are notified for cancellation or until the end of the study, June 1, 2001, whichever comes first (some policyholders will cancel one policy but keep others).

In situation (a) in Figure 1, all the remaining policies are canceled before June 1, 2001, so the household customer residual life is the time from the first notification of cancellation date until cancellation of all other policies occurs. In situation (b) in Figure 1, at the end of the study, we only know that the residual life is greater than the time from the first notification of cancellation until June 1, 2001. In this case, the residual life is listed as the time elapsed from first policy cancellation until June 1, 2001, but it is noted for statistical analysis purposes that the observation is right censored.

Variables in the Database

Table 1 lists the variables in the database and their labels. Further descriptive statistics for the important variables are given in the results section. Variables that may not be immediately self-explanatory to the reader are explained further.

Tenure is the number of years the household has been a customer of the company, calculated as the number of years from the first policy issued to the policyholder, within the types of policies considered here, until the date of the first notification of cancellation. Notice is the time interval from notification of the first policy cancellation until the actual occurrence of the corresponding cancellation.

Since the types of policies (insurance portfolio) held by the household could conceivably affect the retention attributes of the client with respect to the insurer, the following dummy variables were developed: *Contents0*, *House0*, and *Motor0*. They indicate whether the household has contents, house, or automobile policies respectively before the first notification of cancellation. *Contents1*, *House1*, and *Motor1*

TABLE 1
Variables in the Household Data Set and Variable Label Used for Each

Age of named policyholder at the date of the first notification of cancellation (*Age*)
Gender of named policyholder (*Gender*)
Time from notification of first policy cancellation until the actual first cancellation (*Notice*)
Tenure of household with insurer (*Tenure*)
Core customer status = 1 if two policies in addition to contents insurance (*Corecust*)
Change of address prior to cancellation *(Change of Address*, broken into six subcategories)
First cancellation notice furnished by external company A *(External Company A)*
First cancellation notice furnished by external company B *(External Company B)*
First cancellation notice furnished by external company C *(External Company C)*
First cancellation notice furnished by external company D *(External Company D)*
First cancellation notice furnished by another known external company *(Another known external company)*
Claims history: Time since last claim (*Claims*, broken into six subcategories)
Contents insurance prior to cancellation (*Contents0*)
Contents after cancellation of first policy (*Contents1*)
House insurance prior to cancellation (*House0*)
House after cancellation of first policy (*House1*)
Automobile insurance prior to cancellation (*Motor0*)
Automobile after cancellation of first policy (*Motor1*)
Indicator of household having underwritten the first contents policy within the 12 months previous to the date of the first notification of cancellation (*Newcontents*)
Indicator of if household has underwritten the first house policy within the 12 months previous to the date of the first notification of cancellation (*Newhouse*)
Indicator of if household has underwritten the first automobile policy within the 12 months previous to the date of the first notification of cancellation (*Newmotor*)
Premium increase (*Pruning*, broken into three subcategories)

indicate whether the household has contents, house, or automobile policies, respectively, after the first notification of cancellation. *Newcontents*, *Newhouse,* and *Newmotor* indicate whether the household has underwritten the first contents, house, or automobile policies, respectively, within the 12 months prior to the date of the first notification of cancellation.

Corecust indicates whether the customer has a core customer status. A core customer is a customer that has a contents policy and at least two other types of policies (they could be automobile, house, or others like life insurance) with the insurer. In the insurance company data analyzed here, core customers have lower premiums, bonuses, and special advantages. From a marketing perspective, core customers having multiple policies tend to be more profitable and, hence, deserve special consideration.

Information on whether a change of address has occurred was included, as it can affect the probability of house and contents cancellations. Six categories were developed for this variable: no change of address, change of address less than 2 months before the date of the first notification of cancellation, between 2 and 6 months before the date of the first notification of cancellation, between 6 and 12 months before the date of the first notification of cancellation, between 12 and 24 months before the date of the first notification of cancellation, and more than 2 years before the date of the first notification of cancellation.

Since premium increases might impact customer retention, information was included on whether the time period included a substantial increase in premium of 20–50 percent. Such premium increases are commonly termed pruning, since the insurer wants to persuade the customer to lapse, possibly due to a very bad claims history. Three categories were developed: no pruning, pruning within the past 12 months, and pruning more than 1 year before the date of the first notification of cancellation.

The data also included information about recent claims, as they can also affect the probability of notification of cancellation. The six categories for claims developed were: no claim, claim less than 2 months prior to the first notification of cancellation, between 2 and 6 months prior to the first notification of cancellation, between 6 and 12 months prior to the first notification of cancellation, between 12 and 24 months prior to the first notification of cancellation, and more than 2 years prior to the first notification of cancellation.

Finally, considering the competitive nature of the marketplace and the marketing dynamics of alternative brands in a brand-switching model, we have also included information on external company involvement in the cancellation notice.[6] We considered a competitor to be involved if the notification of cancellation was communicated by another insurance company on behalf of the customer. We specifically considered the four most important competitors to the studied insurer and coded these competitors as companies A, B, C, and D. The variable relating to competition involvement thus had six categories: no external company involvement (notification by the customer); notification by company A, company B, company C, or company D; and finally notification by another known external company. In the models these categories were incorporated as binary dummy variables, as is often done in regression analysis involving nonordinal categorical variables.

Table 2 presents a description of the policy portfolio state before versus the state after the first notification of cancellation, thus comparing the types of policies the household had before and after the occurrence of the first notification of cancellation.

As shown in Table 2, the number of households with only a contents policy, 34,998, is slightly smaller than the number of households with the three types of policies, 37,103. The most frequent state before the first notification of cancellation is where the customer has contents, house, and automobile policies, whereas the most frequent

[6] The customer has a choice of notifying the current insurer him/herself of cancellation or of having the new insurer notify the current insurer. It is clear that when the new insurer does the notification, a brand switch has already occurred and, at least for that policy, the customer is entrenched with the new insurer for at least the next year. It is likely, also, that the new insurer will wait until the last moment to signal their competitor of the upcoming brand switch, lest the competitor take measures to try to retain their customer. Further, new insurers will likely be discussing other insurance policy needs with their newly acquired customer, so subsequent policy cancellations are more likely.

TABLE 2
State and Number of Policies in the State Before Versus After First Lapse

		State After Notification							
		None	Contents Only	House Only	Auto Only	Contents & House	Contents & Auto	House & Auto	Total
State before notification	Contents only	34,998	0	0	0	0	0	0	34,998
	House only	10,757	0	0	0	0	0	0	10,757
	Auto only	28,198	0	0	0	0	0	0	28,198
	Contents & house	2,690	3060	4,090	1	0	0	0	9,841
	Contents & auto	3,397	13,764	1	10,613	0	0	0	27,775
	House & auto	166	1	1,409	1,042	0	0	0	2,618
	Contents, house, & auto	4,389	471	2,488	4,535	12,488	5,957	6,775	37,103
	Total	84,595	17,296	7,988	16,191	12,488	5,957	6,775	151,290

state after the first lapse is where the policyholder has no coverage at all (which occurs since many households have just one policy).

Focusing now on households with more than one type of policy (Table 2), initially we observe that for those with just contents and house policies, the most frequent state after the first notification of cancellation is to have house coverage only, so the policy being canceled is the contents policy. However, if the household initially has contents and automobile policies, or house, and automobile policies, or all three of contents, house, and automobile policies, then the automobile policy is the most likely to be canceled.

ANALYTICAL METHODOLOGY

A two-stage model was constructed to analyze the behavioral issue of how long a multipolicy consuming household remains with an insurer following the cancellation of their first policy (the residual life after the first notification of cancellation). The need for a two-stage analysis was in order to examine two cancellation situations: (1) a customer cancels all policies simultaneously or (2) policy cancellations are done sequentially.[7]

In the first stage, we use logistic regression to determine the probability, based upon known covariates of the insured, that a household originally having more than one policy will cancel all the policies simultaneously.[8] In this scenario, a logistic regression estimates the probability: For household i, $i = 1, \ldots, n$, we assume that

$$P(R_i = 1|x_i) = \frac{\exp(\beta' x_i)}{1 + \exp(\beta' x_i)}, \quad (1)$$

where $R_i = 0$ for a partial cancellation and $R_i = 1$ for a total cancellation, x_i is a vector of the observed explanatory variables, and β is a vector of unknown parameters. Consistent and asymptotically efficient estimates of the parameters in the logistic regression model (1) are obtainable using the conditional maximum likelihood method (cf. Snell and Cox, 1989; Agresti, 1990) implemented in many common statistical packages. In this manner we are able to look at the effect of household characteristics (covariates) on the likelihood of total simultaneous cancellation.

In the second stage of the analysis, we use a proportional hazards model to concentrate on those households that do not cancel all their policies simultaneously. For these households, we estimate the length of the time from the initial consumer cancellation

[7] The models used in the two stages both are intrinsically heteroskedastic (the variance depends on the covariates) so the models accommodate potential heterogeneity in characteristics of the policyholders without having a forced constant variance assumption being made. For example, the logistic regression model used in the first stage is heteroskedastic since the variance of the binary dependent variable equals the probability of the event times the probability of no event. Since the probability of the event is specified as a function of the covariates, the variance is also a function of the covariates, and is not constant.

[8] In Guillen et al. (2003) the same methodology was applied for predicting the probability of a contents, house, or automobile policy being canceled within a 3-month period conditional upon assessed information from the previous year.

of the first policy until cancellation of the last policy held by the household with the insurer. This proportional hazards analysis originates in the biostatistical literature (Cox, 1972) and a brief explanation appears below.

Understanding Sequential Cancellations Using Proportional Hazards Models

In the case of sequential withdrawal of the customer, we model the time between first cancellation notification and the final complete withdrawal by assuming that there is a baseline (stochastic) distribution for the time a customer will take for defection, and that the relative risk of an individual customer defecting completely changes from this baseline according to their particular set of individual household covariates. The instantaneous probability of total defection at time t given survival (partial defection) up to time t is called the hazard function at time t. The actual time which the household stays with the company, T, is a random variable, and Cox's proportional hazards regression model specifies that the hazard function for a random survival time T given by

$$\alpha(t) = \lim_{dt \to 0} \frac{P(t \leq T < t + dt | T \geq t)}{dt} \tag{2}$$

is the product of a baseline hazard $\alpha_0(t)$ and a specific covariate dependent factor,

$$\alpha(t|z_i) = \alpha_0(t) \exp(\beta' z_i) \tag{3}$$

where z_i is the p dimensional observed covariate column vector for individual i and β is the unknown regression coefficient column vector.

The hazard function $\alpha(t)$ can be used for determining the survival function $S(t) = 1 - F(t)$, where $F(t)$ is the distribution function, on the basis of the relationship

$$S(t) = \exp\left(-\int_0^t \alpha(s)\, ds\right). \tag{4}$$

Expectation of the time to total withdrawal can be obtained by integrating the survival function. Efron (1977) has shown that a partial likelihood function derived from the data can be maximized independently of the unknown baseline hazard function, $\alpha_0(\cdot)$, to yield estimations of β. For estimating the baseline hazard $\alpha_0(s)$ we use the empirically based Breslow estimator (Breslow, 1974). More complete discussion of the analysis methodology can be found in Guillen et al. (2003) and entries in Kotz and Johnson (1987).

Most of the covariates in our application are binary and can be understood as indicators of the presence of a risk factor (e.g., a change of address or a claim). The sign of the parameter estimate can be interpreted as the effect of the corresponding covariate on the expected time to final withdrawal from the company. When the parameter estimate is positive, we conclude that the hazard for the household with the associated covariate is larger than in the absence of the indicator of this covariate. On the basis of proportionality, the corresponding resulting survival function is also steeper. Thus, a positive parameter estimate is associated with a shorter time to total withdrawal for those households that have the risk factor signaled by the covariate, compared to those without the risk factor.

RESULTS

Some useful initial observations can be made by examining the results for simple descriptive statistics.[9] Among the 151,290 households who notified their first cancellation during the analyzed period, 75.88 percent had a male listed as the policyholder, and 20,740 had not canceled all their remaining policies by June 1, 2001 (the end of the period), making the frequency of censored observations 13.71 percent. The average age of the customers is 45.92 years (standard deviation of 17.22), and the average tenure is 9.03 years with the company (standard deviation of 10.19). The data set consists of 52.05 percent of core customers and 47.95 percent of noncore customers. In 55.26 percent of the cases there is an external company involved in the first cancellation.

This article focuses on that part of the data set with more than one policy before the first notification of cancellation occurs, which totals 77,337 households. Some of these customers cancel all their policies at the same time, so the insurer does not have time to react once the first lapse (and total cancellation) has occurred, but some customers cancel sequentially, leaving the insurer time to avoid completely losing them.[10] Our analysis focuses on the subset of multiple policyholders who cancel sequentially.

Table 3 shows the expectation of the residual life in days, depending on the state before and after the first lapse, for those households with more than one policy at the beginning of the period that do not cancel all the policies simultaneously, that is, the state after the first lapse is not "none." Estimated residual lifetimes have been obtained using the Nelson–Aalen estimator, devised by Nelson (1969, 1972) and Aalen (1978). Transitions have been classified into three subsets: from two initial policies to one policy, from three initial policies to one policy and from three initial policies to two policies.

Those households having three policies at the beginning of the period that retain two policies after the first lapse have the largest overall average residual life—about 558 days. Further, those customers that start with three policies who end up with

[9] In order to examine the potential for multicollinearity effects among the explanatory covariates, we used the standard diagnostic statistics produced by linear regression analysis. As the collinearity diagnostic statistics are based on the independent variables only, this can be used in our context. In doing this analysis, we observe that variance inflation factors are all close to 1 and conclude that there is no sound evidence multicollinearity in the data.

[10] In reality, this comment about completely losing customer is an oversimplification. The forethinking insurer will look to the customer's next stage of brand switch and wish to behave such that the customer might consider returning to the firm from which they are currently defecting. Thus, the customer has broken their current relationship, but if this customer is a good risk, the firm would be wise to make sure the customer is thinking "leaving for now" and not thinking "leaving forever." This is where exit interviews of defecting customers may be very informative for the firm, as well as an educational marketing opportunity to the customer.

TABLE 3
Average Length of Time Between the Time of First Cancellation of a Policy and the Final Cancellation of the Last Household Policy Cross Classified According to the Set of Policies Before Versus After First Lapse

	Transition			
	State Before	State After	n	Average (Days)
From 2 to 1 Policy	Contents & house	Contents only	3,060	644.809
	Contents & house	House only	4,090	306.711
	Contents & auto	Contents only	13,764	600.681
	Contents & auto	Auto only	10,613	357.765
	House & auto	Contents only	1,409	513.986
	House & auto	Auto only	1,042	516.909
From 3 to 1 Policy	Contents, house & auto	Contents only	471	74.006
	Contents, house & auto	House only	2,488	120.675
	Contents, house & Auto	Auto only	4,535	157.319
From 3 to 2 policies	Contents, house & auto	Contents & house	12,488	589.648
	Contents, house & auto	Contents & auto	5,957	702.472
	Contents, house & auto	House & auto	6,775	379.851

one policy after the first lapse have a smaller overall average residual life (140 days) than those who started with two policies (481 days). The difference in these estimated lifetimes (341 days) is substantial and may be indicative of customer dissatisfaction motivating policy change. The number of days the insurer has to respond is important in itself.

Estimation of the Probability of a Total Cancellation

Predicting the probability that a household with more than one policy before the first notification of cancellation will cancel all policies simultaneously is assessed using a logistic regression model (1). The covariates described in Table 1 are used, except for *Contents1*, *House1*, and *Motor1*, which are, of course, all zero after a total cancellation has occurred. Among the observations, 10,317 simultaneously effected a total cancellation of all policies with the insurer.

The overall statistical test of no covariate effect provided a likelihood ratio statistic of $LR = 9{,}178$ with 28 degrees of freedom ($p < 0.001$). Household characteristics significantly affect the probability that a customer will totally simultaneously cancel all policies.[11] Individual parameter estimates are shown in Table 4.

11 As a general comment applicable to the analyses in this article, while the entire set of 28 covariates may not capture all heterogeneity in the data set, they do provide a reasonably good explanation of the customer lifetime duration, which is the emphasis of the article. Moreover, adding more covariates to reduce heterogeneity could be unrealistic from an insurance company perspective since there is shortage of additional covariates of this type available in multiline insurance data sets, making the resulting analysis less transferable to other companies. Analysis, however, was also performed incorporating variable interaction terms in the models. These results, although more difficult to present and interpret, did not

TABLE 4
Logistic Regression Estimates of Covariate Effects on Probability of Total Multiple Policy Cancellation

Parameter	Estimate	Standard Error	Odds Ratio	p-Value
Constant	–2.201	0.112	—	<0.001
Change of address, less 2 months ago	–0.596	0.060	0.551	<0.001
Change of address, 2–6 months ago	–0.122	0.052	0.885	0.019
Change of address, 6–12 months ago	–0.095	0.048	0.909	0.049
Change of address, 12–24 months ago	0.229	0.041	1.258	<0.001
Change of address, more 24 months ago	0.531	0.044	1.701	<0.001
Tenure	–0.011	0.001	0.989	<0.001
Claims, less 2 months ago	0.230	0.040	1.259	<0.001
Claims, 2 and 6 months ago	0.324	0.035	1.383	<0.001
Claims, 6 and 12 months ago	0.440	0.035	1.553	<0.001
Claims, 12 and 24 months ago	0.469	0.037	1.598	<0.001
Claims, more 2 years ago	0.546	0.054	1.727	<0.001
Contents0	0.277	0.087	1.319	0.001
Corecust	0.109	0.025	1.116	<0.001
Age	0.004	0.001	1.004	<0.001
External company A	2.548	0.041	12.779	<0.001
External company B	2.165	0.046	8.718	<0.001
External company C	1.893	0.048	6.637	<0.001
External company D	2.270	0.047	8.834	<0.001
Another known external company	1.686	0.035	9.680	<0.001
Gender (male)	0.099	0.028	1.104	<0.001
House0	–0.657	0.030	0.518	<0.001
Motor0	–1.253	0.033	0.286	<0.001
Newcontents	–0.113	0.043	0.893	0.008
Newhouse	0.073	0.060	1.076	0.225
Newmotor	–0.208	0.050	0.813	<0.001
Notice	–0.002	<0.001	0.998	<0.001
Pruning within past 12 months	–0.187	0.072	0.829	0.009
Pruning more than 1 year ago	0.086	0.111	1.089	0.442

Note: Positive coefficient increases the likelihood of a total household policy cancellation.

All of the parameters in the model are significant, except for having added a new house policy in the last 12 months (newhouse) and having had a premium increase more than 1 year prior to the household first giving a cancellation notice (pruning more than 1 year past). Thus, the potential customer repelling effects of premium increases seems to dissipate after 12 months. The individual parameter tests indicate that the change of address within the first 6 months or more than 2 years prior to the first notification of cancellation, the occurrence of a claim and the existence of a premium increase (pruning) are three factors that influence the probability of a total cancellation.

change the conclusions of the analysis. Accordingly, in the interest of space, these additional results are not presented here.

By looking at the odds ratios, we see that involvement of external companies, claims, change of address more than 1 year ago, and contents policy are the most relevant factors influencing the probability that a total cancellation occurs. Far and away the most important determinant of the probability of a total cancellation is, however, the intervention of an external company (competitive effects). Among external companies, the one coded as A is the one with the largest odds ratio, which identifies company A as an aggressive competitor that frequently captures all household contracts simultaneously.[12]

Both claims occurrence and change of address increase the probability of a total cancellation as the time since the corresponding event has occurred increases. A surprising result was that core customer status actually increases the probability of a total cancellation. A possible explanation is that core customers may be more likely to be solicited by competitors, and they may receive very persuasive offers from competitors. If this is so, the company should increase the efforts to retain them as these are the precise customers that the insurer would like to keep, and, unfortunately, for which the insurer has the least amount of notice (residual time) to recapture the defecting client. Their risk characteristics may make them desirable customers to all insurers and highly sought after.

Estimation of the Amount of Time Between the First Notification of Cancellation and the Final Termination of All Policies for Those Households Not Canceling All Policies Simultaneously

For those households with more than one policy that do not cancel all their policies at the same time, we analyze expected amount of time between the first cancellation and the final termination of all policies with the company (called the residual lifetime of the household with the insurer) by using the proportional hazards regression model described earlier. Table 5 displays the parameter estimates for this analysis. The likelihood ratio test for the overall significance of the model is high at $LR =$ 326, 23.98, which is chi-squared distributed with 31 degrees of freedom ($p < 0.001$),

[12] To further investigate the stability of the effects of the covariates on the probability of total cancellation, a logistic regression was rerun excluding the households whose cancellation was notified by a competitor. The effects of most covariates (claims, gender, etc.) remained the same as with the entire data set; however, in certain cases some covariates decreased somewhat in their level of significance indicating that the competitors may choose who they target. One key covariate (corecust) changed from having a positive and significant coefficient in the total data set but a negative and only marginally significant coefficient in the data set of households whose notice did not come from a competitor. This makes sense since when a competitor encounters a core customer having multiple policies and who is potentially movable, they can "put on the full court press" to have them switch all policies simultaneously, using incentives, etc. If there is no competitor involved, the motivation of policyholders is different and their tendency to stick with the status quo, at least on some of their policies, prevails. Other differences in covariate effect between the two data sets can similarly be explained by competitor or policyholder motivation and incentives when competitors are involved. Nevertheless, the relationship between the majority of the covariates and the likelihood of total defection remains essentially the same in the smaller data set.

TABLE 5

Proportional Hazards Regression Model Estimates of the Effect of Covariates on the Time Between the First Policy Notification of Cancellation and the Final Termination of the Last Household Policy

Parameter	Estimate	Standard Error	Hazard Rate	p-Value
Change of address, less 2 months ago	–0.245	0.019	0.783	<0.001
Change of address, 2–6 months ago	–0.083	0.020	0.920	<0.001
Change of address, 6–12 months ago	–0.023	0.020	0.978	0.252
Change of address, 12–24 months ago	0.044	0.019	1.045	0.021
Change of address, more 24 months ago	0.157	0.025	1.170	<0.001
Tenure	–0.003	0.001	0.997	<0.001
Claims, less 2 months ago	0.096	0.016	1.100	<0.001
Claims, 2–6 months ago	0.161	0.015	1.175	<0.001
Claimsy, 6–12 months ago	0.185	0.015	1.203	<0.001
Claims, 12–24 months ago	0.228	0.017	1.256	<0.001
Claims, more 24 months ago	0.257	0.027	1.294	<0.001
Contents0	0.681	0.029	1.975	<0.001
Contents1	–0.869	0.016	0.419	<0.001
Corecust	–0.042	0.011	0.959	<0.001
Age	–0.003	<0.001	0.998	<0.001
External company A	1.727	0.018	5.625	<0.001
External company B	1.528	0.020	4.611	<0.001
External company C	1.652	0.019	5.217	<0.001
External company D	1.778	0.020	5.919	<0.001
Another known external company	1.643	0.012	5.170	<0.001
Gender (male)	0.103	0.012	1.109	<0.001
House0	0.222	0.017	1.249	<0.001
House1	–0.559	0.017	0.571	<0.001
Motor0	0.415	0.021	1.515	<0.001
Motor1	–0.529	0.018	0.589	<0.001
Newcontents	–0.059	0.016	0.942	<0.001
Newhouse	–0.109	0.024	0.897	<0.001
Newmotor	–0.076	0.017	0.927	<0.001
Notice	–0.001	<0.001	1.000	<0.001
Pruning within past 12 months	0.188	0.029	1.207	<0.001
Pruning more than 1 year ago	0.095	0.053	1.100	0.075

indicating that the covariates have a significant effect on the hazard and so on the amount of time the insurer has to react to a partial withdrawal.

Having made a change of address between 6 and 12 months prior to the first notification of cancellation is not significantly related to the expected time between the first notification of cancellation and the final termination of all policies; however, all other parameters associated in the model are significant at the 0.05 level, except the indicator for having experienced a premium increase more than 1 year before the first notification of cancellation (pruning more than 1 year ago), which is only marginally significant (not significant at the 5 percent level but significant at the 10 percent level).

Change of address, claims, external company, and pruning are the strongest factors contributing to reducing the expected residual life.

According to the parameter estimates in Table 5, a recent change of address slightly increases the expected time between the first policy notification of cancellation and the final termination of the last household policy. But as the elapsed time increases since the household has moved, the contribution of this factor on the expected time until final termination (residual life) has the opposite effect: It reduces residual life. The parameter estimate corresponding to the covariate *age* is significant and negative in sign, indicating that as the age of the policyholder increases there is a slight increase in the expected residual life. The parameter associated with tenure is significant and negative suggesting the shorter time a household has been with the insurer, the less likely they are to switch brands, or the longer it will take them to switch. This finding underscores the importance of customer loyalty. Female customers have a slightly longer expected residual life than do male customers.[13]

The presence of claims reduces residual life, and the effect becomes more dramatic as the time since the claim has occurred increases. This could be connected to some delay in the compensation of claims that may result in a delay in the assessment of the insurer's claims handling process made by the household. Nevertheless, to be sure we should know how promptly the claims are processed. An expected result is that the core customer status increases residual life. Core customer households have some insurer provided advantages, and these seem to be effective for customer retention, or at least to dissuade customers from completely leaving the company. This result is in contrast to the logistic analysis result. This might happen because the critical moment for completely loosing a core-customer is when the household decides to make the first cancellation. Once recruited by a competitor (or motivated on their own to seek out a competitor), the policyholder may be required (or strongly encouraged) to simultaneously move all household policies to retain the same favorable contract conditions with the competitor, such as multipolicy discounts. Once this critical moment has passed or been resisted, and the customer has decided not to move all household policies, it seems reasonable to observe that they are more loyal to the company. This is also motivated by the retention strategies carried out by the company in order to keep that good customer who has given his notification of cancellation on his first policy.

As with the probability of total cancellation discussed earlier, the competitive effects of the market are the most significant factor related to a reduction in residual life of the client household with the insurer. This is particularly true for the external companies coded as A and D. When an external company is involved in a particular cancellation, it seems to attract the new customer toward other lines of business. It is also easier for the customer to get information about the premium costs and the characteristics of other products in the new insurance company. Competitors may also provide information that the current company does not to existing customers,

[13] Beyond the actuarial difference, others studies have also found meaningful purchasing behavioral differences between men and women. For example, Gandolfi and Miners (1996) found gender differences in life insurance ownership.

making the switch more attractive, possibly because of customer ignorance of product opportunities with their current insurer.

Table 5 also shows that variables measuring new business of the household with the insurer within past 12 months (*Newcontents*, *Newhouse*, *Newmotor*) have a significant and negative impact. For this data, there are 11.64 percent of customers who have a new contents policy underwritten within last year (these percentages are 4.96 and 8.61 for house and motor policies, respectively). The significant and negative relationship found suggests that recent business contributes to an increase residual life. Again, this may be related to customer contact and education. Having recently gone through the search and decision process, the policyholder is more likely to remain with his or her decision for a time. This is consistent with the literature that shows a "stickiness" of insurance customers with their current insurer in spite of changing market conditions. The new business that makes the biggest contribution is the purchase of a new contents policy.

The parameter associated with notice is also significant and negative, and as the time since notification until renewal increases, the expectation of residual life increases slightly, also.[14] And, again, a substantial rise in premiums is associated with a reduced residual life, but this effect is less dramatic over time. The average number of days of notice before renewal is 159.03 days with a standard deviation of 112.31 days.

For variables relating to the insurance portfolio of the household before the first notification of cancellation, one causing less reduction in residual life is *House0*, followed by *Motor0*, and finally *Contents0*. The fact that the initial state of the insurance portfolio has a significant effect on residual life can be tested using Wald's statistic (value 306.606, chi squared with 2 degrees of freedom, $p < 0.001$). Concerning the insurance portfolio of the household after the first lapse, the one associated with the largest increase in the expected residual life is *Contents1*, followed by *Motor1*, and finally *House1*. Again, a Wald statistic test confirms that the state of the household's insurance portfolio following the first notification of cancellation also significantly affects the residual time until final total policy cancellation (statistic = 941.135, chi-squared with 2 degrees of freedom, $p < 0.001$).

Although parameter estimates given in Table 5 can be used to assess the impact of covariates on the residual life of the customer with the company, we can also translate the results into expected time until final cancellation. Table 6 presents the estimated expected residual life for different types of households, depending on if they have

[14] The actual numerical size of the coefficient for notice is small in an absolute sense because *Notice* was measured in days. If *Notice* had been measured in weeks, months or years, the coefficient would have appeared larger (with the product of the coefficient times the scaled variable remaining constant). Thus, in interpreting the results, one must look at the *p*-values and statistic tests rather than the absolute sizes of the coefficient. This comment applies to other variables as well. While statistical significance does not always translate into economic or practical significance, neither does the size of the coefficient correspond to its importance. Accordingly, we rely on statistical significance of the coefficient in explaining which variables have effect.

TABLE 6
Effect of Selected Covariates on the Expected Time Until Final Policy Cancellation

Factor	Status	n	Average (days)
Claims	None	32,500	522.541
	At least one	34,195	412.753
Change of address	None	45,284	463.476
	At least one	21,411	482.802
Pruning	None	64,761	477.242
	At least one	1,934	259.967

had any claim, change of address, or a substantial rise in the premium. Expectations have been obtained using the Nelson–Aalen estimator.

Those households that had at least one claim have a smaller average residual life (413 days) than those who did not have any claim (523 days). Therefore, our conclusions are similar to those provided by Schlesinger and Schulenburg (1993). They found that in the German automobile market 14.3 percent of the switchers who filed a claim with their previous insurer had received an indemnity of less than 75 percent of the total insured damages, whereas only 5.4 percent of nonswitchers who filed a claim with their current insurer received less than 75 percent of damages. They also found that for switchers, 52.5 percent of claims filed with previous insurers took 3 weeks or longer to get paid, whereas only 29.6 percent of those customers who filed a claim with current insurer had to wait that long.

According to the results in Table 6, households that suffered a substantial increase in their premium have an average residual life (260 days), smaller than those corresponding with no price increase (477 days). This result was expected, as households who experienced the premium increase probably search for a cheaper product in another company. A lower premium has been shown to be the most important reason for choosing a particular insurer for the German automobile insurance market (Schlesinger and Schulenburg, 1993).

The expected time until final cancellation for those who have had a change of address (483 days) is slightly longer than the corresponding lifetime for those who did not move (463 days). This result suggests that although a contents or a house policy cancellation is more likely to happen when a family moves, this does not seem to affect household behavior regarding remaining policies.[15]

[15] To verify the validity of our interpretations and conclusions, we reran the data analysis excluding those households whose cancellation notice was provided by a competitor. The estimation of the model without the households whose cancellation was notified by a competitor showed that most significant parameters have the same effect as in the original model presented in the text. We conclude that the effects of covariates are the same for the subsets of clients whose cancellation was provided by a competitor and those who self-notified. For brevity we have not included these results here.

FIGURE 2
Survival Function Depending on the First Policy Being Canceled

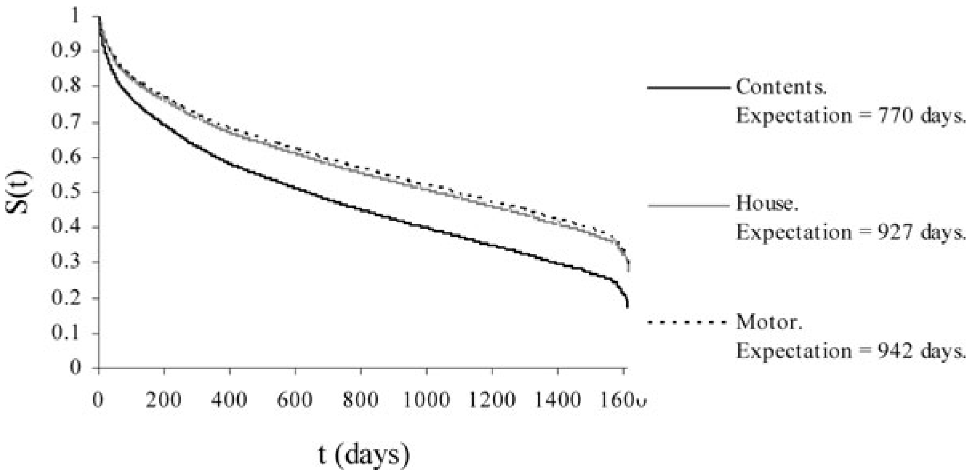


Illustration of the Application of the Proportional Hazards Regression to Customer Retention Modeling

The estimated parameters of the proportional hazards regression model can be used to obtain the survival function to model retention for any given customer, which is potentially useful strategic customer-side information. To do this, we first estimate the baseline hazard rate using the estimator of Breslow (1974). This section develops an illustration of the application of proportional hazards regression modeling for understanding customer retention.

Figure 2 shows the survival function for a 55 year-old male customer with 10 years of tenure with the insurer, no change of address within the last 2 years, a claim between 2 and 6 months ago, and no external company involvement in the notification, giving 150 days of notice before renewal, no new business with the insurer within the past 12 months, no core customer status, and no pruning. Assume also that the customer has contents, house, and automobile policies before the first notification of cancellation. Survival curves and expectations are shown depending on the first policy being canceled.

It can be observed that the survival curve with the steepest slope is the one corresponding to those households who first cancel the contents policy for whom we observe a shorter residual life of about 770 days before final expected exit from the company. The largest expected residual life corresponds to the case in which the automobile policy is the first to be notified for cancellation.

Figure 3 considers the same customer, but with contents and automobile policies before the first notification of cancellation and only an automobile policy after the first lapse. In this case, we compare the survival function and the residual life depending on whether or not any external company was involved in the cancellation. The external competitor coded as company D causes the most reduction in residual life (44 days),

Figure 3
Survival Functions Depending on External Companies Involved in Notification

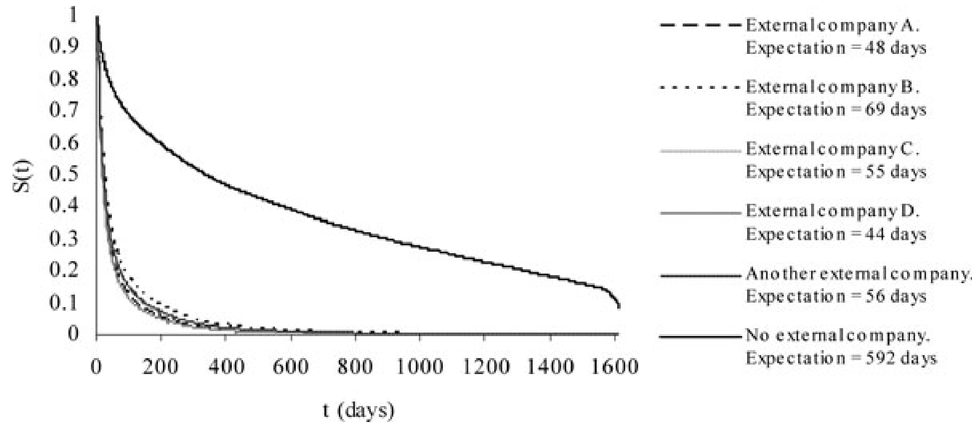
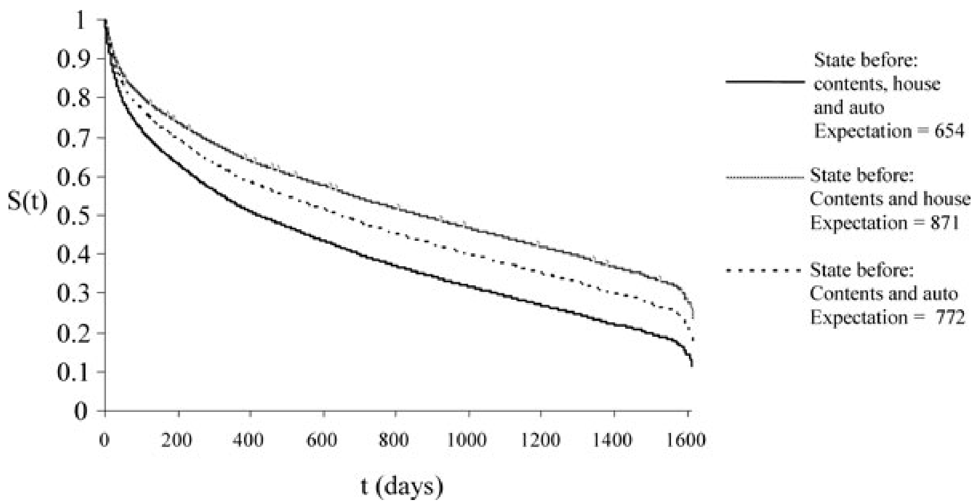


Figure 4
Survival Function for Households With Only the Contents Policy After the First Lapse Depending on the Types of Policies They Had Before the First Notification of Cancellation



whereas the residual life is substantially larger when no external company is involved in the first cancellation (592 days).

Illustrating the importance of the composition of the insurance policy portfolio of the household prior to the first notification of cancellation, consider again the same customer as in Figure 2, but with only the contents policy remaining after the first lapse. Figure 4 compares the survival functions for the portfolio before the first notification of cancellation. The survival function with the steepest slope, as well as the shortest residual life, corresponds to the household that has all three types of policies before the first notification of cancellation (654 days).

The examples above illustrate how dramatic the impact of the covariates can be on the time the insurer has to respond to the first cancellation, before subsequent cancellations take place. These covariates are measurable characteristics of customers in the marketplace and can be employed to help signal customer defection to the competition.

CONCLUSIONS AND IMPLICATIONS

Insurance purchasing is a complex process surrounding an intangible product[16] about which consumers are likely to be ignorant (Gravelle, 1994; Showers and Shotick, 1994; Schlesinger and Schulenburg, 1993). Due to the intangibility of the product, service, and purchasing process uncertainties, customers are likely to be particularly vulnerable to competitive influences that provide some certainty, for example, knowledge that the competitor offers a lower premium. Information provided by insurers to existing and potential customers may be particularly important to the brand switching potential of customers. And the relationships formed by the insurer and its agents or representatives are also particularly important for customer retention (Crosby and Stephens, 1987).

We found that customer retention begets customer retention: the longer customers were with the firm, the less likely they were to cancel a policy. And if one policy is canceled, the longer the customer can be expected to remain with the firm after first cancellation. Thus, the already loyal customers seem to want to remain loyal and are relatively reluctant to switch. These customers are critical and should not be ignored—relationships with them need to be a strategic focus. Loyal existing customers are often easily ignored in the quest for market share expansion.

A warning note from this article is that core customers, those with multiple policies, are among the most likely to switch all policies simultaneously to an external company. These are the most valuable customers from a risk perspective, and those are the most likely to be recruited away, as other firms are likely to see them as valuable, also. Strategically, insurers should pay more specific attention to these core customers in the interest of retaining them or fending off competitive pressures before they switch insurers entirely.

The logistic regression results indicated that external companies, claims, and change of address are the most relevant factors for determining the likelihood of simultaneous total cancellation of all household policies. This leaves the insurer with a need for a longer-term perspective on customer relationship management, because if the insurer is to try to win back the lost customer, it must wait until the customer is willing to brand switch again.

When a partial cancellation occurs, this is the first evidence to the insurer of a reconsideration of the insurance relationship from the customer point of view, and we have

[16] While it is common to speak about insurance as a product, conceptually from a marketing perspective, it is also a service. All products have facilitating services and all services have facilitating products, sometimes blurring the distinction between the product and the service for the customer. The agent may often be viewed as the service provider (to the customer), with the insurer being perceived as the producer of the product. This distinction may be very important to customer relationship management.

shown that the insurer may have time to take action to retain the customer for other policies held by the household (multiple types of coverage). If policies of more than one type are canceled, the expected remaining lifetime of the customer with the firm (before all policies are canceled) is substantially smaller than when only one line of business is canceled.

For the three types of insurance contracts considered in this article (contents, house, and automobile), it may be the case that all the adult household members participate in the decision to cancel (or to purchase). One contribution of this article is an analysis of the behavior of households having more than one policy in the same company, but not necessarily of the same type. A strategic implication of the results is that the insurer should link policyholders in their files those policies that belong to members of the same household, that is, the same decision-making unit. The household is an appropriate unit of analysis for marketing multiple (or individual) insurance products to a decision-making unit.[17]

The amount of time that the insurer has to retain the customer is dependent upon the type of customer. Apart from external companies, claims, and change of address, the policy type first canceled is one of the key factors in predicting the expected residual life, or the estimated time left until the customer–insurer relationship is terminated. And knowledge of the specific estimated residual life corresponding to a particular customer (calculated upon first termination notice in the manner described herein) can allow the insurer to more effectively tailor their marketing strategy to increase customer retention. For example, an informational campaign strategy, which may be effective to combat customer defection if the expected residual life is long, may be ineffective if the expected customer lifetime duration with the firm is short. The procedures presented in this article will allow the insurer to make such customer market segmentation decisions so as to more effectively manage the customer relationship.

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[17] Even though linked as a household decision-making unit, the insurer can still recognize the different decision influences of various individuals (e.g., husband-dominate, wife-dominate, joint-equally, or delegated to one member exclusively). Future research can be conducted to determine the style of decision making for various types of customers or policies held.

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