



Investigating the Theory of Survival Analysis in Credit Risk Management of Facility Receivers: A Case Study on Tose'e Ta'avon Bank of Guilan Province

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Abstract

Nowadays, one of the most important topics in risk management of banks, financial, and credit institutions is credit risk management. In this research, the researchers used survival analytic methods for credit risk modeling in terms of the conditional distribution function of default time. As a practical task, the authors considered the reward credit portfolio of Tose'e Ta'avon Bank of Guilan Province and estimate the bank's probability of default based on the survival analysis method. In order to analyze and verify the research hypothesis, firstly, the researcher estimated the survival analysis, survival function, and then the value of the probability of default function by three parametric, semi-parametric (proportional hazards model), and non-parametric methods. Finally, the author compared these three methods by using the ROC method. In order to analyze data, SPSS, SAS, R, and Minitab softwares were used. The results revealed that the parametric model was better and more suitable than the other models. After the parametric model, it was observed that, the semi-parametric model (proportional hazards model) and then the non-parametric model proved to be the best models. The results of this research suggest using rating or credit score in banks, because, in addition to the proper management of allocation of facility to customers, using a credit score as an explanatory variable can result in more efficient and more accurate estimations of default probability.

Keywords:

credit risk management
survival analysis
Tose'e Ta'avon Bank

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INTRODUCTION

Banking industry in the world is constantly changing. Additionally, transaction registration has become easier with the expansion of electronic banking and the volume of data is growing considerably. By analyzing information of banks' databases, it is possible to improve the productivity of banks by better identification of customers and optimal allocation of resources to profitable customers (Taghva et al., 2009)

One of the main tasks of banking system is to attract and collect all sorts of deposits and allocate them to meet the financial needs and finance various economic activities. In fact, banks and credit institutions are the interface between depositors and applicants of credit facility. It can be contended that the most important banking operations of banks, financial, and credit institutions is granting financial facility to applicants. These activities are economically important since the economic growth and development is not possible without the quantitative increase of capital as a factor in production. Banks and financial institutions can from and increase capital with their credit operations and, consequently, increase the production and economic prosperity. These institutions need to deploy an efficient system to carry out this important activity. The operations of granting facility shall be done in a context where the necessary efficiency and speed are provided and the probability of non-return of the principal and interests on the granted facility is minimized (Taghavi Takyar, 2015).

Currently, due to the large volume of bank facility, the risk of their repayment is a major challenge for banks; as such, this risk lies in the nature of banking activities, and it seems virtually impossible to eliminate the risk of banking operations. Therefore, the only solution is risk management. Banks face a wide variety of risks, and credit risk is among the most important ones [10]. The most important risk facing banks is credit risk, which includes loans that have been paid in the past. Generally, the credit risk for a bank is the probability of losing time or, in general, debts that debtors cannot pay because of their inability to fulfill their obligations to the bank. These obligations typically include the repayment of principal and interest on debt to the bank on a specified date (Yurdakul, 2015).

Credit risk is the most critical and biggest challenge facing banks. In fact, estimation of risks is an important and contributing factor for any credit decision, and the inability to accurately determine the risk that has a negative effect on credit management. Additionally, risk affects approved and non-approved investment decisions. When a credit manager approves a loan, he/she takes a potential risk that the customer may be unable to repay. Conversely, when a loan is rejected, there is the risk of losing a potentially profitable customer to competitors and the risk of opportunity costs. Therefore, credit risk assessment is critical before making a decision to grant a loan (Bekhet, & Fathi Kamel Eletter, 2014).

Calculating the probability of default for the receivers of credit facility, loans, and credit cards, is one of the key issues that should be monitored. When facility receivers do not repay their obligations, default occurs, and the risk of such a situation is called credit risk, which has been the subject of research since the middle of the last century. The importance of credit risk, which is part of a financial risk analysis, is very clear in the Basel Agreement, published in 1999 and revised in 2004 by Banking Supervision Committee. The agreement consists of three parts which define a general theoretical framework with a warranty-like procedure in the form of the least needed capital called the statistical constraint for bankruptcy. Part I of the new agreement defines the parameters that play some roles in the credit risk for a financial firm, such as the probability of default, value of the default, and the damage caused by the default. Methods based on calculating credit risk parameters can be used to calculate these risk parameters and particularly the probability of default. These are standardized methods based on internal rating, and credit companies use them to assess the suitability of their credit models and perform the Basel Committee Guidelines with the help of their estimates (Karani, & Aghaeipoor, 2014).

Banks are seeking to grant their facility to customers who are low-risk and can provide returns that are proportional to the interest of the granted facility. This is only possible when banks are able to identify their credit customers, whether natural or legal, and can classify them based on their

ability and willingness to fully and timely repay their obligations using appropriate financial and non-financial criteria. The reason is that, in such a system, facilities are granted to those applicants who have less credit risk, and they are more likely to repay their debt in due time. Considering that these funds can be used as a financial source for granting further facility, it can be argued that they have a very important role to play in increasing investments as well as the economic growth and development of the country. However, the high number of written off or deferred facilities suggest that there are no suitable models for measuring credit risk and risk management systems in the banking system of the country. By predicting the losses caused by non-repayment of loans, credit risk models will provide some sorts of relative superiority for banks and credit institutions and can reduce the risk of bankruptcy. Thus, the importance of granting facility in banking industry and its key role in economic growth and increasing employment have led to the development of several different models for assessing the credit of the clients applying for facilities. Notwithstanding, many of these models are classic models and do not have the ability to evaluate fully and effectively. Therefore, more sophisticated models such as survival analysis can enter this field. In this research, survival analysis methods and their high potential are used for credit risk modeling in terms of the conditional distribution function of default time, so that we can evaluate the performance of survival analysis methods in optimizing the credit risk assessments of bank customers. In the present study the researchers are trying to evaluate the probability of default for facility receivers in Tose'e Ta'avon Bank of Guilan Province, which is achieved using survival analysis method and based on past studies (Baba & Goko, 2006; Cao, 2009; Carling, 1998; Malik & Thomas, 2006; Narain, 1992).

REAEARCH BACKGROUND

In a study titled Factors Affecting the Risk of Liquidity of Banks (A Case Study of Mellat Bank), Yazdan Panah (2009) stated that risk was interpreted as the probability of failing to achieve the expected results, or in other words, the probability of future predictions not being realized. Risks are possible in each area, including banks

and banking activities. Due to their importance in economic system, banks are receiving particular attention in this regard. The reasons for the existence of risks in a bank can be explained by its type of operation, since banks, on the one hand, collect people's capital that are responsible for it and, on the other hand, use these capitals to carry out banking operations and economic activities. Accordingly, the resaerchers aimed to identify the factors affecting the liquidity Risk in Mellat Bank and study and determine the relationships between these variables and liquidity risk indicators. Next, the researchers sought ot identify the effects of liquidity risk in Mellat Bank and study the relationship between the causes of liquidity risk and the aforementioned effects. Finally, the researchers sought to identify and measure the methods for controlling and monitoring liquidity risk in Mellat Bank (Yazdan Panah & Shakibhaji aghaie, 2009).

In yet another article titled Credit Risk Management in a Banking System with a Data Mining Approach, Jamali et al. (2014) stated that financial transactions could lead to the development of banks commercial activities and the creation of new banks. One of the major problems in banking and financial systems is credit risk management. The reason is that, in these institutions, huge monetary resources are granted to the applicants of facilities in the form of credit, and returning these resources is the undeniable secret for continued existence and development of these institutions. Accordingly, investigating the credit of applicants for the repayment of the facilities is an important process, and various methods have been presented for this purpose. In another article titled Application of Survival Analysis Theory in Credit Risk Management for Facility Receivers; Case Study of Maskan Bank, Karani and Aghaeipoor (2014) noted that, currently, one of the most important issues regarding risk management in banks and financial and credit institutions is credit risk management.

In this research, the authors aimed to survival analysis methods for credit risk modeling in terms of the conditional distribution function of default time. To this end, two different methods based on the conditional distribution function of default time were used: The first approach was based on Cox proportional hazards model, and

the second one was based on generalized least squares estimator. As a practical task, the researchers considered the reward credit portfolio of Tose'e Ta'avon Bank of Guilan Province and estimated the bank's probability of default based on the two above-mentioned methods. Finally one of these methods will be chosen. Findings of both models employed in this research study suggested the application of ROC policies as well as comparison of the two approaches using the control method at the beginning of the repayment period of the facility. Chief among the reasons was that the highest probability of default was observed in life-long loans (Karani & Aghaeipour, 2014).

METHOD

Given the aforementioned objectives, the present study can be categorized as an applied research, since it helps bank managers to decide whether or not to grant loans (to avoid the deferral of claims) by considering the importance of credit risk management for banks. In addition, the present study is descriptive-analytic in terms of the design.

The Statistical population and the sample

The statistical population of this research comprised all usual customers of Tose'e Ta'avon Bank of Guilan Province. The chosen sample consisted of 384 credit records of real clients of reward facility that were collected during 2011-2015, and were divided into two distinct categories: credit-worthy and non-creditworthy. Of the 384 cases, 263 were creditworthy and 121 were non-creditworthy.

Research question

Is it possible to estimate the probability of credit facility receivers using survival analysis methods?

Given the question above, the research variables include:

Y: indicates the maturity or lifespan observed for each loan per month.

X: Indicates the amount of facilities received in millions of IRR.

Σ : Indicator of default or non-censorship (one: loan is defaulted, zero: loan is not defaulted).

In order to analyze data, SPSS, SAS, R and

Minitab software are used.

ESTIMATING THE DEFAULT PROBABILITY

In this section, the default probability will be estimated. Generally, it will be estimated $PD(t|x)$ and calculated Eq.1 in this sub-section:

Eq.1

$$PD(\widehat{t|x})_{PM} = 1 - \frac{S(t + 12|x)_{PM}}{S(\widehat{t|x})_{PM}} \quad \text{Parametric method}$$

$$PD(\widehat{t|x})_{PHM} = 1 - \frac{S(t + 12|x)_{PHM}}{S(\widehat{t|x})_{PHM}} \quad \text{Semi-parametric method}$$

$$PD(\widehat{t|x})_{NPM} = 1 - \frac{S(t + 12|x)_{NPM}}{S(\widehat{t|x})_{NPM}} \quad \text{Non-parametric method}$$

Table 1 shows the results of the test of equality of mean default for parametric, semi-parametric and non-parametric methods. According to the results of Table 1, it can be argued that the mean default probability is not the same in these three methods. The parametric method has the highest mean default probability and then, semi-parametric and non-parametric are placed, respectively.

Table 2 shows the analysis of variance of the mean probability in parametric method. Table 2 is related to the equality test of mean default in parametric method at different levels of loan amount. According to the results of Table 2, it can be argued that the mean default probability is the same in different loan amounts and the down trend shown in Fig.2. is insignificant.

Table 3 shows the analysis of variance of the mean probability in semi-parametric method. Table 3 is related to the equality test of mean default in semi-parametric method at different levels of loan amount. According to the results of Table 3, it can be said that the mean default probability is the same in different loan amounts and the down trend shown in Fig. 3. is insignificant.

Table 1: Analysis of Variance of Mean Default Probability in Different Methods of Survival Analysis

Source	Freedom degree	Mean Squared Displacement	F statistic	Probability value
Survival Analysis Methods	2	0.64	45.13	**0.000
Error	18	0.0048		

* - Source of research findings; output of MINITAB software

** - Test significance at 95% confidence level

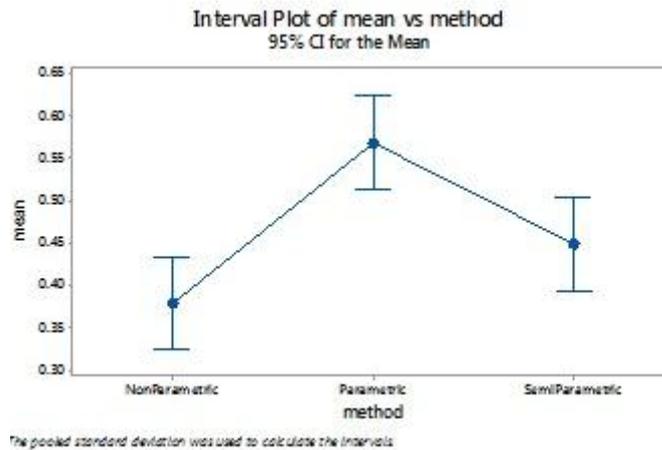


Fig.1. Mean default probability divided by loan amounts

Table 2 : Analysis of Variance of Mean Default Probability in Parametric Method at Different Levels of Loan Amount

Source	Freedom degree	Mean Squared Displacement	F statistic	Probability value
Survival Analysis Methods	6	0.33	33	0.9190
Error	420	0.1023		

* - Source of research findings; output of MINITAB software

** - Test significance at 95% confidence level

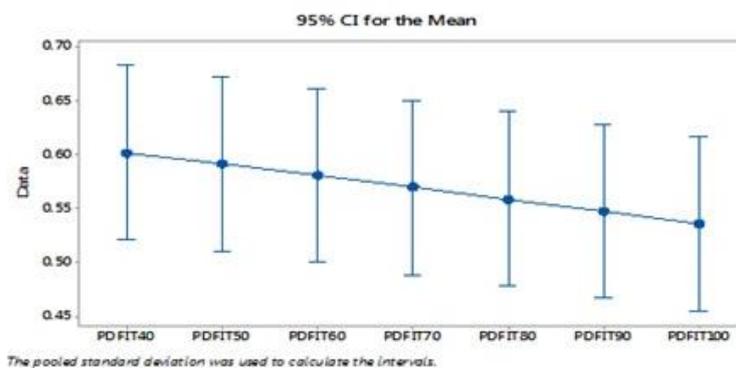


Fig. 2. Mean default probability in parametric method divided by loan amounts

Table 3: Analysis of Variance of the Mean Probability in Semi-Parametric Method at Different Levels of Loan Amount

Source	Freedom degree	Mean Squared Displacement	F statistic	Probability value
Survival Analysis Methods	6	0.079	18.1	0.3140
Error	420	0.0670		

* - Source of research findings; output of MINITAB software

** - Test significance at 95% confidence level

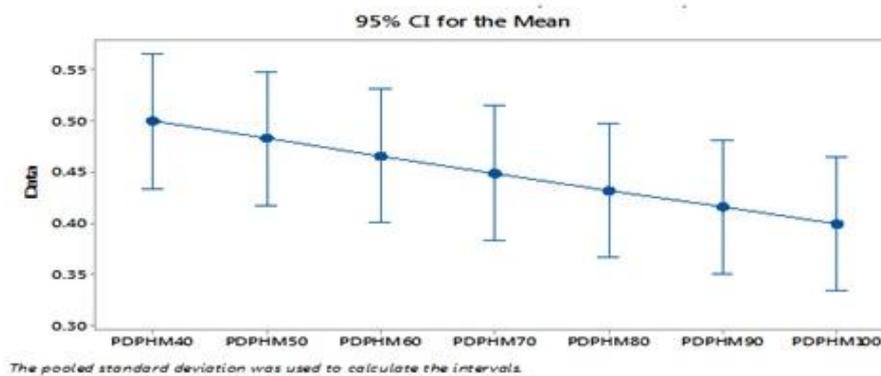


Fig. 3. Mean default probability in semi-parametric method divided by loan amounts

Table 4 shows the analysis of variance of the mean probability in non-parametric method. According to the results of Table 4, it can be said that the mean default probability is not the same

in different loan amounts (the probability value is less than 0.05). Fig. 4 shows the mean default probability in different loan amounts.

Table 4 ;Analysis of Variance of the Mean Probability in Non-Parametric Method at Different Levels of Loan Amount

Source	Freedom degree	Mean Squared Displacement	F statistic	Probability value
Survival Analysis Methods	6	0.7251	36.4	**0.000
Error	420	0.1661		

* - Source of research findings; output of MINITAB software

** - Test significance at 95% confidence level

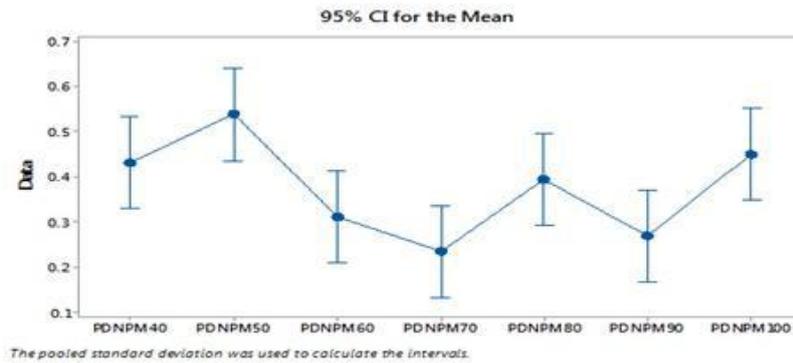


Fig. 4. Mean default probability in non-parametric method divided by loan amounts

Comparison of methods and analysis of research hypothesis

In this sub-section, the researchers will examine the research models and show which models have a better performance in terms of classifying and categorizing the loan applicants.

Table 5 shows the sensitivity, specificity, and ROC indices. As can be seen in the table output, the parametric model is more suitable and better than the other models. After the parametric

model, the semi-parametric model (proportional hazards model) and then the non-parametric model are the best models.

Fig. 5 shows the ROC curves for the three research models. As can be seen, the area below the chart level of the parametric model is larger than other curves which show that the ROC value of the parametric model is much more than that of semi-parametric and non-parametric.

Table 5: Comparison of Research Models

	Parametric model	proportional hazards model	Non-parametric model
Sensitivity	57%	54.9%	65.67%
Specificity	43.93%	43.05%	69.3%
ROC	63.1%**	62.4%**	46.3%

* - Source of research findings; output of SPSS software

** - ROC value of significant difference in statistical terms compared to the value of 0.5

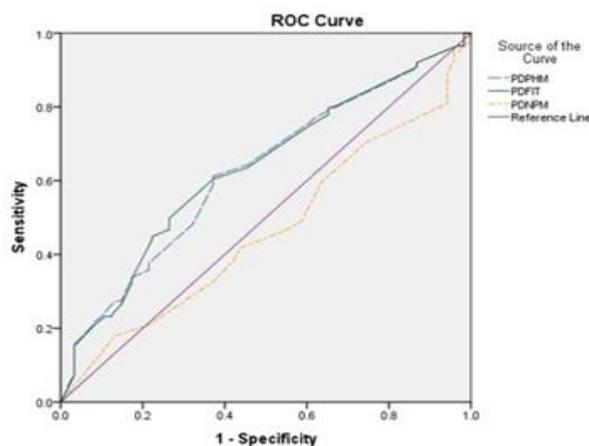


Fig. 5. Research findings; output of SPSS software

In the end, considering that, in this research, the authors were looking for an answer to this hypothesis “It is possible to estimate the probability of credit facility receivers using survival analysis methods” and that, based on the results of Table 5 and the significance of the ROC values which are greater than the number 05, it can be contended that estimating the default probability of credit facility receivers is possible using survival analysis methods and parametric model, which is the best method of estimating the likelihood of a company’s default.

CONCLUSION

In this study, the researchers proposed a new approach for credit risk modeling using survival analysis methods, hoping that the findings of this research could be used in credit risk management. Here, the authors estimated the probability of default, which is one of the important parameters in the Basel committee's view, by the help of parametric, semi-parametric (Cox proportional hazards), and non-parametric methods. Next, the researchers examined the accuracy of the default probability estimates in all the three methods using the ROC model. It was observed that the parametric method had delivered the best performance in comparison to other methods.

What can be said about the method proposed in this research is that if we can use explanatory variables similar to rating or credit score, these methods will show more capability and we will have better results. Unfortunately, however, this is not possible in the country’s banks at this moment. Yet, it is hoped that, in the near future, the country's banks could provide such a possibility for managing their credit risk. The results of this research study recommend using rating or credit score in banks, as, in addition to the proper management of allocation of facility to customers, using a credit score as an explanatory variable is believed to result in more efficient and accurate estimations of the default probability.

REFERENCE

Baba, N., & Goko, H. (2006). Survival analysis of hedge funds. *Institute for Monetary and Economic Studies and Financial Markets Department*, 6.
 Bekhet, H. A., & Eletter, S. F. K. (2014). Credit

risk assessment model for Jordanian commercial banks: Neural scoring approach. *Review of Development Finance*, 4(1), 20-28.
 Cao, R., Vilar, J. M., Devia, A., Veraverbeke, N., Boucher, J. P., & Beran, J. (2009). Modelling consumer credit risk via survival analysis.
 Carling, K., Jacobson, T., & Roszbach, K. (1998). *Duration of consumer loans and bank lending policy: dormancy versus default risk* (No. 70). Sveriges Riksbank Working Paper Series.
 Karani, H., & Aghaeipoor, M. (2014). Application of survival analysis theory in risk management of facility receivers; Case study of Meskan Bank. *Ravand Quarterly Journal*, 21, 65 – 66. 200 - 175.
 Malik, M., & Thomas, L. (2006). Modelling credit risk of portfolio of consumer loans, University of Southampton. *School of Management Working Paper Series* No. CORM-SIS-07-12.
 Narain, B. (1992). Survival Analysis and the Credit Granting Decision, [in:] LC Thomas, J. Crook N., DB Edelman (eds.), *Credit Scoring and Credit Control*.
 Taghva, M. R., Olfat, L., & Hosseini Bamakan, S. M. (2009). Application of data mining techniques for improving customer relationship management in banking industry. Third Data Mining Conference, Poster No. 11.
 Taghavi Takyar, S.M. (2015). *Comparison of credit risk in artificial neural network Models (RBF) and logistic regression in Tose'e Ta'avon Bank of Guilan Province*. Unpublished thesis, Department of Business Management, Rasht Branch, Islamic Azad University, Rasht, Iran.
 Yazdan Panah, A., & Shakibhaji aghaie, S. (2009). Factors affecting liquidity risks of banks (A case study of Mellat Bank). *Journal of Financial Studies*, 3, 27-54.
 Yurdakul, F. (2015). Macroeconomic modeling of credit risk for banks. *Procedia Social and Behavioral Sciences* , 109 , 784-793.