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MODELLING THE BANK CUSTOMER ACTIVITY DURATION BASED ON THE COX ECONOMETRIC SURVIVAL MODEL

ABSTRACT

The banking sector is constantly evolving, seeking effective ways to attract and retain clients, especially those with high financial potential. One of the ways to achieve this goal is to provide car loans at low interest rates, such as 0.01%. However, the untimely outflow of clients after repayment of the car loan becomes a significant problem for banks leading to the loss of potential income from other banking services. The research aims to evaluate the impact of selling additional banking services on increasing clients' activity duration. The research used statistics on opening new bank clients, whose first product was a car loan at an interest rate of 0.01%, from 2018 to 2022. The dataset included 9,224 records. The Cox proportional hazards model is used to determine the impact of a credit card on the duration of car loan client activity. The analysis of the model coefficients showed that with a credit card, clients closed at a rate of 0.86 of the rate of closing clients without a credit card. However, during the verification of the proportional hazard assumption, it was determined that the credit card's influence level changes significantly over time, indicating the model's inadequacy. The next phase of the study was the search for an influencing parameter that meets all the quality conditions of the Cox model. Having a credit card with at least one transaction was selected. For this model variation, all indicators of model adequacy were met. The coefficient estimation results showed that clients with an active credit card closed at a rate of 0.36 of the rate of closing clients without it. The evaluation of the active credit card impact confirms that selling a credit card allows for an increase in the bank clients' activity duration. However, a critical success factor is the sale of a credit card and its activation. The obtained research results can be used to optimize the bank's marketing and sales strategies, ensure more effective customer retention and increase the bank's profits.

Keywords: car loan, clients' retention, credit cards, marketing activity, survival analysis, survival curve

JEL Classification: C24, M31, G21

INTRODUCTION

The banking industry is constantly evolving, looking for effective ways to attract and retain customers. Banks worldwide actively use car loans as an effective means of attracting new customers, particularly those with high financial potential. However, some banks use strategies to remain competitive by providing loans at meagre interest rates, such as 0.01% per annum.

However, untimely client retention after the repayment of a car loan becomes a big problem for banks because a client who does not see additional value in the bank's products can easily switch to a competitive offer (Lupenko et al., 2022; Yereshko et al., 2022). The main problem that the bank has to solve is to find effective strategies to retain customers after the full repayment of the car loan. This is especially important because prematurely closing customers can result in potential revenue loss from other banking products.

One option for retaining clients after the repayment of a car loan is to offer a credit card that allows the client to carry out everyday banking operations using credit funds while allowing the bank to generate income from the services provided. However, banks face

challenges and obstacles in selling credit cards to clients with car loans. In particular, the client's interaction with the bank during the car loan process is limited since all registration procedures are carried out directly with the car dealer in the car showroom. This makes establishing an emotional connection between the bank and the customer difficult. It also reduces the likelihood of the client using additional banking products (credit cards) after the repayment of the car loan. Another challenge is the short-term financing period, as loans at 0.01% are provided for up to 2 years.

LITERATURE REVIEW

In recent years, survival analysis has become increasingly popular for studying factors that affect the duration of a particular process (Novykova et al., 2023; Hutorov et al., 2020). Survival analysis is a statistical tool that can be used to assess the time until an event of interest, such as bankruptcy, or customer churn (Voynilovych et al., 2023). The application of survival analysis is widespread in finance and banking. Existing research on survival models in the banking sector mainly focuses on assessing credit risks, estimating time to default, and identifying factors leading to bankruptcy. However, there is currently a lack of research in the scientific community on customer retention. Most of the mentioned research is focused on increasing the accuracy of credit scoring models and improving the quality of models and algorithms for their calculation.

Rozo et al. (2023) investigated the role of customer web browsing data in predicting credit risk. They found that models that included only predictors related to customer activity on the website could be highly predictive, especially for applicants with insufficient credit histories.

Meanwhile, Medina-Olivares et al. (2023) proposed a new approach to creditworthiness assessment using joint models for longitudinal and discrete survival data. The longitudinal approach belongs to linear models with mixed effects with serial correlation (including Bayesian inference and Markov Chain Monte Carlo methods). The Cox model was used to build a discrete model. The authors showed that their joint modelling approach leads to more accurate creditworthiness predictions than traditional models.

Staudt and Wagner (2022) investigate the duration of purchasing a second insurance product from the same insurer by customers of a Swiss insurance company. The authors found that demographics and product characteristics influence the company's product sales duration. These findings suggest that selling related products can be an effective tool for improving customer retention. In the study's first phase, the authors provided descriptive statistics using Kaplan-Meier estimates for key customer characteristics, contract history, and distribution channel usage. For the econometric survival analysis, the results of the Cox models and the accelerated failure time model were compared.

Bai et al. (2021) proposed a new non-parametric ensemble tree model called Gradient Boosting Survival Tree (GBST), which extends survival tree models using the Gradient Boosting algorithm, and demonstrates its applicability for credit risk quantification on two large-scale real market datasets.

Batiz-Zuk et al. (2021) found that the characteristics of the enterprise at the time of loan disbursement, as well as macro-economic factors with lag, significantly affect the loan survival time. The authors used an Accelerated Failure Time Model.

Billio et al. (2019) investigate the relationship between building energy efficiency and the probability of mortgage default in the Netherlands using a panel dataset with information on mortgage loans and building energy efficiency ratings. Using logit regression and an extended Cox model, the authors found that building energy efficiency is associated with a lower probability of mortgage default. They suggest that energy efficiency ratings complement borrowers' credit information, and lenders using data from both sources can make better lending decisions.

Caselli et al. (2021) revealed the determinants influencing the time to default of approximately 15,000 loans in Italy between 2007 and 2009. The authors used a Cox proportional hazards model to examine the role of a financial intermediary requesting a guarantee on behalf of a company. The authors found that loans are more likely to default if a bank, rather than a mutual guarantee institution, participates in the guarantee process. They suggest that MGIs perform better than banks in verifying and monitoring the performance of borrowers, especially for loans granted to companies in the manufacturing sector.

Overall, the literature review suggests that including new data sources and modelling methods can improve the accuracy of credit rating models. The proposed models and approaches can provide lenders with valuable tools to assess credit risk better and provide loans to a broader range of applicants. Most studies' disadvantages are that survival models are used mainly to assess credit risks, estimate time to default, and identify factors that lead to bankruptcy rather than to identify signs of customer retention. That is, the main goal is the client's return of funds rather than for the client to continue using banking services even after the debt has been repaid. This study aims to fill this gap.

In addition, most studies are focused on improving the calculation algorithm and model quality (Edeh et al., 2022; Dvigun et al., 2022). This is often achieved by combining several existing methods, which complicates the process of building and evaluating models.

In this study, the Cox proportional hazards model was used (Giray and Ömür, 2022; Sakun et al., 2021), the wide approbation of which in scientific research testifies to its effectiveness in solving customer survival problems and ease of its building and evaluation.

Additionally, the current study, for the first time, proposed an algorithm for evaluating the impact of cross-selling on bank customer retention using survival models. For the first time, the importance of such research for improving the bank's financial indicators and improving marketing activities' strategies in customer retention is emphasized.

AIMS AND OBJECTIVES

This article aims to investigate the issue of extending the period of activity of bank clients who used a loan to purchase new cars through the additional sale of a credit card. To solve the problem, it is proposed to investigate the impact of the bank's credit card ownership on the duration of customer activity based on econometric modelling methods.

The research results can be used to optimize the bank's marketing and sales strategies, ensure more effective customer retention, and increase profits.

METHODS

Analysis of clients' survival rate using the Cox proportional hazards regression method

To study the "survival" level of bank clients, we will use survival analysis - a statistical method for analyzing the time until an event of interest occurs. The event of interest can be a binary event, such as loan default or customer churn.

The hazard rate is the probability of the event of interest occurring in a short period of time, given that it has not occurred before. Survival analysis differs from other statistical methods because part of the information being analyzed is censored data, meaning data in which the event has not yet occurred at the end of the study or observation period.

We will apply Cox proportional hazards regression. Cox regression analysis is a statistical method investigating the relationship between time to the event of interest and one or more predictor variables. A regression model is a powerful tool for analyzing survival data, the advantage of which is that its coefficients essentially represent hazard ratios (HR) for each predictor variable.

The formula of the Cox regression model is as follows:

$$h(t|x) = h_0(t) \exp(\beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p) \quad (1)$$

where $h(t|x)$ is the hazard function at time t with given predictor variables x ; $h_0(t)$ – the basis hazard function at time t , that represents the risk when all predictor variables are equal to zero; $\beta_1, \beta_2, \dots, \beta_p$ – regression coefficients, which represent the log-hazard ratio for each predictor variable; x_1, x_2, \dots, x_p – predictor variables.

The main features of the Cox regression model:

- The Cox regression model is semi-parametric, meaning that it makes no assumptions about the shape of the hazard function over time. Instead, it estimates the hazard ratio for each predictor variable.
- The Cox regression model is designed to analyze time-to-event data, data that measures the time between an initial event and a subsequent event, such as the time between opening and closing a bank customer.
- The Cox regression model considers the censoring that occurs when the event has not yet occurred, for some objects, by the end of the study period.
- The Cox regression model can analyze both continuous and categorical predictor variables.
- The Cox regression model assumes that hazard rates are proportional over time. In other words, the effect of the predictor variables on the hazard function does not change over time.

Evaluation of the built model's quality

All calculations and visualization in the study were performed in the R environment using RStudio software. To perform survival analysis in R, the data must be structured in a particular format, including information on survival time, data censoring status, and any additional predictor variables. Survival time is usually represented as a continuous variable, and censoring status is a binary variable indicating whether the event of interest occurred (1) or was censored (0).

The hazard ratio (HR) measures the influence of each predictor variable on the hazard function and is determined by the formula:

$$HP = \exp(\beta_p) \quad (2)$$

where β_p - Cox regression coefficient.

The positive value of the Cox regression coefficients means that the risk of customer churn is higher for objects with higher values of the predictor variables or a particular category of the variable to the base category.

HR less than 1 indicates that the predictor variable is associated with a decrease in the hazard of customer churn. In contrast, an HR equal to 1 indicates that the predictor variable does not affect the level of customer closure hazard.

The Wald statistic (z) evaluates whether the β coefficient of a given variable is statistically significantly different from 0, and is calculated by the formula:

$$z = \beta_p / se(\beta_p) \quad (3)$$

where β_p – Cox regression coefficient; $se(\beta_p)$ – standard error of the Cox regression coefficient.

The p – value for each predictor variable indicates the statistical significance of the Wald test (3). The coefficients β_p , for which the p – value is less than 0.05 are considered statistically significant.

Building confidence intervals (CI 95%) for each risk ratio is also necessary. A qualitative influence is a variable for which the confidence interval of the hazard ratio does not cross 1.

The final step in testing the Cox model's quality is verifying the proportional hazard assumption. Assumptions of proportional hazards (PH) can be tested using statistical tests and graphical diagnostics based on scaled Schoenfeld residuals. For each predictor variable, the `cox.zph` function correlates the corresponding set of scaled Schoenfeld residuals with time to test for independence between residuals and time. The proportional hazards assumption is supported by an insignificant relationship between the residuals and time and rejected by a significant relationship.

To interpret the results of the `cox.zph` test, a plot of the Schoenfeld residuals against time can also be built for each factor in the model. The proportional hazards assumption is met if the residuals are randomly distributed around zero. However, if there are any noticeable patterns in the residuals over time, the proportional hazards assumption is violated, and the Cox regression model may need to be revised.

If the proportional hazards assumption is met, the estimated trend of the residuals over time should have a straight horizontal line shape, indicating that the expected and observed values of the variable do not change systematically over time. If the estimated trend of the residuals over time has stepped shape with a positive or negative slope, this indicates a violation of the proportional hazards assumption. A curved or U-shaped trend indicates that the hazard ratio changes over time (Moore, 2016).

Data

The study used statistics on opening new bank clients whose first product was a car loan. In order to appear competitive in the market, the bank offers a loan at an interest rate of 0.01% per annum. The strategy of this activity is that clients who buy new cars are usually wealthy consumers, and car loans are an excellent channel for attracting such customers. The bank plans to earn directly from the client's activity with other banking products, particularly credit cards. A significant limitation of this product is that it is issued for up to 2 years, so there is little time to earn money from the client.

Therefore, the effectiveness of cross-selling additional products is critical. Given this, this study focused only on car loans with an interest rate of 0.01% per annum from 2018 to 2022. The dataset included 9,224 records.

The basis of the study was a variable that reflects the duration of the client's activity (time_to_deactivation - the number of days from opening to closing the client), the values of which were modelled. The variable "deactivated" - an indication of the client's closure (1 - closed; 0 - active) - served as a sign of whether an observation is censored.

Other variables, the impact of which on the client activity duration have been investigated, are:

- credit_card – an indication of the sale of a credit card to a client (0 – no sale, 1 – sale of a credit card);
- active_credit_card indicates the client's activation of a credit card (0 – no activated credit card, 1 – the presence of an activated credit card).

RESULTS

Modelling the impact of credit card sales on clients' survival rate

A visual representation of the built model can be seen in Figure 1, where the upper dashed line is the survival curve for clients with a credit card and the lower for clients without a credit card. The graph shows that clients with credit cards statistically have a more extended period of activity. In general, the higher the survival curve of credit card clients, the more significant the impact of this variable on the customer closure hazard level. In Figure 1, the distance between the curves is insignificant, indicating a negligible effect. It can also be noted that the distance between the survival curves of clients with and without a credit card decreases to a minimum in different periods. A visual analysis of the graph does not allow for excluding a possible intersection of the curves, which means a violation of the proportional hazard's assumption over time. Hence, a more thorough statistical analysis of the built model quality is necessary.

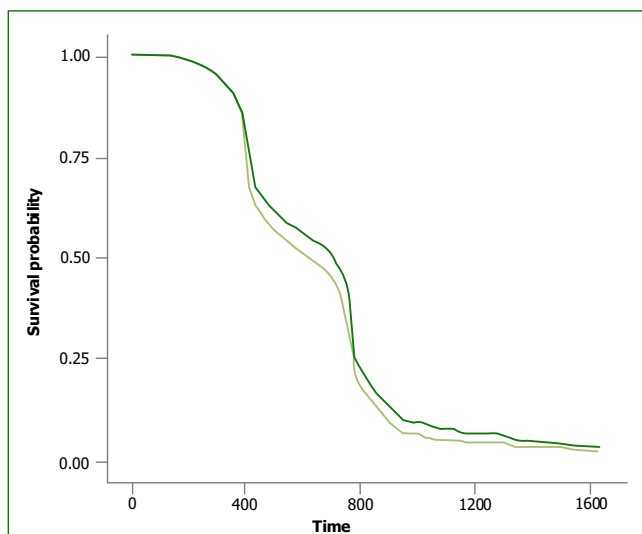


Figure 1. Visualization of the survival curve for clients with a credit card.

The statistical evaluation of the built model is presented in Table 1.

Table 1. Results of modelling the impact of a credit card on the client's survival rate.

Model quality characteristics	Value
β	-0.14890
HR	0.86166
HR-	1.161
CI 95% Lower	0.807
CI 95% Upper	0.9201
$se(\beta)$	0.03346
z	-4.45
$p - value$	<8.6e-06

p-value <8.6e-06

In this model $\beta = -0.15$, which means that the presence of a credit card reduces the risk of client closure. The hazard ratio (HR) reflects the risk of churn for the second group (credit_card = 1) relative to the first group (credit_card = 0). In our case, HR = 0.86, which means that with a credit card, clients close at a rate of 0.86 relative to the closing rate of clients without a credit card. Alternatively, if we examine the HR = 1.16, we can conclude that clients without a credit card close at a rate of 1.16 relative to the closing rate of clients with a credit card.

For the HR coefficients, the upper value of the confidence interval (CI 95% Upper = 0.92) is close to 1, indicating a negligible statistical impact of a credit card's presence on clients' survival rate.

The results in Table 1 show that the credit_card variable has a statistically significant Cox regression coefficient since p-value < 0.05.

Verifying the proportional hazards assumption is the final step in checking the built model's quality. Figure 2 shows the plot of Schoenfeld residuals over time for the credit_card variable. The thin solid line on the graph represents the estimated trend of the residuals over time, based on the Cox regression model.

Figure 2 shows a step line explaining the previous rejection of the proportional hazards assumption.

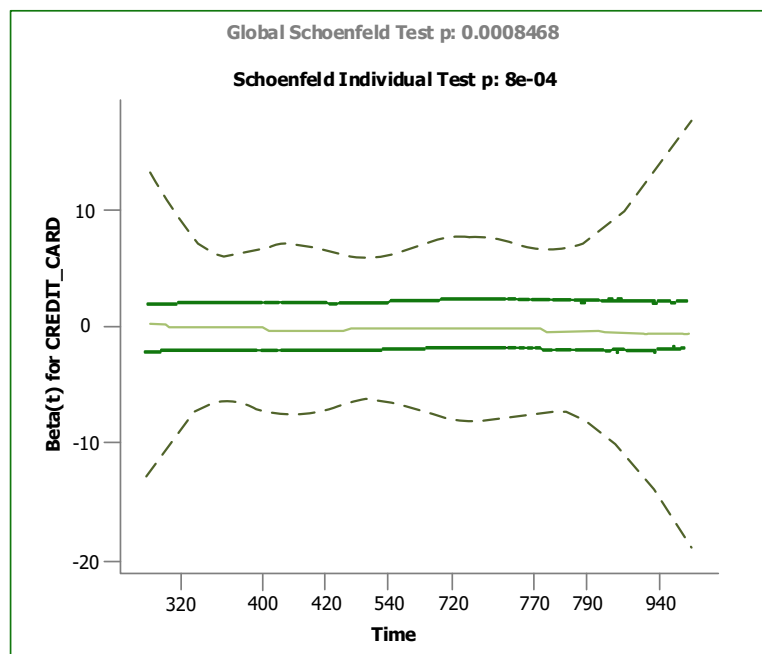


Figure 2. Visualization of Schoenfeld residuals for the credit card variable.

Additionally, Figure 2 shows the value of the statistical estimation of the relationship between Schoenfeld residuals and time - Global Schoenfeld Test $p = 0.0008$. The test is statistically significant for the credit card variable since the p-value < 0.05. Therefore, our assumption of proportional hazards is rejected for this variable. Accordingly, we need to find the factor whose influence does not change significantly over time.

Modelling the impact of credit card sales and activation on clients' survival rate

Let us now consider not just having a credit card but an activated one. Activation means that the client has used it at least once.

A visual representation of the built model can be seen in Figure 3, where the upper dashed line is the survival curve for clients with an activated credit card and the lower for clients without an activated credit card.

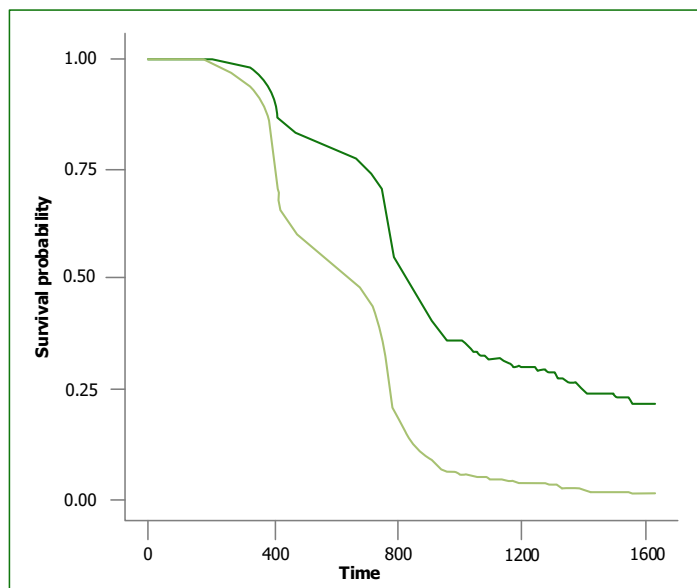


Figure 3. Visualization of the survival curve for clients with an activated credit card.

It can be seen from Figure 3 that the active credit card significantly slows down the process of client closure, thereby extending the period of cooperation for a large part of customers. This can be determined from the considerable distance between the curves, indicating a significant effect of active credit cards on clients' survival. It can also be noted that the distance between the survival curves for clients with and without a credit card changes over time, but the curves never intersect. This situation suggests a possible violation of the proportional hazards assumption. Therefore, a statistical analysis of the built model quality is necessary.

The statistical evaluation of the built model is presented in Table 2.

Table 2. Results of modelling the impact of an activated credit card on the client's survival rate.

Model quality characteristics	Value
β	-1.01209
HR	0.36346
HR-	2.751
CI 95% Lower	0.3125
CI 95% Upper	0.4227
$se(\beta)$	0.07702
z	-13.14
p - value	<2e-16

In this model $\beta = -1.01$, which means that the presence of an activated credit card reduces the risk of client closure. The hazard ratio (HR) reflects the risk of churn for the second group (active credit card = 1) relative to the first group (active credit card = 0). In our case, $HR = 0.36$, which means that with an activated credit card, clients close at a rate of 0.36 relative to the closing rate of clients without an activated credit card. Alternatively, if we examine the $HR- = 2.75$, we can conclude that clients without an activated credit card close at a rate of 2.75 relative to the closing rate of clients with an activated credit card.

For the HR coefficients, the upper value of the confidence interval (CI 95% Upper = 0.42) is far from 1, indicating a significant statistical impact of an activated credit card's presence on clients' survival rate.

The results in Table 2 show that the active credit card variable has a statistically significant Cox regression coefficient since $p\text{-value} < 0.05$.

Verifying the proportional hazards assumption is the final step in checking the built model's quality. Figure 4 shows the plot of Schoenfeld residuals over time for the active credit card variable. The thin solid line on the graph represents the estimated trend of the residuals over time, based on the Cox regression model.

Figure 4 shows a stepped line, partially explaining the previous rejection of the proportional hazard assumption.

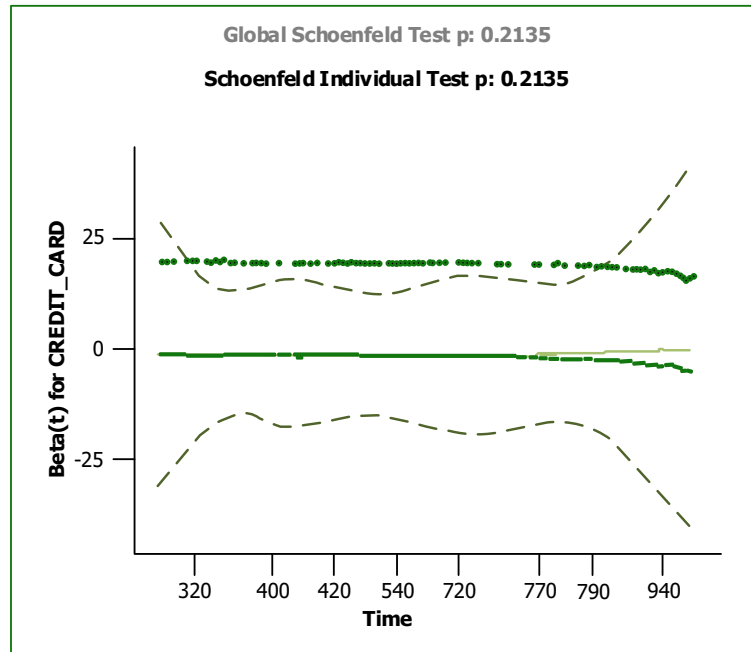


Figure 4. Visualization of Schoenfeld residuals for the active credit card variable.

Nevertheless, at the same time, Figure 4 shows the statistical estimate of the relationship between Schoenfeld residuals over time - Global Schoenfeld Test $p = 0.2135$. The test is not statistically significant for the active credit card variable, as the p -value < 0.05 . Therefore, our assumption about proportional hazards is not rejected for this variable. Accordingly, the built model meets all generally accepted quality criteria of the Cox regression model.

The modelling results confirm the hypothesis that selling a credit card allows for prolonging the activity of the bank's customers, whose first product was a car loan. However, a critical success factor is the sale of a credit card and its activation. The card activation provides a qualitative, statistically confirmed statement that the credit card extends a client's life.

DISCUSSION

The banking industry is a global entity characterized by common challenges and strategies. The research's practical implications extend beyond Ukraine's borders. It examines data from customers whose initial interaction with the bank was through a car loan with a remarkably low interest rate, which is a common strategy employed by banks to attract high-potential customers. Client acquisition takes place through a wide network of partners, which makes it difficult to establish an emotional connection with potential customers.

The current study, for the first time, proposed an algorithm for evaluating the impact of cross-selling on bank customer retention using survival models. For the first time, the importance of such research for improving the bank's financial indicators and improving marketing activities' strategies in customer retention is emphasized.

Banks worldwide can benchmark their customer retention strategies, for clients acquired through partner networks, against the findings of this research. The research presents statistically significant findings regarding the impact of credit card ownership on customer retention. By understanding that selling and activating credit cards can lead to prolonged customer engagement, banks can optimize their marketing and sales strategies to boost customer retention and ultimately increase profitability.

The research recognizes a gap in the current literature, where most studies in the banking sector focus on credit risk assessment (Rozo et al., 2023), time to default (Billio et al., 2019), and factors leading to bankruptcy (Grynko et al., 2017; Caselli et al., 2021). This study addresses the lack of research on customer retention, emphasizing the importance of not just recovering funds but encouraging customers to continue using banking services even after their loans are repaid. The use of survival analysis is a notable strength of this research. Survival analysis, widely used in finance and banking, provides a robust statistical framework for assessing the duration of customer activity, which is vital in this context.

Most of the mentioned research is focused on increasing the accuracy of credit scoring models and improving the quality of models and algorithms for their calculation (Bai et al., 2021; Sumets et al., 2022b). This is often achieved by combining several existing methods, which complicates the process of building and evaluating models (Medina-Olivares et al., 2023; Mia et al., 2022; Staudt and Wagner, 2022). In this study, the Cox proportional hazards model was used, the wide approbation of which in scientific research testifies to its effectiveness in solving customer survival problems and ease of its building and evaluation.

Upon critically evaluating the obtained results, it is advisable to pay attention to certain limitations that are inherent in them as follows:

1. The research primarily focuses on the relationship between credit card ownership and customer retention, but it may not fully control for confounding variables that could impact these outcomes. Unaccounted factors could introduce bias into the results. Understanding how age, gender, income, and region influence customer retention could provide a more holistic view of the issue.
2. The study provides quantitative data but does not explore qualitative aspects of customer behaviour or feedback.
3. The research identifies correlations between credit card ownership and customer retention but does not establish a causal relationship. Causality can be influenced by numerous unaccounted factors, and further studies may be needed to validate causation.
4. While this research highlights possible challenges related to the proportional hazards assumption, it emphasizes the importance of considering time-varying effects. This recognition is relevant for banks worldwide as they seek to adapt their strategies over time to accommodate evolving customer preferences and market conditions.

CONCLUSIONS

This study investigated the impact of credit card selling on the duration of activity for new bank clients whose first product was a car loan. An econometric survival analysis was conducted using a Cox proportional hazards model.

The impact of the model factors on the survival rate, as well as the quality of the built econometric models, was studied using both graphical and statistical methods. The results indicated that owning a credit card, that is sold to clients with a car loan to retaining them after loan repayment, alone did not significantly impact the duration of clients' activity. Clients continue to close their accounts with the bank immediately after the loan agreement expires.

However, the presence of an activated credit card, a card that has been used at least once, demonstrated a substantial influence in prolonging the client's engagement. The proposed credit card allows the client to carry out everyday banking transactions using credit funds even after the expiration of the loan agreement, allowing the bank to generate additional income from the provided services.

The research results will encourage the bank's marketing specialists to work not only on selling additional banking products but also on developing a strategy for their activation.

Further research could be focused on exploring the reasons for credit card activation. The impact of socio-demographic characteristics such as age, gender, income, and region of the client could be investigated to identify correlations with client survival.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

All authors have contributed equally.

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МОДЕЛЮВАННЯ ТРИВАЛОСТІ КЛІЄНТСЬКОЇ АКТИВНОСТІ В БАНКУ НА ПІДҐРУНТІ ЕКОНОМЕТРИЧНОЇ МОДЕЛІ ВИЖИВАННЯ КОКСА

Банківська сфера постійно еволюціонує, шукаючи ефективні шляхи залучення та утримання клієнтів, зокрема тих, які мають високий фінансовий потенціал. Одним зі шляхів досягнення цієї мети є надання автокредитів під низькі відсоткові ставки, такі як 0.01% річних. Однак несвоєчасний відтік клієнтів після погашення автокредиту стає великою проблемою для банків, оскільки це призводить до втрати потенційного доходу від інших банківських послуг. Дослідження має на меті оцінити вплив продажу додаткових банківських сервісів на збільшення тривалості активності клієнтів банку. Для виконання дослідження було використано статистику відкриття нових клієнтів банку, першим продуктом яких був кредит на авто з відсотковою ставкою 0.01% річних за період із 2018 по 2022 рік. Масив даних включав 9 224 записів. У дослідженні використано модель пропорційних небезпек Кокса для визначення впливу кредитної картки на тривалість утримання клієнтів банку з автокредитом. Аналіз коефіцієнтів моделі показав, що за наявності кредитної картки клієнти закриваються зі швидкістю 0.86 порівняно зі швидкістю закриття клієнтів без кредитної картки. Але впродовж перевірки виконання умови пропорційного ризику було визначено, що рівень впливу кредитної картки значно змінюється з часом, що свідчить про неадекватність моделі. Наступним етапом дослідження був пошук параметра впливу, що відповідає всім умовам якості моделі Кокса. Цим фактором було обрано наявність кредитної картки, за якою було здійснено хоча б одну транзакцію. Для цієї варіації моделі всі показники адекватності моделі були виконані, а результати оцінки коефіцієнтів показали, що клієнти з активною кредитною картою закриваються зі швидкістю 0.36 порівняно зі швидкістю закриття клієнтів без активної кредитної картки. Результат підтверджує, що продаж кредитної картки дає змогу збільшувати тривалість активності клієнтів банку, але важливим фактором успіху є не тільки продаж кредитної картки, а й її активація. Отримані результати дослідження можуть бути використані для оптимізації маркетингових і продажних стратегій банку, забезпечення більш ефективного обслуговування клієнтів та збільшення прибутків банку.

Ключові слова: автокредит, утримання клієнтів, кредитні картки, маркетингова активність, аналіз виживання, крива виживання

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