Prediction of Consumer Credit risk in Vietnamese Commercial Banks

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Abstract

The study seeks to test factors that can influence the credit risk of individual consumer borrowers of commercial banks in Vietnam through the use of discriminant analysis. Age, number of dependents, years in current job and salary are independent variables relating to demographic and socioeconomic condition of borrowers while loan amount is independent variable relating to characteristic of the loan. The results show that the estimation function is significant at the 1% level and can predict the financial position of the borrower (customer) with an average accuracy of 74.5%. Therefore, in this study, the demographic, socioeconomic and loan related variables can be used to classify individual borrowers of Vietnamese commercial banks into payment group and non-repayment group.

1. Introduction

In general, consumer credit is a loan for consumption purposes, not used for any commercial purposes. The demand for consumer credit has been on the rise in recent years[1], but at the same time, lending rates have risen, in the view of banks, the risk of these loans is often higher than commercial loans. Therefore, a relatively common method used by commercial banks to limit risks in consumer lending is to use discriminant analysis to evaluate, classify customers and make credit granting decisions (Abdou & Pointon, 2011). The study of Hand & Henley, 1997 and Desai, 1996, also confirmed that an attempt to quantify credit risk of customers was made by commercial banks through discriminant analysis. The important objective of the study is to identify customers with insolvent consumer loans using the demographic and socio-economic characteristics and analyze the two groups of good and bad customers. In order to achieve this overall goal, the specific objectives will be set out as follows: (i) Developing the differential function or linear combination of the predictor or independent variables, which will distinguish well between the criteria categories or the dependent variable. (ii) Using the values of the predictor variables to classify consumer loan customers into two different groups. (iii) Evaluate the accuracy of the classification. With the above objectives, the use of discriminatory models is completely suitable and meets the research objectives. Therefore, in this study, the authors will use discriminant

[1] According to HSBC (2020), the percentage of consumer loan balance at the 4 largest commercial banks in Vietnam was only 28% in 2013, but will go up to 46% in 2020. As a result, this ratio increased rapidly from 25% of GDP to 61% of GDP in the same period.

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analysis to develop predictive models. It allows differentiation between good borrowers and bad borrowers.

2. Literature Review

2.1. Factors affecting the credit risk of individual consumer borrowers

There have been many studies that have shown the factors that affect the ability of individual customers to repay debts and classify them into main groups, as a basis for proposing variables to predict credit risk with individual customers such as:

- *Goodwill of the borrower:* Greenbaum (1991); Hoque (2000); Ozdemir & Boran (2004) said that when the loan is not repaid, it can be the result of bad faith from the borrower. Stiglitz (1990) recommended that banks should screen and select good borrowers and monitor them closely to ensure that they use the loans for their intended purpose (avoiding ethical risk). Crook and Banasik (2004) argue that the history of debt repayment is also a decisive factor. Their research also emphasizes the importance of other qualitative factors such as the borrower's personality and attitude.
- *Demographic factors (age, sex, marital status ...):* Crook (2004) analyzes the effects of factors such as age, income, home ownership status, occupation and concludes that a family has less debt when the head of the household is over 55 years old and credit risk will decrease if the income/ loan balance is high, borrowers own their own homes and are still working. According to Miller (2012), women pose less credit risk than men because they are more cautious and pose less ethical risks. Research by Weber and Musshoff (2012) also confirm the above opinion.
- *The borrower's capacity (educational attainment, professional characteristics and income characteristics, consumption habits).* Chapman (1990) proposes that the repayment ability is ranked from high to low according to the following subjects: High-income customers, medium-income customers and low-income customers.

In another study by Kohansal and Mansoori (2009), the ability of farmers to repay debts in the Korasan-Razavi province of Iran show positive correlation to the experience of farmers. Roberts and Sepulveda (1999) argue that attitudes of borrower and spending purpose and spending habits can also be used to predict whether borrowers are likely to default or not. Because spending habits will affect customers' repayment behavior. Hayhoe et al. (1999) also argued that the attitude of borrowers including money attitude and credit cognitive attitudes can also be predictors of credit behavior. In short, in addition to demographic factors, the attitude, spending habits and consumption habits are also factors affecting credit score and the likelihood of a customer defaulting.

- *Loan value and loan term:* Loan term and amount are closely related to the individual customer's credit risk. Research by Rock (1984) concludes that the longer the loan term and the greater the value of the loan and the higher the credit risk. The reason is that, in the longer term, macro factors such as recession, economic crisis and so on have a greater impact on income (as the main source of debt repayment) of individual customers. Loans with large value, exceeding the repayment capacity of individual customers in 1 period are usually provided with long-term credit by commercial banks and paid by installments in many terms. Therefore, if a commercial bank does not closely monitor changes in the borrower's goodwill and ability to repay debts, the credit risk may increase.

Sumit Agarwal (2008), in the study of determining the repayment capacity of individual customers in relation to the rate of recurring loan liabilities and changes in loan interest rates. Research results show that: in terms of income, when the income over the periodic loan repayment increases, the ability to repay debts of individual customers also increases. This is consistent with conventional reasoning because an increase in the ratio of income to the amount of loan payable periodically means higher financial ability of the customer.

2.2. Model of credit risk prediction of individual consumer borrowers

Building a thorough model to predict individual customers' credit risk at commercial banks has been a popular topic among both domestic and international researchers and it has appeared in many research articles, magazines and dissertations.

In the study of the Banks Slovenija (2015), Mahen Priyanka Peiris (2016) introduces the concept of credit risk early warning system. While Accenture (2014) McKinsey (2012) agrees on the important role of this system in risk management. Typical credit risk measurements and forecasting models apply differentiated analysis to measure and forecast the default and early warning of credit risk for typical science and technology such as Awh & Waters (1974), Grablowsky (1975), Wiginton (1980), Beaver (1966), and Altman (1968). Ohlson (1980) was the first to apply logistic regression analysis (Logit) to predict credit risks and he affirmed that this method is more preeminent and less restrictive than the MDA method. He has successfully built a logit risk prediction model with 9 predictor variables. After that, many other studies also used his method in place of MDA such as Zavgren 1983; Altman and Sabato 2007; Altman, Sabato and Wilson 2008.

In Vietnam, several studies have applied quantitative models to study customer ratings or credit scores. However, the practical application of credit risk early warning tools is not complete and most administrators choose the Alman model or the logit model to build the customer signal rating system to evaluate customers before lending, but little attention to assessing customers after lending to detect credit risk early and propose appropriate measures.

Introduced by Fisher in 1938, discriminant analysis is described as a statistical technique used to discriminate between two or more groups of which characteristics are expected to differ. More importantly has long been used by researchers for distinguishing between good and bad clients (Raimi, Lukman & Adeleke, I.A. & E O, Esan, 2009) as well as building an early warning system identifying the possible causes of bad performance (Altman, 1968; Al-Osaimy & Bamakhramah, 2004; Sinha & Dhaka (2015).

Thus, it can be seen that there are many quantitative models used for measuring the credit risk of individual customer, in which discriminant analysis model is one of the models with high accuracy in studies around the world. However, there have not been many studies in Vietnam using this model to determine credit risk of individual customer. Therefore, we decided to collect data of 10 Vietnam commercial banks and apply discriminant analysis model to predict credit risk of customers.

3. Research Methodology

Our study inherits the results of research using a discriminant analysis model to classify consumer borrowers into different solvency groups of Hand & Henley (1997), Awh & Waters (1974), Wiginton (1980), Abdou & Pointon, 2011 and Kim & Sohn (2004).

In this article, discriminant model will also be used and designed comprising the significant characteristics (income, education, salary, years at present job, loan amount and number of independents) as explanatory variables and the customer's ability to pay loan as dependent variable. Particularly, the model is written as:

$$\mathbf{Zi = \beta_0 + \beta_1 * X_1 + \beta_2 * X_2 + \beta_3 * X_3 + \beta_4 * X_4 + \beta_5 * X_5 + \varepsilon.}$$

Where:

Z: Discriminant score

$\beta_{0:}$ Constant.

$\beta_{1\text{-}5}$: Slopes of independent variables.

X_1: Income

X_2: Education

X_3: Years at present job

X_4: Number of dependents

X_5: Loan amount

ε: Random error.

Z score will be extracted and used to distinguish between clients who are credit worthy and clients who are defaulters, thus forming a possible early warning system for the default

Table 1. Variables used in the model

Numerical Order	Variable	Symbol	Previous Research
X1	Income	Income	Awh & Waters (1974), Hand & Henley (1997)
X2	Education	Education	Awh & Waters (1974), Hand & Henley (1997)
X3	Years at present job	YAPJ	Wiginton (1980), Hand & Henley (1997)
X4	Number of dependents	NoD	Abdou & Pointon (2011)
X5	Loan amount	Loan amount	Kim & Sohn (2004)

Source: Author's calculation

risk prediction.

The authors sent a questionnaire to the loan management unit of 10 commercial banks in Hanoi to collect information on individual customers taking consumer loans at banks in the period from 2018 to 2020. Information about borrowers and their repayment status was extracted by commercial banks from the bank's database and sent to the research team in September 2020. Particularly, banks provided information on both good and bad customers, in which good customers are people who do not have past due debts, and bad customers are people who have overdue debt (Details of information collection form are described in the model). The Education variable is coded into four levels: secondary school level corresponds to one, high school level corresponds to two, university level corresponds to three, graduate level corresponds to four.

Data of 720 customers was collected. However, after filtering data, there are only 651 customers with enough information to be used in the study.

The available sample of customers will be divided into two sub samples named analysis sample and hold out sample in which the former includes 456 customers and is used to estimate the discriminant co-efficients, while the latter includes 195 and is used to test the predicting power of the model.

We start with data descriptive statistics, aiming at describing characteristics of all variables before checking assumptions of discriminant function analysis as suggested by many researchers. This step includes the one sample Kolmogorov- Smirnov test for testing if a variable is normally distributed, of which result did lead to logarithmic transformations of both income and loan amount. The following step is to looking at graph named histogram to find out potential outliers, which after that will be eliminated. Finally, using a correlation threshold of 0.7 as recommended by Pallant (2013) to detect explanatory variables which are highly correlated with each other, multicollinearity does not happen in this study. Discriminant analysis after that is run using the SPSS discriminant program.

4. Results

It is clear that there is huge differences in means of variables between default and non-default groups, especially for income and loan amount. In particular, while average income per month of default group is about nearly VND 14 million, non-default group's ones is 1.6 times higher at just under VND 22 million, which might be partly explained by the fact that the more income customer receive, the more savings they have; therefore, good borrowers can recover from financial shock more easily than not good borrowers. More importantly, this difference might contributes to point out that average loan amount of trust worthy borrowers are higher than that of defaulters.

Besides, the dissimilarity in means of years at present job between two groups quite fit to

Table 2. Group statistic

	Ability to pay loan	N	Mean	Std. Deviation
Income	Not good Good	237 414	13,723,254.44 21,723,197.28	7,107,605.044 25,779,816.30
Education	Not good Good	237 414	2.483 3.811	1.306 .921
YAPJ	Not good Good	237 414	5.147 9.183	2.636 5.807
NoD	Not good Good	237 414	2.081 1.683	2.091 .668
Loan amount	Not good Good	237 414	399.749.562,1 663.227.861,4	261.862.420,4 665.404.955,6

Source: Author's calculation

Table 3. Correlations

		Ability to pay loan	Income	Education	YAPJ	NoD	Loan amount
Ability to pay loan	Pearson Correlation	1	.181**	.518**	.326**	-.151**	.224**
Income	Pearson Correlation	.181**	1	.092*	.051	-.05	.579**
Education	Pearson Correlation	.518**	.092*	1	.255**	-.178**	.126**
YAPJ	Pearson Correlation	.326**	.051	.255**	1	-.088	.094*
NoD	Pearson Correlation	-.151**	-.05	.178**	-.088	1	-.053
Loan amount	Pearson Correlation	.224**	.579**	.126**	.094*	-.053	1
**. Correlation is significant at the 0.01 level (2-tailed).							
*. Correlation is significant at the 0.05 level (2-tailed).							

Source: Author's calculation

average earnings each group has. Particularly, people with higher years'experience tend to have a higher earnings than those with lower years'experience.

The table shows the correlations between variables of which the value can range from -1 to +1 and more importantly, the closer the value of correlation coefficient to -1 or +1 is, the more closely are the variables are related. As can be seen from the table, the largest correlation occurs between income and loan amount, which might be explained by the fact that repayment source of consumer credit customers is often from income, leading to more closely relationship between income and loan amount. However, this pair-wise correlation was only 0.579 which was lower than 0.7; therefore, according to Pallant (2013), multicollinearity does not happen in this study. Besides, the sig. (2-tailed) value for predictors are all below 0.01 (Table 4) indicating statistically significant difference in income, education, year at present job, number of independents loan amount between good and bad borrowers.

In order to find out which are the most discriminating variables between defaulters and non-defaulters, three tests namely Wilks' Lambda test, Fisher test and signification are taken and presented in table below:

Proving the existence or non-existence of relationship between dependent and independent variables, the value of Wilks' lambdas test is between 0 and 1 in which a lambda value of 0 indicates the most discriminating variable. Besides, the discriminating power of the variable is indicated by the Fisher test of which the higher F statistic is the more significant. As a result of that, in this study, education and years

Table 4. Tests of Equality of Group Means

	Wilks' Lambda	F	Sig.
Logincome	.953	15.734	.000
Education	.738	114.522	.000
YAPJ	.860	52.35	.000
NoD	.981	6.294	.013
LogLoanamount	.966	11.243	.001

Source: Author's calculation

Table 5. Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.524a	100.0	100.0	.586

First 1 canonical discriminant functions were used in the analysis

Source: Author's calculation

Table 6. Wilk's Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1	.656	134.668	5	.000

Source: Author's calculation

at present job may best discriminate between the two groups of borrowers. Moreover, all variables show significant univariate differences between those who are trustworthy borrowers and those who not

Indicating the proportion of variance explained and correlation between the discriminant scores and the levels of dependent variable, an eigenvalue and canonical correlation is 0.524 and 0.586 respectively.

To be used to measure how well each function separates cases into groups, wilks' Lambda in this study is 0.656 and has a significant value (Sig. = 0.000); thus, observed group means are different.

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions.

Variables ordered by absolute size of correlation within function.

The correlation of each predictor variable with the discriminant function is showed in structure matrix in which predictors are ordered from highest to lowest. Therefore, education best discriminates between defaulters and non-defaulters. By contrast, number of dependents

Table 7. Structure matrix

	Function 1
Education	.824
YAPJ	.557
Logincome	.305
LogLoanamount	.258
NoD	-.193

Source: Author's calculation

Table 8. Canonical discriminant function coefficients

	Function 1
Education	0.704
Logincome	1.183
YAPJ	.102
NoD	-.016
LogLoanamount	-.010
(Constant)	
Unstandardized Coefficients	

Source: Author's calculation

Table 9. Functions at Group Centroids

Ability to pay loan	Function 1
Not good	-.929
Good	.561
Unstandardized canonical discriminant functions evaluated at group means	

Source: Author's calculation

is the less important variable in determining the group membership.

Indicating the unstandardized scores concerning the independent variables, the "Canonical discriminant function coefficients" is presented in the table above and will be used to create the model used to calculate the discriminant score:

Zi = -11.482 + 0.704*Education + 1.183*Logincome + 0.102*YAPJ - 0.016*NoD - 0.010 LogLoanamount.

As can be seen from the model, while education, income and years at present job increase Zscore or have positive effect on customer's ability to pay loan; number of dependents and loan amount did have negative impact.

More importantly, using this equation, customer's score on the discriminant function will be calculated and compared with group centroids to find out the meaning of discriminant function score.

If customer's score on the discriminant function is closer to -.929, then those customers were probably defaulters. By contrast, if score of answerers is closer to .561, then the data came from the non-defaulter. Moreover, by calculating a cut score halfway between the two centroids (cut score = (-.929 + .561)/2 = -.184), which group customer is in will be figured out. If score on the discriminant function is above -.184, then customer was in regular group; if score is below -.184, customer was in default group.

Table 10. Classification Results

			Ability to pay loan	Predicted group membership 0	Predicted group membership 1	Total
Cases selected	Original	Count	0	107	64	171
			1	52	232	284
		%	0	62.3	37.7	100
			1	18.3	81.7	100
	Cross – validated[c]	Count	0	107	64	171
			1	55	229	284
		%	0	62.3	37.7	100
			1	19.3	80.7	100
Cases not selected	Original	Count	0	43	23	66
			1	19	110	129
		%	0	66.0	34.0	100
			1	15.2	84.8	100

a. 74.5% selected original grouped cases correctly classified

b. 78.5% of unselected original grouped cases correctly classified

c. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

d. 73.8% of selected cross-validated grouped cases correctly classified.

Source: Author's calculation

The practical results of using the discriminant model is shown in the classification table indicating that of the cases used to create model overall 74.5% are classified correctly. In particular, 107 of the 171 defaulters are classified correctly, 232 of the 284 people who previously non-defaulted are classified correctly. Moreover, to be sure that the model is not to be too optimistic when cases used to create the model are again used for classifications, cross-validated section will be used. In this study, there is still 73.8% of selected cross-validated grouped cases correctly classified

Besides, by classifying hold out sample, the result is also quite optimistic when 78.5% of past customers who were not used to create the model, were correctly classified, or in other words this model corrects about three out of four times.

5. Conclusion

The need of consumer credit today is at its highest, but at the same time the default rates have risen, leading to the need of determining status as well as building an early warning model for predicting future customer failure of banks in Vietnam.

Two- group discriminant analysis is applied and the results from this paper obtained the conclusion that, from variables while education is shown as the best discriminates between defaulters and non-defaulters, number of dependents has lowest predictor value. More importantly, by applying the above discriminant function to data of new customers, we can predict the performance of new customer with percent correctly predicted at about 78.5%.

Due to the issue of credit risk, credit risk management and information of borrowers at commercial banks are confidential issues. Therefore, the collected data source is still small compared to the overall, leading to limited results in this research. ■

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