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CHURN PROPENSITY MODEL FOR CUSTOMERS WHO MADE A COMPLAINT IN RETAIL BANKING

Serpil KILIÇ DEPREN
Assist. Prof. Dr., Yıldız Technical University,
Faculty of Arts and Science, Statistics Department,
Davutpaşa Campus, Esenler, 34220, İstanbul, Turkey.

ABSTRACT

Customer Intelligence Analytics is a heavily researched topic in business. With Customer Intelligence Analytics, companies can handle the key business challenge, which is increasing the number of profitable customers using specialized offers. Customer Journey Mapping, which is one of the important procedures for obtaining a better understanding of customers, is measured and monitored by companies to identify a solution to the key business challenge. Since the complaint step is one of the most important steps of the journey in terms of the churn decision of a customer, the primary purpose of this study is to determine the customer lifetime and identify factors that affect the lifetimes of customers using Survival Analysis and Cox Regression. To achieve this objective, the data from a complaint survey of a Turkish bank are used. It is revealed that the critical time-period for customer retention is the first three months in the complaint management process.
Keywords: *survival analysis, cox regression, complaint management, customer journey, churn*
JEL codes: C31, C83, G21

1. Introduction

Customer Journey Mapping (CJM) is a systematic approach for obtaining greater customer insight and can be used for improving customer experience and reducing the cost of services. CJM is also known as Customer Journey, User Journey, User Scenario and Customer Lifecycle. In general, the names of the CJM steps are similar for each sector, although CJM processes can be extremely complex, depending on the number of touchpoints. These steps are awareness, information gathering, purchase/use, retention/complaint and advocacy/churn (Richardson, 2010).

Awareness, which is the first step of the customer journey, is the step in which customers search for a solution to or collect information about their problems (Gamble, 2014). In this step, top-of-mind awareness is when a product or brand comes to a customer’s mind first when the customer is thinking about a particular industry. If the customer remembers a brand when prompted with a cue, it is named aided-recall awareness.

The second step of the customer journey is information gathering. Customers look for materials from which they can learn about possible solutions to their problem or needs in this step. Therefore, customers might investigate websites of related companies, products or services, ask their friends or call the call centre of a company to obtain accurate information about their needs. Furthermore, word-of-mouth recommendations from friends or people who have used a product or service have an important effect on the choice of company (Noble, Cooperstein, Kemp, & Madigan, 2010).

Then, customers decide to purchase or use the product. In this step, it is important for companies to keep their customers on their side by providing accurate service according to customers’ expectations. In addition, companies should offer some similar products to their customers to retain their relationship in this step (Noble, Cooperstein, Kemp, & Madigan, 2010).

Complaint management is a crucial step for a company. A complaint is a verbal or written expression of dissatisfaction with the policies, products or services that are provided by a company. Since a complaint is the result of dissatisfaction with a process, one of the most important parts of the journey is complaint management. In this step, customers decide to leave (or stay with) a company. Thus, if a company can manage the complaint process efficiently, more customers will likely continue to work with the company. Therefore, complaint management handling has a substantial impact on customer retention.

The last step of the customer journey is advocacy/churn. Customers decide to stay and continue working with the company, or they stop working with the company according to their previous experience (Lawer & Knox, 2006).

Figure 1. Customer journey steps.

The steps in the customer journey and some factors in each step are shown in Figure 1. For example, customer awareness can be created by advertisement, TV/internet news or word-of-mouth effects. Then, customers start to gather information using the company's website, media or blogs of other customers. In the third step, customers decide to buy (or not to buy) the product via a branch/store or website. If customers are not satisfied with the product or company, they will probably make a complaint and share their bad experiences on social media or websites, or with the call centre, in step four. In the last step, companies are able to create advocate customers (or lose their customers). Similar to the fourth step, customers share their experiences via word of mouth, social media or forums in the advocacy/churn step.

Customer journey analytics can help researchers understand customer behaviour in the journey steps, identify focus areas for customer experience, and profile customers across journeys. Thus, researchers might determine problems/deficiencies of journey steps and how to solve the problems or meet the customers' needs (Kamaladevi, 2009).

The aim of this study is to determine customer lifetime and factors that affect the lifetimes of customers who made complaints. To achieve this aim, Survival Analysis and Cox Regression Modelling are used.

The remainder of this paper is organized as follows: A literature review is given in Section 2. Survival Analysis and the Cox Regression Model are introduced in Section 3. In Section 4, the complaint survey and discuss the outputs of Survival Analysis and Cox Regression are described. The conclusions of the study are presented in Section 5.

2. Literature Review

Many researchers have studied the estimation of customer churn propensity and customer acquisition (Chen & Hitt, 2002; Syam & Hess, 2006). In this research, different statistical and mathematical methods have been used to predict customer churn ratio (Nath & Behara, 2003; Bin, Peiji, & Juan, 2007; Lu & Park, 2003), especially in banking and finance (Mutanen, 2008; Van den Poel & Larivière, 2004).

Statistical/Mathematical modeling is the most important tool for churn prediction in banking sectors. These models are based on logistic regression, decision trees, clustering, neural networks and survival analysis (Mutanen, Ahola, & Nousiainen, 2006; Van den Poel & Larivière, 2004, Chitra & Subashini, 2013).

Larivière and Van den Poel examined whether offering suitable product sets and features could affect customer churn decisions using survival analysis (Larivière & Van den Poel, 2004). To test their hypothesis, a hazard model was built to determine best product set for reducing customer churn propensity. In this study, it was emphasized that customer characteristics are not the only factors that affect customer retention; products features should be taken into consideration when attempting to understand customer churn propensity.

Popović and Bašić developed a churn prediction model using Canonical Discriminant Analysis and the Fuzzy C-Means algorithm with balanced and unbalanced data sets (Popović & Bašić, 2009). They proposed four different prediction models, which they called prediction engines. It was shown that proposed technique was superior to classical approaches in terms of prediction accuracy.

In the literature, hybrid or mixed models have been used for churn modelling. Xie et al. proposed an improved balanced random forests approach and demonstrated its application to churn prediction (Xie, Li, Ngai, & Ying, 2009). The accuracy rate of predicting customer churn of the proposed approach was higher than those of most existing algorithms. Similar to the study of Xie et al., Tsai and Lu proposed a new hybrid technique that combines two different neural network techniques for churn prediction. Their proposed technique significantly outperformed classical algorithms in terms of estimation accuracy (Tsai & Lu, 2009).

Gorgoglione and Panniello defined personalized retention approaches, and the benefits and risks of each approach were discussed (Gorgoglione & Panniello, 2011). Furthermore, they proposed a new approach for generating personalized actions to retain customers. It was shown that the proposed approach was superior to classical approaches in terms of classification accuracy.

Nie et al. investigated the churn propensity of credit card users of a Chinese bank in 2011 using two different data-mining techniques (Nie, Rowe, Zhang, & Shi, 2011). The 135 independent variables in the model were classified into four dimensions: customer information, card information, risk information and transaction activity information. In this study, the regression technique provided better parameter estimates than the decision tree technique in terms of accuracy of parameter estimation.

Prasad and Madhavi studied the prediction of churn behaviour of bank customers using the CART and C5.0 algorithms. The results of the CART and C5.0 algorithms were compared in terms of churn estimation accuracy. The CART algorithm produced a better per-client classification rate than the C5.0 algorithm (Prasad & Madhavi, 2012).

Özden and Umut proposed a dynamic churn prediction model for private banking customers in 2014 (Gür Ali & Arıtürk, 2014). It was shown that the new approach increased the prediction accuracy.

In all of these studies, researchers tried to increase prediction accuracy of customer churn propensity and provided comparisons of different approaches in terms of estimation accuracy. In this research, factors that affect the churn propensity of customers who made complaints are examined. It is believed that this research will be a valuable resource for further studies.

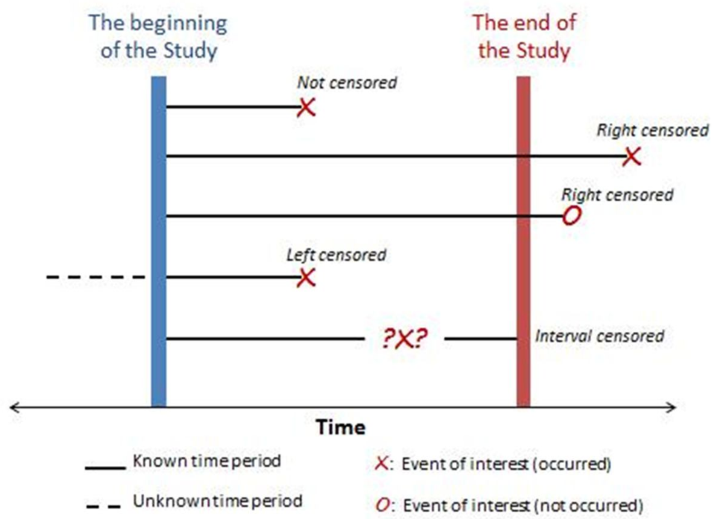
3. Methodology

In this section, fundamental terms, definitions, assumptions and formulas/notation of Survival Analysis and the Cox Regression Model are explained in detail.

3.1 Survival Analysis

"Event of Interest", "Censored Data" and "Survival Time" are fundamental terms in Survival Analysis. The main objective of Survival Analysis is to analyse data in which the outcome variable is the time until the occurrence of an event of interest (Steinberg, 1999). The events can be defined as not only negative and unpleasant experiences, such as the occurrence of a disease, divorce, churn or death but also positive and pleasant experiences, such as passing an exam, graduation, promotion or opening an account. The time to event (in other words, the survival time) is measured in minutes, hours, days, weeks or years, based on the nature of the event. For instance, if the event of interest is death, then survival time can be measured in years. "Censored Data" can be classified into three different types: right-censored, left-censored and interval-censored (Klein & Moeschberger, 2003).

- An individual's data are classified as right censored if all that is known is that an individual's event of interest does not occur in a certain time period.
- Data is defined as left-censored if all that is known is that an individual's event of interest has occurred before the start of the observation duration.
- If the only known information is that the event of interest occurred in a certain period of time, the data are defined as interval-censored.



- Figure 2. Definitions of censored data (Huang, Lee, & Yu, 2008).

The Probability Function (*f(t)*), Survival Function (*S(t)*) and Hazard Function (h(t)) are the three basic components of survival analysis. The probability function is described in Equation (1) as the limit of the probability of the event of interest occurring in a period of time (Austin, Lee, & Fine, 2016), where t represents the survival time of an individual.

$$f(t) = \lim_{\Delta t \to 0} \frac{P\{occurance\ of\ event\ of\ interest\ in\ the\ interval(t, t+\Delta t)\}}{\Delta t} \qquad (1)$$

The survival function (*S(t)*), which is also known as the cumulative survival rate, is described as the probability that an individual survives longer than t (Lee & Wang, 2003).

$$S(t) = P(survival\ time\ of\ an\ individual\ is\ longer\ than\ t) = P(T < t) \quad (2)$$

The hazard function (*h(t)*) is a time-to-event-occurrence function.

$$h(t) = \lim_{\Delta t \to 0} \frac{P\{Individual's\ event\ of\ interest\ occurs\ in\ the\ interval(t,t+\Delta t)\}}{\Delta t} \quad (3)$$

In 1958, Kaplan and Meier developed a method, which is named the Kaplan-Meier Limit method, for estimating the survival function (Kaplan & Meier, 1958), which is given in Equation 4.

$$\widehat{S(t)} = \begin{cases} \prod_{i=1}^{k} \left(\frac{n_i - d_i}{n_i}\right) & , t_{(k)} \le t \le t_{(k+1)},\ k = 1,2,\dots,r \\ 1 & t < t_{(1)} \end{cases} \quad (4)$$

In Equation 4, t_i and d_i are the exact survival time of the i^{th} individual and the number of individuals of who die at time t_i, respectively.

3.2 Cox Regression Model

The Cox regression method, which is also known as the proportional hazards model, is a statistical method that allows researchers to generate the hazard function as a function of the time variable, risk factors, and baseline hazard. With this method, researchers are able to measure the relative risk (or relative hazard) and interpret the hazard ratio. The Cox regression model can be expressed as in Equation 5 (Hosmer & Lemeshow, 1999; Kleinbaum, 1996; Lee, 1992).

$$h(t) = h_0(t)e^{\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p} \quad (5)$$

The hazard function *h(t)* is a function of baseline hazard $h_0(t)$ and the risk factors (*X*). The Cox regression model is similar to the linear regression model. For example, the baseline hazard function is similar to the constant in the linear regression model. It represents the value of the hazard function if the risk factors (*X*) are not taken into consideration. In addition, the baseline hazard does not depend on *X*, but only on time. The risk factors, which are time-independent, can be included in the model as continuous or categorical variables, as in the linear regression model. Regression coefficients (β) are estimated by using the partial maximum likelihood estimation approach (Hosmer & Lemeshow, 1999; Kleinbaum, 1996).

The hazard ratio represents the effects of the risk factors on the dependent variable. Thus, researchers study this ratio to determine the strength of the relationship among risk factors. The hazard ratio can be expressed as the ratio of two risk factors, which is given in Equation 6.

$$HR = \left[\frac{h_M(t)}{h_N(t)}\right] \quad (6)$$

For example, in Equation 6, $h_M(t)$ is the hazard for the placebo group and $h_N(t)$ is the hazard for the treatment group. If the hazard ratio is greater than 1, the relative hazard is positively associated with the risk factor. In contrast, if the hazard ratio is less than 1 (but still positive), the relative hazard is negatively associated with the risk factor.

Researchers are able to assess the model goodness of fit using the likelihood ratio test, which compares the model that considers only the intercept effect to the model that contains the risk factors.

4. Survey

The objective is to determine the customer lifetime and identify factors that affect the lifetimes of customers of a Turkish Bank.

4.1 Methodology

A quantitative research method is used for data collection in this study. A web-based survey with 6 questions is sent to customers who made a complaint about any service or product of the bank. Survey links are sent automatically to customers immediately after closing their complaint record. The time span of this research is between 01.01.2015 and 31.12.2015.

4.2 Data Set and Preliminary Results

Responses are gathered from 1 000 individual customers of a Turkish bank. Six attributes are compiled to identify the satisfaction levels of customers. Furthermore, internal data of the bank are combined with the survey data to determine customer lifetime.

The attributes of the questionnaire are as follows:

(1) Satisfaction with the general complaint process (5-point Likert scale)
(2) Reaching related department of the bank easily (Yes, No)
(3) Satisfaction with the solution time of a complaint (5-point Likert scale)
(4) Satisfaction with the agent's service quality (5-point Likert scale)
(5) Satisfaction with the agent's explanation about complaints (5-point Likert scale)
(6) Future financial relationship with the bank (increase, stable, decrease)

The attributes of the internal data of the bank are as follows:

(1) Communication with the bank (Telephone, e-mail, other)
(2) Socioeconomic status of the customer (indices were calculated using salary, education level, credit card limits, spending habits, etc.)
(3) Number of products that are actively used by the customer (number)
(4) Main topic and sub-topic of the complaint (complaints were classified into the following problem types, including ATM, Internet Banking, Mobile Banking, and Personnel).

Table 1 shows descriptive statistics of the survey questions.

Table 1. Descriptive statistics.

	Mean	**Std. Dev.**	**Min**	**Max**
Satisfaction with solution time of a complaint	2.22	1.12	1	5
Satisfaction with agent’s quality	3.35	1.15	1	5
Satisfaction with agent’s explanation about complaints	2.38	1.15	1	5
Satisfaction with general complaint process	2.48	1.05	1	5

Satisfaction with the agent’s quality is the only attributes that registers an average overall satisfaction level of greater than 3.

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Of all customers, 67% are able to reach the relevant team easily to complain about their bad experiences and 61% stated that they will decrease their financial relationship with the bank within 6 months, while only 12% stated that they will increase their financial relationship with the bank.

The top three topics of customers' complaints are cards (22%), fees & commissions (20%) and personnel (16%). Of customers who made a complaint about loans, 72% state that they will decrease their financial relationship with the bank. This ratio is 62% for customers who made a complaint about fees & commissions.

In Table 2, the output of regression analysis is given. Regression analysis is conducted to identify factors that affect the satisfaction level with the general complaint process.

Table 2. Output of regression analysis.

	β	**Std. Err.**	**p**
Intercept	0.260	0.026	0.000
Satisfaction with agent's explanation about complaints	0.480	0.007	0.000
Satisfaction with agent's quality	0.124	0.007	0.000
Reaching related department of the bank easily (No)	-0.270	0.012	0.000
Type of response to customers (e-mail)	-0.031	0.014	0.022
Type of response to customers (other)	-0.035	0.015	0.017
Satisfaction with solution time of a complaint	-0.004	0.001	0.000

According to the regression analysis, relatively important attributes that affect satisfaction with the general complaint process are "satisfaction with explanations made by agent", "reaching related department of the bank easily" and "satisfaction with agent's quality". The adjusted R^2 is 73%.

4.3 Understanding Customer Lifetime

Customer retention has a significant effect on growth and profit, which are critical topics for a bank. Thus, customer lifetime is analysed with the topic of the complaint and the future financial relationship with the bank.

Figure 3 shows the hazard curve of all customers who participated in the survey.

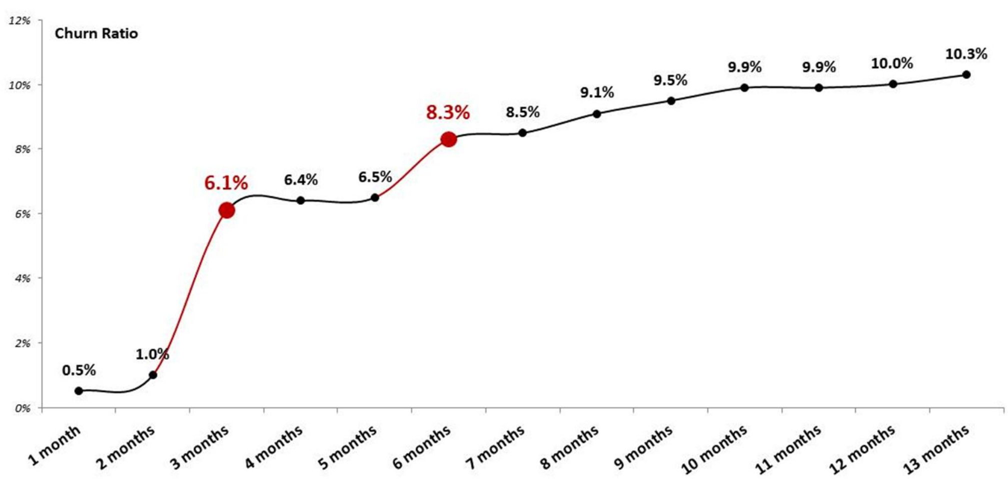

Figure 3. Churn ratio of customers.

In Figure 3, the bank has two thresholds for continuing to work with their customers: 3 months and 6 months. The churn ratio increases to 6% in the 3rd month, from 1% in the 2nd month after the customer makes a complaint. Since the churn ratio after 6 months might be related to any factor, it is not taken into consideration in this study. According to Figure 3, customers expect the bank to solve their problems within two months; otherwise, 6% of them will leave the bank. Thus, the bank has two months to win back the customers who made a complaint about something.

The customer churn ratio is analysed according to topic of the complaint, as shown as Figure 4.

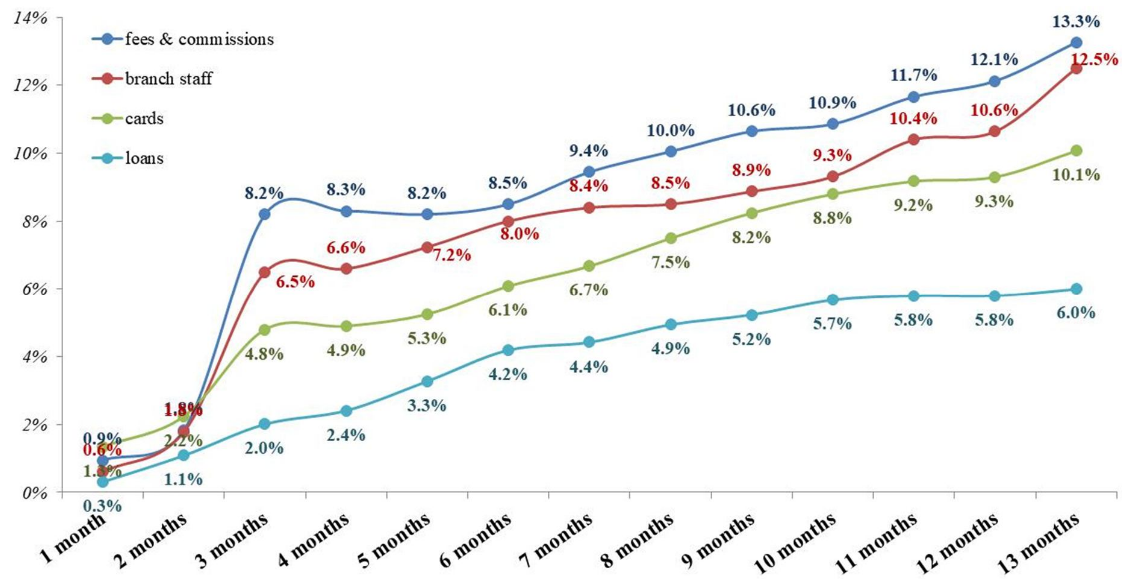

Figure 4. Customer churn ratio by topic.

According to Figure 4, 8.2% of customers who have a problem regarding fees & commissions will stop working with the bank within 3 months. In addition, branch-staff-related and card-related problems are factors that affect customer churn probability. However, loan-related problems have no significant direct effect on customer churn (the average churn ratio of all customers is approximately 6%). This is because loan products are long-term products and customers cannot stop using these products whenever they want because of the early payment fees.

Similar to the results on the overall churn probability, the bank has two months to win back customers who made a complaint about fees & commissions, branch staff and cards. For customers who made a complaint about loans, the bank needs more time to measure the effect on customer churn because the minimum loan period is 12 months. Generally, customers are working with the bank during this period.

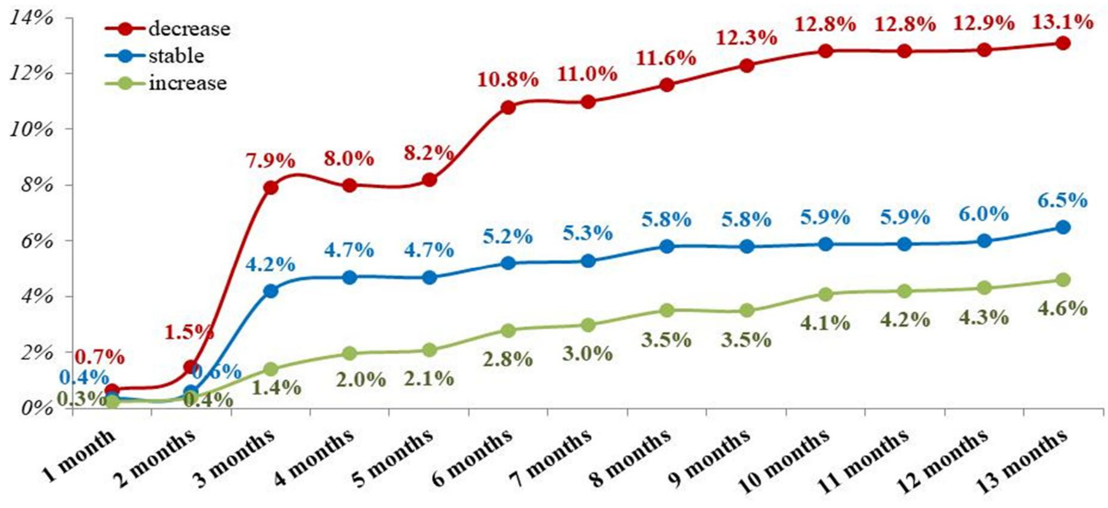

Figure 5. Customer churn ratio versus future financial relationship with the bank.

The churn probabilities of customers who state that their future financial relationship with the bank will increase or be stable show a similar trend after 6 months. However, 7.9% of customers who state that their future financial relationship will decrease leave the bank within 3 months. The gap between the red line and blue line is 3.7%, 5.6% and 6.6% at 3, 6 and 12 months, respectively. In addition, there is a statistically significance difference according to the possible future financial behaviour of customers (Generalized Wilcoxon Test, $p < 0.05$).

4.4 Factors that Affect Customer Lifetime

The Cox regression model is used to determine the factors that affect customer lifetime. In this analysis, the number of active products of customers (# of products), socioeconomic status (ses), communication type (communication type), main topic of the complaint (main topic), future financial relationship with the bank (financial relationship), satisfaction with the overall complaint management process (satisfaction) and solution time of the complaint record (solution time) are added into the model as independent variables.

Table 3. Output of Cox regression analysis.

	β	**Std. Err.**	**p**	**exp(β)**
# of products	-0.546	0.028	0.000	0.579
Ses	-0.019	0.003	0.000	0.981
Communication type (ref: telephone)				
E-mail	0.110	0.106	0.301	1.116
Other	0.171	0.124	0.168	1.187
Main topic of a complaint (ref: staff related complaints)				
Cards related complaints	-0.150	0.123	0.229	0.861
Credits related complaints	-0.601	0.247	0.015	0.548
Fees & commissions related complaints	0.208	0.121	0.085	1.232
Financial relationship (ref: decrease business)				
Increase business	-0.128	0.204	0.029	0.879
Stable	0.308	0.201	0.125	1.361
Satisfaction with complaint process	-0.113	0.046	0.034	0.893
Satisfaction with solution time of a complaint	-0.002	0.004	0.641	0.998

The number of active products, socioeconomic status and satisfaction with the complaint management process each has a positive effect on customer lifetime. The effects of solution time and communication type with customers on customer churn are not statistically significant. Furthermore, customers who complain about fees & commissions face 1.232 times the hazard that is faced by customers who complain about staff. In addition, customers who will increase their financial relationship with the bank face 0.879 times the hazard that is faced by customers who will decrease their financial relationship with the bank.

5. Discussion and Conclusions

In this study, determination of customer lifetime duration and factors that affect the lifetime of customers after the complaint process are analysed using Survival Analysis and Cox Regression Modelling.

Since the churn behaviour of customers is highly correlated with the complaint behaviour of customers (Day & Landon, 1977; Bearden & Teel, 1983), first, the satisfaction level with complaint management and the factors that affect the general satisfaction level are analysed with classical regression analysis according to the survey results. Similar to previous research (Gerpott, Rams, & Schindler, 2001; Lee, Lee, & Feick, 2001; Kim & Jeong, 2004; Kim & Yoon, 2004; Ang & Buttle, 2011), “satisfaction with explanations made by the agent”, “reaching related department of the bank easily” and “satisfaction with the agent’s quality” are the most important factors that affect the general call satisfaction level in this study. According to the regression analysis, a well-managed complaint management process increases general satisfaction and decreases customer churn (Fornell & Wernerfelt, 1987), and first action that should be taken is that employees who work in the complaint management team should explain the final decision of the bank to customers clearly. The manager should prepare a training course about specific cases that are frequently encountered and create scripts according to the customer profile. Simplifying the IVR menu according to the complaint topic might be the second action of the bank.

Second, customer lifetime is analysed using Survival Analysis. The main finding of the analysis is that the bank has 3 months to win back customers who complain about any subject; otherwise, the bank will lose 6% of their customers, and 6 months later, 8% of the customers will go dormant. Furthermore, customer lifetime is analysed according to customers’ perceptions of their future financial relationship with the bank and the main topics of complaints. Of customers who state they will decrease their financial relationship with the bank, 8% go dormant, while 1.4% of customers who state they will increase their financial relationship with the bank go dormant. When the customer churn ratio by topic is analysed, it is observed that staff- and card-related complaints are more important than others, because complaints about fees & commissions and loan-related complaints are mostly related to the bank policy, which cannot be changed in the short term because of the regulations. Thus, the bank should concentrate on staff- and card-related problems. Thus, the relevant teams should focus on these customers, understand what they really need and, if necessary, call these customers within 2 months to win them back, which is the third recommended action.

Finally, factors that affect customer lifetime are analysed with Cox Regression Analysis. Apart from the main complaint topic and future financial relationship variables, the number of active products of customers, socioeconomic status and satisfaction with the complaint management process are the factors that affect customer lifetime. Customer complaint management teams should create profiles using these variables to classify their customers, so that the service level might be differentiated according to these personas, which is the fourth recommended action of the bank.

In conclusion, this study can serve as a starting point for further investigation and validation of churn modelling. This research might provide important information for complaint management teams, as it did regarding action planning in the Turkish Banking sector. Therefore, additional investigation with alternative models should be conducted to cross-validate this research.

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