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Determinants of credit risk at Vietnam bank for agriculture and rural developments in Can Tho City

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ABSTRACT

The aim of this study is to investigate factors affecting credit risks of the borrowers (both corporate and individual customers) of Vietnam bank for agriculture and rural development's branch at Can Tho city (lender), thereby proposing several solutions to improve the bank's operational efficiency in the upcoming years. Simultaneous qualitative and quantitative research methods are applied and secondary data from 102 corporate customers and 2100 individual clients are collected directly from the financial report of the Can Tho branch of Vietnam bank for agriculture and rural development (Agribank) until the end of 2018. A binary logistics model is employed to identify the determinant factors of the credit risk of bank customers. Estimation results reveal that the credit risk of corporate customers is affected by the factors of sales growth, return on sales ratio, Debt to equity ratio, collateral-to-outstanding loan balance ratio, and customer's loan history which are consistent with those of previous studies, whereas the credit risk of individual customers is influenced by the factors of age, educational level, loan purpose, loan maturity, type of collateral, customer income, and customer loan history, which are confirmed by previous studies. The empirical findings of the article imply that the Can Tho branch of Agribank should take precautions in order to limit the credit risk of bank customers. In addition, several governance recommendations are given for bank's manager to improve the operational efficiency of bank.

1. Introduction

The banking industry has always played an important role in the country's economic development, which facilitates regulating the flows of capital in a country. A country's economic development can be assessed through the development of the banking system in that country. Through previous crises in the banking sector, it has been proved that once the banking system is in crisis or collapses, this will lead to serious consequences in all aspects for that country. The banking crisis stems from the risks that the banks face during the banking business process. There are many different types of risk causing a crisis, but the main factor is credit risk. This arises from the main function of the bank, which is to attract idle capital and to find ways to use them effectively through many functions of the bank where credit function plays the most important role.

The year 2018 witnessed the comprehensive success of Vietnam's economy when all 12 socio-economic criteria have been fulfilled and many new records have been set. GDP growth reached 7.08%, which is the highest growth rate in the past decade. Total import and export turnover set a record at $475 billion, and trade surplus reached $7.7 billion. These important achievements of the economy have created favorable conditions for the banking system to expand and develop strongly. The State Bank of Vietnam continues directing proactive and flexible monetary policy, ensuring liquidity, stabilizing interest rates and exchange rates, as well as directing financial institutions, especially commercial banks to increase lending to prioritized production sectors, restructure and resolve non-performing loans. Besides these aforesaid highlights, it is worth noting that the global economic situation underwent complicated changes in this year, the domestic economy also faced many difficulties,

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especially in the agricultural sector and rural areas that were constantly suffering from natural disasters, storms, floods, epidemics, etc. These challenges dramatically impacted the performance of commercial banks, especially Vietnam bank for agriculture and rural development (Agribank). In fact, there have been several times that the banking system in Vietnam has coped with challenges, which was mainly caused by credit risk. Therefore, the prevention of commercial banks' credit risk is extremely necessary. If credit risk occurs, it will directly affect the existence and development of individual financial institutions at first, and then the entire banking system due to the fact that the financial system is one intricate and connected network.

Currently, the Vietnamese banking sector has not been stable yet, it is still in the process of integrating with the banking industry in the region and in the world, thus the efficiency and safety of credit activities are still not high. Prevention of credit risk is a challenge for many commercial banks in general as well as for Agribank in particular. Therefore, it is crucial to carry on a more in-depth study of the determinant factors of credit risk in the banking sector, particularly at Agribank. Hence, this study aims to investigate the factors impacting the credit risk of Agribank's branch in Can Tho city to provide empirical evidence to serve as a foundation for limiting this type of risk for Vietnamese commercial banks in general.

2. Literature reviews

In recent decades, credit risk has become a topic of broad public interest, numerous researchers studies on this topic. These papers mainly emphasize the importance of credit risk in the operation of a commercial bank. There are many scientific textbooks written by domestic and foreign authors on this issue, which provide the scientific theories of credit risk. Depending on the research object which is credit risk from corporate and institutional customers, credit risk from individuals in the form of consumers, or general credit risk (including individual and business), these authors have analyzed different factors affecting these specific research objects.

2.1. Literature review on personal credit risk

With the development of information technology, retail credit products emerged and the reduction of the risks associated with these products has become imperative. Many researchers have deeply identified the causes of personal credit risks in order to provide optimal solutions to reduce this type of credit risk in the bank's operations.

Perlin et al. (2019) introduced an approach designed for personal credit risk, with possible applications in risk assessment and optimization of debt contracts. They define a structural model related to the financial balance of an individual, allowing for cash flow seasonality and deterministic trends in the process. Based on the proposed model, we develop risk measures associated with the probability of default rates conditional on time. This formulation is best suited to short-term loans, where the dynamics of individuals' cash flow, such as seasonality and uncertainty, can significantly impact future default rates. In the empirical section of this paper, we illustrate an application by estimating risk measures using simulated data. We also present the specific case of optimization of a financial contract, where, based on an estimated model, we find the yield rate/time to maturity pair that maximizes the expected profit or minimizes the default risk of a short-term debt contract.

Himali (2020) studied the Determinants of Personal Loan Default and Performance of the Proportional Hazards Model with that of a Random Survival Forests Models. Data used in this study were collected from 1,500 customers who take a personal loan from a major Sri Lankan financial institution. The three models of Binary logistic regression, proportional hazards, and random survival forest were applied as analytical statistics. The findings showed that customer-related factors highly influenced the personal loan default such as occupation, monthly income, and purpose of the loan. The Random Survival Forest model considered monthly income, occupation, the purpose of the loan, and the amount of loan is significant. The Cox Proportional Hazard Model additionally regressed other liabilities and frequency paid as important. Given findings suggested possible solutions for the government to reduce the strains to the general economy in order not only to facilitate economic growth but also enhance the minimization of the customer-related factors that precipitate loan default.

Previous studies on credit risk mainly identified factors influencing credit risk but did not accurately quantify operational risks. Van Hon (2020) implemented the advanced measurement approach (AMA) to estimate operational risks. The advantage of this approach is that the bank builds an internal risk measurement model to measure operational risk. The conditions for applying this approach require the approval of regulations and a demonstration that the cost of capital for operational risk meets capital adequacy for one year at the 99.5 percent confidence level. AMA method contains four main elements, which are (i) the loss database in operations, internal incidents, market factors; (ii) key risk indicators (RIs) measuring performance and risk; (iii) scenario analysis which assumes risks related to processes or infrastructure that may cause major losses for banks; and (iv) self-assessment of operational risks regarding of different types of risk. Banks use these four factors to identify risks in order to manage operations effectively. Specifically, the loss database and scenario analysis are used to calculate capital according to the AMA method. The AMA method brings numerous benefits, such as that the cost of capital is calculated on the basis of risk, better risk management, and the enhancement of the bank's reputation.

Most of the above studies used descriptive statistical methods, regression analysis to examine determinant factors of personal credit risk. In addition, these studies have suggested several factors influencing personal credit risk in credit activities such as type of collateral, income, inspection and supervision process, the experience of credit officer, and experience of borrower. However, these papers still have some limitations, specifically, these articles have not pointed out specific causes of credit risk derived from customers. This may provide further development opportunities for more in-depth research.

2.2. Literature review on corporate credit risk

Pham and Lensink (2007) examined the difference in lending policies and default risk of formal, informal, and semiformal loans with respect to household lending in Vietnam. The results of this study suggested that borrowers who are able to provide collateral, a guarantor, and/or borrow for business-related activities tend to choose formal or semiformal credit. Additionally, small households and male loan contractors prefer formal and semi-formal financing. However, the formal financial sector provides loans to rich households, while the semi-formal sector focuses on lending to the poor. On the other hand, households that have little collateral and/or cannot back their loan via a guarantor, households that need credit for consumption purposes, poor households, and female contractors, are more likely to use credit from informal sources. This article also discerned the determinants of the probability of default across these three lender types. These authors claimed that informal lenders are at higher risk than formal and semi-formal lenders. Besides that, there are some contract and borrower characteristics that are important for one type of creditor but not for the others. In specific, the default risk of formal loans is significantly impacted by formal loan contract terms such as loan maturity, loan interest rate, etc., whereas default risk on informal credit is strongly correlated to the presence of propinquity and other internal characteristics of the borrowing household. It is crucial to notice that one distinctive feature of informal lending, as well as the determinant of repayment rates, is the use of kinship relationships. This paper clearly stated that borrowing from relatives significantly reduces the default risk.

The study of Bonfim (2009) confirmed that during periods of economic growth, sometimes in parallel with strong credit growth, commercial banks, as well as other financial institutions, tend to take excessive risks. However, the imbalance created during this time period can only be visible when economic growth slows down. This paper used the theoretical modeling setup underlying the empirical analysis of previous work done by Rosch (2003) and Hamerle et al. (2004), and time series as well as events of the macroeconomy and financial sector. Using an extensive dataset with detailed financial information of more than 30,000 enterprises, the author stated that default probabilities are affected by several firm-specific characteristics, such as financial structure, profitability, and liquidity, as well as recent sales performance or investment policy. When taking into account time-effect controls or macroeconomic variables, the results stressed that macroeconomic dynamics significantly contribute to explain the reason why companies default. Therefore, though default risk at the micro-level is mainly caused by firm-specific financial situations, there are important relationships between overall macroeconomic conditions and the default probabilities. Briefly, this article focused on the factors that affect credit risk, both at an aggregate and at a firm-specific level.

The study of Ahmed and Hassan (2018) on the determinants of Credit risk: A study of Pakistan's banking sector. Data used in the paper was gathered from the 15-year annual report of 21 banks to examine the bank-specific, banking industry-specific, and macroeconomic determinants of credit risk. By using the Random Effect Model, the findings found that bank ownership has a negative and insignificant relationship with credit risk. The efficiency of management has a negative and significant relationship in the credit risk model 1 but an insignificant relationship with credit risk in model 2. Financial sector development has a positive and significant influence on credit risk model 2. Competition and GDP growth rate variables have a negative and insignificant impact on credit risk model 1 and positive and significant in credit risk model 2. In addition, the inflation rate has been significantly positive in both credit risk models.

The study of Chelagat (2012) on determinants of loan defaults (risks) by small and medium enterprises among commercial banks in Kenya. The data used in the paper were gathered from all the commercial banks in Kenya by a questionnaire that made use of both open and closed-ended questions. By using the multiple linear regressions, the findings found that Loan defaults by SMEs have significantly been increasing and a number of determinants affected the loan defaults key among them interest rates and how long the business has been in operation. The characteristics of the enterprises' managers have been found to have a significant impact on loan defaults. Poor credit analysis and monitoring, type of loan, repayment period, and economic conditions also affect the loan defaults by SMEs.

2.3. Literature on the banks' reaction to the risks

In order to mitigate the customers' risk, possible solutions are likely conducted by the banks. Following are studies in which the bank may mitigate the customers' risks.

First, Habibi and Hosseini (2016) investigated the ranking systems to control and manage risk in banks.

The ranking is the separation and classification of customers into various groups. This study has presented a solution for improving the accuracy of ranking customers of banks based on the hybrid Neuro-Fuzzy networks modeling and optimization algorithms. In this case, two major parts namely selecting the features and rating were targeted. In features selection, particle swarm algorithm is used in addition to genetic algorithm, which is used frequently in the field of risk management. In addition, the Neuro-Fuzzy network technique is used for ranking. The mentioned solution was applied to the data obtained from the customers of one of the German banks with a population of 1,000 people; then, they were evaluated. The findings showed that the particle swarm algorithm has a better performance to achieve the goal, fewer features, and errors in selecting features. Also, in modeling customers' ranking, the Neuro-Fuzzy network technique provides more favorable results than the neural network technique.

Secondly, Oreski et al. (2012) studied the hybrid system with a genetic algorithm and artificial neural networks and its application to retail credit risk assessment. Data used in this study was gathered from the banks around the world that have accumulated large quantities of information clients and their financial and payment history. This paper aimed at investigating the extent to which the total data, owned by a bank, can be a good basis for predicting the borrower's ability to repay the loan on time. They proposed a feature selection technique for finding an optimum feature subset that enhanced the classification accuracy of neural network classifiers. Experiments were conducted on the credit dataset collected at a Croatian bank to assess the accuracy of our technique. The findings showed that the hybrid system with a genetic algorithm is competitive and can be used as a feature selection technique to discover the most significant features in determining the risk of default.

The above studies applied descriptive statistical methods, a Logistic regression model, and regression analysis to identify factors affecting corporate credit risk. The empirical results of prior studies provided a general view of determinant factors of corporate credit risk, including lending interest rates, collateral value, loan repayment history, loan amount, customer equity, financial structure, profitability and liquidity, recent sales performance, investment policy, ethics and the qualifications of credit officers.

Through the comprehensive review of prior studies related to the research topic, it is important to address those previous researchers only conducted studies on decisive factors of general credit risk. While the operations of commercial banks exist in both corporate and individual customer groups, each customer group has different factors that affect credit risk. Thus, in this study, the authors select the factors influencing the overall credit risk in order to investigate the impact of these factors on the credit risk of each customer group and expect significant effects of major factors, thereby proposing measures to limit the credit risk.

3. Research methodology

3.1. Data

To apply the regression analysis method, the article uses secondary data including 102 corporate customers and 2100 individual customers who have been provided loans before June 30, 2015, and still have outstanding loans by December 31, 2018. Data are collected directly from the Corporate customer department, Household and Personal customer department at Can Tho city branch of Agribank. The sample selection method is presented as follows:

- For businesses data, this study selects all outstanding loans until December 31, 2018.
- For individual data: Sample is taken by using random sampling method according to the debt group ratio of individual customers on December 31, 2018, and the expected sample size is 2100 observations. The sampling process is done in two steps:

  - Step 1: Calculating the proportion of the individual customers for each debt group.
  - Step 2: Selecting a random sample of 2,100 personal customers based on the estimated proportion. The random selection method will ensure the representativeness of the sample.

The sample structure of the debt group for individual customers is presented in Table 1.

Table 1: Sample structure of debt group for individual customers

Criteria	Debt Group 1	Debt Group 2	Debt Group 3	Debt Group 4	Debt Group 5	Total
Total number of individual customers	10,329	233	38	31	54	10,685
Proportion (%)	96.67	2.18	0.36	0.29	0.51	100.00
The number of observations randomly taken for each debt group	1,822	68	130	35	45	2,100

3.2. Analysis methodology

According to Pindyck and Rubinfeld (1981), the Binary logistics model has the following form:

$$Ln\left[\frac{P_1}{1-P}\right] = \alpha_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n = \alpha_0 + \sum_{i=1}^{n} \beta_i X_i \quad (1)$$

where P_1 is the probability of credit risk, β_i (i=1, 2, ..., n) is the correlation coefficient and X_i (i=1, 2, ..., n) is the independent variable.

Expression 1 is used to determine the influence of independent variables X_i on the probability of credit risk. Assuming that other variables are constant and Δ is the degree of variation in the quantities, expression 1 can be rewritten assuming that the other variables are constant and Δ is the degree of variation in the quantities as follows:

$$\Delta Ln\left[\frac{P_1}{1-P_1}\right] = \Delta \sum_{i=1}^{n} \beta_i X_i = \beta_i \Delta \sum_{i=1}^{n} X_i = \beta_i \Delta X_i \tag{2}$$

Since α_0 is constant, $\Delta\alpha_0$ equals 0. As ln(x/y)=lnx –lny, and Δlnx ≈ Δx/x, thus:

$$\Delta Ln\left[\frac{P_1}{1-P_1}\right] = \Delta LnP_1 - \Delta Ln[1-P_1] = \frac{\Delta P_1}{P1(1-P_1)} \tag{3}$$

From Eqs. 2 and 3, Eq. 4 is deducted as follows:

$$\frac{\Delta P_1}{\Delta X_i} = \beta_i P_1 (1-P_1) \tag{4}$$

Eq. 4 allows determining the effects of variables X_i on P_1. Pindyck and Rubinfeld (1981) and Youn and Gu (2010) used the initial value P_1 of 50% because if a random phenomenon (such as credit risk) has two possibilities, the probability of one possibility is 50%. These researchers also considered the quick ratio, which is the ratio of highly liquid assets such as cash, accounts receivable, etc., to short-term liabilities). If this ratio is greater than 1, the firm can quickly repay matured debts, so the credit risk is low (Tang, 2009).

This paper employs the Logistics model to investigate the determinant factors of credit risk from individuals as well as the decisive factors of credit risk from corporate and institutional customers. The estimation models are proposed as follows:

$$PCR = \beta_0 + \beta_1 SEX + \beta_2 AGE + \beta_3 EDU + \beta_4 MEM + \beta_5 PURPOSE + \beta_6 AMOUNT + \beta_7 TERM + \beta_8 MATURITY + \beta_9 COLLATERAL + \beta_{10} INCOME + \beta_{11} HISTORY + \varepsilon \tag{5}$$

$$CCR = \beta_0 + \beta_1 INDUSTRY + \beta_2 CONSTRUCTION + \beta_3 TRADE + \beta_4 OTHER + \beta_5 EXP + \beta_6 SG + \beta_7 ROS + \beta_8 CR + \beta_9 D/E + \beta_{10} SEA + \beta_{11} COL + \beta_{12} HIST + \varepsilon \tag{6}$$

where *PCR* is the personal credit risk, which is the dependent variable in model 5; *CCR* is the corporate credit risk, which is the dependent variable in model 6; β are the estimated coefficients of the Logistics regression model; ε is error terms; *SEX, AGE, EDU, MEM, PURPOSE, AMOUNT, TERM, MATURITY, COLLATERAL, INCOME, HISTORY* are the independent variables in model 1, respectively; *INDUSTRY, CONSTRUCTION, TRADE, OTHER, EXP, SG, ROS, CR, D/E, SEA, COL, HIST* are the independent variables in model 6, respectively. The dependent variable *PCR* in model 1 and the dependent variable *CCR* in model 6 has a value of 1 for loans in debt group 3, 4, or 5 with overdue debts of 90 days or more, and a value of 0 for risk-free loans in debt group 1 or 2. Loans are classified in accordance with Circular No.02/2013/TT-NHNN of SBV (2013). With two values of the dependent variable in each model, the binary logistics model is used to estimate the effects of the independent variables on the probability of personal credit risk in model 1 and the effects of the independent variables on the probability of corporate credit risk in model 6. Table 2 shows the independent variables used in model 5 and model 6.

Table 2: Description of independent variables in the regression models

Variables	Measurement Methods	Expected Signs
	Panel A: The regression model for personal credit risk	
SEX	Gender of borrower (Dummy variable, 1 = male, 0 = female)	+
AGE	Age of borrower (years)	-
EDU	Education level of borrower (Dummy variable, 5 = post graduate, 4 = undergraduate, 3 = associate, 2 = intermediate, 1 = less than intermediate)	-
MEM	Number of people in the household (person)	+
PURPOSE	Purpose of loan (Dummy variable, 1 = business investment purpose, 0 = consumption purpose)	-
AMOUNT	Loan amount (million VND)	-
TERM	Term of loan (Dummy variable, 1 = more than 12 months, 0 = less than or equal 12 months)	+
MATURITY	Maturity times (times)	+
COLLATERAL	Type of collateral (Dummy variable, 1 = secured loans, 0 = unsecured loans)	-
INCOME	Average monthly income of borrower (million VND)	-
HISTORY	Loan history of borrower (Dummy variable, 1 = used to have overdue debts, 0 = never have overdue debts)	+
	Panel B: The regression model for corporate credit risk	
INDUSTRY	Loans for investment in industrial sector	-
CONSTRUCTION	Loans for investment in construction sector	+
TRADE	Loans for investment in trade sector	-
OTHER	Loans for investment in other sectors	+/-
EXP	Number of years since borrower operated in the current business sector (years)	-
SG	Annual sales growth rate = ($Sales_t$ – $Sales_{t-1}$) / $Sale_{t-1}$ (percentage)	-
ROS	Return on sales ratio = Operating profit / Net sales (percentage)	+
CR	Current ratio = Current assets / Current liabilities (times)	-
D/E	Debt to equity ratio = Total liabilities/ Total shareholder equity (times)	-
SEA	Shareholder equity ratio = Total shareholder equity / Total assets (times)	-
COL	Collateral-to-outstanding loan balance ratio = The amount of collateral that secures a particular loan / Outstanding loan balance (times)	-
HIST	Credit history of borrower (Dummy variable, 1 = used to have overdue debts, 0 = never have overdue debts)	+

4. Results and discussions

4.1. Statistics description

Table 3 shows the number of firm customers classified by debt group at the Can Tho branch of Agribank. Each customer loan is categorized into a certain debt group, depending on the risk level of that loan. The quality of loans is divided into 05 different levels: Group 1 is the highest-quality loan and group 5 is the lowest-quality loan. Credit risk has an inverse relationship with the quality of the loan, which means that loans in group 1 have the lowest risk, whereas loans in group 5 have the greatest risk.

Based on the results in Table 3, there are 91 out of 102 corporate customers in debt groups 1 and 2 (accounting for 89.22%), while debt groups 3, 4, and 5 consist of 11 firm customers (making up 10.78%).

Table 3: Debt group of corporate customers (Obs.=102)

Debt Group	Frequency	Proportion (%)
Debt group 1,2	91	89.22
Debt group 3,4,5	11	10.78

From the results in Table 4, it can be seen that a firm's borrowing purpose is shown quite similarly in different business sectors. In specific, the number of corporate customers borrowing loans for investment in the industry sector, construction sector, and trade sector is 35, 29, and 25, corresponding to 34.31%, 28.43%, and 24.51%, respectively. In debt group 3,4,5, the group of customers who borrowed for commercial purposes has the highest proportion of 45.45%, followed by the group of customers who borrowed for industrial purposes at 27.27% and the rest is the group of clients who borrowed for construction purposes, namely at 18.18%. Since customers' loan history is regularly updated by CIC, once a customer has had overdue or non-performing loans, it is difficult for that firm to borrow money from financial institutions. The customer debt payment situation is most clearly shown through the debt repayment history which provides a signal of whether the customer is in trouble or has good faith in repaying the debt when the loan matures. If a corporate has a bad repayment history, it is likely that this event will continue in the future (Kano et al., 2011). In the sample of this study, in total, there are 7 customers (6.86%) who used to have overdue debts, including 4 cases in debt group 1,2, and 3 cases in debt group 3, 4, and 5 (Table 4).

Table 4: Loan purpose and credit history classified by debt group in model 2 (Obs.=102)

Variables		Debt Group 1,2		Debt Group 3,4,5		Total	
		Frequency	Proportion (%)	Frequency	Proportion (%)	Frequency	Proportion (%)
LOAN PURPOSE	INDUSTRY	32	35.16	3	27.27	35	34.31
	CONSTRUCTION	27	29.67	2	18.18	29	28.43
	TRADE	20	21.98	5	45.45	25	24.51
	OTHER	12	13.19	1	9.09	13	12.75
HIST	Never have overdue debts	87	95.60	8	72.73	95	93.14
	Used to have overdue debts	4	4.40	3	27.27	7	6.86

Table 5 illustrates the mean, standard deviation, minimum and maximum value of seven variables in model 2. Enterprise with the longest experience is 17 years, the average number of years since the business operation is 8.08.

Table 5: Descriptive statistics of the other variables in model 2 (Obs.=102)

Variables	Mean	Standard Deviation	Minimum	Maximum
EXP	8.08	3.55	1.00	17.00
SG	41.61	136.14	-98.46	905.31
ROS	7.62	9.99	0.00	47.00
CR	21.79	80.95	0.43	743.71
D/E	1.17	1.74	0.00	10.49
SEA	0.51	0.28	0.04	1.00
COL	6.33	27.70	0.24	270.00

The sales growth rate is averaged at 41.61%, the businesses with the lowest and highest sales growth rates are 98.46% and 905.31%, respectively. Firms operating in many different fields have a mean ROS ratio of 7.62%. Besides that, other indicators such as current ratio, return on equity ratio, shareholder equity ratio, and collateral-to-outstanding loan balance ratio are quite good. Specifically, on average, companies have a current ratio of 21.79 times, with the highest value of 743.71 times. Additionally, some firms self-finance their operations, while some corporates heavily depend on borrowing money from banks. Finally, the collateral-to-outstanding loan balance ratio is averaged at 6.33 times, of which the companies with the lowest and highest ratio are 0.24 times and 270 times, respectively.

The results in Table 6 reveal that the debt group 1, 2, which are considered as good debts, account for 90.00% of the total, while the debt groups 3, 4, and 5, which are considered as bad debts, made up 10.00%. The proportion of non-performing loans at Agribank' Can Tho branch is relatively higher than the average non-performing loans ratio of commercial banks during the study period.

Table 6: Debt group of personal customers (Obs.=2,100)

Debt Group	Frequency	Proportion (%)
Debt group 1,2	1,890	90.00
Debt group 3,4,5	210	10.00

Research results from Table 7 indicate that the number of business loans accounts for only 18.86% while consumer loans account for 81.14%. This is completely consistent with the practice of personal credit loans of banks. Individual clients borrow mainly for the purpose of serving their basic necessities such as building and repairing houses, buying new houses, buying cars, buying appliances. In addition, another feature of the consumer loan purpose is that the loan term is usually greater than 12 months, thus, it can be clearly seen from Table 7 that the number of customers borrowing medium and long-term loans accounts for a huge proportion (77.67%). Besides that, that consumer loans make up a high proportion of the total implies that retail credit products have been substantially developing. Moreover, these loan products are mainly secured by collateral assets. Therefore, in the study area, real-estate mortgage loans account for 89.67%, compared to unsecured loans with a relatively small proportion of 10.33%.

Other features of personal customers are also mentioned in Table 8.

Table 7: Loan purposes, loan term, collateral type, borrower gender classified by debt group in model 1 (Obs.=2,100)

Variables		Debt Group 1,2		Debt Group 3,4,5		Total	
		Frequency	Proportion (%)	Frequency	Proportion (%)	Frequency	Proportion (%)
PURPOSE	Business	378	20.00	18	8.57	396	18.86
	Consumption	1,512	80.00	192	91.43	1704	81.14
TERM	Short-term	427	22.59	42	20.00	469	22.33
	Medium-term and Long-term	1,463	77.41	168	80.00	1631	77.67
COLLATERAL	Secured	1,738	91.96	145	69.05	1883	89.67
	Unsecured	152	8.04	65	30.95	217	10.33
SEX	Male	1,287	68.10	143	68.10	1430	68.10
	Female	603	31.90	67	31.90	670	31.90

Table 8: Descriptive statistics of the other variables in model 1 (Obs.=2,100)

Variables		Frequency	Proportion (%)
AGE	From 18 to 35 years old	595	28.33
	From 35 to 50 years old	764	36.38
	Above 50 years old	741	35.29
EDU	Higher education level	873	41.57
	Other education levels	1227	58.43
MEM	From 1 to 4 people	1754	83.52
	More than 4 people	346	16.48
AMOUNT	Less than 100 million VND	1038	49.43
	From 100 to 500 million VND	879	41.86
	More than 500 million VND	183	8.71
MATURITY	Less than 1 time	598	28.48
	From 1 to 3 times	663	31.57
	More than 3 times	839	39.95
INCOME	Less than 3 million VND	20	0.95
	From 3 to 14 million VND	777	37.00
	More than 14 million VND	1303	62.05
HISTORY	Never have overdue debts	1890	90.00
	Used to have overdue debts	210	10.00

4.2. Determinants of credit risk at Can Tho City branch of Agribank

Based on the results, it can be seen that all the pairs of correlation coefficients among the variables in the models are less than 0.8. The results of the correlation matrix in this study imply that multicollinearity is no issue in the models, in other words, the explanatory variables included in the model are not correlated with each other.

As can be seen from the regression results in Table 9, annual sales growth rate (SG), return on sales ratio (ROS), Debt to equity ratio (D/E), collateral-to-outstanding loan balance ratio (COL), and credit history of the borrower (HIST) have statistically significant effects on the corporate credit risk. The impacts of these five independent variables on corporate credit risk can be explained as follows.

The estimated result in Table 9 shows that the annual sales growth rate (SG) negatively influences corporate credit risk in our sample with the negative estimated coefficient ($\beta6=-0.0004$) at the significance level of 0.05. This means that the higher the annual sales growth rate of the borrower, the lower the probability of credit risk occurring, and vice versa. When revenue grows by 1%, the probability of credit risk decreases by 0.0004%. This empirical finding is in accordance with the original hypothesis and the previous studies conducted by Pham and Lensink (2007), Bonfim (2009), Ahmed and Hassan (2018), and Chelagat (2012).

From the estimated results in Table 9, it can be seen that the return on sales ratio (ROS) has a positive correlation with corporate credit risk with the estimated coefficient ($\beta_7=1.8607$) at the significance level of 10 percent. This result is in line with the original assumption and the prior studies of Pham and Lensink (2007). A higher return on sales ratio leads to a rise in credit risk. Specifically, when this ratio of borrowers increases by 1%, the credit risk increases by about 1.86%.

It can be seen from the results in Table 9 that the D/E ratio has a negative impact on corporate credit risk with the estimated coefficient ($\beta9=-0.407$) at the significance level of 0.1. This result indicates that the higher the rate of return on equity, the higher the income to repay the debt, thus lowering the probability of corporate credit risk. In specific, when the return on equity rises by 1%, the credit risk from firm customers decreases by 0.407%, provided that other factors remain constant. This empirical finding is similar to the original assumption and previous studies such as Pham and Lensink (2007), Bonfim (2009), Ahmed and Hassan (2018), and Chelagat (2012).

The estimated result in Table 9 points out that the collateral-to-outstanding loan balance ratio (COL) is inversely correlated with the probability of credit risk at the significant level of 10 percent, meaning that a rise in the collateral-to-outstanding loan balance ratio leads to a decrease in the corporate credit risk, vice versa. Specifically, when this ratio of firm borrowers increases by 1%, the probability of credit risk decreases by 0.016%. This result confirms the empirical findings of previous studies such as Pham and Lensink (2007) and Nguyen et al., (2016).

As expected, the positive relationship between the credit history of the borrower (HIST) and corporate credit risk exists. This is clearly shown through the research results in Table 9 that the estimated coefficient is positive ($\beta 12=0.8222$) at the significance level of 5 percent. This finding is completely consistent with the study of Nguyen et al. (2016), Pham and Lensink (2007), Bonfim (2009), Ahmed and Hassan (2018), and Chelagat (2012). Firms that have ever had overdue debts tend to have greater credit risks than corporates with good credit repayment history.

Table 9: Estimated results of the model 2 using binary logistics regression method (Obs.=102)

Variables	Estimated Coefficient
INDUSTRY	1.0823 (1.42)
CONSTRUCTION	0.2660 (0.89)
TRADE	-0.3278 (-0.37)
EXP	0.1444 (1.59)
SG	-0.0004** (2.24)
ROS	1.8607* (1.65)
CR	0.0089 (0.82)
D/E	-0.4070* (1.66)
SEA	-0.0934 (-0.07)
COL	-0.0161* (-1.82)
HIST	0.8222** (2.03)
Constant	-3.9544*** (-2.92)
LR (10)	20.89
Prob >	0.0219
Log-likelihood	-38.5965

Notes: Values in parentheses () are z-values; *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively

Table 10 presents the estimated results from model 1 with personal credit risk (PCR) as the dependent variable by using the Logistic regression method. The results in Table 10 show that there are 07 out of 11 independent variables significantly affecting the personal credit risk, including the age of the borrower (AGE), education level of the borrower (EDU), the purpose of loan (PURPOSE), maturity times (MATURITY), type of collateral (COLLATERAL), average monthly income of the borrower (INCOME), loan history of the borrower (HISTORY). The effects of these factors on the personal credit risk are consistent with the original expectation. The impacts of these seven independent variables on the personal credit risk can be explained as follows.

Firstly, the research results show that the age of the borrower (AGE) is negatively correlated with the probability of credit risk with the estimated coefficient ($\beta 2=-0.057$) at the significance level of 1 percent, which means that the older the client gets, the less likely the credit risk occurs, and vice versa. This result supports the study of Perlin et al. (2019), Himali (2020), and Nguyen et al. (2016).

The second decisive factor of personal credit risk in the model is the education level of the borrower (EDU), which is statistically significant at the significance level of 1 percent. This explanatory variable has an inverse relationship with the personal credit risk with the estimated coefficient ($\beta_3=-0.486$) (Table 10). These authors also stated that the borrower who attains high education level tends to pay off debt on time, therefore the probability of credit risk is low.

Thirdly, from the results in Table 10, the purpose of loan (PURPOSE) negatively impacts personal credit risk in the study area with the negative estimated coefficient ($\beta 5=-1.517$) at the significance level of 0.01. This result implies that the probability of credit risk of customers borrowing for consumption purposes is higher than that of customers borrowing for business investment purposes. In fact, financial institutions, especially commercial banks are implementing measures to facilitate credit restructuring in the direction of prioritizing the concentration of loans for production and business purposes. As a result, production and business are less risky. This result has been proved in the study of Perlin et al. (2019), Himali (2020), and Nguyen et al. (2016).

Another determinant factor of personal credit risk is maturity times (MATURITY), which is statistically significant at the significance level of 10 percent. This factor is positively associated with the probability of credit risk with the estimated coefficient ($\beta_8=0.309$), which means that when the number of maturity increases by 1%, the probability of credit risk also goes up by 0.309%. This empirical result is consistent with the prior study of Nguyen et al. (2016).

The estimated result in Table 10 also points out that type of collateral (COLLATERAL) is negatively correlated with the probability of credit risk with the estimated coefficient ($\beta_9=-0.919$) at the significant level of 10 percent. This finding is in accordance with the article of Menkhoff et al. (2006) and Campa (2011), implying that good collateral is believed to be a mitigating factor to deal with the problems of adverse selection and moral hazard (Menkhoff et al., 2006) and help to increase access to credit (Campa, 2011). Collateral is a source of provision when the income source is at risk.

As expected, the inverse relationship between the average monthly income of the borrower (INCOME) and personal credit risk exists, meaning that when a borrower generates more income, the probability of credit risk from that customer decreases, and vice versa, provided that other factors remain constant. This is clearly shown through the research results in Table 10 that the estimated coefficient is negative (β10=-0.154) at the significance level of 1 percent. This result confirms the empirical findings of previous studies conducted by Perlin et al. (2019) and Himali (2020).

Last but not least, it can be seen from the results in Table 10 that the loan history of the borrower (HISTORY) positively impacts personal credit risk with the estimated coefficient (β11=3.432) at the significance level of 0.01. This result indicates that personal borrowers who have ever had overdue debts have a higher possibility of credit risk than other customers who have never had overdue debts. Specifically, when customers have bad credit repayment history, the probability of credit risk increases by 3.43%. This empirical finding is similar to the previous studies such as Perlin et al. (2019), Himali (2020), and Nguyen et al. (2016).

Table 10: Estimated results of the model 1 using binary logistics regression method (Obs.=2,100)

Variables	Estimated Coefficient
SEX	-0.329 (-0.81)
AGE	-0.057*** (-2.00)
EDU	-0.486*** (-2.48)
MEM	-0.104 (-0.82)
PURPOSE	-1.517*** (-2.12)
AMOUNT	-0.002 (-1.54)
TERM	-0.629 (-1.21)
MATURITY	0.309* (1.78)
COLLATERAL	-0.919* (-1.69)
INCOME	-0.154*** (-2.79)
HISTORY	3.432*** (5.71)
Constant	3.909** (2.53)
LR (11)	22.78
Prob >	0.0256
Log-likelihood	-42.9834

Notes: Values in parentheses () are z-values; *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively

5. Conclusions and recommendations

This study is conducted to assess the current situation of credit risk for both corporate and individual customers at the Can Tho branch of Vietnam bank for agriculture and rural development (Agribank), thereby proposing several recommendations to improve the performance of the bank. This paper collects secondary data from 102 corporate customers and 2,100 individual customers at Agribank's Can Tho city branch. Through the use of a rational approach and binary logistics regression model, the article investigates the effects of determinant factors on credit risk from corporate customers as well as from personal customers at Agribank's Can Tho city branch.

The research results show that the credit risk from corporate customers at Agribank is significantly affected by the factors of sales growth, return on sales ratio, Debt to equity ratio, collateral-to-outstanding loan balance ratio, and customer's loan history, whereas the credit risk from individual customers at Agribank is considerably influenced by the factors of age, educational level, loan purpose, loan maturity, type of collateral, customer income, and customer loan history.

The empirical findings from this study serve as a scientific basis to provide several solutions to prevent and reduce credit risks from corporate as well as individual customers at the Can Tho branch of Agribank, thereby improving credit risk management at Agribank. This study also proposes some recommendations for the State Bank of Vietnam and for the local government, which are mentioned in the next section.

Agribank's head office should regularly organize professional training courses, guide the implementation of the credit process for branch officers thoroughly so that they can understand, grasp and implement it effectively. Monitoring the loan repayment schedule of customers is extremely necessary, which may reduce the credit risk from customers. Hence, the bank should consider expanding its facilities as well as hiring more staff to manage the credit process effectively so as to improve the competitiveness for Agribank. Additionally, the Head office continues to improve the modern transaction system to help customers access products and services easily and efficiently.

The world economy has had remarkable movements. The international standards, principles, and game rules of major international institutions have become the dominant foundation for the movement and development of the world economy. The global financial sector is likely to be more regulated by the new legal frameworks. The trend of the world banking system is to increase mergers and acquisitions; to strongly develop retail banking services and modern banking services, and to strengthen supervision and risk management in the operations of banks. Therefore, the State Bank of Vietnam should closely monitor, promptly adjust the policies, and set the right direction in the operations of commercial banks across the country. In addition, the State Bank of Vietnam should enact suitable policies to stabilize the exchange rate as well as the domestic gold price, control inflation, keep fluctuations in interest rate reasonable, and facilitate capital distribution. The State Bank of Vietnam should also control the implementation of regulations on the quality of capital mobilization as well as lending activities and should apply stronger sanctions to improve the process of economic restructuring in the upcoming time, paving the way for the financial market to strongly develop.

The local authority should strengthen the inspection of the land use to ensure that public land is exploited effectively and is used for the right purpose, thereby loosening the land use bottlenecks in the study area. The local authority should also connect banks with people, creating favorable conditions for people to access low-income housing credit. Besides that, the local government should develop infrastructures such as roads, bridges, and culverts, and should enhance pollution control activities in order to create favorable conditions for travel, production, and business, which simultaneously helps credit staff to perform their duties well. Moreover, local government should regularly review, amend, supplement policies and mechanisms on business environment; abolish or adjust regulations that are no longer suitable for the market mechanism; create favorable investment conditions to attract new investors as well as to expand production and business; create more jobs for individuals; ensure social security, and improve living standards of the local people. Last but not least, local authorities should support the bank's credit operations by providing information on the economic and financial status of potential customers who want to borrow money from the commercial bank so as to help credit officers make an appropriate decision.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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