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PERSONAL FACTORS AFFECTING THE PROBABILITY OF OVERDUE DEBT OF INDIVIDUAL CUSTOMERS AT BANK FOR AGRICULTURE AND RURAL DEVELOPMENT OF VIETNAM, TAY DO BRANCH

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In order to provide more view of using personal credit risk measurement tools at Vietnamese commercial bank branches, this study collected data from 386 individual customer profiles of Agribank - Tay Do branch and applied logistic regression technique. The results show that 8 factors including Age, Marital status, Education, Collateral, Income before loan, Income after disbursement, Loan term, Credit history have statistically significant influences on personal credit risk with the model's explanatory level of 82.6%. The study also made recommendations for Agribank - Tay Do branch in particular and Vietnam's commercial bank branches in general to use logistic regression model and to attach importance to income and credit history factors instead of focusing too much on collateral elements in measuring personal credit risk.

Keywords*: Credit risk, Credit risk measurement, probabilities of overdue debt, logistic regression*

JEL Classifications*: G21*

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1. Introduction

Measuring personal credit risk is an important part of credit risk management, because the results of this work are the basis for making credit judgments and applying debt monitoring measures to customers. In Vietnam, in recent years, along with the rapid expansion and development of personal credit products and supplying methods, commercial banks have been developing their personal credit risk management in the direction of applying centralized and semi-centralized credit risk management models, building clear processes for information collection, appraisal, control, monitoring and credit risk handling. In fact, many commercial banks have applied "5C" or "6C" standards to assess the ability to meet credit conditions for individual customers. In addition, many of them succeeded in building and implementing internal credit rating systems which exclusively appliep to individual customer groups. At the same time, with the operation of the credit rating system of individual customers of the National Credit Information Center (CIC), commercial banks have more convenience in referencing information to make loan decisions as well as classifying and tracking customers' debts. This shows the innovations of commercial banks in the process of applying international standards on risk management to specific conditions in Vietnam (Tan.Le Thi Thanh, 2016). In the internal credit rating system, lenders mainly rely on information collected from customers about their personal characteristics, financial capabilities, living standards and credit history. Each borrower is assigned a credit score that shows their creditworthiness and ability to repay (Bennouna & Tkiouat, 2019). Although this technique can provide quick and timely information for credit decision making, it is highly subjective in assessment and rating and problems of information asymmetry cannot be completely solved. In addition, the use of credit scoring techniques for internal credit rating has not yet reached consensus on the criteria and rating scale of commercial banks, and at the same time it cannot help predict personal credit risk before and after loan disbursement of commercial banks. To contribute to solving this shortcoming, methods of determining the probability of overdue debt based on statistical data will be a good support solution for the tendency to choose individual

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customers for safer lending. Stemming from that fact, on the basis of collecting individual customer data at a typical commercial bank branch, the Bank for Agriculture and Rural Development of Vietnam (Agribank), Tay Do branch, this article conducted an experimental logistic regression model on the influence of factors on personal credit risk in order to clarify the significance of applying this model in measuring credit risk and forecast debt repayment ability of individual customers before and after the time of disbursement.

2. Theories and literature review

2.1. Theoretical framework

Credit risk measurement is the endeavor concerned with estimating the probability of an adverse event occurring and its potential impact on the credit performance of a credit institution. The measurement of personal credit risk can be done by many different methods, in which personal credit rating is considered a very common method today. According to (Abdou & Pointon, 2011) there are two main methods of personal credit rating used including expert method and statistical method. In which, the expert method is a method of collecting and processing information obtained through consulting experts with deep knowledge in the credit field to determine the risk and quality of the credit. This method has the advantage of taking experiences and in-depth knowledge of experts. However, it is costly and time consuming to implement. Statistical method is a credit rating method based on data collected from customers and using statistical testing techniques to detect variables affecting credit risk. This method can be implemented fairly quickly with low cost and gives objective results. However, if the observed sample is not large enough, the data quality is not guaranteed, or the model is not suitable, then this method is difficult to ensure reliability. Because of the objectivity of the statistical method, this method is more commonly used in personal credit ratings and is often implemented through credit scoring models using various techniques such as descriptive statistics based on specific criteria and scales, linear regression, logistic regression.

2.2. Literature review

The logistic regression method is one of the most widely used methods in measuring individual credit risk(Abdou & Pointon, 2011). In this method, the factor reflecting personal credit risk is always a binary dependent variable that receives one of two values (0,1). Some studies used dependent variable reflecting risk status in the form of contract compliance/non-compliance (Lieli & White, 2010), or reflecting status risk attitudes are good/bad (Shuai et al., 2013); (Abdou et al., 2019). Other studies used the dependent variable as a binary variable representing the on-time/overdue debt repayment according to the standard of debt classification (Agbemava et al., 2016); (Bennouna & Tkiouat, 2019); (Phước et al., 2017) . The use of the dependent variable to reflect credit risk based on the customer's behavior as reflected in the compliance/non-compliance with the contract or the on-time/overdue repayment according to the debt classification standards is dependent on the nature of data collected, but all reflected the credit risk of customers in different approaches.

Regarding the observed variables, the factors affecting the credit risk of individual customers included variables identifying the borrower's personal characteristics, financial situation, assets and borrower's family, characteristics of the loan and the behavior of borrowers. Variables identifying the borrower's personal characteristics usually include Age, Gender, and Marital Status. The Gender (male/female) and Marital Status (single/married) were formatted as binary variables, while Age was continuous variable based on the actual age of borrowers (Lieli & White, 2010); (Agbemava et al., 2016); (Abdou et al., 2019), or formatted as categorical variables by age groups (Steenackers & Goovaerts, 1989); (Dinh & Kleimeier, 2007).

Occupation variable was classified according to different approaches such as by skill requirements (Not requiring trained skills; requiring little trained skills; requiring sufficient trained skills)(Lieli & White, 2010) or by field of activity (Freelance; business; office work)(Bennouna & Tkiouat, 2019). The Education variable is formatted as a categorical variable according to different criteria such as being divided into 4 groups (Below high school; high school; university graduated; post graduated) (Bennouna & Tkiouat, 2019); (Dinh & Kleimeier, 2007) or into 2 groups (university graduated; not graduated) (Abdou & Pointon, 2011). Some studies added Number of working years variable and formatted as categorical variable according to researcher's judgment (Dinh & Kleimeier, 2007); (Shuai et al., 2013).

Variables reflecting the borrower's physical conditions and family size were used such as Accommodation, Number of Dependents, Means of Transport,... Accommodation variable was identified in 2 groups (inner city; suburban) (Bennouna & Tkiouat, 2019) or 3 groups (rent; own; free to use) (Lieli & White, 2010); (Shuai et al., 2013), or 4 groups (own home; rent; live with parents; other)

(Dinh & Kleimeier, 2007); The Number of Dependents is used by some studies because it is included in the mining data set and was identified according to the actual number (Shuai et al., 2013); (Bennouna & Tkiouat, 2019) or divided into 4 groups (0; 1; 2; 3; >3) (Dinh & Kleimeier, 2007). Some studies also used the Phone variable(Steenackers & Goovaerts, 1989); (Dinh & Kleimeier, 2007) or the Vehicle variable (Abdou et al., 2019) and wered identified by 2 group (yes; no).

The variables that reflect the borrower's financial situation used by the researchers are quite diverse and depend on the data source. Some studies used the variables such as Savings Account, Current Account or Checking Account status, were identified in 4 groups (no balance; low balance; medium balance; large balance) (Lieli & White, 2010) or divided into 5 groups (Shuai et al., 2013). The Remaining Income for Installments variable was identified by interval into 4 groups (Lieli & White, 2010). Total Monthly Income, Total Monthly Expenditure were identified by intervals into 3 group (below average; moderate; above average)(Steenackers & Goovaerts, 1989). Total Annual Income was divided into 4 groups(Dinh & Kleimeier, 2007) and the format of this interval was tied with the meaning of assessing the borrower's income range. In some studies, Monthly Net Income variable was used as a continuous variable that received the actual value of income (Abdou et al., 2019).

Loan characteristics are also used by researchers to consider the possible influence on credit risk. The Loan Amount variable was formatted as a continuous variable that identified its actual value(Lieli & White, 2010) (Shuai et al., 2013); (Agbemava et al., 2016); (Bennouna & Tkiouat, 2019). The Borrowing Purpose variables were identified according to the content of using the loan (buying a house, buying a car, studying abroad, and so on.) (Lieli & White, 2010) or divided into 2 groups (consumption; business development) (Bennouna & Tkiouat, 2019). The Loan term variable was formatted as a continuous variable with real values (Bennouna & Tkiouat, 2019); (Shuai et al., 2013); or divided into 3 groups (short-term, medium-term, long-term) (Steenackers & Goovaerts, 1989); (Abdou et al., 2019) (Dinh & Kleimeier, 2007). The Collateral variable was formatted as a binary variable or classified in 2 groups (yes; no)(Agbemava et al., 2016); (Bennouna & Tkiouat, 2019).

The variables used to describe the borrower's behavior are also quite diverse and depend on the data source and data mining ability of researchers. The variables used were Loan Number, Installment Number, Unpaid Installment, Overdue Days were formatted as continuous variables that received the actual value(Bennouna & Tkiouat, 2019), while the Credit History variable was formatted as a binary variable and identified in 3 groups (no history recorded; good history; bad history) (Shuai et al., 2013) or in 2 groups (have had overdue debt, have not had overdue debt) (Lieli & White, 2010).

Regarding the number of explanatory variables and the combination of explanatory variable formats in the research model. The number of explanatory variables used in the research models are not the same for depending on the data sources and the researcher's data mining ability. Some studies used a combination of the group of explanatory variables as binary, categorical, and interval variables with some explanatory variables as continuous variables (Lieli & White, 2010); (Shuai et al., 2013); (Agbemava et al., 2016); (Bennouna & Tkiouat, 2019); (Abdou et al., 2019).There are also some studies that only used the explanatory variable as binary variables combined with categorical and interval variables (Steenackers & Goovaerts, 1989); (Dinh & Kleimeier, 2007).

Regarding the survey sample, some studies used data collected from a large-scale survey sample of up to 1000 individual customer records by a commercial bank(Lieli & White, 2010); (Abdou et al., 2019) or a microfinance institution(Bennouna & Tkiouat, 2019). However, some studies collected data from a survey sample with a scale of over 100 to about 500 customer records of a commercial bank(Agbemava et al., 2016) or a branch of a commercial bank (Sơn, 2018); (Phước et al., 2017). This shows that the survey sample size depends on the approach and data source that researchers have.

Regarding the regression results, the Age variable did not have statistical significance in the research models when formatted as a continuous variable(Lieli & White, 2010);(Shuai et al., 2013); (Agbemava et al., 2016). Meanwhile, when this variable is formatted as a categorical variable, it has a statistically negative significant effect on default or credit risk (Steenackers & Goovaerts, 1989). The Gender variable was found to have a statistically significant and negative effect on the probability of default in some studies (Lieli & White, 2010);(Bennouna & Tkiouat, 2019);(Dinh & Kleimeier, 2007) with coefficients of 0.247, - 0.738, -1,557 respectively and it is explained that the risk of women tends to be lower than that of men. However, there are also some studies that did not find a statistically significant relationship of Gender to Credit Risk (Agbemava et al., 2016);(Steenackers & Goovaerts, 1989). Most studies did not find a statistically significant relationship of Marital Status to credit risk due to its strong correlation with other variables. Some studies found that Marital Status has a negative effect on Credit Risk(Agbemava et al., 2016);(Bennouna & Tkiouat, 2019) with the corresponding coefficients of -0.843, 0.99 and explained that getting married increased the customer's probability of default.

Education level did not have a statistically significant effect on credit risk in the study of (Dinh & Kleimeier, 2007), but had a negative effect on the probability of default in the study of (Bennouna & Tkiouat, 2019) with a coefficient of -1.231 and showed that the higher the education level, the lower the credit risk. Although some studies found a significant relationship of Occupation with Credit Risk (Shuai et al., 2013) with a negligible influence (coefficient 0.064), most did not find this relationship. Work experience has been found to have a significant effect on credit risk in some studies(Lieli & White, 2010);(Steenackers & Goovaerts, 1989) but in some cases it did not have significant effect (Shuai et al., 2013).

All studies did not find a statistically significant relationship of the Accommodation and Means of Transport variables with Credit Risk. The Phone variable has a significant and negative impact on Credit Risk in the study of(Dinh & Kleimeier, 2007) with a coefficient of -0.181, but did not find a significant relationship in the study of (Lieli & White, 2010). The Number of Dependents has a significant effect on Credit Risk in some studies(Shuai et al., 2013);(Agbemava et al., 2016), but this was not the case in some other studies (Steenackers & Goovaerts, 1989);(Dinh & Kleimeier, 2007).

The Current or Checking Account Status variables were found to have a significant effect in some studies (Lieli & White, 2010); (Shuai et al., 2013) but insignificant with coefficients of 0.058, - 0.098 respectively and is explained that the larger the balance, the smaller the credit risk. However, this relationship is not significant in the study of (Dinh & Kleimeier, 2007). Savings accounts also have a negative effect on credit risk (Lieli & White, 2010); (Dinh & Kleimeier, 2007) with coefficients of -0.237 and -0.75 respectively, and it is explained that the higher the balance, the lower the credit risk. The Ratio of Income used to Installments was found to have a negative effect on credit risk in one study (Lieli & White, 2010) with a coefficient of -0.294, but it was not significant in the other study (Shuai et al., 2013). The Income variable, when formatted as a continuous variable, did not have a statistically significant effect on credit risk (Abdou et al., 2019), but when formatted as a categorical variable, had a negative effect on credit risk (Steenackers & Goovaerts, 1989); (Dinh & Kleimeier, 2007).

Out of the total of 3 studies using the Loan amount variable, 2 studies (Shuai et al., 2013); (Agbemava et al., 2016) did not find a significant relationship of this variable with credit risk. In the other study(Lieli & White, 2010) found a negative effect of this variable on credit risk but with a very little influence (coefficient -0.0000931). The Loan Term variable had a significant effect on credit risk in some studies (Lieli & White, 2010);(Shuai et al., 2013);(Agbemava et al., 2016) but the degree of influence is insignificant (coefficients are 0.0245, 0.007, 0.0737). Most studies did not find a significant relationship of Loan Purpose to Credit Risk (Lieli & White, 2010); (Agbemava et al., 2016);(Steenackers & Goovaerts, 1989), but some studies showed the significant effect of this variable in the direction that consumer loans are riskier than business loans (Bennouna & Tkiouat, 2019);(Dinh & Kleimeier, 2007). Collateral did not have a significant effect on Credit Risk in the study of(Lieli & White, 2010), but had a significant effect on reducing credit risk in the study of (Agbemava et al., 2016) with a coefficient of 0.871.

The variables reflecting the borrower's behavior including Number of loans, Number of Installments and Number of Unpaid Installments had a significant negative effect on Credit Risk in the study of (Bennouna & Tkiouat, 2019) with coefficients of -2,467, -0.137, -1,347 respectively. The study of(Dinh & Kleimeier, 2007) also found a negative influence of Number of Loans on Credit Risk with a coefficient of -0.938. Credit history has a significant negative effect on credit risk in 3 studies(Lieli & White, 2010);(Shuai et al., 2013) with corresponding coefficients of -2,467, -0.137, -1,347 respectively but in (Dinh & Kleimeier, 2007) with the coefficient of 0.3847.

Thus, the studies on measuring personal credit risk by logistic regression method have used the dependent variable which is a binary variable that represents the ability to repay on time or the credit risk status of individuals assessed as good/bad or identified by the compliance/non-compliance with the contract or the borrower's on-time/overdue payment status. In those studies, the independent variables used are quite diverse and not exactly the same, depending on the nature of the collected data, but focus on identifying and characterizing customers (Age, Gender, Marital status, Housing…) and loan characteristics (Loan size, Loan term, Loan purpose...). In addition, some studies added variables describing customer behavior (Credit history, Number of loans, Number of installments...). Regarding the research results, the all studies found variables that have a statistically significant influence on personal credit risk, but they are not completely consistent with each other in terms of the number of influential variables and the influence direction.

In Vietnam, there have been a number of studies on measuring personal credit risk using logistic regression technique. In which, some studies focussed on the individual credit scoring model in relation to the bank's profitability fluctuations (Dinh & Kleimeier, 2007) and was studied in the period before 2007 when the benchmark of credit risk control was not strict (according to Decision No. 493/2005/QĐ-NHNN) and the socio-economic context and conditions of borrowers' access to information were not as developed as today. A number of new studies mainly focus on identifying and measuring the factors that affect individual credit risk through a number of observed variables and simulations based on the credit risk identification model of corporate customers (expressed through the variables: Financial ability, Loan to collateral ratio, Diversification of business lines, Experience of credit officers)(Sơn, 2018);(Phước et al., 2017).This shows that the selection of independent variables in the above studies has not really fully described the basic characteristics of customers, loans and borrowers' behavior. Meanwhile, identifying and measuring these variables in many cases may be difficult due to insufficient information. In addition, relying on Decision No. 493/2005/QĐ-NHNN to divide into two groups of risky/no-risk debts or to identify customers' probability of default/non-default has become outdated and have not yet approached new standards and regulations. In addition, in the context of changes in income, expenditure, information access conditions and debt management standards as in Vietnam today, research results on the influence of factors on probabilities of credit risk for individual customers of commercial banks or branches of Vietnamese commercial banks may no longer be relevant. This leads to new research questions.

3. Research methodology

3.1. Research model

According to(Agbemava et al., 2016) and (Bennouna & Tkiouat, 2019), the logistic regression model has the explanatory variable (Y) as a binary variable receiving one of two values (0, 1) [corresponding to case of non-default (no overdue debt)/default (have overdue debt)]. The explanatory variables include continuous random variables or categorical variables describing the characteristics and behaviors of customers Xi (X1, X2, …, Xn). The research model is established on the basis of determining and comparing the probability of the case Y receiving the value of 1 with the probability that the case Y receiving the value of 0. This model is described through two equations as follows:

$$P(Y=1/X)=\pi(x)=\frac{\exp(\beta_0+\beta_1X_1+...+\beta_iX_i)}{1+\exp(\beta_0+\beta_1X_1+...+\beta_iX_i)} \quad (1)$$

Where: is the regression coefficient; is a probability function that obeys the logistic law, and the LOGIT function is described:

$$\ln(\frac{P(Y=1/X)}{P(Y=0/X)})=\ln(\frac{\pi(x)}{1-\pi(x)})=\beta_0+\beta_1X_1+...+\beta_iX_i \quad (2)$$

Here, π(x)/(1-π(x)) is the odds ratio describing the ratio between the probability of the event Y=1 to the probability of the event Y=0 when the variable X takes on a specific value Xi.

When applying the above research model to the specific case of Agribank - Tay Do Branch, some adjustments has been made: For the dependent variable reflecting personal credit risk is the probability of overdue debt (Y) is identified by the borrower's repayment status. According to Circular 11/2021/TT-NHNH of the State Bank of Vietnam, group 1 debts are considered to have no credit risk, so credit institutions do not have to make provisions, while loans belonging to the remaining groups (2,3,4,5) all contain credit risks to different degrees, so they all have to make provisions. Therefore, to be consistent with this regulation, if the borrower repays the loan on time or is overdue for less than 10 days, then Y is assigned the value of 0, whereas when the borrower repays the loan overdue for 10 days or more, Y is assigned a value of 1.

For the independent variables, based on the data source collected from the survey unit (Agribank - Tay Do branch) does not contain some information (Work experience; Number of dependents; Monthly Total expenditure; Percentage of remaining income used for installment payments; Number of loans) and based on the results of previous studies in the literature review, this study has selected variables that describe the characteristics of customers, of loans and customers'behaviors (including: Age, Gender, Marital status, Education, Occupation, Loan purpose, Collateral, Income before loan, Income after disbursement, Loan term, Credit history).

The author did not choose the Accommodation and Means of Transport variables because they are not significant in the research model (shown in the literature review). Phone variable is also not selected, because in the current situation, 100% of borrowers have their phones. The Current account status, Checking account, Savings account variables are also not included in the research model, because, on the one hand, under current conditions, many customers open accounts at many different banks, so it is difficult to collect enough information to summarize, on the other hand, the vast majority of individual customers in Vietnam still receive income and spend in cash, the use of these variables cannot be fully reflect the financial situation of individual customers. Based on reference to previous research (Dinh & Kleimeier, 2007) and refer to Agribank's classification of monthly income of individual customers. The author uses the Income before borrowing variable (disaggregated into 3 groups) and Income after borrowing variable (divided into 3 groups on the basis of comparison with Income level after borrowing). The Loan amount variable is not included in the research model, because it has no significance or has too little explanatory significance and can be considered as not affecting the variation of the dependent variable (shown in the literature review). The Number of installments, Number of unpaid installments, Number of overdue days variables are not included in the research model, because, on the one hand, Number of installments depends on each credit contract, on the other hand, Number of unpaid installments and the number of overdue days will be the same as the delay payment status and will be reflected in the Credit History variable.

3.2. Variable measurement

The variables in the research model are described as follows:

3.3. Research hypotheses

The research hypotheses are stated as follows:

H1: Age has an effect on credit risk and when age group increases, credit risk decreases (Agbemava et al., 2016); (Bennouna & Tkiouat, 2019).

H2: Gender has an influence on credit risk, men have higher credit risk than women (Lieli & White, 2010); (Agbemava et al., 2016); (Bennouna & Tkiouat, 2019).

H3: Marital status has an effect on credit risk and loans to married customers have higher credit risk than single customers(Agbemava et al., 2016); (Bennouna & Tkiouat, 2019)

H4: Education level has an effect on credit risk and the higher the education level of the customer, the better the customer tends to repay the loan on time (Dinh & Kleimeier, 2007); (Bennouna & Tkiouat, 2019); (Abdou et al., 2019).

H5: Occupations have an effect on credit risk and occupations with higher stability are associated with lower credit risk (Lieli & White, 2010); (Bennouna & Tkiouat, 2019)

H6: The purpose of lending has an effect on credit risk in the direction that consumer loans have higher risks than business loans(Lieli & White, 2010); (Bennouna & Tkiouat, 2019)

H7: Collateral has an effect on credit risk and secured loans have lower credit risk than unsecured loans (Agbemava et al., 2016); (Bennouna & Tkiouat, 2019)

H8: Pre-borrowing income has an effect on credit risk and the higher a customer's pre-borrowing income, the better the customer's ability to repay (Shuai et al., 2013); (Steenackers & Goovaerts, 1989); (Dinh & Kleimeier, 2007)

H9: Post-borrowing income has an effect on credit risk, and the higher the post-borrow income compared to pre-borrowing income, the better the customer's ability to repay the loan (Shuai et al., 2013); (Steenackers & Goovaerts, 1989); (Dinh & Kleimeier, 2007)

H10: The loan term has an effect on credit risk and the longer the loan term, the higher the credit risk (Shuai et al., 2013); (Abdou et al., 2019); (Dinh & Kleimeier, 2007)

H11: Credit history has an effect on credit risk and customers with poorer credit history will also have higher credit risk (Shuai et al., 2013); (Lieli & White, 2010)

3.4. Data

Agribank is one of the 4 biggest commercial banks in Vietnam, in the group of 10 biggest enterprises in VNR500 (Top 500 enterprises in Vietnam). As of December 31, 2020, Agribank continued to maintain its position as the bank with the largest network, covering all provinces, cities, remote areas in Vietnam. Besides the head office and 03 representative offices, Agribank's network also includes 171 Type I branches, 768 Type II branches, 1,286 transaction offices and 68 mobile transaction points by specialized cars. Among the affiliated branches, Agribank - Tay Do Branch is considered a typical branch, because this is a large-scale branch with outstanding loans to individual customers at the end of 2020 about VND 1,300 billion (Agribank Tay Do

Table 1: *Description and measurement of variables*

No	Variables	Codes	Types	Measurement	References
1	Age	X1	Independent	18-30 (= 1) 31-45 (= 2) 46-55 (=3) Over 55 (= 4)	(Agbemava et al., 2016);(Bennouna & Tkiouat, 2019); (Steenackers & Goovaerts, 1989); (Dinh & Kleimeier, 2007)
2	Gender	X2	Independent	Male (= 0) Female (= 1)	(Lieli & White, 2010);(Agbemava et al., 2016);(Bennouna & Tkiouat, 2019); (Abdou et al., 2019)
3	Marital status	X3	Independent	Single (=0) Married (=1)	(Shuai et al., 2013);(Agbemava et al., 2016); (Bennouna & Tkiouat, 2019);(Abdou et al., 2019)
4	Education	X4	Independent	High School/Under High School (=1) Intermediate/College (=2) University (=3); Post graduate (=4)	(Bennouna & Tkiouat, 2019);(Dinh & Kleimeier, 2007);(Abdou et al., 2019)
5	Occupation	X5	Independent	Workers/Freelancers (=1) Business/Trading (=2) Office staff (=3)	(Lieli & White, 2010);(Bennouna & Tkiouat, 2019)
6	Loan purpose	X6	Independent	Consumption (=0) Business (=1)	(Lieli & White, 2010); (Bennouna & Tkiouat, 2019); (Dinh & Kleimeier, 2007)
7	Collateral	X7	Independent	No collateral (=0) Collateral (=1)	(Agbemava et al., 2016); (Bennouna & Tkiouat, 2019)
8	Income before loan	X8	Independent	Under 10 million (=1); 10 - 15 million VND (=2); Over 15 million VND (=3)	(Lieli & White, 2010); (Shuai et al., 2013); (Steenackers & Goovaerts, 1989); (Dinh & Kleimeier, 2007)
9	Income after loan	X9	Independent	Lower than before having loans (=1) No changes (=2) Higher than before having loans (=3)	(Lieli & White, 2010); (Shuai et al., 2013); (Steenackers & Goovaerts, 1989); (Dinh & Kleimeier, 2007)
10	Loan term	X10	Independent	Short term (=1) Medium term (=2) Long term (=3)	(Steenackers & Goovaerts, 1989); (Abdou et al., 2019); (Dinh & Kleimeier, 2007)
11	Credit history	X11	Independent	Never had overdue debt (=0) Ever had overdue debt (=1)	(Shuai et al., 2013); (Lieli & White, 2010)
12	Probability of overdue debt	Y	Dependent	Paid on time or delayed payment less than 10 days (=0) Delayed payment for 10 days or more (=1)	(Agbemava et al., 2016); (Bennouna & Tkiouat, 2019)

Source: Author's recommendation

Branch (2020) and has transaction offices in some urban and suburban districts of Hanoi where individual borrowers come from both urban and rural areas. Therefore, this study chose Agribank - Tay Do branch for the survey.

According to Slovin's Formula (1960), when the population size is known, the research sample size can be selected according to the formula: . Where: n is the minimum sample size; N is the overall quantity; e is the allowable error, normally 5%.

As of December 31, 2020, the total number of individual customers currently borrowing at Agribank - Tay Do Branch is 4,330, from the above formula, the appropriate minimum sample size in this case is determined to be n=366. From a list of 4,330 individual customer records, in order to select a suitable survey sample for the population, this study applied a systematic sampling method with a jump of 11 (4,330/366=11.8, rounded down to 11 to ensure that the sample size is large enough compared to the minimum), a survey sample of 393 individual customer records was obtained. On the basis of reviewing and eliminating customer records with insufficient data, the remaining sample of 386 individual customer records of Agribank - Tay Do Branch was selected.

4. Results and discussions

4.1. Checking for the fit of the model

The results in Table 2 shows that, for the 386 observations included in the analysis, none were missing and none were unselected.

Enter method is used to include independent variables at the same time for testing. The Sig value < 0.05 (Table 3) in all cases shows that the regression model built on the survey sample is statistically significant.

With a value of -2 Log likelihood (denoted by -2LL), showing that the regression model has a good fit and the Nagelkerke coefficient R Square = 0.826 shows that independent variables included in the research model explained 82.6% of the variation of the dependent variable.

The value of Sig = 0.525 > 0.05 (Table 5), showing that the fit of the regression model to the population is acceptable.

4.2. Analysis of regression results and discussions

Table 6 shows the first regression results for the estimates in the logistic regression model. Wald statistic indicates the importance or influence of independent variables in measuring and predicting per-

Table 2: *Case Processing Summary*

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	386	100.0
	Missing Cases	0	.0
	Total	386	100.0
Unselected Cases		0	.0
Total		386	100.0

a. If weight is in effect, see classification table for the total number of cases.

Source: Author's calculation results from SPSS 20

Table 3: *Omnibus Tests of Model Coefficients*

		Chi-square	df	Sig.
Step 1	Step	356.725	11	.000
	Block	356.725	11	.000
	Model	356.725	11	.000

Source: Author's calculation results from SPSS 20

Table 4: *Model Summary*

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	148.899a	.603	.826

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

Source: Author's calculation results from SPSS 20

Table 5: *Hosmer and Lemeshow Test*

Step	Chi-square	df	Sig.
1	7.107	8	.525

Source: Author's calculation results from SPSS 20

Table 6: *Variables in the Equation for the first logistic regresion*

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	X1 (Age)	-1.277	.276	21.402	1	.000	.279	.162	.479
	X2 (Gender)	.359	.452	.630	1	.427	1.432	.590	3.472
	X3 (MarritalStatus)	-1.444	.609	5.618	1	.018	.236	.071	.779
	X4 (Education)	-.824	.262	9.888	1	.002	.439	.262	.733
	X5 (Occupation)	.207	.287	.523	1	.470	1.230	.701	2.158
	X6 (LoanPurpose)	.973	.545	3.189	1	.074	2.646	.909	7.696
	X7 (Collateral)	-2.509	.550	20.799	1	.000	.081	.028	.239
	X8 (IncomeBeforeLoan)	-1.828	.336	29.536	1	.000	.161	.083	.311
	X9 (IncomeAfterDisbursement)	-2.333	.387	36.321	1	.000	.097	.045	.207
	X10 (LoanTerm)	.953	.315	9.127	1	.003	2.593	1.398	4.813
	X11 (CreditHistory)	1.644	.548	8.991	1	.003	5.177	1.767	15.162
	Constant	13.694	2.062	44.123	1	.000	885142.163		

a. Variable(s) entered on step 1: X1, X2, X3, X4, X5, X6, X7, X8, X9, X10, X11.

Source: Author's calculation results from SPSS 20

sonal credit risk. If Sig values < 0.05, Wald statistics are really meaningful.

The value of Sig = 0.427>0.05 in Table 6 shows that the X2 (Gender) has no statistically significant effect on the probability of overdue debt or personal credit risk. This supports the results of previous studies of the following authors: (Lieli & White, 2010); (Agbemava et al., 2016); (Bennouna & Tkiouat, 2019). There is evidence that women do not frequently default on loans (Schreiner, 2004) but the effect of gender on default disappears when other gender-related risk factors are taken into account such as income or marital status. In Vietnam, the average income of men is often higher than that of women (GSO, 2018, 2019, 2020). However, this only indicates financial ability but not attitude towards willingness to repay by gender. For the individual who represents the household to borrow money, the influence of gender on the probability of arising overdue debt will be no longer meaningful when many factors combined in the family are taken into account as income and collateral.

The value of Sig=0.47>0.05 show that the variable X5 (Occupation) also has no statistically significant effect on the probability of overdue debt or personal credit risk. This is consistent with the results of previous studies by(Lieli & White, 2010) and (Abdou et al., 2019). Occupational differences show differences in employment opportunities, income, and personal development, but do not directly reflect the level of income that each individual has. Occupational differences also do not clearly show a relationship with individuals' attitudes towards loan repayment(Abdou et al., 2019).

The X6 (LoanPurpose) variable has a Sig value of =0.074>0.05, showing that does not have a statistically significant effect on the probability of overdue debt or personal credit risk. This supports the results of previous studies by (Lieli & White, 2010) and (Agbemava et al., 2016). Credit risk in consumer loans is generally said to be higher than business loans. However, if commercial banks control risks well, such as checking and tracking income flows to ensure debt repayment of consumers, the possibility of bad debt arising in consumer loans can be reduced. Then, the purpose of lending is for consumption or business no longer has much significance in affecting the probability of customer default. Agribank Tay Do Branch's bad debts in the years 2019, 2020 are 1.46% and 1.64% respectively, NPL ratios in personal loans of Agribank - Tay Do Branch during this period are 1.2% and 1.05% respectively (Agribank Tay Do Branch, 2020). This shows that Agribank's ability to control bad debt is relatively good in compare to the safety threshold of credit activities and this also contributes to the explanation for the difference in lending purpose as consumer or business which has an ambiguous effect on the probability of default of individual customers.

The study removed each variable which had no statistical significance in the order of X5, X2, X6 associated with decreasing Sig value and checking the significance of the remaining variables in the model. The final regression results of the significant estimates in the model are shown in the following table:

Table 7: *Variables in the Equation for the last logistic regresion*

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	X1 (Age)	-1.359	.272	24.899	1	.000	.257	.151	.438
	X3 (MarritalStatus)	-1.329	.582	5.204	1	.023	.265	.085	.829
	X4 (Education)	-.803	.249	10.430	1	.001	.448	.275	.729
	X7 (Collateral)	-2.130	.477	19.969	1	.000	.119	.047	.303
	X8(IncomeBeforeLoan)	-1.806	.326	30.684	1	.000	.164	.087	.311
	X9 (IncomeAfterDisbursement)	-2.337	.378	38.263	1	.000	.097	.046	.203
	X10 (LoanTerm)	.899	.302	8.840	1	.003	2.456	1.358	4.441
	X11 (CreditHistory)	1.635	.545	9.002	1	.003	5.130	1.763	14.928
	Constant	14.497	1.979	53.653	1	.000	1977667.938		
a. Variable(s) entered on step 1: X1, X3, X4, X7, X8, X9, X10, X11.									

Source: Author's calculation results from SPSS 20

tion associated with their knowledge base helps to use and manage the loan better. (Bennouna & Tkiouat, 2019) also suggested that increasing the level of education in the customer base will reduce the likelihood of default because customers have a basis for better loan management.

The results in Table 7 show that variables include X1 (Age), X3 (Marrital Status), X4 (Education), X7 (Collateral), X8 (Income Before Loan), X9 (Income After Disbursement), X10 (Loan Term), X11 (Credit History) have statistically significant effects on the probability of overdue debt or personal credit risk. In which, the X3 (Marrital Status) has a negative effect on personal credit risk and this supports the research results of (Agbemava et al., 2016); (Bennouna & Tkiouat, 2019). This means that the probability of default is higher for married people than for single borrowers, because after marriage, customers often have more financial pressure with family expenses and responsibilities to dependents. (Agbemava et al., 2016) also suggested that, after marriage and having children, due to the increase in the number of dependents, the probability of default increases. Variable X4 (Education) has a negative effect on personal credit risk, which is consistent with the results in the study of (Abdou et al., 2019) and (Bennouna & Tkiouat, 2019). This shows that the higher the customer's education level, the lower the probability of default or credit risk, because the customers' level of educa-

Variable X7 (Collateral) has a negative effect on credit risk and this also supports the research results of (Agbemava et al., 2016), (Phước et al., 2017). Collateral is considered an affirming factor about the customer's financial resources or ability, and is also the basis for hedging risks for the bank. Therefore, when customers have collateral, the probability of default will be lower.

Variables X8 (Income Before Loan) and X9 (Income After Disbursement) have negative impacts on personal credit risk, which is in agreement with the research results of (Lieli & White, 2010), (Shuai et al., 2013) and (Abdou et al., 2019). These authors confirmed that the factors of net income, savings account balance are factors that reflect the financial ability of customers and are negatively related to the probability of customer default.

The variable X10 (Loan Term) has a positive effect on the probability of default or credit risk, which is consistent with the research results of (Shuai et al., 2013) and (Agbemava et al., 2016). This shows that the longer the loan term, the more risks the borrower has to face with due to changes in the business environment, leading to a higher prob-

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ability of default. Variable X11 (CreditHistory) is positively correlated with personal credit risk and this supports the research results of (Lieli & White, 2010) and (Shuai et al., 2013). This shows that when a customer has a poorer credit history, the probability of default is higher.

The above results show that, hypotheses H1, H3, H4, H7, H8, H9, H10, H11 are confirmed with statistical significance less than 5%, while hypotheses H2, H5, H6 are not accepted.

The probability equation for the case of credit risk has the following specific form:

$$P(Y=1/X)=\pi(x)=$$

$$=\frac{\exp(14.497-1.359X_1-1.329X_3-0.803X_4-2.13X_7-1.806X_8-2.337X_9+0.899X_{10}+1.635X_{11})}{1+\exp(14.497-1.359X_1-1.329X_3-0.803X_4-2.13X_7-1.806X_8-2.337X_9+0.899X_{10}+1.635X_{11})} \quad (3)$$

The LOGIT equation is written as follows:

$$\ln\left(\frac{P(Y=1/X)}{P(Y=0/X)}\right)=\ln\left(\frac{\pi(x)}{1-\pi(x)}\right)=14.497-1.359X_1-1.329X_3-0.803X_4-2.13X_7-1.806X_8-2.337X_9+0.899X_{10}+1.635X_{11} \quad (4)$$

Odds or Exp(B) shows how credit risk or probability of default changes when the risk predictor variable changes by one unit. For the X1 variable, the value of odds = 0.257 shows that, in terms of other factors unchanged, the customer's age group increases by one unit, the probability of default decreases by 0.257 times and vice versa. This reinforces the view that older customers are usually more cautious and experienced, so the probability of default will be lower. The X3 variable has odds ratio of 0.265, showing that when the marital status changes from unmarried to married, the probability of default increases by 0.265 times. This reinforces the assumption that married customers often have higher financial responsibilities for the family, so the ability to repay on time will be lower. The odds ratio of X4 is 0.448, indicating that when a customer's education level increases by one level, the customer's probability of default decreases by 0.448 times. The odds ratio of variable X7 shows that when customers have collateral, the probability of default is reduced by 0.119 times. Similarly, the odds ratio of X8 indicates that when a customer's income increases by one step, the probability of default decreases by 0.164 times. This means that the higher the customer's income, the lower the credit risk. The odds ratio of variable X9 shows that when a customer's income after disbursment increases by one step, the probability of default decreases by 0.097 times. This shows that the increased financial resources of customers will contribute to reducing the risk of default. The odds ratio of the variable X10 is 2,456, showing that an increase of one level in the loan term increases the probability of defaulting by 2,456 times. The odds ratio of variable X11 shows that when a customer moves from a state of no overdue debt to a state of having overdue debt, the probability of default is 5.13 times higher.

Logistic regression model allows to predict the probability of overdue debt of customers. The data in Table 8 shows that, out of a total of 122 + 18 = 140 cases observed as risk-free, the model predicted 122 cases, with an accuracy of 87.1%. Out of a total of 14 + 232 = 246 cases of credit risk, the model predicted 232 cases with an accuracy of 94.3%. Thus, the overall average correct prediction rate of the model is 91.7%.

5. Conclusions, implications and recommendations

5.1. Conclusion and limitations of the study

In this study, the author used logistic regression model to examine the influence of personal factors on the probability of overdue debt of individual customers. The results of the study found that 3 variables (Gender, Occupation, Loan purpose) had no clear and statistically significant influence on the probability of overdue debt or personal credit risk. Meanwhile, 8 variables (Age, Marital status, Education, Collateral, Income before loan, Income after disbursment, Loan term, Credit history) have statistically significant influences on personal credit risk. Loan term and Credit history have positive impacts while the remaining 6 factors have negative effects on personal credit risk. Personal factors included in the research model explained 82.6% of the variation in the probability of overdue debt or personal credit risk. The research model also shows that the rate of accurately predicting the customer's ability to pay debts overdue for 10 days or more is up to 94.3%, while this rate for the customer's ability to pay debts on time or less than 10 days is 87.1%. The overall average prediction accuracy rate of the model reached 91.7%.

Table 8: *Classification Table*

Observed			Predicted		
			RuiroTD		Percentage Correct
			0	1	
Step 1	RuiroTD	0	122	18	87.1
		1	14	232	94.3
	Overall Percentage				91.7
a. The cut value is .500					

Source: Author's calculation results from SPSS 20

The limitation of this study is that the survey sample is still limited, just collected data from 386 individual customers of an Agribank branch, while many branches and many other banks have not been selected in the survey sample. In addition, the explanatory variables in the model only included 11 observed variables, while other observed variables such as number of dependents, housing status, number of installment payments have not been included in the research model. Therefore, future studies can expand the research sample, adding more variables to the research model to be able to find more interesting research results.

5.2. Implications and recommendations

Implications

Experimental results of a research model based on logistic regression technique have shown that personal factors including information of customer characteristics, loan characteristics and customer behavior description are important input information that affects the probability of overdue debts or personal credit risk. The model also allows to predict the possibility of overdue debt of individual customers with relatively high accuracy. This implies that this is not a model to replace the internal credit scoring model being applied at commercial banks which inherently carries a lot of subjective meanings in scoring and determining the scoring spectrum, but it provides an additional tool that contributes to increasing objectivity in assessing the probability of overdue debt or personal credit risk based on statistical data. Therefore, based on the available data in the customer database system, commercial banks can completely apply this model to have more certainty in credit appraisal, evaluation and monitoring customers as well as adjusting credit policies.

Recommendations

From the results of the research model, this study made some recommendations for Agribank - Tay Do Branch in particular and other commercial banks' branches with similar business conditions in general as follows:

Firstly, besides the internal credit scoring system, it is necessary to use a logistic regression model based on information about customer characteristics, loan characteristics and customer behavior, because this model will show which factors are less significant and which are actually significant in measuring individual credit risk. On that basis, banks can consider and adjust the weight or scoring scale of the factors in their internal credit scoring systems. In addition, the research model has provided an effective tool of forecasting customers' overdue debts, and this helps bank credit officers can make decisions. This helps the bank's credit officers to make more effective decisions to accept/refuse credits to individual customers. For example, if there are two customers with the following information: Customer A is 35 years old, married, with a university degree, a collateral, an income of 15 million VND/month and this income level unchanged after borrowing, short-term borrowing, with no overdue debt. Customer B has the same information as Customer A, but with an income of 17 million VND/month. Applying formula (3), the probabilities of not paying on time or being overdue for less than 10 days for customers A and B are calculated as:

$$P(A) = \frac{\exp(14.497 - 1.359*2 - 1.329*1 - 0.803*3 - 2.13*1 - 1.806*2 - 2.337*2 + 0.899*1 + 1.635*0)}{1 + \exp(14.497 - 1.359*2 - 1.329*1 - 0.803*3 - 2.13*1 - 1.806*2 - 2.337*2 + 0.899*1 + 1.635*0)} = 18.6\%$$

$$P(B) = \frac{\exp(14.497 - 1.359*2 - 1.329*1 - 0.803*3 - 2.13*1 - 1.806*3 - 2.337*2 + 0.899*1 + 1.635*0)}{1 + \exp(14.497 - 1.359*2 - 1.329*1 - 0.803*3 - 2.13*1 - 1.806*3 - 2.337*2 + 0.899*1 + 1.635*0)} = 3.6\%$$

For customer A, with an income level in group 2, the probability of not paying on time or being overdue for less than 10 days is 18.6%, while customer B with a higher income level (belong to group 3), has the probability of not paying on time or being overdue for less than 10 days decreased to 3.6%. This shows that, based on logistic regression model, when banks choose customers with higher income to provide credit, it is usually safer.

Second, when considering personal credit risk, bank credit officers should not attach too much importance to the factors of Gender, Occupation and Loan purpose for business or consumption. Because, the research model has shown that all these 3 factors have no statistically significant influences on personal credit risk. On the one hand, this also means that banks need to attach more importance to and consider other personal factors that have real impacts on individual credit risk such as Age, Marital status, Education level, Income level, etc. On the other hand, banks can completely change the view that business loans are safer than consumer loans, thereby, they can expand consumer loans to increase profits while still being able to manage credit risk. This also means that the bank's credit policy makers, credit appraisers and credit officers need to change their views on credit risk assessment for consumer loans.

Third, the income factor should be considered more important than the collateral factor when evaluating and making a loan decision. Because, the odds ratio of variable X7 (Collateral) in the model shows that when customers have collateral, the probability of overdue debt or credit risk is reduced by 0.119 times. Meanwhile, the odds ratio of the variable X8 indicates that when a customer's income increases by one level, the probability of default is reduced by 0.164 times. This means that the use of collateral as a condition of personal loans makes only a small contribution to reducing credit risk, while the income factor can bring about a significant reduction in credit risk. This is also the reason for banks to adjust their credit policies in the direction of being able to expand personal loans based on income streams instead of relying on collateral while still being able to manage and minimize credit risks. Appraisers and credit officers themselves also need to focus on assessing and monitoring the customer's income stream, instead of paying too much attention to collateral.

Fourth, banks need to focus on developing credit for customers with good credit history. The odds ratio of the variable X11 (Credit history) in the research model have shown that when a customer change from the state of no overdue debt to the state of having an overdue debt, the probability of not paying on time or being overdue for less than 10 days is 5.13 times higher. Therefore, focusing on expanding credit to individual customers with good credit history not only significantly reduces credit risk but also saves costs for banks, because information of this customer group is usually available in the database systems of banks. This also implies that banks need to pay more attention to solutions to take care of customers who have had a credit relationship with them in order to be able to create new loans effectively.◆

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Summary

Nhằm cung cấp thêm cách nhìn về việc sử dụng các công cụ đo lường rủi ro tín dụng cá nhân tại các chi nhánh ngân hàng thương mại Việt Nam, nghiên cứu này đã thu thập dữ liệu từ 386 hồ sơ khách hàng cá nhân vay vốn tại Agribank – chi nhánh Tây Đô và áp dụng kỹ thuật hồi quy logistic. Kết quả cho thấy có 8 yếu tố gồm Tuổi, Tình trạng hôn nhân, Học vấn, Tài sản bảo đảm, Thu nhập trước vay, Thu nhập sau vay, Thời hạn vay, Lịch sử tín dụng đều có ảnh hưởng có nghĩa thống kê đến rủi ro tín dụng cá nhân với mức độ giải thích của mô hình là 82,6%. Nghiên cứu cũng đã đưa ra khuyến nghị đối với Agribank – chi nhánh Tây Đô nói riêng và các chi nhánh ngân hàng thương mại Việt Nam nói chung về việc sử dụng mô hình hồi quy logistic và xem trọng các yếu tố thu nhập và lịch sử tín dụng thay vì quá chú trọng đến yếu tố tài sản bảo đảm.

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