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Investigating the role of product features in preventing customer churn, by using survival analysis and choice modeling: The case of financial services

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Abstract

The enhancement of existing relationships is of pivotal importance to companies, since attracting new customers is known to be more expensive. Therefore, as part of their customer relationship management (CRM) strategy, many researchers have been analyzing 'why' customers decide to switch. However, despite its practical relevance, few studies have investigated how companies can react to defection prone customers by offering the right set of products. Additionally, within the current customer attention 'hype', one tends to overlook the nature of different products when investigating customer defection.

In this research, we study the defection of the savings and investment (SI) customers of a large Belgian financial service provider. We created different SI churn behavior categories by introducing two dimensions: (i) duration of the products (fixed term versus infinity) and (ii) capital/revenue risks involved. Considering these product features, we first gain explorative insight in the timing of the churn event by means of Kaplan–Meier estimates. Secondly, we elaborate on the most alarming group of customers that emerged from the former explorative analysis. A hazard model is built to detect the most convenient product categories to cross-sell in order to reduce their churn likelihood. Complementary, a multinomial probit model is estimated to explore the customers' preferences with respect to the product features involved and to test whether these correspond with the findings of the survival analysis.

The results of our study indicate that customer retention cannot be understood by solely relying on customer characteristics. In sum, it might be true that 'not all customers are created equal', but neither are all products.

Keywords: Data mining; Customer relationship management; Cross-sell analysis; Multinomial probit; Survival analysis; Savings and investment features; Retention behavior

1. Introduction

Understanding and reacting to changes of customer behavior is an inevitable aspect of surviving in a competitive and mature market. As a consequence, firms in the financial services industry, which are facing new entrants (Ritter, 1993), intensive European financial integration (Dawes & Swailies, 1999; Pastor, Pérez, & Quesada, 1997) and rapid changing customer needs (Krishnan, Ramaswamy, Meyer, & Damien, 1999), are striving to succeed by putting the topic of customer retention on their agenda.

The economic value of customer retention has been demonstrated in previous research. In their study, Reichheld and Sasser (1990) reveal that a bank is able to increase its profits by 85% due to a 5% improvement in the retention rate. Similar findings emerged in Van den Poel and Larivière (2004), who calculated the financial impact of an increase in retention rate of just one percentage point. However, the underlying challenge for companies is not restricted to just gaining understanding of churn, but to find an appropriate remedy to convert defection proneness into stronger relationships (Baesens, Verstraeten, Van den Poel, Egmont-Petersen, Van Kenhove, & Vanthienen, 2004). In their study, Chiang, Wang, Lee, and Lin (2003) emphasize the need to establish systems that are able to alert before customers leave in order to take the appropriate actions before it is too late. Despite its importance, this topic has received relatively little research attention. Unlike previous research, this study adopts a more comprehensive perspective on customer retention by examining both 'why' and 'how companies can prevent' customers from taking the decision to leave the company.

In this study, we analyze the savings and investment (SI) customers of a large Belgian financial service provider.

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We defined a churned SI customer as someone who closed all his SI accounts. The purpose of the analysis is to identify the impact of cross-selling new product categories on the customers' vulnerability to churn. With the help of the financial services firm, we segmented their set of existing products into seven new SI product categories by considering two dimensions: (i) duration of the products (fixed term versus infinity) and (ii) capital/revenue risks involved. Considering these product features we first investigate its importance with respect to customer churn. Furthermore, we test whether the *ideal* product categories in terms of lowering the churn likelihood correspond with the customers' desired SI product characteristics.

The findings of this study show evidence that not all products are created equal when considering customer retention. As expected, considering product features allows significant contributions for managers striving for valuable and strong relationships with their current customer base.

The rest of this paper is organized as follows. In the next section we elucidate the methodological underpinnings of survival analysis and multinomial probit models used in the study. In Section 3, we present the data set and the identified product features. The results and its business implications are reported in Section 4. In the final section, we summarize our contributions and outline some areas for future research.

2. Methodology

In this study we use the Kaplan–Meier estimator to gain insight into the timing of the SI churn event. A multinomial probit model and a proportional hazard model are performed to find the most convenient products to cross-sell in terms of customer preferences and the likelihood to lower the customers' defection proneness respectively.

2.1. Investigating the timing of the churn event

Survival analysis is a class of statistical methods modeling the occurrence and timing of events (in this case: customer churn). It follows that T, the churn time for some particular SI customer, is a random variable having a probability distribution. Let us denote the probability density function (p.d.f.) of this variable by $f(t)$. The cumulative distribution function (c.d.f) of variable T, denoted by $F(t)$. Hence,

$$F(t) = \Pr\{T \leq t\}. \tag{1}$$

For some individuals the time to failure may be observed completely, whereas for others we only have partial observation until some specific censoring time c. The survivor function is defined as:

$$S(t) = \Pr\{T > t\} = 1 - F(t). \tag{2}$$

We investigate the timing of the SI churn event by calculating Kaplan–Meier estimates. The Kaplan–Meier estimator-also known as the product—limit estimator—is the most widely used method for estimating survival functions and is seen as an important tool for analyzing censored data (Efron, 1988). Survival probabilities are presented as a survival curve. The 'curve' is a step function with sudden changes in the estimated probability corresponding to times at which events are observed (Bland & Altman, 1998).

2.2. Hazard estimates of cross-sell opportunities

The aim of a hazard function is to quantify the instantaneous risk that an event will occur at time t. The hazard function is defined as:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr\{t \leq T < t + \Delta t / T \geq t\}}{\Delta t}. \tag{3}$$

The proportional hazard model introduced by Cox dominates the field of hazard models (Stare, Harrell, & Heinzl, 2001). The technique is widely used due to its convenient advantages; the technique (i) allows incorporating time-varying covariates and both discrete and continuous measurements of event times and (ii) can handle observations that did not experience the event (that is, censored observations).

The proportional hazard model proposed by Cox can be written as:

$$H_i(t) = \lambda_0(t) \exp\{\beta_1 x_{i1} + \cdots + \beta_j x_{ij} + \gamma_1 y_{i1}(t) + \cdots + \gamma_k y_{ik}(t)\}. \tag{4}$$

In which: $H_i(t)$ represents the hazard for an individual i at time t;

$\lambda_0(t)$ represents the baseline hazard function;
β_j represents the coefficient of non-time varying covariate j;
x_{ij} represents the value of an individual i for non-time varying covariate j;
γ_k represents the coefficient of time varying covariate k;
$y_{ik}(t)$ represents the value of an individual i for time varying covariate k at time t.

In this study we use the technique to test the impact of cross-selling new products on the churn likelihood. The technique is appropriate to use since our research design involves a time-varying and right-censored data window. Fig. 1 depicts the lifecycle information of two fictitious customers, A and B.

It is clear from Fig. 1 that customer A only possessed one product (of category X) during his lifecycle of being a customer. On the other hand, customer B opened a second product of category Y at duration t_2 and another product of category Z at duration t_3. The former customer churned (at t_2), whereas the second subject is right-censored at the end of observation. As a consequence, the inclusion of time-varying covariates—represented by $y_{ik}(t)$ (cf Eq. (4))—is required, since one need to specify that customer B has

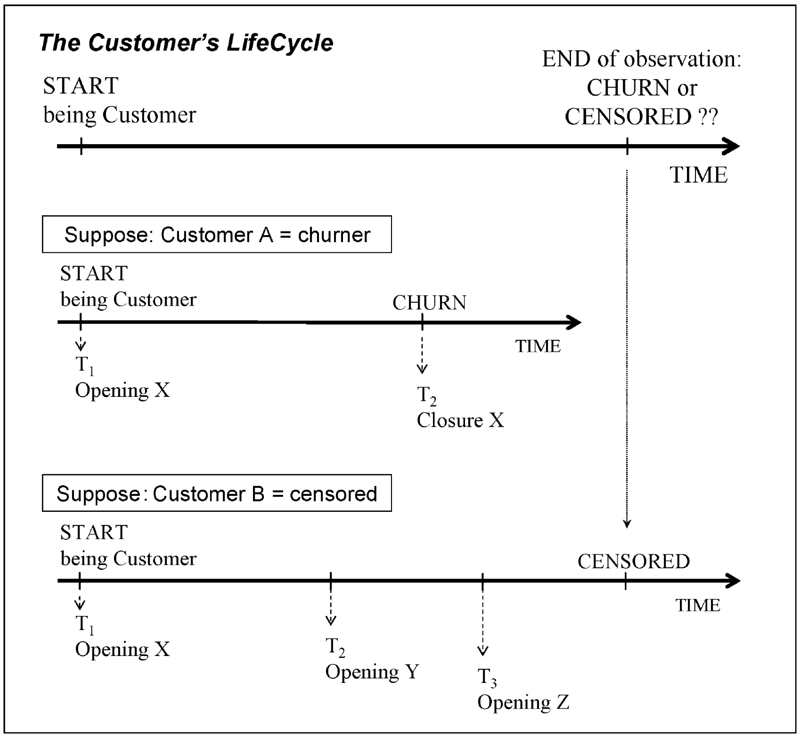

Fig. 1. The customer's lifecycle.

the value of '0' with respect to the possession of products from category Y *before*the moment of t_2, and the value of '1' afterwards (i.e. $\geq t_2$) in order to reliably define the impact of acquiring new products, represented by its corresponding hazard estimates. Hence, both dependent and independent variables are situated in time.

2.3. Multinomial probit estimates of feature preferences

When faced with a choice set, a customer is presumed to view each option as a bundle of attributes. The customer is then thought to form an overall evaluation of each option by combining perceptions of the option's attributes through a cognitive 'integration rule' or utility function (Meyer & Kahn, 1991). The probability of a specific choice can be interpreted as the relative pleasure or happiness that the decision maker derives from that choice with respect to other alternatives in the finite choice set. However, it is assumed that these utilities are not fully observable by the analyst. Rather, the utility of each option is considered to be a random variable, defined by a distribution of possible values. The random utility function of customer i for choice j is defined as follows:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \tag{5}$$

where

$$V_{ij} = x'_{ij}\beta \tag{6}$$

V_{ij} is a deterministic utility function assumed to be linear in the explanatory variables, and ε_{ij} is the unobserved random variable or error disturbance component. Given a choice set A, the likelihood that customer i will choose option j from the set, is thus the likelihood that the latent variable U_{ij} is the highest at the time of choice. Formally,

$$\Pr(j|A) = \Pr(U_{ij} > U_{ik}) \ \ \forall k \in A, k \neq j \tag{7}$$

Different assumptions on the disturbance of the error components result in different discrete choice models. The two most common models are the multinomial logit (MNL) and the multinomial probit (MNP) in which the disturbances are assumed to be distributed Weibull and multivariate normal, respectively. In practice, most applied work has been carried out using MNL (Breslaw, 2002), since it has a closed form that can be easily calculated (Horrowitz, 1981; Keane, 1992). However, MNL suffers from 'the independence of irrelevant alternatives' (IIA) property and consequently, ignores the similarities among alternatives in an individual's choice set-which is not realistic in many consumer behavior contexts (Chintagunta, 1992; Currim, 1982). In addition to this, Allison (1999) cautions for additional bias in the parameter estimates, due to IIA violations in case individuals are not presented with the same set of alternatives.

Contrary to the MNL model, the MNP model alleviates the IIA assumption (Haaijer, Wedel, Vriens, & Wansbeek, 1998) since similarities across alternatives are explicitly taken into account as the random component of the individual's utility function which is assumed to have a multivariate normal distribution with nonzero covariances between alternatives and consequently, allows for a general pattern of dependency among the alternatives (Chintagunta, 1992). Despite this well-known advantage, the MNP model has been rarely used as a model of choice in applied work. The major drawback of the MNP used to be the complexity in its estimation as a consequence of the burdensome computation (Keane, 1992) involving multiple integrals; certainly when the number of alternatives increases. As a consequence, the use of MNP models used to be restricted to situations where there are at most three or four alternatives in the choice set (Chintagunta, 1992).

However, recent developments in simulation methods, such as SML (simulated maximum likelihood) or MSM (method of simulated moments), and Bayesian analysis (e.g. Bayesian interference based on Gibbs sampling), have raised renewed interest in MNP as a model of choice (Breslaw, 2002; Chintagunta, 1992; Geweke, Keane, & Runkle, 1994; Keane, 1992), even (or certainly) when the choice set becomes larger (Breslaw, 2002). Furthermore, the development of the highly accurate GHK probability simulator (proposed by Geweke, Hajivassiliou and Keane), has also led to the renewed interest in simulated maximum likelihood as a method for estimating MNP models (Breslaw, 2002). In their study, Hajivassiliou, McFadden, and Ruud (1996) compared 13 simulators using 11 different simulation methods. Their findings reveal that GHK is the most reliable simulation method. Similar results in favor of GHK are reported by Geweke et al. (1994).

In this study, (i) the choice set is composed of seven different alternatives, (ii) some of them share the same or similar product characteristics and (iii) not all customers have the same choice set available, since not every intermediary is selling the whole range of financial products to its customers. Hence, the MNP model is the appropriate tool to estimate the impact of product features on the customer's final product choices. In this research, we apply the simulated maximum likelihood estimator using the GHK recursive probability estimator. The choice probability of the multinomial probit model is written as:

$$P(y_i = j) = P[\varepsilon_{i1} - \varepsilon_{ij} < (x_{ij} - x_{i1})'\beta, \ldots, \varepsilon_{iJ} - \varepsilon_{ij} < (x_{ij} - x_{iJ})'\beta] \tag{8}$$

where

$$\begin{bmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \\ \cdot \\ \cdot \\ \cdot \\ \varepsilon_{iJ} \end{bmatrix} \sim N(0, \Sigma) \tag{9}$$

and

$$\sum = [\sigma_{jk}]_{j,k=1,\ldots,J} \tag{10}$$

3. Empirical study

3.1. Data set

A major Belgian financial services company provided the data for this study. The data is extracted from the time interval of becoming a customer through the end of observation (i.e. censoring on 1 March 2003) or the end of the customer relationship (i.e. churn). The data sample only considers individuals that became customer after the date of 1 January 1992, due to reasons of data quality and to ensure reliable choice sets. Particularly, some product(s) (categories) did not exist before the date of 1 January 1992 at the investigated company and/or financial market. Hence, it would be unfair to compare the product possessions of a customer A who became customer in 1980, with those of another customer B who started being a customer six years ago. It is quite conceivable that the former customer was not able to acquire some products the second customer had access to.

This study focuses on SI customers; consequently, we only consider SI products to determine whether a customer is (still) a SI customer. The analysis is based on the total sample of 519.046 customers; i.e. all customers that owned SI products during the window of observation at the investigated company.

3.2. Product features

Customers are faced with a large assortment of financial products when they want to acquire a new product. When purely considering product features, it is well known that a simple savings account is far from being similar compared to a product originating from the stock market. In this research we elaborate on these differences and we test for the behavioral differences with respect to specific product categories.

With the help of the financial services product managers, we first sought to define the most appealing product features that characterize the SI products. After careful review and discussion, we identified two important feature dimensions, which we further subdivided into different categories in order to classify each SI product.

The first feature dimension considers the duration of the SI product. Some products do not have fixed duration terms, whereas others automatically expire after a specific 'expiration' date. In the search to understand churn, it is appealing to know whether the first group of products is able to enhance customer retention proneness, since customers with no fixed duration products are assumed to remain customer forever until they explicitly cancel their products.

The second feature dimension refers to the risks involved with the SI products. We distinguish two different types of risks: capital risks and revenue risks. Capital risks involve the invested money, whereas revenue risks represent the risks with respect to the potential revenues. For example, bonds are free from both revenue and capital risks; i.e. the customers know in advance the amount of money they will get due to a fixed and in advance communicated interest rate (revenue part) and because the invested money is available at the end of the investment term (capital part). Fig. 2 presents the two product feature dimensions and the seven SI categories that emerge from the proposed framework.

In terms of SI product categories possibilities, it is clear from Fig. 2 that there is still room for new duration—risks combinations for this particular financial services company. In general, in terms of the risks involved, customers perceive the first three SI categories (i.e. SI 1, SI 2 and SI 3) as being different from the latter three (i.e. SI 5, SI 6 and SI 7) in the sense of being ‘safe, but lower and more guaranteed revenues’ versus ‘risky, but potential high or in worst case extremely low revenues’, respectively (cf. Fig. 2, graph below). Within the SI diagram, the fourth group takes a special place, since the products involved are both positioned and communicated as being the stepping stone between the ‘safe’ and ‘risky’ SI groups. Additionally, although these products have a recommended minimum duration of 5 years, but are advised to be owned for a period of 8 years for fiscal reasons, they usually do not have a fixed duration term in reality. Typically, SI 4 products are communicated as ‘high revenue generating products, but in a safe way’, hence, they both combine the advantages of the safe versus risky SI groups. The typical features of these kinds of products originate from the investigated financial company and have been copied extensively throughout the financial services sector. Although the fourth SI category only encompasses one particular SI product, we thought it to be appealing to investigate this product as a separate and unique category.

Table 1 provides insight into the portfolio of the SI customers during their lifecycle (i.e. from the start of being customer until churn or censoring). In sum, a number of interesting findings emerge from the table, such as:

- More than half of the SI customers only owned a savings account (cf. 51.3% which corresponds with portfolio situation 1 and SI category 2). Expertise from the marketing department confirms this finding and indicates a large group of customers who consider this particular financial institution as a ‘second savings banking institute’;
- More than 80% of the customers only possessed products from one category (cf. portfolio situations 1, 2, 4, 5, 6, 7 and 12), of whom most tend to acquire low risk SI products (i.e. SI category 1, 2 and 3).

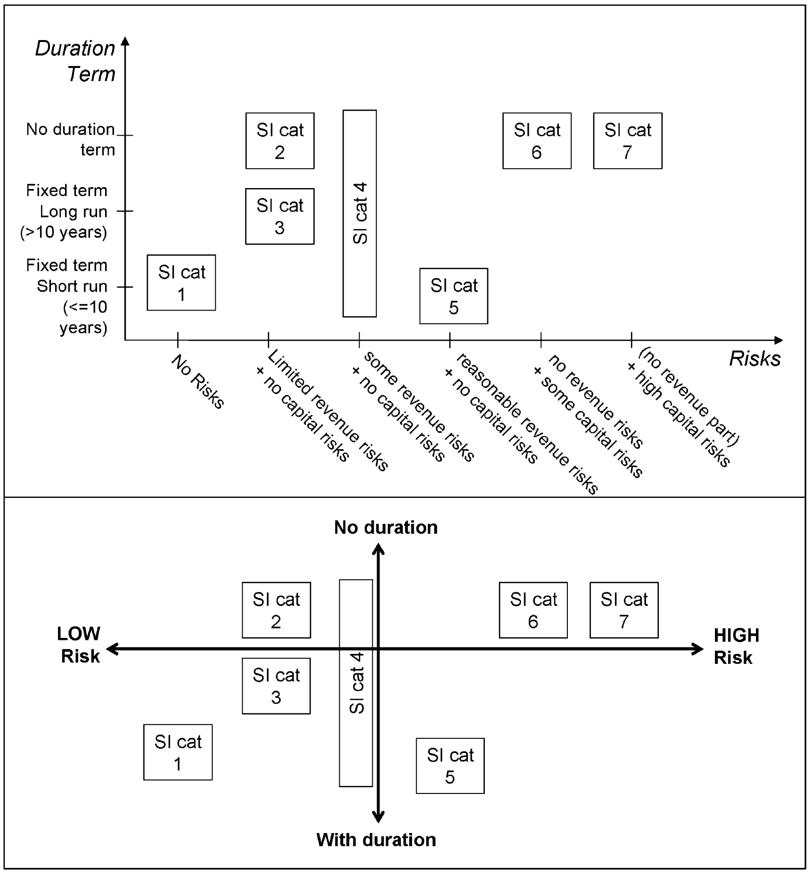

Fig. 2. The SI features and categories.

Table 1
Portfolio insight of the SI customers

Portfolio situations[a]	Possession of SI products from category[b]							Number of customers	
(SI customers)	1	2	3	4	5	6	7	Abs.	%
1[c]	0	1	0	0	0	0	0	266.178	**51.3**
2	0	0	1	0	0	0	0	77.622	**15.0**
3	1	1	0	0	0	0	0	32.722	6.3
4	1	0	0	0	0	0	0	31.785	**6.1**
5	0	0	0	1	0	0	0	19.788	**3.8**
6	0	0	0	0	1	0	0	13.028	**2.5**
7	0	0	0	0	0	0	1	9.785	**1.9**
8	0	1	1	0	0	0	0	7.562	1.5
9	0	1	0	0	1	0	0	5.083	1.0
10	0	1	0	1	0	0	0	4.807	0.9
11	0	1	0	0	0	1	0	4.444	0.9
12	0	0	0	0	0	1	0	3.972	**0.8**
13	1	1	0	0	1	0	0	3.880	0.7
14	0	1	0	0	0	0	1	3.307	0.6
15[d]	Other cases							35.083	6.8
								519.046	100

[a] Only situations that represent at least 0.5% of the SI customers are reported as individual cases (i.e. situations 1–14).
[b] '1' Means that the customer own(s)(ed) products from that category, whereas '0' means that the customer does not (did not) possess a product from the particular category during his lifecycle (i.e. from the start being a customer until churn or censoring).
[c] Portfolio situations that represent customers that only possess(ed) products from just one SI category are marked in bold.
[d] Situation 15 represents the residual category (cf. the summation of cases that represent less than 0.5% of the SI customers).

4. Findings

The next paragraphs present the findings of this study. First, we report the survival estimates for each SI category. Then we discuss and compare the results from the hazard model with those of the multinomial probit analysis.

4.1. Survival estimates

Fig. 3 represents the Kaplan–Meier Survival Estimates of the investigated SI categories. Each graph corresponds with one of the seven SI categories and explores the defection proneness with respect to that category. Hence, each graph only considers the customers that owned the corresponding SI category; regardless of the fact whether they also possessed other SI categories. The analysis is justified since we want to explore the effect of different product categories and because most SI customers only possessed one particular SI category during their lifecycle of being a SI customer (cf. Section 3.2, Table 1).

When investigating the survival probabilities of the seven SI categories, we can conclude that churn behavior differs among the range of SI products. In general, some interesting findings emerge from our analysis:

- The possession of savings accounts (i.e. SI category 2, characterized by an infinity duration time) is no guarantee to remain a SI customer. SI 2 products show the highest defection rates; i.e. almost half of the population churns within the first 10 years of being a SI customer. Given the fact that this category is the most popular (i.e. possessed) within the range of SI products (see Table 1) we can ascertain the need to find the appropriate marketing strategy and actions to revert this SI behavior.
- The most retention prone SI customers are those that own high-risk products in the long run (i.e. SI category 6 and 7) or low-risk products on the fixed long run (i.e. SI category 3). Notice that the former two SI categories (6 and 7) mainly embrace banking products, whereas category 3 products only contain insurance products (e.g. mainly life insurances). This finding underlines the benefits of both offering banking and insurance products to the customer. Selling the whole range of financial products creates the opportunity of both maximizing the customers' financial needs (e.g. risk versus safety) and their retention proneness.
- When observing the higher survival estimates of SI categories 6 and 7 compared to the rates of the first category, one could argue that 'objective' switching barriers might have an impact on churn, since the decision to dispose of some products belonging to the two latter categories involves substantially higher penalty costs.
- The survival curve of the SI products characterized by reasonable revenue risks and a fixed term (i.e. SI category 5) reveals that these customers show high defection rates when products expire *automatically*. It is crucial to approach these kinds of customers with the appropriate message and product, since the graph shows a quite linear curve after each impressive reversion (i.e. the customers who reinvest).
- Similar to SI category 5, products in the short run characterized by zero risks (i.e. SI category 1) also show

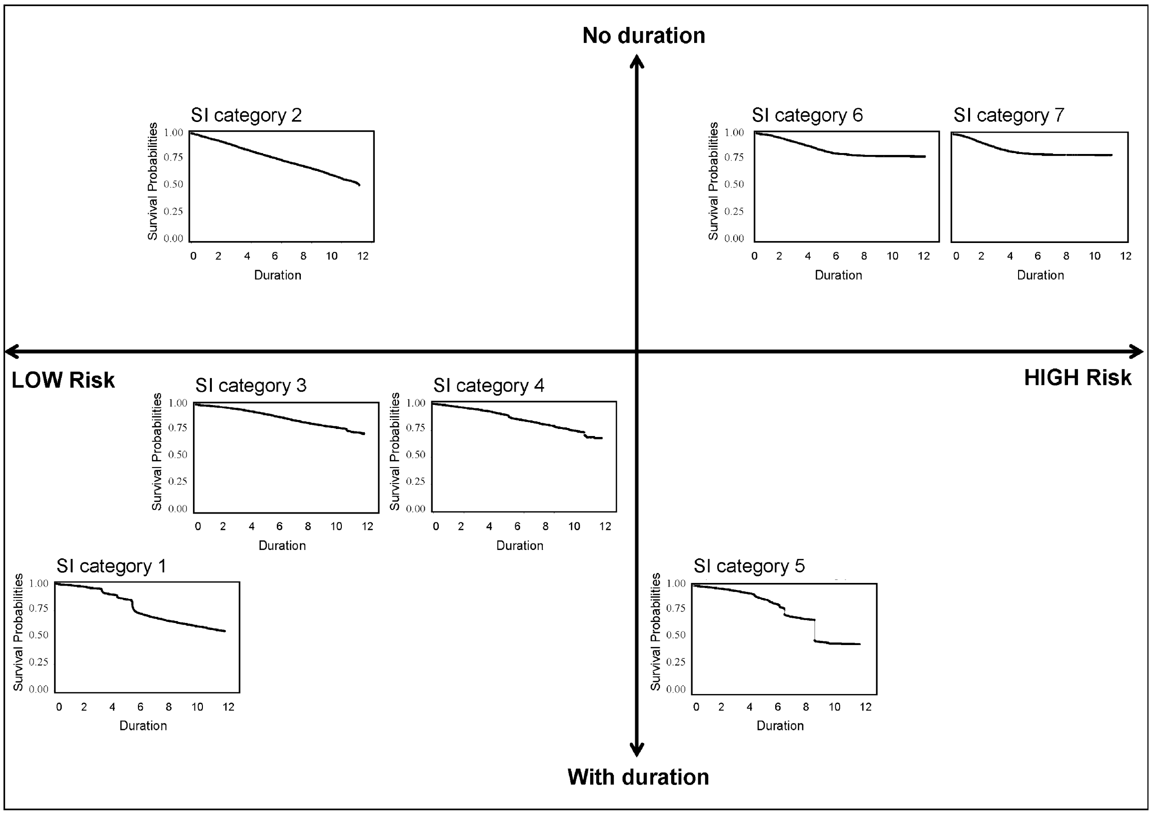

Fig. 3. Survival probabilities of the SI categories.

some critical churn periods. A potential explanation might be that there exist some interactive SI customers who continuously decide to reinvest in similar SI products with low risks and fixed terms, when expiration dates come closer.

- Compared to SI categories 1 and 5, category 4 reveals to be the best retention-prone category in the short and fixed term. Hence, it offers a viable opportunity for the financial services company to strengthen their competitive advantage by cross-selling and diversifying these kinds of SI products.

4.2. Hazard ratios

Since the savings account customers (i.e. SI category 2) not only represent the largest group of customers (cf. Table 1), but at the same time also the most alarming in terms of defection rates (cf. Section 4.1), we decided to elaborate the analysis on these customers. The obvious question is 'What can we do about the high defection proneness of these customers?', or in other words: Which products are most convenient to cross-sell to lower their probability to churn?

Based on a hazard model we tested for the impact of acquiring a second SI product. We included seven explanatory variables into the model; each variable corresponds with one of the seven SI categories. Note that each variable is operationalized as a time-varying covariate, as proposed in Fig. 1.

Table 2 reveals that all estimates are significant (<0.0001) different from zero. Furthermore, all estimates have negative values, meaning that each new product opening lowers the churn likelihood of the savings-account customer. In sum, this finding highlights the necessity of the customer's share of wallet; it is beneficiary that a customer fulfills all his financial SI needs within one and the same company. Hence, it offers a viable opportunity for financial service companies to both supply and cross-sell the whole range of SI products; in such a way that a customer is not obliged to visit another company when he needs a specific SI product.

In terms of *best* SI products—that is, the SI products having the highest impact on lowering the attrition probability—the SI products of category 4 are most promising to convert defection-prone customers into clients with stronger relationships. The churn tendency of the savings-account customers who acquire a SI product of category 4, decreases by 91.5% (that is, $100(\exp(-2.47044)-1)$). In other words, the churn likelihood of the customers opening a SI product of category 4 equals 8.5% of the likelihood of their counterparts who did not open a product of that category (cf. hazard ratio $=0.085$). Given the fact that SI category 4 products originate from the investigated company, it offers an opportunity to exploit this competitive advantage.

Similarly, products of SI category 3 (which mainly contain life insurance products), also prove to stimulate

Table 2
Hazard estimates of cross-sell opportunities

Time-varying explanatory variables	Parameter estimate	Hazard ratio
Start_SI_1	−1.31285*	0.269
Start_SI_3	−2.11817*	0.120
Start_SI_4	−2.47044*	0.085
Start_SI_5	−1.87790*	0.153
Start_SI_6	−0.97483*	0.377
Start_SI_7	−1.03140*	0.357
Second_SI_2	−0.18722*	0.829

* Significant at <0.0001.

retention behavior. Moreover, all other SI categories also show evidence to lower the churn likelihood substantially. Summarized, the findings support the necessity to supply the whole range of financial products to the customers, in such a way that an intermediary can offer those products that both support the customer's financial needs and his retention proneness.

4.3. Multinomial probit analysis

While the hazard rate analysis in the previous section objectively state the products that are most convenient to cross-sell in order to lower the churn likelihood of the savings account customers, it neglects the customers' preferences with respect to SI products. Hence, a multinomial probit model is performed to find the preferred SI product characteristics. Based on the proposed framework in Fig. 2, we distinguish the following product characteristics: duration of the product, capital risks and revenue risks. Analogous to the hazard analysis, we focus on the most churn-prone group of the savings account customers. More specifically, we consider the second SI purchase of customers who first acquired a savings account. As such, we can determine the most preferred product features chosen by savings account customers who decided to open a second SI product.

It is clear from Table 3 that all investigated product features have an impact on the customer's final choice. When savings-account customers decide to buy another SI product they prefer products on the longer run. Furthermore, it is abundantly clear that the customers are extremely risk averse with respect to their invested capital. The high t-value reveals that they certainly do not want to loose their invested money. On the other hand, they are receptive to take some revenue risks. When translated to the seven SI product categories, the preferred SI features indicate that SI categories 3 and 4 are the most preferred ones. Consequently, these findings perfectly reconcile with the hazard findings: the preferred products are the ones that lower the churn likelihood most. In sum, the appropriate churn remedy message for the investigated company is very clear: 'Try to cross-sell SI products from category 3 and 4'.

Table 3
Multinomial probit estimates of product features

Product features	Parameter estimate	t Value
Duration term	0.0234*	6.32
Revenue risks	0.0620*	12.15
Capital risks	−0.2303*	−58.87

* Significant at <0.0001.

5. Conclusions and directions for further research

This research investigates the retention proneness of the SI customers of a large Belgian financial services provider. Unlike previous research, this study explicitly emphasizes the natural differences between SI products and explores the most convenient products to cross-sell in terms of both maximizing the customers' retention proneness and their preferences with respect to SI products. With the help of the financial services company we were able to create seven different SI categories based on two feature dimensions: duration and capital versus revenue risks.

When considering churn, it offers a viable opportunity for financial services companies to consider product features, since not all products are created equal. Although they have infinity duration terms, savings accounts belong to the most alarming product group, because they yield the highest defection rates. Furthermore, the findings reveal the importance to supply the whole range of financial products so that a customer can fulfill all his financial needs within one and the same service provider. Moreover, the hazard findings reconcile with the multinomial findings, implying both the possibility and the challenge to stimulate a financial environment in which customers and intermediaries can build valuable relationships through products and services that both satisfy customer needs and strengthen the company's future market position.

The most direct opportunities for further research reside in validating the proposed cross-sell opportunities. Exploring to which extent a financial company can *actually* convert churn proneness into stronger relationships by offering the right message or mailing with a specific product proposition, would yield insight into the effectiveness of both the remedy and the appropriate medium to exploit that opportunity. This challenge implies the need for a field test with a well-defined control group.

Furthermore, extending the research area of product features to other (than SI) product categories and a profound analysis of the customer's share of wallet with respect to other product categories and/or competitors also offers a fruitful area for further research.

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