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What policyholder and contract features determine the evolution of non-life insurance customer relationships? – A case study analysis

Abstract

Purpose. Over the last decade, technological and social trends have significantly influenced the relationship between customers and insurers. New buying patterns, price comparison platforms, and the usage of different interaction channels driving single-product purchases and impacting lapses have influenced insurers' customer portfolios and development. This paper studies the features driving the customer relationship along three areas, namely, customer acquisition, development and retention.

Design/methodology. After defining 14 related hypotheses, we use econometric analyses to quantitatively support these hypotheses in the three areas of interest. We build on a large-scale longitudinal dataset from a Swiss insurance company covering the period from 2005 to 2014 and including 2 757 000 customer-years. The data comprise information on private customers, their contract history, including coverage and losses, and the channels used for buying insurance. Our analysis focuses on the two most common non-life insurance products, namely, household/liability and car insurance.

Findings. We provide descriptive statistics and results from econometric analyses to determine the significant features and patterns affecting customer development and retention. Among our main results, we underline the significant influence on cross-selling given by the customer's age and the interaction channel. Customers from rural regions are more loyal and likely to conduct cross-buying when compared to their peers from urban regions. Car insurance holders are more likely to lapse than household/liability insurance clients. Finally, while newly acquired customers tend to buy only a single product, we show the importance of cross-selling for retaining customers. In fact, customer retention is positively influenced by the number of products hold.

Research limitations/implications. Our work is relevant for academics and practitioners alike, adding a quantitative basis to the understanding of managing customer relationships and for the development of further prospective models. Further work could investigate or add products, extend the study to other companies and focus on customer development with time.

Originality/value. The presented study explores a large-scale longitudinal dataset. The analyses of customer acquisition, development and retention can support insurers to construct their own models for customer relationship management.

Keywords. non-life insurance · customer acquisition · customer development · customer retention · econometric analysis

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1 Introduction

The competition for new insurance customers has increased during recent years. Established firms drive their strategic agenda along profitability and growth priorities. Such guidelines include increasing profitability in terms of adequate premium levels and risk selection, growth in saturated markets through offering competitive prices and developing new interaction points, rejuvenating the customer portfolio, and improving customer loyalty while increasing retention (Maas et al., 2008; Bieck et al., 2010). At the same time, the world of retailing has changed dramatically. Especially in non-life insurance, customers can compare the prices of products much more easily since they are available online. They can use new interaction points such as insurers' websites and online brokers, to buy insurance. The emergence of aggregator platforms has also had an impact on shopping behavior (Bieck et al., 2013). The above elements may lead to changes in the composition of insurers' portfolios, the customer base and the products customers hold.

As laid out by Guillen et al. (2008), European insurers operate in a highly competitive market. Roughly speaking, an insurer can only acquire a new customer when a competitor loses one (Prinzie and Van Den Poel, 2006). Often, customers can switch easily from one insurer to another one. Given the insurers websites, as well as the comparison, aggregator, and online broker platforms, it is easier than ever to obtain transparent price information to compare the quotes of various companies and to conclude online. This applies mostly to the domain of non-life insurance. In fact, non-life contracts are easier to understand, and most of them are yearly renewable. New policies are constantly being underwritten or canceled, so that the quality of an insurer's portfolio is in a continuous change (Knott et al., 2002; Kamakura, 2007). Customer loyalty (cf. Dick and Basu, 1994) monitoring allows insurers to capture these changes and thus to prevent potential profit losses.

Typically, companies have limited resources to allocate to the different marketing activities to ensure the optimal development of all their customers. Therefore, it is important to identify the objective factors and personal incentives that lead customers to cross-buy. What are the drivers that influence customer development? Unfortunately, many service transactions are now mediated by information technology, eliminating direct human communication, and thereby reducing the opportunities for active cross-selling as practiced in the past (Kamakura, 2007). Human intuition needs to be transformed into an analytical model. Thus, the identification of the drivers for cross-buying gives the firm an important tool to maximize the effectiveness of the cross-promotion of product categories or brands (Knott et al., 2002; Kamakura, 2007; Kumar et al., 2008). Limited research (Verhoef et al., 2001; Ngobo, 2004; Verhoef and Donkers, 2005; Kumar et al., 2008) has been conducted to determine the drivers for cross-selling/-buying, specifically in non-life insurance. Several studies address the channel strategy in the insurance market and other related markets (Rangaswamy and Van Bruggen, 2005; Verhoef et al., 2007; 2015; Mau et al., 2015; 2016; Campo and Breugelmans, 2015). One of the goals of this paper is also to include how the emerging Internet channel influences customer buying behavior in Switzerland.

Finally, insurers strive to retain their customers and build long-term relationships (Gupta et al., 2006), i.e., they aim to minimize the lapses, as it is five times more cost effective to serve an existing customer than to acquire a new one (Kamakura, 2007; Fornell and Wernerfelt, 1987).

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Furthermore, customers within a longer lasting relationship become less costly to serve because of learning effects and decreased servicing costs (Ganesh et al., 2000). The quality of the services provided and the customer satisfaction has proven to be an important driver (Zeithaml et al., 1996; Oliver, 1999; Homburg, 2001). Finding the balance between acquistion and retention efforts including the profitability dimension has been studied, for example, by Reinartz et al. (2005). Deciding about what segments to target specifically (e.g., with dedicated marketing efforts) is only possible with a thorough understanding of the customer base (see, e.g., Ganesh et al., 2000). The identification of loyal (and profitable) customer segments is an important task for management (Oliver, 1999). What characteristics are responsible for contract surrenders? Frost et al. (2008) show that customer loyalty is an antecedent of cross-buying, i.e., buying additional products and services from the existing provider in addition to the ones currently held (Dick and Basu, 1994; Ngobo, 2004). Eling and Kiesenbauer (2014) conduct a large-scale study on lapse behavior in German life insurance. Their methodology is like ours because they use a regression analysis to analyze the impact of product and policyholder characteristics. The dataset used is one of the largest used in the academic literature and includes approximately 2.5 million contracts.

In the present research, we extend the existing academic literature on customer acquisition, development and retention and focus on the area of non-life insurance and, more specifically, on the two major non-life products, household/liability and motor insurance. After introducing a set of 14 hypotheses covering the three areas of acquisition, development and retention, we first study the evolution of the characteristics of the customers acquired by a large Swiss insurance firm. Thereby, we provide comprehensive descriptive statistics on the new customers over a 10-year period. Trends on customers' age and residence area, the products bought and the channel used for buying can be observed when comparing the cohorts. We support our findings from these statistics by providing selected statistical tests. Second, we determine the key factors that influence customer development through cross-buying additional products. With a logistic regression analysis, we assess the significance of the impact of selected features linked to the customers and the contracts they hold. For example, customer age-specific differences and generally better cross-selling performance among tied agents can be observed. Finally, we analyze the effect of customer relationship characteristics on lapse behavior and the impact on customer retention. Here, we provide a similar regression analysis to that for customer development and we study the relevance of the variables of interest. We show, among other results, a positive retention effect linked to multi-product customers. In our study, we build all analyses on a single large-scale longitudinal dataset from a top-tier Swiss insurance company comprising information on customers, contracts history and channel usage. The dataset covers the period from 2005 to 2014 and includes more than 600 000 new customer relationships incepted during that period and counts a total of 2 757 000 customer-years. For example, we can follow the evolution of the 37 225 customers acquired in 2005 for a 10-year period. For the 2011 cohort, we study 71 999 paths of new customers over four years. The database used in this study ranges among the largest non-life insurance datasets used in academic research for such econometric analyses on customer development.

This paper is structured as follows. In Section 2, we introduce the research framework and express the hypotheses guiding our analyses. The dataset is described in Section 3. In that section, we also describe the statistical methods applied to the data. We divide the presentation of our results into three chapters of interest: the analysis of customer acquisition (Section 4),

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customer development (Section 5), and customer retention (Section 6). We discuss our findings and conclude in Section 7.

2 Research framework and development of hypotheses.

A major reasoning of this research and a practical application of customer relationship management is the common understanding that it is more cost efficient and effective to expand on or to retain an existing business relationship than to acquire a new customer (Prinzie and Van Den Poel, 2006; Kamakura, 2007, Verhoef et al., 2010). To develop a long-term relationship, it is important to understand the customer characteristics that influence cross-buying and loyalty (Frost et al., 2008). Starting from the above, we focus on the following three areas of interest (see Figure 1):

1. characterization of newly acquired customers,
2. customer development through cross-buying and, respectively, cross-selling,
3. characteristics of customer lapses and retention.

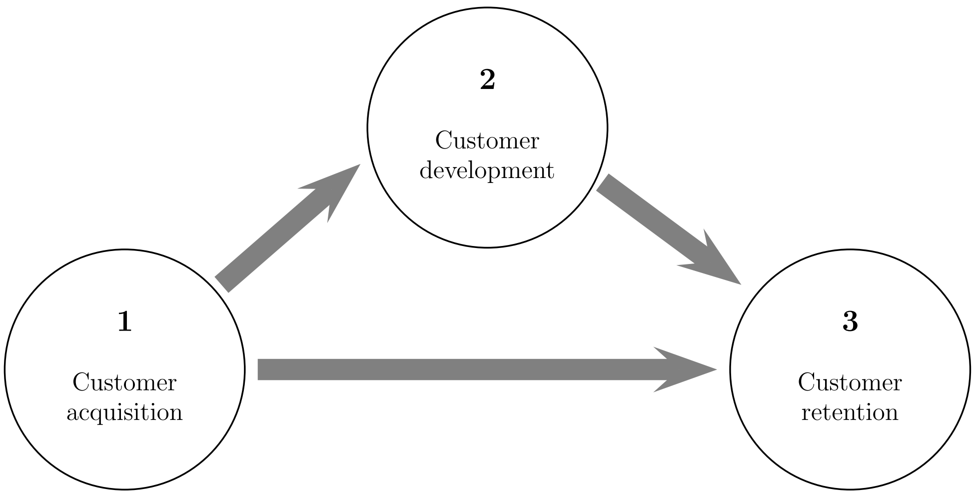

Figure 1: Development and retention of a new customer relationship.

In these three domains, we aim to identify relevant drivers for the customer development. We construct hypotheses in each area in the three sections below. The considered variables include

- the *age* of the customer respectively its relationship duration in Hypotheses 1.1, 2.1, 3.1,
- the *region of residence* of the customer in Hypotheses 2.2, 3.2,
- the *products* held by the customer in Hypotheses 1.2, 2.3, 3.3,
- the *channels* used by the customer in Hypotheses 1.3, 1.4, 2.4, 3.4,
- the *claims* history of the customer in Hypotheses 2.5, 3.5.

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2.1 Customer acquisition

In the first step of our study, we focus on the characteristics of newly acquired customers. Hereby, the idea is to establish the basis for our further analyses. In fact, as discussed by Kumar et al. (2008), the first product or service chosen when starting the customer relationship has a significant effect on the future development of it. In the following, we state our hypotheses and assumptions on trends linked to the features of these customers, the products they bought and the channels they used.

Age. The age of newly acquired customers is important since it directly drives the expected value of the future customer relationship, see, e.g., Haenlein et al. (2007) and Kim et al. (2006). (We will hypothesize on the specific importance of the customer age for development and retention later.) Since the customer relationship of younger adults is shorter, they are less bound to a given firm and brand. Further, higher lapse rates of younger policyholders are often explained by changes in family circumstances. Young adults leaving their parents' home, living with or without a partner, getting married, etc. imply changing circumstances and entail different insurance needs (Eling and Kiesenbauer, 2014). Thus, at younger ages, customers more often subscribe to new insurance contracts, as they are easier to acquire. We propose the following assumption that we want to verify with our data:

Hypothesis 1.1. *New customers tend to be young adults.*

Products. Gupta et al. (2006) and Felício and Rodrigues (2015) highlight that customers' needs and confidence in their insurers drive the companies' income and market value. Since new customers do not know a company well yet, they still must build confidence in their insurers. Furthermore, customer loyalty is the antecedent of cross-buying (Frost et al., 2008). The trend to single product purchases and shorter contract terms makes switching from one insurer to another easier. Transparency of prices and easiness to compare them allows price-sensitive customers to pick the best-priced single product from a given insurer. Further, most insurers' websites allow only for one product purchase at a time, impacting the number of products initially bought by new customers. This means that customer development starts with a portfolio with lower multi-product customer share. We look for empirical support for the following trend:

Hypothesis 1.2. *New customers tend to purchase only a single product at the beginning of the relationship.*

Channel. The Internet not only can be used to gather information and compare prices but also allows customers to conclude purchases, leading to so-called research-shopping events (Rangaswamy and Van Bruggen, 2005; Verhoef et al., 2007; 2015; Mau et al., 2015; 2016). Balasubramanian et al. (2005) and Campo and Breugelmans (2015) explain that the consumer's choice of channels, while forming their consideration sets, depends on the confidence in their abilities to evaluate products with and without experiential input. Emrich et al. (2015) state that shopping confidence is related to the perceived risk of the channel. In retailing, for example, the Internet is perceived to be risky because of security factors or the inability to physically touch and test a product. As the online buying experience increases (Herhausen et al., 2015), the perceived risk of Internet purchases decreases. Konus et al. (2008) explore how multi-channel behavior differs across different product categories. Products differ in terms of their complexity, the purchase frequency and tangibility. As the complexity of the task grows (choice, options, and impact of decisions), the consumer is more likely to prefer personal contact linked to the company (Konus et al., 2008). This leads us to formulate the following hypothesis:

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Hypothesis 1.3. *New customers mostly use the tied agent channel for contracting as the broker and the Internet access points start to gain a stronger influence.*

First channel vs (later) channel. Customers use a "first" channel to interact in the initial process of buying a policy from an insurer. Over time, the customer's behavior and preferences may change, and he may later use another interaction channel. According to status quo bias (Kahneman et al., 1991), customers prefer to stay with their actual channel, irrespective of potential benefits of alternative channels, see also, e.g., Falk et al. (2007). Existing customers become accustomed to shopping in a certain environment and are connected to the features it offers (Cao and Li, 2015). Any change or effort to move from one channel to another creates the risk of disappointing those customers (Neslin and Shankar, 2009), such that they may become dissatisfied or withdraw their trust. Therefore, experienced customers would be reluctant to shift to other channels. Thus, we expect no major changes in the interaction channel during the first year.

Hypothesis 1.4. *During the first year of their relationship, new customers do not switch the interaction channel.*

2.2 Customer development

During the past decade, marketers have focused primarily on retaining customers (see also Section 2.3). More recently, the awareness of developing customer relationships through cross-selling has increased (Kamakura, 2007). Customer development has become an important aspect of customer relationship management. In this section, we identify potential drivers of cross-buying and formulate selected hypotheses.

Age. Kumar et al. (2008) prove that the customer's age influences cross-buying through an inverted U-shaped relationship, i.e., customers in their thirties or forties are associated with higher cross-buying probability. First, cross-buying is increasing with age, as young adults need to develop their own insurance contracts, given their stage in life. For example, young adults renting a flat and living in single person households typically have different insurance needs than families with children that are homeowners. After a certain age threshold, the propensity to cross-buy decreases because customers have covered all insurance requirements. We state the following hypothesis:

Hypothesis 2.1. *Cross-buying is related to age by an inverted U-shape.*

Urbanicity and regions. It is still a common belief that, in rural regions, customers are more loyal: personal contacts, proximity and habits will make customers stay with their personal contact and, respectively their company (see also, e.g., Kahneman et al., 1991). Thus, they should be more likely to become multi-product customers. Given that the German-speaking region contains the major urban areas, while the Italian-speaking region is more rural (Lüdi and Werlen, 2005), we expect corresponding differences per language region.

Hypothesis 2.2. *Customers from rural regions are more loyal and likely to conduct cross-buying.*

Product. The results of Kumar et al. (2008) show that cross-buying depends on the first purchase. In relation to this result, Verhoef and Donkers (2005) state that customers purchasing automobile insurance are less likely to stay, but when retained, they are more likely to cross-buy. In our study, we focus on car and household/liability insurance and hence state the following:

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Hypothesis 2.3. *Customers with car insurance are more likely to conduct cross-buying than customers with household/liability insurance.*

Channel. The behavior and way customers interact in different channels will differ (Verhoef and Donkers, 2005). For example, in certain industries, the Internet leads to cross-buying since the customer takes the initiative to communicate with the company. In insurance, customers signing their first contracts over the Internet need to change their access point for cross-buying since not all products may be offered online. As the complexity of the product rises, more personal contact is preferred (Konus et al., 2008). Thus, we can conclude:

Hypothesis 2.4. *Customers using personal contact touchpoints are more likely to conduct cross-buying.*

Number of damages. Guillen et al. (2008) state that high customer satisfaction reduces the propensity for insurance policy cancellations. People with a higher number of damages have more in-depth contact with their insurer and, hence, a better understanding of the quality of the insurer (Kamakura, 2007). Further, damages may show a lack of coverage to the customer, who is then interested in buying additional insurance. To our belief, this tighter relationship has a positive effect on cross-buying, as confirmed by Verhoef et al. (2001), which leads to the following hypothesis:

Hypothesis 2.5. *Customers with a higher number of damages are more likely to conduct cross-buying.*

2.3 Customer retention

Lapse behavior is particularly analyzed in the valuation and in the management of relationships. Thereby, many studies have focused on the life insurance market. One research direction uses environmental characteristics (Kiesenbauer, 2012), while a second one uses product and policyholder characteristics regarding lapses (Renshaw and Haberman, 1986; Kagraoka, 2005; Cerchiara et al., 2009; Milhaud et al., 2011; Eling and Kiesenbauer, 2014). For example, Kiesenbauer (2012) states that lapse risk accounts for half of the capital requirements in life insurance. In non-life insurance, the contract duration and the capital requirements are less important; therefore, fewer studies have been conducted on it. However, with new retailing models, changing shopping behaviors and additional retention efforts, the analysis of lapses along contract characteristics in non-life insurance is becoming more relevant.

Age and years of relationship. Many studies analyze the influence of the policyholder's age on the probability of surrender in life insurance. Renshaw and Haberman (1986), Kagraoka (2005) and Milhaud et al. (2011) use the underwriting age, i.e., the age at policy inception. Cerchiara et al. (2009) and Eling and Kiesenbauer (2014) use the actual policyholder's age, which has a higher influence on describing the lapses than the underwriting age. Only Eling and Kiesenbauer (2014) consider the effects of each age. This leads to decreasing lapse rates with higher ages, related to Hypothesis 1.1, and for life insurance, it becomes more difficult and expensive to be accepted by insurers. Supported by the analysis from Verhoef and Donkers (2005), we are led to hypothesize that older customers are less likely to lapse. Furthermore, Verhoef et al. (2001) show that the lapse rate can be predicted by the contract age, i.e., the lapse rate is steadily decreasing with the contract age. The satisfaction judgments are based on several years (Verhoef et al., 2001; Reinartz and Kumar, 2000), i.e., as relationship holds for

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longer, the effect of satisfaction becomes stronger. This leads to our first hypothesis regarding lapse behavior:

Hypothesis 3.1. *Older customers with a longer insurance relationship are less likely to lapse.*

Urbanicity and regions. In accordance with the description of the urbanicity in Section 2.2, urban people give more importance to the best offer in terms of price, and we state that they are less loyal. This is in line with ideas by Verhoef and Donkers (2005) and leads to Hypothesis 3.2.

Hypothesis 3.2. *Customers from rural regions are less likely to lapse.*

Product. Frost et al. (2008) analyze the problem of whether customer loyalty is an antecedent or a consequence of cross-buying or if cross-buying and behavioral loyalty are bidirectional. Most business papers consider that customer loyalty is a consequence of cross-buying (Kamakura et al., 1991; Knott et al., 2002; Kamakura et al., 2003; Kamakura, 2007; Li et al., 2011). This cannot be proven by Frost et al. (2008), who state that customer loyalty is an antecedent of cross-buying; therefore, multi-product customers are more loyal. Verhoef and Donkers (2005) prove that customers with household/liability insurance are less likely to lapse, i.e., car policyholders have the highest lapse rates, due to more frequent transitions. Hence, we hypothesize the following:

Hypothesis 3.3. *Customers with multi-product/car insurance are less/more likely to lapse.*

Channel. Eling and Kiesenbauer (2014) confirm that the access point influences lapses through the service quality provided to customers. Consumers with personal contact are more loyal than multichannel enthusiasts (Verhoef et al., 2007; Konus et al., 2008). In non-life insurance, the search for the lowest price is relatively straightforward because of the use of the Internet, attracting younger customers. In accordance with Hypothesis 3.1, Internet customers are less loyal. This leads us to study the following hypothesis:

Hypothesis 3.4. *Customers using personal touchpoints are less likely to lapse.*

Number of damages. Customer satisfaction with claims management and the frequency of contacts reduces insurance policy cancellations. The literature related to insurance claims management and customer satisfaction is relatively limited; some information can be found, for example, in Mahlow and Wagner (2016). In our belief, if the customer experience with claims management is good, this leads to a more personal customer-insurer relationship, i.e.,

Hypothesis 3.5. *Customers with a higher number of damages are less likely to lapse.*

3 Dataset and statistical methods

In this section, we describe the data available for our study. We outline the dataset, provide a sketch of the available variables and introduce the notations used in the sequel to this paper. Then, we introduce the statistical methods used in our empirical analysis.

3.1 Description of the dataset and notations

We base our analysis on a longitudinal dataset from a top-tier Swiss insurance company for the period from 2005 to 2014. The data cover all the non-life insurance contracts held by private

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Attribute	Variable	Description
Customer		
Start of relationship	t_0	Starting year of the customer's relationship (2005, ..., 2014).
Years of relationship	y	Describe how long the relationship subsists.
Age	AGE	Age of the customer, grouped into the following age classes: ages below 18 years ($A0$), ages $18-25$ ($A1$), ages $26-35$ ($A2$), ages $36-45$ ($A3$), ages $46-55$ ($A4$), ages $56-65$ ($A5$), ages $66-75$ ($A6$), and ages above 76 ($A7$).
Urbanicity	URB	Urbanicity of the customer's residence area taking two values: urban (UU) and rural (UR).
Language region	LAN	Main language spoken in the customer's residence area taking three values: German (LG), French (LF) and Italian (LI).
Geographic region	GEO	• East Swiss Plateau (GE) including Zurich and Winterthur, • West Swiss Plateau (GW) including Berne and Basel, • Alps and Prealps (GA) incl. St. Gallen, Chur, Lucerne, Brig, • Romandy (GR) including Geneva, Lausanne and Sion, • Italian Switzerland (GI) including Lugano and Locarno.
Product		
Type of product	PRO	• Household and private liability insurance (HL), • Car insurance (CA).
Contract premium	PRE	Premium paid by the customer.
Number of damages	NDA	Number of damages declared to the insurer.
Channel		
Access channel	CHA	Access used by the customer to interact with the insurer: • Tied agent: agent linked exclusively to an insurance (TA), • Independent intermediary (IY), • Brokers selling on behalf of a tied agent (BR), • Head office and brokers linked to head office (HO), • Internet / insurer's website (IT), • Service center / telephone contact (SC).

Table 1: Summary of the variables used in the data analyses.

customers. In our study, we use all the policyholders contained in the dataset, i.e., the only selection bias is related to the specific company the data comes from. Since the firm is one of the largest Swiss insurers, its portfolio can be considered representative of the market. The product and multi-channel marketing strategy of the company is to have a "single brand" using a "single price" approach and offer the same products across all channels. This strategy is followed by many companies in the Swiss insurance market. In our analyses, we focus on the two most common non-life insurance products: household/liability and car insurance. In the sequel, we concentrate on that subset of the portfolio data.

The dataset comprises information on (a) the customers, including age, residence information, and length of relationship, (b) the contracts, product line and number of components underwritten, the premiums, number of losses, and (c) the channel usage with the first channel, actual channel over the years and the usage of channel combinations for interacting with the insurer. Details on the available variables and a short description are reported in Table 1.

While data are available for the years 2005–2015, we concentrate in several analyses on the 2005 and 2011 cohorts, i.e., for development and retention, we follow up on the newly acquired customers in calendar years 2005 and 2011. For the evolution of the cohort from the year 2005, our data include 10 years of customer relationships (from 2005 to 2014). Approximately 37 225 cus-

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tomers began their relationship in 2005 and 26 609 remained with the insurer in 2014. For that cohort, we count 334 255 customer-years available for the analysis. In the 2011-cohort, we have 259 083 customer-years available: 71 999 policyholders are acquired in 2011 and 56 707 remain in 2014. For the analysis of all new customers in their first year, we can reach out to 620 128 customer relationships over the years 2005–2014, i.e., we have an average of approximately 62 000 new customers per cohort. More details about the cohorts at customer relationship inception are reported in the descriptive statistics in Section 4 (see Table 2).

To describe the different cohorts and groups of customers, we introduce the following notations. Let $\mathcal{C}_{t_0}^y$ represent the set of customers who signed their first insurance contract with the company in year t_0 and are in the yth year of the relationship; thereby, t_0 represents the start of the relationship between the insurer and the customer and y is linked to the duration of the relationship. Furthermore, we formally introduce the subset of customers that did cross-buying in year y. Let $\mathcal{Y}_{t_0}^y$, defined by

$$\mathcal{Y}_{t_0}^y = \mathcal{C}_{t_0}^y \setminus \left\{ i \in \mathcal{C}_{t_0}^{y-1} | Y_{i,y-1} = 1 \right\}, \qquad y = 2, 3, \ldots, \tag{1}$$

denote the customers with their first contract incepted in year t_0, who hold either a single or multiple products in year y, while having only one single product in the previous year $(y-1)$. The indicator variable $Y_{i,y}$ is 1 if the customer has both products in the year y, else $Y_{i,y} = 0$. Finally, we use the notation $\mathcal{D}_{t_0}^y$ to represent the customers who entered the relationship in year t_0 and lapsed their last contract after y years, i.e., before the end of the year $(y+1)$. We have

$$\mathcal{D}_{t_0}^y = \mathcal{C}_{t_0}^y \setminus \mathcal{C}_{t_0}^{y+1}, \qquad y = 1, 2, \ldots. \tag{2}$$

3.2 Description of the statistical methods

Beyond the descriptive statistics for our dataset that we present in the first part of the Sections 4 to 6, we apply statistical analyses and regression models to further test our hypotheses. In the following, we describe the methods used in each of the areas of customer acquisition, development and retention.

Customer acquisition

Analysis of variance (ANOVA). The cohorts $\mathcal{C}_{t_0}^y$ in our analysis are determined by the respective starting years t_0 from 2005 to 2014 of the customer relationship. Thus, every year t_0, $t_0 \in \{2005, \ldots, 2014\}$, represents a "class". With an ANOVA, the differences among the mean values of the cohorts can be measured. The ANOVA is a statistical test, where the hypotheses are the following:

$$\begin{aligned} &\text{(H0)} \quad \mu_{2005} = \mu_{2006} = \ldots = \mu_{2014}, \\ &\text{(H1)} \quad \mu_i \neq \mu_j, \qquad \text{for } i \neq j, \end{aligned}$$

where μ_{t_0} represents the average value taken by a variable in the class t_0. With the test, we check if at least two means differ. Note that this test will not state which cohorts are different.

χ^2-test. A homogeneity χ^2-test analyzes if the customer distribution over different categories (e.g., age class and channel) changes between the classes t_0. The hypotheses of the test are the

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following ones:

$$\begin{aligned}&(\text{H0}) \quad F_{2005} = F_{2006} = \ldots = F_{2014},\\&(\text{H1}) \quad F_i \neq F_j, \quad \text{for } i \neq j,\end{aligned}$$

where F_{t_0} is the density function of the class t_0 for a given analyzed variable. The test can state if the distributions of at least two classes are different. The results of an application of this test to the access channels used are reported in Table 4 in Section 4.

Logistic regression on the urbanicity variable. The urbanicity URB is a binary variable that can take the values urban and rural (UU respectively UR, see Table 1). With the application of the ANOVA introduced above on a binary variable, we can merely obtain an idea of the behavior of the data, i.e., of the urbanicity share. In fact, an ANOVA is not adapted for this analysis because it should only be applied on continuous or interval scaled variables. Thus, to strengthen the result, we apply a logistic regression as follows:

$$URB_i = \begin{cases} 1 & \text{urban residence area,} \\ 0 & \text{rural residence area,} \end{cases} \tag{3}$$

where the index i stands for the different customers. The probability is calculated by

$$\ell(t_{0,i}) = \log\left(\frac{P(URB_i = 1|t_{0,i})}{1 - P(URB_i = 1|t_{0,i})}\right), \tag{4}$$

and the model is $\ell(t_{0,i}) = \alpha_0 + \alpha_1 \cdot t_{0,i}$, where $t_{0,i}$ denotes the starting year of the relationship of customer i. The results of this regression can be found in Table 3 in Section 4.

Customer development

A customer is considered to have conducted cross-buying in year t of his relationship with the insurer, if he holds a combination of both a household/liability contract (HL) and a car insurance contract (CA) in year t, and only had a single insurance contract in the previous year $(t-1)$. The state of a customer can be represented by the dummy variable $Y_{i,t}$ defined by

$$Y_{i,t} = \begin{cases} 1 & \text{multi-product customer holding both } HL \ \&\ CA \text{ in year } t, \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

The case $Y_{i,t} = 1$ corresponds to a multi-product customer in year t.

We aim to determine the influence of the customer, products and distribution characteristics on cross-buying using a regression analysis. Because the dependent variable $Y_{i,t}$ is a dummy variable, we use the logistic regression method. Therein, the dependent variable is transformed with the help of the logit function as follows:

$$\ell(X_{i,t-1}) = \log\left(\frac{P(Y_{i,t} = 1|X_{i,t-1})}{1 - P(Y_{i,t} = 1|X_{i,t-1})}\right), \tag{6}$$

where the function log represents the natural logarithm and the vector $X_{i,t-1}$ denotes the customer relationship characteristics in year $(t-1)$. More specifically, we solve the following

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model:

$$\begin{aligned}\ell(X_{i,t-1}) &= \alpha_0 + \alpha_1 \cdot AGE_{i,t-1} + \alpha_2 \cdot URB_{i,t-1} + \alpha_3 \cdot LAN_{i,t-1} + \alpha_4 \cdot PRO_{i,t-1} \\ &\quad + \alpha_5 \cdot CHA_{i,t-1} + \alpha_6 \cdot NDA_{i,t-1}. \end{aligned} \tag{7}$$

As a baseline for the logistic regression, we use the age class 26 to 35 ($A2$), the urban (UU) and the German-speaking (LG) regions, the product household/liability insurance (HL) and the tied agent (TA) as an access point. We chose the age class 26 to 35 for the baseline because this is the first age class in which no youth or young adult rebates are granted. The urban and German-speaking regions represent the largest regions in Switzerland. Regarding the access channels, the tied agent channel is the most used access point. Furthermore, clients with a household/liability insurance represent the highest new customer portfolio share. We do not include the geographical regions in our model since they are highly correlated with the language regions and the urbanicity indicators. The logistic regression is evaluated separately for every cohort t_0 and every year t. The results are reported in Tables 7 and 8 in Section 5.2.

Customer retention

For the quantitative analysis of lapses, generalized linear models, such as the logistic regression (Cerchiara et al., 2009, Eling and Kiesenbauer, 2014) and the Poisson regression (Kagraoka, 2005), are most often used. Cerchiara et al. (2009) use the logistic regression because binomial error terms are the typical approach for modeling lapses. Kagraoka (2005) prefers the Poisson regression since the lapses are response variables close to zero and the model output is used qualitatively rather than quantitatively. In our study, we apply a logistic regression as follows. We introduce a dummy variable that defines lapses. A customer is considered to have lapsed in year t if no database entry on its contracts is found at the end of the calendar year. We introduce

$$D_{i,t} = \begin{cases} 1 & \text{lapse,} \\ 0 & \text{otherwise,} \end{cases} \tag{8}$$

denoting if the customer i has lapsed during the year t.

Our objective is to analyze the influence of the customer, products and distribution characteristics in year $(t-1)$ on the lapsing behavior in year t. $D_{i,t}$ being a binary variable, we use a logistic regression and transform the dependent variable with the help of the logit function (cf. above),

$$\hat{\ell}(X_{i,t-1}) = \log\left(\frac{P(D_{i,t}=1|X_{i,t-1})}{1-P(D_{i,t}=1|X_{i,t-1})}\right), \tag{9}$$

and solve the following model:

$$\begin{aligned}\hat{\ell}(X_{i,t-1}) &= \alpha_0 + \alpha_1 \cdot y_{i,t-1} + \alpha_2 \cdot AGE_{i,t-1} + \alpha_3 \cdot URB_{i,t-1} + \alpha_4 \cdot LAN_{i,t-1} \\ &\quad + \alpha_5 \cdot PRO_{i,t-1} + \alpha_6 \cdot CHA_{i,t-1} + \alpha_7 \cdot NDA_{i,t-1}. \end{aligned} \tag{10}$$

For the lapse analysis, all data from the customer relationships are taken from inception until the lapse. For the regression analysis, we use the same baseline as in the previous analysis of cross-buying (see Section 5), i.e., age class 26 to 35 ($A2$), the urban (UU) and German-speaking

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region (LG), the product household/liability insurance (HL) and the tied agent (TA) as an access point. The number of years of a relationship is a continuous variable and thus excluded from the baseline. The results using the above model are reported in Table 11 (Section 6).

4 Customer acquisition: results and discussion

In this section, we statistically describe the data characterizing newly acquired customers in the period from 2005 to 2014 and study Hypotheses 1.1 to 1.4 introduced in Section 2.1. To strengthen the observed results in the descriptive statistics (see Table 2) and to statistically verify the hypotheses, we apply two statistical tests, an ANOVA and a χ^2-test as introduced in Section 3.2. Further, we perform a logistic regression on the urbanicity criterion. The results are reported in Table 3.

Age. The average age of new customers increases from 31.7 to 35.2 over the studied period. This development is underlined by the result of the ANOVA, where the test results show that the average age of at least two cohorts are statistically significantly different (F-value of 273.5 and p-value smaller than 0.1%). The new customers in the age class from 18 to 25 years represent the largest share of the analysis, even if that share is decreasing. Accordingly, the share of customers from ages 26 to 35 and from 46 to 55 is increasing, leading to an aging of the portfolio. Note that the age class from 26 to 35 represents the first age, where no discounts for young customers are granted. With a χ^2-test ($df = 63$, $X^2 = 3586.3$), we analyze if the distribution of the ages is differing over the years. With a p-value smaller than 0.1%, we conclude that there are significant changes. Regarding the assumption laid out in Hypothesis 1.1, our data supports that young adults aged between 18 and 35 years represent the major share of the new customers. Considering the trend that the average age of new customers is increasing through the calendar years (for this insurer), given that the potential future value of younger customers is often larger, the attention of marketing initiatives may focus on keeping the entry age low by targeting the corresponding customer segments.

Urbanicity. The intake of new customers, along the urbanicity of their residence area, the language and the geographical regions, is closely linked to the company's management decisions and history. We have not formulated a hypothesis about these dimensions but rather present statistics for background information. The major residence area for customers is the rural region, but we observe a development of the share of residents in the urban region; especially since 2013, the share of customers from urban regions has increased. (This relates to a marketing campaign engaged by the underlying company.) The result of the ANOVA (F-value 70.31, ***) and the logistic regression (Table 3) underline these changes. In fact, the logistic regression shows an increase of the share of the urban regions since 2009, with a p-value smaller than 5%. The χ^2-test ($df = 9$, $X^2 = 632.15$) supports these results, by stating that the distribution of the urbanicity is changing over the years. Statistics published by the Swiss Federal Office for Spatial Development (2003) show that, since 1998, the population has grown more quickly in the urban than in the rural regions. This, combined with company-specific marketing efforts, underlines the evolution of the urbanicity share.

Language and geographical regions. Table 2 further reports the shares of new customers from each of the language and geographical regions. Comparing the customer distribution by regions in our dataset with the data from statistics for the total Swiss population, we observe similar

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Characteristics	$\mathcal{C}^1_{2005}$	$\mathcal{C}^1_{2006}$	$\mathcal{C}^1_{2007}$	$\mathcal{C}^1_{2008}$	$\mathcal{C}^1_{2009}$	$\mathcal{C}^1_{2010}$	$\mathcal{C}^1_{2011}$	$\mathcal{C}^1_{2012}$	$\mathcal{C}^1_{2013}$	$\mathcal{C}^1_{2014}$
No. of cust.	37 225	43 835	58 225	63 371	67 491	66 551	71 999	72 848	69 377	69 176
Age										
Average	31.7	32.3	34.0	33.6	34.0	34.6	34.9	34.6	35.0	35.2
$A0$: < 18	11.8%	10.3%	8.8%	9.3%	8.7%	8.4%	7.8%	7.9%	7.7%	8.0%
$A1$: $18 - 25$	35.8%	34.6%	30.1%	30.9%	30.3%	29.6%	29.3%	30.0%	29.2%	28.6%
$A2$: $26 - 35$	18.0%	18.8%	20.1%	20.6%	20.8%	20.5%	20.8%	21.3%	21.6%	21.5%
$A3$: $36 - 45$	15.8%	16.6%	18.0%	17.1%	17.2%	16.7%	16.7%	15.8%	15.7%	15.5%
$A4$: $46 - 55$	10.2%	10.7%	12.5%	12.2%	12.4%	13.4%	13.7%	13.4%	13.6%	13.6%
$A5$: $56 - 65$	5.5%	6.0%	6.8%	6.2%	6.7%	7.1%	7.2%	7.0%	7.2%	7.4%
$A6$: $66 - 75$	2.1%	2.2%	2.7%	2.7%	2.9%	3.2%	3.4%	3.3%	3.7%	3.9%
$A7$: ≥ 76	0.7%	0.8%	1.0%	1.0%	1.2%	1.1%	1.2%	1.2%	1.3%	1.4%
Urbanicity										
UU	35.5%	35.6%	34.9%	35.6%	36.1%	36.4%	36.1%	36.6%	39.2%	39.7%
UR	64.5%	64.4%	65.1%	64.4%	63.9%	63.6%	63.9%	63.4%	60.8%	60.3%
Language region										
LG	79.6%	79.0%	78.5%	79.8%	79.2%	78.7%	77.2%	77.4%	76.7%	77.3%
LF	16.8%	17.1%	17.3%	16.3%	16.7%	16.7%	17.9%	18.0%	18.9%	18.3%
LI	3.6%	3.8%	4.2%	3.8%	4.0%	4.6%	4.9%	4.6%	4.3%	4.4%
Geographical region										
GE	25.0%	25.7%	26.1%	27.2%	26.6%	26.7%	26.0%	26.4%	26.1%	26.9%
GW	27.8%	27.1%	25.7%	25.8%	25.6%	25.6%	25.4%	25.4%	25.7%	25.8%
GA	27.0%	26.5%	26.9%	27.0%	27.3%	26.6%	26.1%	25.8%	25.1%	24.9%
GR	16.7%	16.9%	17.1%	16.2%	16.6%	16.5%	17.7%	17.9%	18.8%	18.1%
GI	3.5%	3.8%	4.1%	3.8%	3.9%	4.5%	4.8%	4.5%	4.3%	4.3%
Products	42 215	48 431	64 114	68 533	72 098	71 088	77 027	77 996	74 378	73 972
HL	65.8%	62.3%	55.8%	53.5%	54.4%	52.7%	48.0%	50.3%	53.0%	54.6%
CA	20.8%	27.2%	34.2%	38.3%	38.8%	40.5%	45.0%	42.6%	39.8%	38.4%
HL & CA	13.4%	10.5%	10.1%	8.1%	6.8%	6.8%	7.0%	7.1%	7.2%	6.9%
No. of prod.[1]	1.13	1.10	1.10	1.08	1.07	1.07	1.07	1.07	1.07	1.07
Channel										
TA	84.7%	82.7%	80.9%	80.4%	78.6%	77.4%	74.0%	74.6%	72.6%	73.4%
IY	12.8%	12.5%	13.2%	13.0%	13.9%	12.7%	13.1%	13.6%	15.1%	14.8%
BR	0.6%	3.4%	4.6%	5.6%	6.3%	8.2%	10.4%	9.4%	8.5%	7.5%
IT						0.4%	0.9%	0.9%	2.1%	2.4%
TA & IY	1.3%	0.9%	0.8%	0.5%	0.4%	0.5%	0.5%	0.6%	0.6%	0.5%
Other[2]	0.7%	0.6%	0.5%	0.5%	0.7%	0.8%	1.1%	0.9%	1.1%	1.3%
First channel										
TA	84.8%	83.3%	82.0%	80.9%	79.3%	78.1%	74.4%	74.6%	73.1%	73.3%
IY	13.3%	13.1%	12.4%	12.6%	13.5%	13.3%	13.0%	13.6%	14.6%	14.8%
BR	0.0%	2.0%	4.3%	5.4%	6.1%	6.9%	10.0%	9.3%	8.4%	7.3%
IT						0.4%	1.0%	1.0%	2.3%	2.6%
TA & IY	1.3%	1.0%	0.7%	0.5%	0.4%	0.5%	0.5%	0.6%	0.6%	0.5%
Other[2]	0.6%	0.6%	0.6%	0.6%	0.7%	0.9%	1.1%	0.9%	1.1%	1.4%

Table 2: Descriptive statistics of the newly acquired customers in their first year.

shares. We take this as an indicator that our data sample is largely representative for Switzerland.

Products and premium volume. The number of products sold and the premium volume increase as the number of customers over the cohorts increases. More than half of the new customers buy household/liability insurance. The share of customers buying both household/liability and motor insurance products at relationship inception decreases from 13.4% (2005) to 6.9% (2014). These changes are graphically represented in Figure 2(a). Thus, most new customers are single product buyers, which supports Hypothesis 1.2. Cross-selling becomes increasingly crucial for developing the customers (see Section 5), given the positive impact on customer retention that

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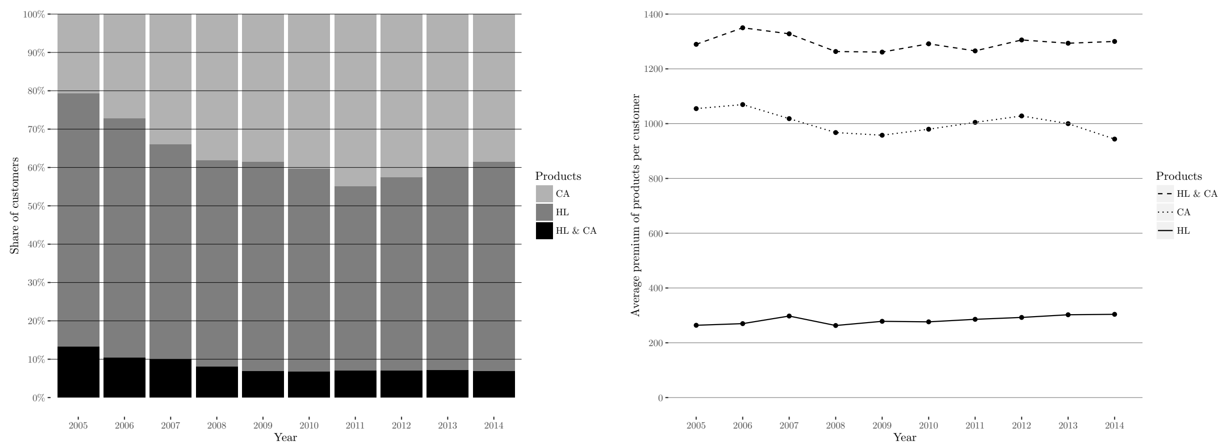
Staudt, Y. and Wagner, J. (2018), International Journal of Bank Marketing, Vol. 36 No. 6, pp. 1098-1124.

Variables	$\mathcal{C}^1_{2005:2014}$	
Intercept/baseline=2005	−0.598	***
2006	0.004	
2007	−0.024	.
2008	0.006	
2009	0.027	*
2010	0.038	**
2011	0.029	*
2012	0.050	***
2013	0.159	***
2014	0.179	***
N	620 128	

Note: Significance levels for p-values: *** $p \leq .001$, ** $p \leq .01$, * $p \leq .05$, . $p \leq 0.1$.

Table 3: Logistic regression on the urbanicity variable for newly acquired customers.

we show in Section 6. Regarding the premium volume, we observe cyclical fluctuations especially in the motor premiums (see Figure 2(b)). The relative size of the motor premium to the household/liability premium also influences the total multi-product premium.



(a) New customers' product differences.

(b) New customers' average premiums.

Figure 2: Evolution of products and premiums in the first year for the 2005 to 2014 cohorts.

Channel. The tied agent remains the major access point for new customers, despite its decreasing share from 84.8% to 73.3% over 10 years. We notice that the broker has gained importance, as observed in the Swiss market in general. Since the year 2010, the underlying insurer providing the data offers products through its online website. A rapid growth of the Internet access point can be observed. The χ^2-test ($df = 45$, $X^2 = 14\,558$) with a p-value smaller than 0.1% underlines the evolution of access channels and thereby supports Hypothesis 1.3.

First channel vs (later) channel. Overall, there seem to be some differences between the distribution of the last channel used in the year the customer is acquired and the first channel used at the time of issuing the contract. However, a χ^2-test applied to statistically compare this evolution in channel usage over all cohorts $\mathcal{C}^1_{2005}$ to $\mathcal{C}^1_{2014}$ rejects the hypothesis of no significant differences between the channels (the intermediary and the broker channels however yield

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significant differences, cf. Table 4). Thus, Hypothesis 1.4 about switching interaction points in the first year is rejected.

Access channel	χ^2-test	
TA	$df = 9$, $X^2 = 4.46$	
IY	$df = 9$, $X^2 = 44.46$	**
BR	$df = 9$, $X^2 = 378.75$	**
IT	$df = 9$, $X^2 = 0.56$	
TA & IY	$df = 9$, $X^2 = 10.38$	
Other	$df = 9$, $X^2 = 6.88$	

Note: Significance levels for p-values: *** $p \leq .001$, ** $p \leq .01$, * $p \leq .05$, . $p \leq 0.1$.

Table 4: Results of the χ^2-test of the comparison of the channel used at acquisition time versus other channels used during the first relationship year for the $\mathcal{C}^1_{2005}$ to $\mathcal{C}^1_{2014}$ cohort customers.

5 Customer development: results and discussion

5.1 Descriptive statistics

We start by describing the longitudinal data for the 2005 and 2011 cohorts. For this, we provide yearly cross-sectional statistics. In the 2005 cohort $\mathcal{C}_{2005}$, we consider the first five years of relationship (Table 5), while for the 2011 cohort $\mathcal{C}_{2011}$, we have four years of relationship data (Table 6).

Number of customers. For both the 2005 and 2011 cohorts, we observe a decreasing number of customers over the years, which is due to policy surrenders (see Section 6). In fact, when comparing the number of customers and lapses reported in Tables 5 and 6, we observe that the retention rate within the 2005 cohort $\mathcal{C}_{2005}$ in the period 2005–2010 is much higher than the same rate for the 2011 cohort in the years after 2011. Although no publicly available figures are reported by other companies in the Swiss market (making a comparative analysis impossible), we note the strong difference between both time periods. This may be partly explained by technological changes (e.g., digitization and Internet platforms) making prices more transparent and thus motivating customers to change their companies more frequently. We will come back to this point in the concluding remarks.

Products. Related to the decrease in the number of customers, the total number of products is decreasing. However, the average number of products held per customer rises for the 2005 cohort, from 1.13 to 1.21 within five periods, and for $\mathcal{C}_{2011}$, from 1.07 to 1.20 over four periods. In line with this, the share of multi-product customers is increasing in both cohorts, reaching a share of approximately 20% after four years of a relationship. We further observe that the share of the multi-product customers in the 2011 cohort is only half of the share of that in the 2005 cohort in their first year of relationship. Regarding the customer loyalty discussed in Section 6, this may be alarming. At the same time, more customers from the $\mathcal{C}_{2011}$ cohort are cross-buying, showing the specific effort of the underlying company and supporting the importance of analyzing the drivers of this development (see also Section 5.2). In fact, using marketing efforts efficiently is crucial to optimizing customer development and increasing loyalty. The shares of the single products differ in both cohorts. In $\mathcal{C}_{2005}$, the household/liability insurance is the

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Year	$\mathcal{C}^1_{2005}$		$\mathcal{C}^2_{2005}$		$\mathcal{C}^3_{2005}$		$\mathcal{C}^4_{2005}$		$\mathcal{C}^5_{2005}$		
No. of cust.	37 225		37 130		37 010		36 910		36 155		
Lapse[3]			95		120		100		755		2 444
Products	42 215		43 462		43 987		44 227		43 629		
HL	24 495	(65.8%)	23 411	(63.1%)	22 844	(61.7%)	22 407	(60.7%)	21 684	(60.0%)	
CA	7 740	(20.8%)	7 387	(19.9%)	7 189	(19.4%)	7 186	(19.5%)	6 997	(19.4%)	
HL & *CA*	4 990	(13.4%)	6 332	(17.1%)	6 977	(18.9%)	7 317	(19.8%)	7 474	(20.7%)	
No. of prod.[4]	1.13	(0.34)	1.17	(0.38)	1.19	(0.39)	1.20	(0.40)	1.21	(0.40)	
Channel											
TA	31 526	(84.7%)	30 713	(82.7%)	29 708	(80.3%)	29 439	(79.8%)	28 797	(79.6%)	
IY	4 758	(12.8%)	4 640	(12.5%)	5 299	(14.3%)	5 339	(14.5%)	5 184	(14.3%)	
BR	208	(0.6%)	1 068	(2.9%)	1 166	(3.2%)	1 191	(3.2%)	1 264	(3.5%)	
TA & *IY*	489	(1.3%)	483	(1.3%)	595	(1.6%)	697	(1.9%)	702	(1.9%)	
Other[2]	244	(0.7%)	226	(0.6%)	242	(0.7%)	244	(0.7%)	208	(0.6%)	
Damages	2 684[5]		6 179		6 507		6 776		7 413		
HL	0.03[5]	(0.18)	0.09	(0.33)	0.09	(0.33)	0.09	(0.34)	0.10	(0.35)	
CA	0.11[5]	(0.39)	0.25	(0.60)	0.25	(0.60)	0.25	(0.61)	0.27	(0.64)	
HL & *CA*	0.22[5]	(0.58)	0.36	(0.74)	0.38	(0.75)	0.39	(0.75)	0.45	(0.81)	
Per customer	0.07[5]	(0.32)	0.17	(0.49)	0.18	(0.51)	0.18	(0.52)	0.21	(0.55)	

Table 5: Development of the 2005 cohort customers $\mathcal{C}^y_{2005}$ in years $y = 1$ to 5 (i.e., from 2005 to 2009).

Year	$\mathcal{C}^1_{2011}$		$\mathcal{C}^2_{2011}$		$\mathcal{C}^3_{2011}$		$\mathcal{C}^4_{2011}$	
No. of cust.	71 999		67 194		62 183		57 707	
Lapse[3]			4 805		5 011		4 476	
Products	77 027		75 900		72 653		69 113	
HL	34 594	(48.0%)	30 395	(45.2%)	27 444	(44.1%)	25 075	(43.5%)
CA	32 377	(45.0%)	28 093	(41.8%)	24 269	(39.0%)	21 226	(36.8%)
HL & *CA*	5 028	(7.0%)	8 706	(13.0%)	10 470	(16.8%)	11 406	(19.8%)
No. of prod[4]	1.07	(0.25)	1.13	(0.34)	1.17	(0.37)	1.20	(0.40)
Channel								
TA	53 250	(74.0%)	49 593	(73.8%)	45 225	(72.7%)	42 128	(73.0%)
IY	9 461	(13.1%)	8 575	(12.8%)	8 256	(13.3%)	7 353	(12.7%)
BR	7 474	(10.4%)	6 907	(10.3%)	6 392	(10.3%)	5 965	(10.3%)
IT	666	(0.9%)	497	(0.7%)	373	(0.6%)	231	(0.4%)
TA & *IY*	384	(0.5%)	815	(1.2%)	1 105	(1.8%)	1 232	(2.1%)
Other[2]	764	(1.1%)	807	(1.2%)	832	(1.3%)	798	(1.4%)
Damages	6 451[5]		15 938		16 772		15 529	
HL	0.03[5]	(0.20)	0.10	(0.35)	0.11	(0.36)	0.11	(0.36)
CA	0.14[5]	(0.43)	0.33	(0.71)	0.36	(0.75)	0.35	(0.73)
HL & *CA*	0.19[5]	(0.51)	0.43	(0.80)	0.49	(0.90)	0.48	(0.87)
Per customer	0.09[5]	(0.35)	0.24	(0.61)	0.27	(0.66)	0.27	(0.65)

Table 6: Development of the 2011 cohort customers $\mathcal{C}^y_{2011}$ in years $y = 1$ to 4 (i.e., from 2011 to 2014).

major product (60% of the customers). In $\mathcal{C}_{2011}$, the shares of the household/liability and car insurance are much more balanced. In $\mathcal{C}_{2011}$, the share of motor insurance as a single product decreases more quickly than in $\mathcal{C}_{2005}$. This reflects the idea laid out in Hypothesis 2.3. The evolution of the products held by both cohorts is represented in Figure 3.

Channel. The tied agents remain the most important interaction points over the years in both the 2005 and 2011 cohorts (Figure 4). In the 2005 cohort $\mathcal{C}_{2005}$, the influence of the brokers is progressively increasing. From a low level of 0.6% at the time of acquisition, the share tripled over the five years under consideration. In the cohort $\mathcal{C}_{2011}$, the broker channel has a larger influence after acquisition and remains constant over the years. This finding is in line with the overall evolution observed in the Swiss market. Recall that the insurer underlying our data

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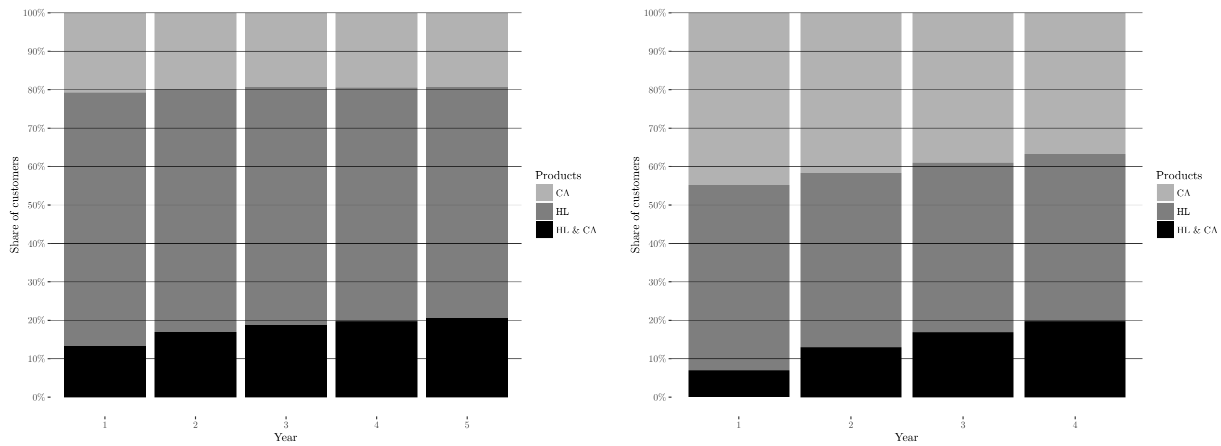
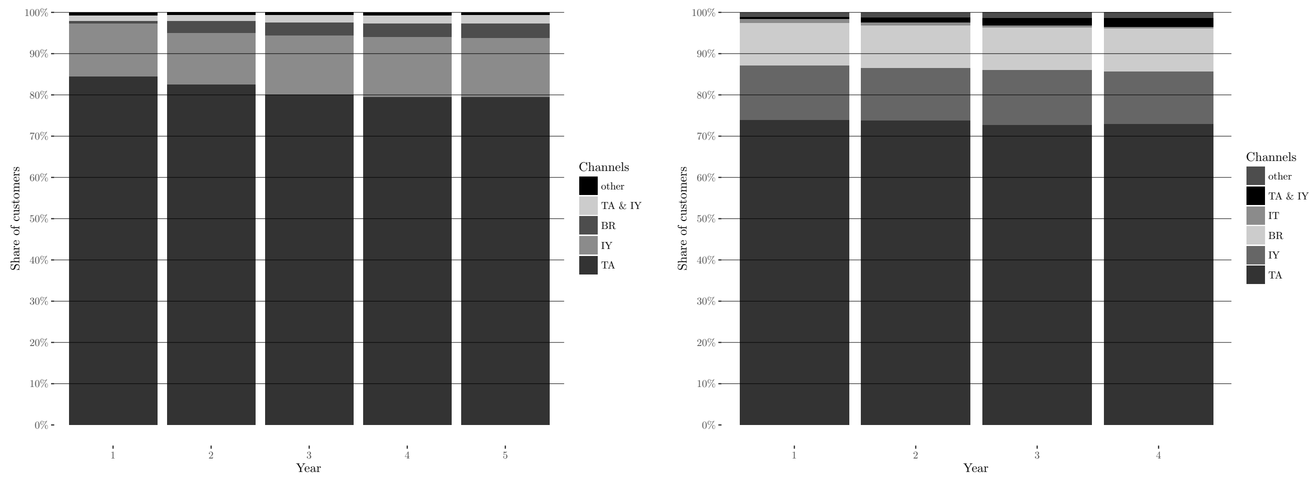


(a) 2005 cohort customers.

(b) 2011 cohort customers.

Figure 3: Development of products held by the $\mathcal{C}_{2005}$ and $\mathcal{C}_{2011}$ customers in their first years.

offered the Internet as an access point only beginning in 2010. This leads to a major difference between the two cohorts.



(a) 2005 cohort customers.

(b) 2011 cohort customers.

Figure 4: Development of the channels used by the $\mathcal{C}_{2005}$ and $\mathcal{C}_{2011}$ customers in their first years.

Number of damages. The reported number of damages in the second year is two to three times larger than in the first year. This is partially a technical artifact related to the fact that the average first-year contract duration is about half a year (with some customers contracting earlier and some later in the year). The number of damages recorded in the first year should be multiplied by a factor two to make them comparable with the numbers observed the following years. Hence, after correction, only a small increase over the years can be observed. The number of damages per customer is slightly higher in the 2011 cohort than in the 2005 cohort. Since both confidence intervals of the average number of damages overlap, no significant difference for both cohorts can be observed.

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5.2 Regression results

In the following, we provide the results when applying the logistic regression model introduced in Equation 7 (Section 3.2) to our data. Thereby, we aim to find what characteristics of the customer relationship are relevant for cross-selling and to check if the hypotheses described in Section 2.2 are supported or not. The parameter estimates of the logistic regression are reported in the Tables 7 and 8 for the 2005 and 2011 cohorts, respectively. Recall that this analysis is retrospective, i.e., the results are linked to the specific marketing strategy of the insurer.

Variables	$\mathcal{Y}^2_{2005}$		$\mathcal{Y}^3_{2005}$		$\mathcal{Y}^4_{2005}$		$\mathcal{Y}^5_{2005}$		$\mathcal{Y}^6_{2005}$	
Intercept	−3.076	***	−3.410	***	−3.686	***	−3.515	***	−3.516	***
Age										
$A0$	−0.515	***	0.199	.	0.177		0.205		−0.738	
$A1$	0.350	***	0.438	***	0.602	***	0.609	***	0.610	***
$A2$	(Intercept)									
$A3$	−0.156	.	−0.103		−0.298	**	−0.420	***	−0.213	.
$A4$	−0.185	.	−0.451	***	−0.442	***	−0.318	**	−0.473	***
$A5$	−0.127		−0.480	***	−0.354	*	−0.509	**	−0.486	**
$A6$	−0.582	**	−0.762	**	−0.770	**	−0.537	*	−0.570	*
$A7$	−1.339	**	−1.905	**	−1.140	*	−1.558	**	−1.283	*
Urbanicity										
UU	(Intercept)									
UR	0.382	***	0.366	***	0.470	***	0.253	***	0.196	**
Language region										
LG	(Intercept)									
LF	−0.089		−0.192	*	−0.116		−0.302	***	−0.235	*
LI	0.010		0.043		−0.235		−0.091		−0.332	
Products										
HL	(Intercept)									
CA	0.339	***	0.667	***	0.434	***	0.398	***	0.067	
Channel										
TA	(Intercept)									
IY	−0.228	**	−0.534	***	−0.140		−0.181	*	−0.115	
BR	−0.518		−0.973	***	−0.243		−0.372	.	0.142	
TA & IY	−0.185		−0.208		−0.743		0.889	*	0.425	
Other[2]	−0.742		−1.354	.	−0.476		−0.149		−12.939	
Damages										
NDA	0.053		0.223	***	0.164	**	0.216	***	0.152	*
N	32 235		30 798		30 033		29 593		28 681	

Note: Significance levels for p-values: *** $p \leq .001$, ** $p \leq .01$, * $p \leq .05$, . $p \leq 0.1$.

Table 7: Results from the logistic regression cross-buying analysis for the 2005 cohort in year $t = 2, \ldots, 6$ (i.e., from 2006 to 2010).

Age. All statistically significant parameter estimates for the age classes, except for the age class 18 to 25 ($A1$), have a negative estimate parameter. Thus, young adults aged 18 to 25 are most likely to cross-buy and thus present an interesting target group for development. They are followed by the reference class $A2$, grouping the customers with ages between 26 and 35 years. Furthermore, higher age classes are accompanied by lower cross-buying propensities. The numbers remain relatively stable up to age 65. In most years, a significant decrease can be observed for the age classes $A6$ and $A7$ (see Tables 7 and 8). This provides support for Hypothesis 2.1.

Urbanicity and language regions. In both considered cohorts and for all years, we observe that

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Variables	$\mathcal{Y}^2_{2011}$		$\mathcal{Y}^3_{2011}$		$\mathcal{Y}^4_{2011}$	
Intercept	−2.922	***	−3.419	***	−3.444	***
Age						
$A0$	−0.589	***	0.368	***	0.120	
$A1$	0.456	***	0.737	***	0.772	***
$A2$	(Intercept)					
$A3$	0.035		−0.133	.	−0.324	***
$A4$	−0.028		−0.204	**	−0.297	***
$A5$	−0.049		−0.022		−0.178	.
$A6$	0.114		−0.215	.	−0.129	
$A7$	−0.532	**	−0.402	.	−0.998	**
Urbanicity						
UU	(Intercept)					
UR	0.364	***	0.260	***	0.163	***
Language region						
LG	(Intercept)					
LF	−0.127	**	−0.283	***	−0.201	***
LI	−0.331	***	−0.180	.	−0.370	**
Products						
HL	(Intercept)					
CA	−0.037		0.292	***	0.402	***
Channel						
TA	(Intercept)					
IY	−0.211	***	−0.312	***	−0.155	*
BR	−0.707	***	−0.570	***	−0.724	***
IT	−0.473	*	−0.352		−0.432	
TA & IY	0.647	.	0.274		0.427	.
Other[2]	−0.953	***	−0.952	**	−0.693	*
Damages						
NDA	0.074		0.080	*	0.096	**
N	66 971		58 488		51 713	

Note: Significance levels for p-values: *** $p \leq .001$, ** $p \leq .01$, * $p \leq .05$, . $p \leq 0.1$.

Table 8: Results from the logistic regression cross-buying analysis for the 2011 cohort in year $t = 2, \ldots, 4$ (i.e., from 2012 to 2014).

the customers living in rural regions (UR) are significantly more likely (***) to cross-buy than those from urban regions. This supports Hypothesis 2.2 and gives an indication for directing marketing efforts. Increasing the development of urban customers may prove to be more difficult. Further, we observe that customers from the German-speaking region (LG) are most likely to cross-buy. In most years, no statistically significant differences can be found regarding the Italian-speaking region (especially for the 2005 cohort; see Table 7).

Product. Since the objective of this analysis is to study the impact of the product held by a single-product customer on the customer's likelihood to buy an additional service, we have of course excluded all multi-product customers (no line HL & CA in the results tables). For both cohorts, the results indicate that holders of motor insurance (CA) are significantly more likely (***) to cross-buy (a household/liability contract) than those holding a household/liability contract (HL) (to buy car insurance). This supports Hypothesis 2.3 and the research of Verhoef and Donkers (2005). Thus, the development of household/liability insurance holders may require more management and marketing attention.

Channel. Most access channels significantly influence the customers' cross-buying behavior.

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The tied agent (TA), which is included in the statistically significant intercept, positively influences cross-buying. Further, the combination TA & IY including interactions with a tied agent and an intermediary has a partially positive impact on cross-buying. Customers buying from a broker (BR) are less likely to cross-buy, especially for the more recent 2011 cohort (***, significantly negative parameter estimates for BR compared to the TA baseline). Hence, Hypothesis 2.4 is only partially verified because most brokers in Switzerland still operate on personal contacts. This may change with the ongoing digitization toward online brokerage that might become comparable with Internet sales. Note that the Internet channel (IT) also shows a negative impact of customer development (although these numbers for the 2011 cohort are not significant, most likely due to the smaller number of observations regarding this type of customer, cf. Table 6).

Number of damages. For several periods, a positive impact of the number of damages (NDA) on cross-buying can be shown. All statistically significant results have positive parameter estimates. We can state that Hypothesis 2.5 is partially supported. From a management perspective, this entails that losses have a positive effect on customer development. This supports a common understanding that, in a loss situation, claims management may strengthen the customer relationship. Further, such situations give place to interactions between the customer and the insurer, providing a chance for cross-selling or up-selling additional coverage in the existing contract.

6 Customer lapses: results and discussion

6.1 Descriptive statistics

Focusing on lapses, we summarize the descriptive statistics of the surrenders by the 2005 and 2011 cohorts in Tables 9 and 10, respectively. In both tables, we summarize all the lapses registered within the 10-year and 4-year periods, respectively, where observations are available. For the 2005 cohort, a total of 3 514 data points is available; for the 2011 cohort, we count 14 292 lapses. The frequencies and distribution of the characteristics found in the canceled relationships are reported.

We observe that the average age of the lapsing customers is 35.0 in the 2005 cohort and 34.4 in the 2011 cohort. The age class from 26 to 35 seems to be most impacted. In fact, in terms of frequency, customers between ages 18 and 35 entail most lapses (totaling approximately 60% of all observed lapses). This gives a sound indicator of where retention efforts should be focused. The average ages above can also be compared to the average ages of the customers at the moment of acquisition reported in Table 2: 31.7 years in the 2005 cohort and 34.9 years in the 2011 cohort. This observation hints that the number of lapses from younger customers is large (especially when comparing the higher average age at acquisition 34.9 and lower at attrition 34.4 in the 2011 cohort).

Customers from urban regions seem over-represented in the lapse statistics. At acquisition, 35.5% of the customers are from urban regions (2005 cohort, cf. Table 2). In the attrition statistics, they represent more than 40% of the lapses. We will give statistical evidence of this observation through the regression analysis below. Further, we observe that customers holding household/liability and car product combinations (HL & CA) represent a lower share of lapses.

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Staudt, Y. and Wagner, J. (2018), International Journal of Bank Marketing, Vol. 36 No. 6, pp. 1098-1124.

Characteristics	Freq.	Share	Characteristics	Freq.	Share
No of cust.	3 514		*Last product configuration*		
Age[6]	35.0	(15.2)	HL	2 227	63.4%
$A0$: < 18	30	0.9%	CA	1 108	31.5%
$A1$: $18 - 25$	1 161	33.0%	HL & CA	179	5.1%
$A2$: $26 - 35$	1 054	30.0%	No. of prod.[4]	1.21	(0.41)
$A3$: $36 - 45$	532	15.1%	*Last channel*		
$A4$: $46 - 55$	356	10.1%	TA	2 772	78.9%
$A5$: $56 - 65$	191	5.4%	IY	528	15.0%
$A6$: $66 - 75$	93	2.6%	BR	111	3.2%
$A7$: ≥ 76	97	2.8%	TA & IY	18	0.5%
Urbanicity			Other[2]	85	2.4%
UU	1 422	40.5%	*Last year no. of damages*	583	
UR	2 092	59.5%	HL[7]	0.12	(0.37)
Language region			CA[7]	0.22	(0.55)
LG	2 865	81.5%	HL & CA[7]	0.46	(0.91)
LF	565	16.1%	Avg. damage p.c.[7]	0.17	(0.48)
LI	84	2.4%	*Avg. no. of damages*		
Geographical Region			HL[8]	0.10	(0.20)
GE	964	27.4%	CA[8]	0.24	(0.37)
GW	997	28.4%	HL & CA[8]	0.35	(0.47)
GA	909	25.9%	Avg. damage p.c.[8]	0.15	(0.29)
GR	560	15.9%			
GI	84	2.4%			

Table 9: Descriptive statistics on customers' lapse from the 2005 cohort ($\bigcup_{y=1}^{5} \mathcal{D}_{2005}^{y}$).

To quantitatively assess the relevance of these and other characteristics we provide and analyze the results of the related logistic regression model in the next section.

6.2 Regression results

Using the logistic regression introduced in Equation (10) (see Section 3.2) we analyze the hypotheses related to the lapse factors. As noted above, for the 2005 cohort $\mathcal{C}_{2005}$, we use the 10 years of available history, while for the 2011 cohort $\mathcal{C}_{2011}$, we have four years of relationship data available for analysis. The regression results for both cohorts are summarized in Table 11.

Age and years of relationship. All age classes obtain a negative estimation parameter compared to the baseline age class ($A2$), with customers older than 75 (class $A7$) being the most probable to terminate their relationship (typically because of the death of these customers). This means that customers aged 26 to 35 are the most likely to lapse, supporting Hypothesis 3.1 regarding age. Customers between the ages 35 and 65 show significantly lower lapse propensities in both cohorts. Further, in both 2005 and 2011 cohorts, the probability of lapsing increases with the number of years of the relationship (*** significance). This contradicts the second part of Hypothesis 3.1 linked to the positive effect of relationship duration. This result requires further study, combining, for example, the variable of the product(s) held with the length of the relationship. The higher lapse rate may be linked to single-product customers (see below).

Urbanicity and regions. We state in the Hypothesis 3.2 that customers from rural regions (UR) are less likely to lapse, as supported by the results of our logistic regression. In line with the urbanicity criterion, the customers of the Italian-speaking region (LI) are similarly less likely to lapse in the 2005 cohort. This cannot be supported for the 2011 cohort. A negative impact

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Characteristics	Freq.	Share	Characteristics	Freq.	Share
No of cust.	14 292		*Last product configuration*		
Age[6]	34.4	(15.1)	HL	6 228	43.6%
$A0$: < 18	660	4.6%	CA	7 564	52.9%
$A1$: $18-25$	4 356	30.5%	HL & CA	500	3.5%
$A2$: $26-35$	3 947	27.6%	No. of prod.[4]	1.14	(0.34)
$A3$: $36-45$	2 204	15.4%	*Last channel*		
$A4$: $46-55$	1 694	11.9%	TA	10 042	70.3%
$A5$: $56-65$	797	5.6%	IY	2 224	15.6%
$A6$: $66-75$	367	2.6%	BR	1 594	11.2%
$A7$: ≥ 76	267	1.9%	IT	194	1.4%
Urbanicity			TA & IY	53	0.4%
UU	5 953	41.7%	Other[2]	185	1.3%
UR	8 339	58.3%	*Last year no. of damages*	3 061	
Language region			HL[8]	0.09	(0.37)
LG	10 831	75.8%	CA[7]	0.30	(0.72)
LF	2 736	19.1%	HL & CA[7]	0.47	(0.96)
LI	725	5.1%	Avg. damage p.c.[7]	0.21	(0.62)
Geographical Region			*Avg. no. of damages*		
GE	3 784	26.5%	HL[8]	0.07	(0.26)
GW	3 506	24.5%	CA[8]	0.23	(0.49)
GA	3 575	25.0%	HL & CA[8]	0.35	(0.59)
GR	2 710	19.0%	Avg. damage p.c.[8]	0.17	(0.42)
GI	717	5.0%			

Table 10: Descriptive statistics on customers' lapse from the 2011 cohort ($\bigcup_{y=1}^{3} \mathcal{D}_{2011}^{y}$).

of the French-speaking region (LF) on lapses can be affirmed for both cohorts.

Products. As predicted by the theory, multi-product customers (HL & CA) are less likely to stop their contracts, and the holders of motor insurance (CA) are more likely to lapse. Thus, our Hypothesis 3.3 is supported by the data.

Channel. Not all interaction channels have a statistically significant impact on lapses. The tied agent and its combination with an intermediary come along with lower lapse probabilities. All other statistically significant parameters for the access points have a positive estimated parameter, implying a higher likelihood to lapse. It is noticeable that the broker channel has no significant impact on lapsing. The increase of lapses by Internet customers can be affirmed in the 2011 cohort (coefficient 0.321 ***). Thus, Hypothesis 3.4 cannot be accepted. From a distribution management perspective, our results also underline the importance of the tied agents for cross-selling insurance products (cf. Section 5) and for retaining customers. Often, the tied agent channel is the most expensive one, but in a cost-benefit analysis, the benefits of successful customer development and retention may outweigh the costs.

Number of damages. The number of damages significantly influences the lapses. However, we find opposite influences in the 2005 and 2011 cohorts: while in the first one, a strong decrease in the lapse probability with the number of damages can be observed, the data for the 2011 cohort significantly yield the opposite. Further analysis, potentially including the size and type of the damages, may give further insights. With our data, we cannot support Hypothesis 3.5.

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Variables	$\mathcal{C}_{2005}$		$\mathcal{C}_{2011}$	
Intercept	−605.4	***	−175.2	***
Years of relationship				
YOR	0.300	***	0.086	***
Age				
$A0$	−1.341	***	−0.342	***
$A1$	−0.084	**	−0.073	**
$A2$	(Intercept)			
$A3$	−0.540	***	−0.376	***
$A4$	−0.689	***	−0.512	***
$A5$	−0.672	***	−0.641	***
$A6$	−0.610	***	−0.734	***
$A7$	0.288	***	0.119	.
Urbanicity				
UU	(Intercept)			
UR	−0.094	***	−0.219	***
Language region				
LG	(Intercept)			
LF	−0.058	*	0.054	*
LI	−0.300	***	−0.002	
Products				
HL	(Intercept)			
CA	0.422	***	0.364	***
HL & CA	−1.441	***	−1.232	***
Channel				
TA	(Intercept)			
IY	0.147	***	0.158	***
BR	0.067		0.045	
IT			0.321	***
TA & IY	−0.339	**	−0.483	***
Other	0.878	***	0.152	.
Damages				
NDA	−0.077	***	0.070	***
N	307 646		201 376	

Note: Significance levels for p-values: *** $p \leq .001$, ** $p \leq .01$, * $p \leq .05$, . $p \leq 0.1$.

Table 11: Logistic regression lapse analysis for the cohorts 2005 and 2011.

7 Conclusion

Through this study, we aim to gain new insights on the development of customer-insurer relationships and, thus, potential indications of the management of customer acquisition, development and retention. We provide a practical contribution to the understanding of the customer base (Ganesh et al., 2000) and identify selected purchase and loyalty patterns as described by Oliver (1999) that can help to improve the balance of strategic acquisition and retention decisions (Reinartz et al., 2005). Based on a large-scale longitudinal dataset of non-life insurance contracts in Switzerland, several conclusions can be drawn. Table 12 summarizes the hypotheses considered in this work.

First, and not surprisingly, we find that most acquired customers are young adults. We identify that the influence of the access points used by the customers has changed in recent years. Brokers, intermediaries and the Internet are gaining importance, while the share of the traditional tied agents channel significantly decreased, from 85% to 73% between 2005 and 2014. This trend

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Hypothesis	Supported
1.1 New customers tend to be young adults.	✓
1.2 New customers tend to purchase only a single product at the beginning of the relationship.	✓
1.3 New customers mostly use the tied agent channel for contracting as the broker and the Internet access points start to gain a stronger influence.	✓
1.4 During the first year of their relationship, new customers do not switch the interaction channel.	×
2.1 Cross-buying is related to age by an inverted U-shape.	✓
2.2 Customers from rural regions are more loyal and likely to conduct cross-buying.	✓
2.3 Customers with car insurance are more likely to conduct cross-buying than customers with household/liability insurance.	✓
2.4 Customers using personal contact touchpoints are more likely to conduct cross-buying.	(✓)
2.5 Customers with a higher number of damages are more likely to conduct cross-buying.	(✓)
3.1 Older customers with a longer insurance relationship are less likely to lapse.	✓/×
3.2 Customers from rural regions are less likely to lapse.	✓
3.3 Customers with multi-product/car insurance are less/more likely to lapse.	✓
3.4 Customers using personal touchpoints are less likely to lapse.	×
3.5 Customers with a higher number of damages are less likely to lapse.	×

Table 12: Summary of the stated hypotheses and resulting conclusions.

may entail a significant impact on the development of the insurers' portfolio since customers buying from tied agents are more likely to cross-buy other insurance products. In addition, because increasing numbers of new customers take only a single product at the beginning of the relationship, more development efforts are required.

Our data supports that customer age, the urbanicity of the residence area, the products held and the number of damages reported are significant drivers of cross-buying. Our results show that young adults are most likely to cross-buy. The considered covariates, as shown by Konus et al. (2008), produce different perceptions of the costs and benefits, supporting that rural inhabitants are more loyal. Thus, we support the theory of Verhoef and Donkers (2005) that a motor insurance customer is more likey to lapse, but when staying, he is more likely to cross-buy. Further, the customers using a tied agent are more likely to cross-buy than those using a broker. That means that the personal contact of the access point is not the only factor that has an impact. The tied agent directly represents the insurer and follows the underlying strategy, which is not the case for the broker who is not tied to a single company. The number of damages can be related to the customer interaction frequency, i.e., the probability of cross-buying increases with the number of damages. Not all the stated hypotheses are supported by our data. In line with the lapse research in the existing literature, we show a significant effect of young adults on lapsing. However, to obtain a deeper understanding of lapses, further (combined) studies on the products held, the access channels used and further information (such as the residence area) on the customer may be useful. The inclusion of indicators on the quality of services provided and customer satisfaction (cf. Zeithaml et al., 1996) could reveal insightful. For example, customer satisfaction with claims management is an important driver for cross-selling and retention.

From a managerial perspective, the maximization of customer lifetime value is a critical concern. Thus, developing and retaining customers is of foremost importance. Our study provides several hints about the segments of customers that must be addressed. For example, the segment of

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single-product customers who are often less loyal may be the focus of customer development. In fact, avoiding attrition is key to customer relationship management. Recalling that most new customers are young adults and that they often present a high expected future “value”, they are an important segment to focus on not only in terms of investments for the future – to gain them as new customers – but also in terms of avoiding attrition. Hereby, the optimal pace and channel of interaction play an important role, since younger generations may expect different communication styles than older customers. Attention must also be paid to customers from urban regions, who seem to be more difficult to develop and more eager to switch insurers than their counterparts in rural regions. For sales management in a multi-channel distribution context, it is important to keep in mind that channels other than the tied agents channel present lower cross-selling success. Additionally, customers using the broker and the Internet channels for interaction often show a higher propensity to lapse. Regarding the customer claims history it is important to consider the customer profitability. A firm might want to retain customers after they have reported damages given their profitability record from past years and given their specific potential for customer relationship development (e.g., with younger customers).

Technological changes and innovation may further change the “game” in the future. Digitization may be an opportunity to attract, develop and retain customers in new and different ways by incorporating a new culture of interaction. However, the threat of this trend may include adverse changes in the customer portfolio towards more single-product customers who require costly development to increase loyalty and towards customers with more loose ties to their insurers and who change their contracts more frequently, e.g., whenever a better price becomes available at a competing firm. In terms of managing customer relationships it becomes even more critical to possess a comprehensive view on the relationship of all individual customers, to analyze their behavioral patterns to seize business opportunities with the customer base when they appear.

Several open research questions remain. While in this paper, we have focused on customer development and lapses in general, additional insights may be generated by explicitly including the time component. The application of Markov-type models can enable the study of customer development after certain time spans and give access to transition probabilities. Covariates on customer relationship characteristics could also be included in such models. In future research, the impact of other products such as life, health or homeowners' insurance, may be incorporated. Further, modeling on the classification of the customers may also be useful. Additional information from customer lifestyles, habits and behaviors may improve cross-buying and lapse prediction models. The inclusion of the overall customer profitability, beyond product history and number of damages, including the premiums paid, the service costs incurred and the amounts of claims paid could strengthen the managerial implications.

Notes

[1]Average number of products per customer.

[2]This includes all other less frequently used access channels and combinations proposed by the insurer, as described in Table 1.

[3]In our model, we consider that the departures occur at the end of the year, so this column represents the total departures at the end of the previous year. A lapse happens when the customer does not have household/liability or car insurance anymore.

[4]Average number of products and standard deviation (in parentheses).

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[5]1 is the year of contract inception. Since clients sign their contracts over the whole year, they are customers for six months in their first year on average. Thus, damages should be multiplied by 2 in order to make them comparable to the figures from following years.

[6]Average age and standard deviation (in parentheses).

[7]Average number of damages in the last year and standard deviation (in parentheses).

[8]Average number of damages and standard deviation (in parentheses).

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