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The Front-End's Lending Decision System for the Agricultural Bank in Thailand

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Abstract

The main objective of this study is to develop the front-end's lending decision system of the Bank for Agriculture and Agricultural Cooperatives, a major lender in Thailand's agricultural sector. The logit model and the artificial neural network model have been developed to reflect risk factors to identify the probability of default by each new borrower. The study supports the use of the logit model to develop the system because it gives more accuracy in predicting the probability of default and debtor classification than the artificial neural network model. The working process of the system is classified into two sections including credit risk management, which is the process of screening the loan applications and setting the credit approval or rejection criteria, and affordability risk management, which is the process of determining the maximum loan amount for the debtor who has passed the credit approval criteria. In this study, the author caps the debt service ratio as a threshold for determining the amount of credit (the loan amount approved and interest expense) at 70% and determines that the maximum loan principal is 63% of the debtor's total annual income. The system is also used as an instrument to support the implementation of appropriate credit

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policies in handling agricultural households' excess debt and promote the building of financial discipline for agricultural households in the rural sector of Thailand.

Keywords: front-end's lending decision, agricultural sector, household's excess debt
JEL Classification: G21, G51, Q14

1. Introduction

Bank for Agriculture and Agricultural Cooperatives (BAAC), a major lender in Thailand's agricultural sector, is a state-owned bank that plays a role as a rural development bank in Thailand. The main mission is to provide credit to help finance a career in agriculture and encourage small farmers of the country to access funding at fair lending rates and a reasonable amount of credit necessary for a career and able to live properly.

From the BAAC's new loan applicants information used as production expenses as of July 31, 2020 (operation period from April 2019 to July 2020), the loan amount was 20,704 million baht. The amount of the 138,027 new loan applicants, 16,163 defaulted, a very high number for a bank's new loan. This may be due to the BAAC's credit assessment process, which mainly depends on the discretion of credit appraisers and credit approvers. However, this process appears to be inefficient and it leads to the negative impact that farmers who apply for credit may be in debt from the cause of receiving excessive credit until they are at default or even if they can pay the debt, the residual income is not enough for living.

The front-end lending decision system will be the BAAC's new credit assessment system that integrates risk factors such as economic factors, geographic factors, etc. into the new debtor's credit assessment process based on the statistical and mathematical methods. It can reduce the bias of credit decisions and add efficiencies to the credit assessment process.

This research article aims to study "the front-end's lending decision system for the agricultural bank in Thailand" with the following two main objectives.

1. To develop the front-end's lending decision system for managing risks in the front-end agricultural loan portfolio of the agricultural bank in Thailand.

2. To implement the front-end's lending decision system as an instrument to support the implementation of appropriate credit policies in handling agricultural household's excess

debt and promote financial discipline building for agricultural households in the rural sector of Thailand.

2. Literature review

2.1 The policy guidelines for appropriate retail credit to take care of the problem of excessive debt of the household sector

Bank of Thailand (BOT) has set the policy guidelines for appropriate retail credit to take care of the problem of excessive debt of the household sector. The key focus is the financial business operator looks at retail loans from the borrower's perspective in addition to their credit risk exposure. It also gives households access to credit that is consistent with their debt repayment ability without incurring excessive debt. This will reduce the likelihood that Thai households will have insolvency problems, but will also reduce the credit risk of financial institutions and lead to the stability of the financial institution system in the long term. In considering credit approval, the financial business operator should carefully assess the debtor's repayment ability. The consideration is to cover all debt obligations against the income that is the source of debt repayment of the debtor which should be consistent income, can be reliably proven or estimated. It should also be considered whether the debtor will have the residual income after deducting all debt obligations for living or not. The Debt Service Ratio (DSR) should be used as one of the important factors for credit approval. In determining a bank's DSR level, in principle, banks must not approve loans to debtors whose DSR levels are higher than those that will cause debtors to have difficulties in debt repayment, which will pose a credit risk to the bank (Bank of Thailand, 2019).

Banks in Asia, such as Malaysia and Singapore, have adopted DSR configuration measures to tackle household debts or economic bubble issues. For example, Malaysia imposes a DSR of 60 percent on all types of loans lending with vulnerable borrowers, and Singapore has set a limit of the DSR level at 60 percent with mortgage loans, etc. In Thailand, The BOT recently asked banks to apply its retail lending guidance that caps DSR for vulnerable groups at 70 percent and pushed these banks to adopt the principle of responsible lending to provide credit for help finance and encourage people to access funding at fair lending rates and a reasonable amount of credit necessary for a career and able to live properly with enough money to sustain their living after debt repayment (Bank of Thailand, 2019).

2.2 Credit risk management, the application scoring model, and the internal rating model

Credit risk management is a process or system which a financial institution uses to specify, monitor, and control risks arisen from the borrower or counterparty is unable to comply with any condition or agreement under the contract that includes loans, investments, and contingent liabilities to enable the financial institution to manage risk to be within the tolerance level while realizing returns commensurate with the risk which, herewith, will focus on loan portfolio management (Bank of Thailand, 2005).

The application scoring (front-end) is a model that assists risk measuring and management of retail loan portfolio of financial institutions by calibrating information related to nature and behavior of customer to scores by analyzing and compiling related statistics from historical data with the objectives of classification of good / bad accounts and calculation of the probability of default based on the assumption that future behavioral of a borrower is the same as the past behavior of a debtor with a similar profile. The front-end model studies risk according to the profile of the population, geography, and financial information of the new credit applicants at the time of the application to be used for screening the loan applications, setting the credit approval, and loan pricing (Bank of Thailand, 2005).

The internal rating model is a method for measuring risk and managing the loan portfolio of financial institutions by converting information on related aspects including estimated factors and qualitative features prescribed by the financial institutions into scores. It is to classify debtors into various grading buckets according to the risk profile of each debtor. The internal rating model must be capable of grading and measuring risk accurately. It must be reliable and reflects the risk of the debtors in separating debtors with different risks and in measuring the probability of default and must categorize good debts into at least 7 grades and bad debts into at least 1 grade (Bank of Thailand, 2005).

2.3 Credit risk management tools for the agricultural bank in Thailand

Over the past 10 years, studies on the development of statistical and mathematical tools for credit risk management for agricultural banks in Thailand have been gaining more attention, such as the credit risk portfolio management system for agricultural lending of the rural financial market in Thailand (Somboon, 2015a), the credit scoring system for managing risk in the agricultural loan portfolio of the Thai rural financial market (Somboon, 2015b), the credit risk management system for managing risk in the farmer loan portfolio of the agricultural financial institution in Thailand (Somboon, 2017), etc. However, considering the importance and necessity of the country's agricultural financial institution's development, it is considered that Thailand still has relatively few studies of these types of work. In addition, the business environment is changed rapidly, the presence of increased risk factors including the necessity of credit operations following the current financial institution supervision policy of the Bank of Thailand. The author, therefore, studies “the front-end's lending decision system for the agricultural bank in Thailand", which differs from the mention aforementioned studies in 2 main points as follows:

1. This study is an extension of the study from those previous studies by developing a risk management system called "affordability risk management" in addition to the former only credit risk management system. There is a section on whether agricultural banks have to consider the ability to repay the debt of farmers or manage customer risks in addition to managing specific credit risks that will occur to the bank. The development of such tools is to support the Bank of Thailand’s financial institution supervision policy that requires financial institutions to consider responsible lending. Criteria are set and pushed for financial institutions to develop credit assessment and credit risk management tools such as determining the appropriate DSR for determining the appropriate amount of credit, etc., to formulate policies to solve the problem of excess debt of retail debtors and debt problems in households of the country. Bank for agriculture also needs credit risk assessment tools to support the implementation of the BOT's regulatory policies. The author, therefore, builds on previous research and develops an additional affordability risk management system to cover changing business situations and support the current BOT's regulatory policy.

2. The author reviewed and added variables reflecting the default risk of debtors in accordance with the bank's current business conditions in this newly developed risk management system, such as debt service ratio, facing/ not facing agricultural prices decrease and/ or highly fluctuating, and the number of dependents in the household, etc., to provide the agricultural bank with a practical tool and use it to support the Bank of Thailand's financial institution supervision policy.

3. Conceptual framework

This study conceptualizes a theory of loan default for farmer borrowers. A theoretical model is developed based on the default theory with some assumptions to simplify the development of the front-end's lending decision system for the agricultural bank in Thailand. The conceptual framework of this study is presented in Figure 1.

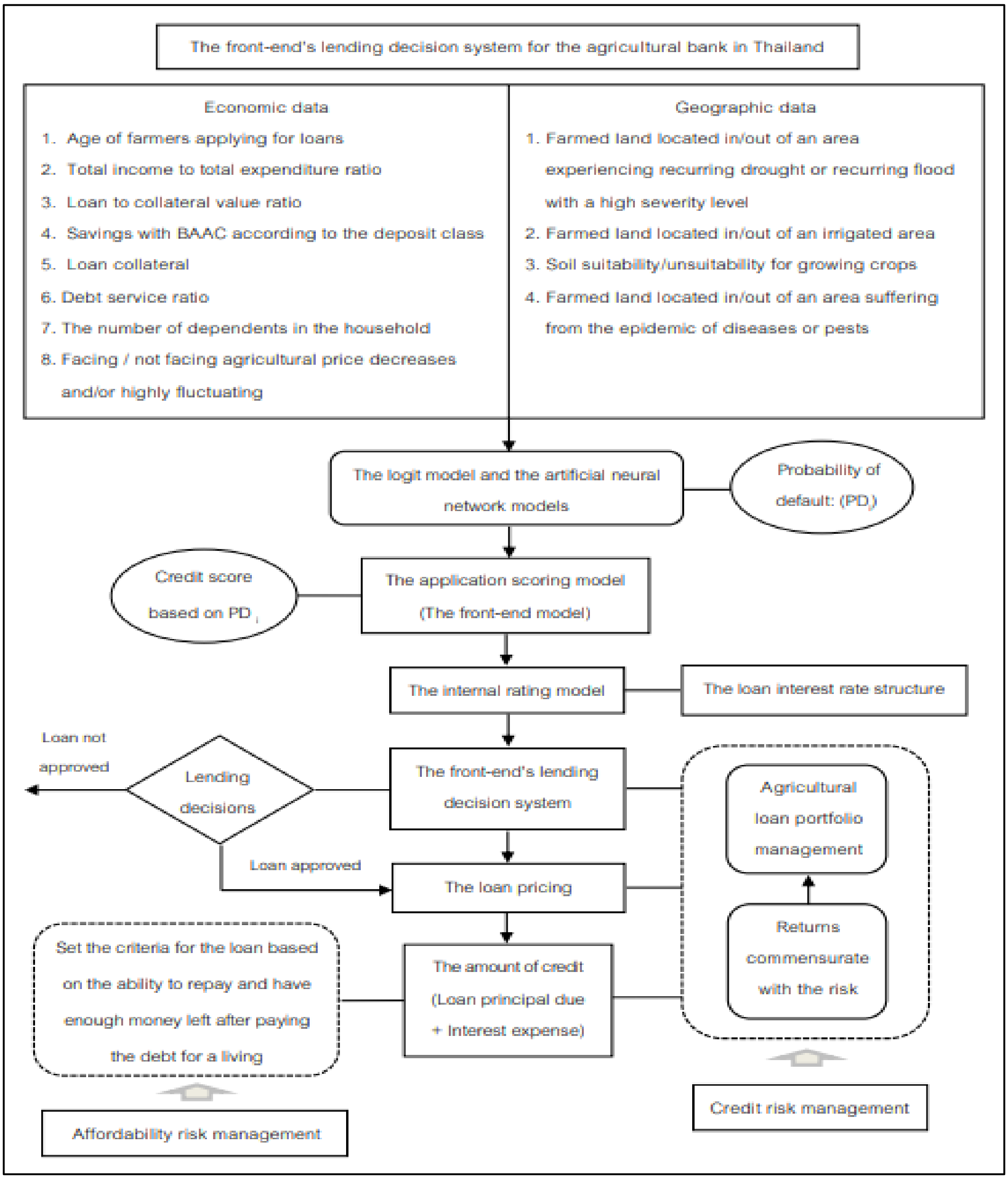


Figure 1: Conceptual framework

Source: Author's explanations.

4. Methods and data

4.1 Model estimation methods to estimate, and develop the probability of default equation

Statistical and mathematical methods have been used to estimate and develop the probability of default equation, such as discriminant analysis (Turvey, 1991; Altman, Glancario, & Varetto, 1994), linear probability model (Turvey, 1991; Barney, Graves, & Johnson, 1999), logit model (Turvey & Brown, 1990; Turvey, 1991; Turvey & Weersink, 1997; Lee & Jung, 2000; Limsombunchai, Christopher, & Minsoo, 2005; Bandyopadhyay, 2007; Somboon, 2015a, 2017), artificial neural network (ANN) model (Altman, Glancario, & Varetto, 1994; Coakley, & Brown, 2000; Lee & Jung, 2000; Wu & Wang, 2000; Limsombunchai, Christopher, & Minsoo, 2005; Hu, 2008; Somboon, 2015b, 2017). The logit model has dominated the literature and has been widely used because of its simplicity. The details of the logit model and the ANN model are briefly described as follows:

The logit model

The logit model is a limited dependent regression that assumes a logistically distributed error term and uses the maximum likelihood function for estimating the coefficients (or weights) of the independent variables. The dependent variable is described as a form of probability, such as the probability of default (Prob (Y_i = 1)). The sign of the independent variables shows the relationship between these variables with the probability of default (see Equation 1).

$$prob(Y_i = 1) = \frac{\exp(Z_i)}{1 + \exp(Z_i)} \tag{1}$$

Y_i = 0 if a debtor has not owed interest and principal, or a debtor who has overdue interest or principal but not more than 90 days from the due date.

Y_i = 1 if a debtor owes interest or principal payment more than 90 days from the due date.

$\exp$ = Exponential function (value is approximately 2.71828)

Z_i = $\hat{\beta}_0 + \hat{\beta}_1 X_{i1} + \hat{\beta}_2 X_{i2} + ... + \hat{\beta}_j X_{ij}$

$\hat{\beta}_0$ = The constant value

$\hat{\beta}_i$ = The coefficients

X_{ij} = The characteristic of debtor i

The artificial neural network model

The artificial neural network (ANN) model, inspired by the structure of the nerve cells in the brain, can be represented as a massive parallel interconnection of many simple computational units interacting across weighted connections. Each computational unit consists of a set of input connections that receive signals from other computational units, a set of weights for input connection, and a transfer function. The output for the computational unit (node j), U_j, is the result of applying a transfer function F_j to the summation of all signals from each connection (X_i) times the value of the connection weight between node j and connection i (W_{ij}) (see Equation 2).

$$U_j = F_j(\sum w_{ij} x_i) \qquad (2)$$

The calculation of the neural network weights is known as the training process. The process starts by randomly initializing connection weights and introducing a set of data inputs and actual outputs to the network. Then, the network calculates the network output and compares it to the actual output, as well as, calculates the error. In an attempt to improve the overall predictive accuracy and to minimize the network total mean squared error, the network adjusts the connection weights by propagating the error backward through the network to determine how to best update the interconnection weights between individual neurons. The multi-layer feed-forward neural network computational units are grouped into 3 main layers including, the input layer (Xi), hidden layer (s), and output layer (Limsombunchai, Christopher, & Minsoo, 2005).

4.2 Data and data preparation used to develop the front-end's lending decision system

The data in this study are credit data under the normal loan scheme (excluding the government loan for specific projects) for new loan applicants for production expenses (loan repayment less than 1 year), including rice, corn, cassava, sugarcane, longan, rubber, and oil palm. BAAC's operating period from April 2019 to July 2020, which had a default rate of 11.71% for new loan applicants, consisted of good debt 121,864 and bad debt 16,163). Credit files were retrieved from the core banking system database. In August 2020, a total of 10,000 observations consisted of 8,829 good debts and 1,171 bad debts (according to the default rate of new loan applicants at 11.71%). The author collected the data, which were distributed according to the new loan applicant proportion covers operating areas of BAAC throughout the country.

From the 10,000 data sets, the author classified them into two groups, with 80% of the data (8,000 samples) used to develop the model (development samples) and 20% of the data (2,000 samples) used to test the validity of the model (Hold-out samples). However, the dependent and independent variables are specified. It also describes the characteristics of each variable into two groups, which can be shown in Table 1.

Table 1: Characteristics of variables

Variables	Development samples (8,000 samples)	Hold-out samples (2,000 samples)
Dependent variable		
Debt status (Y; 0,1)	8,000 (100.00%)	2,000(100.00%)
Good debt (Y=0)	7,063 (88.29%)	1,766 (88.30%)
Bad debt (Y=1)	937 (11.71%)	234 (11.70%)
Independent variables		
1. Average of the age of farmers applying for loans (years)	46.63	46.69
2. Average of the total income to total expenditure ratio (times)	1.87	1.86
3. Average of the loan to collateral value ratio (times)	0.72	0.72
4. Savings according to the deposit class	8,000 (100.00%)	2,000 (100.00%)
(4.1) Does not saving with BAAC or savings with BAAC less than or equal to 5,000.99 baht	6,092 (76.15%)	1,529 (76.45%)
(4.2) Savings with BAAC 5,001 to 10,000.99 baht	567(7.09%)	136 (6.80%)
(4.3) Savings with BAAC 10,001 to 20,000.99 baht	424 (5.30%)	96 (4.80%)
(4.4) Savings with BAAC equal to or more than 20,001 baht	917 (11.46%)	239 (11.95%)
5. Loan collateral	8,000 (100.00%)	2,000 (100.00%)
(5.1) Land mortgages	3,078 (38.48%)	805 (40.25%)
(5.2) Person guarantees	2,262 (28.27%)	568 (28.40%)

(5.3) Person guarantees and land mortgages	2,660 (33.25%)	627 (31.35%)
6. Average of the debt service ratio (times)	0.71	0.70
7. Average of the number of dependents in the household (man)	2.56	2.53
8. Facing/not facing agricultural prices decrease and/or highly fluctuating	8,000 (100.00%)	2,000 (100.00%)
(8.1) the borrower who is not facing agricultural prices decrease and/ or highly fluctuating	4,144 (51.80%)	1,012 (50.60%)
(8.2) the borrower who is facing agricultural prices decrease and/ or highly fluctuating	3,856 (48.20%)	988 (49.40%)
9. Farmed land located in/out of an area experiencing recurring drought or recurring flood with a high severity level	8,000 (100.00%)	2,000 (100.00%)
(9.1) the borrower who has farmed land located in an area experiencing recurring drought or recurring flood with a high severity level	5,186 (64.83%)	1,313 (65.65%)
(9.2) the borrower who has farmed land not located in an area experiencing recurring drought or recurring flood with a high severity level	2,814 (35.17%)	687 (34.35%)
10. Farmed land located in /out of an irrigated area	8,000 (100.00%)	2,000 (100.00%)
(10.1) the borrower who has farmed land located in an irrigated area	4,050 (50.63%)	994 (49.70%)
(10.2) the borrower who has farmed land not located in an irrigated area	3,950 (49.37%)	1,006 (50.30%)
11. Soil suitability/unsuitability for growing crops	8,000 (100.00%)	2,000 (100.00%)
(11.1) the borrower who has soil unsuitability for growing crops	3,932 (49.15%)	995 (49.75%)
(11.2) the borrower who has soil suitability for growing crops	4,068 (50.85%)	1,005 (50.25%)
12. Farmed land located in/ out of an area suffering from the epidemic of diseases or pests	8,000 (100.00%)	2,000 (100.00%)
(12.1) the borrower who has farmed land located in an area suffering from the epidemic of diseases or pests	1,131 (14.14%)	300 (15.00%)
(12.2) the borrower who has farmed land not located in an area suffering from the epidemic of diseases or pests	6,869 (85.86%)	1,700 (85.00%)

Source: Author's calculations.

4.3 Data analysis methods

The risk factors/variables presented in Table 1 can be developed into the front-end's lending decision system for the agricultural bank in Thailand as shown in the data analysis framework (see Figure 2).

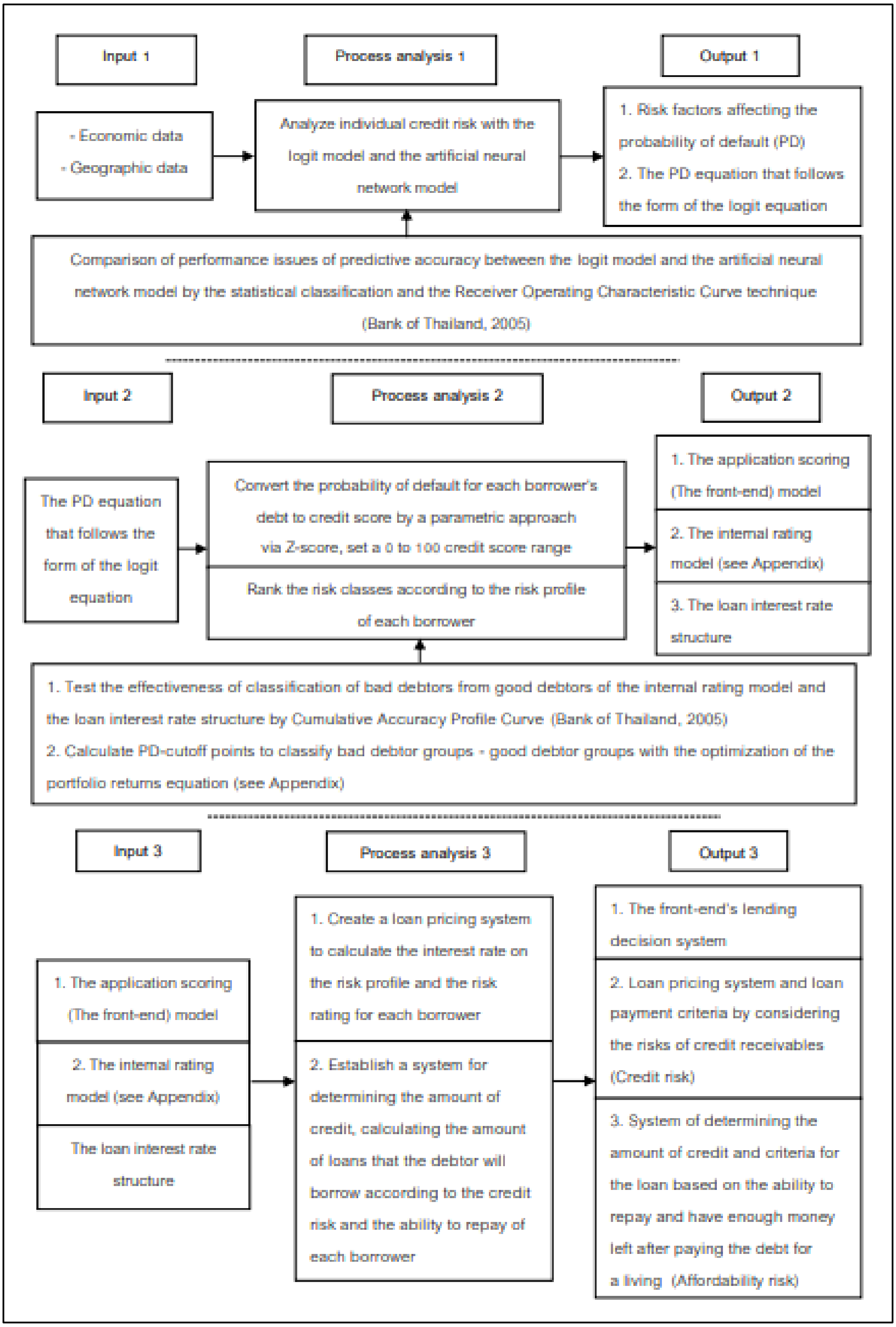


Figure 2: Data analysis framework

Source: Author's explanations.

5. Results and discussion

5.1 Relevant risk factors that have been identified as a predictor of default risk in each of BAAC's new borrowers

The estimated results of the artificial neural network model are shown in Figure 3. The risk factors are affecting and influencing the probability of default of BAAC's new borrowers including, debt service ratio (46.60%), total income to total expenditure ratio (9.66%), farmed land located in/ out of an area suffering from the epidemic of diseases or pests (8.69%), soil suitability/ unsuitability for growing crops (5.09%), facing/ not facing agricultural prices decrease and/ or highly fluctuating (4.95%), the number of dependents in the household (4.95%), savings according to the deposit class (4.50%), loan collateral (3.97%), loan to collateral value ratio (3.81%), farmed land located in /out of an irrigated area (3.11%), farmed land located in/ out of an area experiencing recurring drought or recurring flood with a high severity level (3.01%), and age of farmers applying for loans (1.65%).

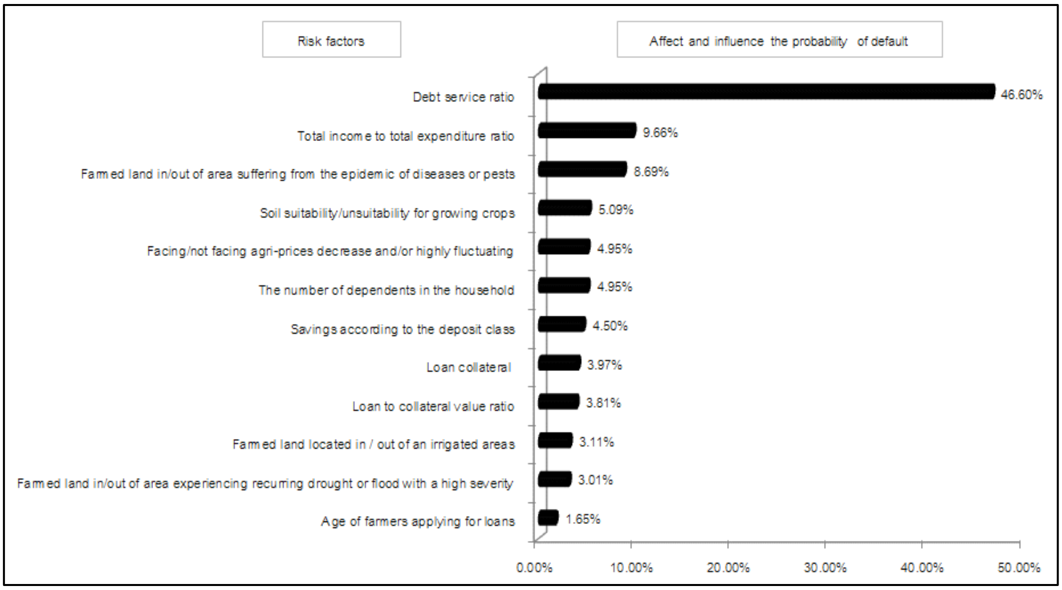


Figure 3: Risk factors that affect and influence the probability of default in each of new borrowers

Source: Author's estimations.

Comparison of the efficiency in predicting the probability of default and classification of debtors from the dataset used to develop the model (8,000 samples) found that the logit model gives more accuracy and gives less error than the artificial neural network model (see Table 2 and Table 3).

Table 2: Comparison of performance issues of predictive accuracy between the logit model and the artificial neural network (ANN) model by the statistical classification

Observed		Forecasting results from development samples (8,000 samples)					
		The logit model			The ANN model		
		Debt status		Percentage of accuracy	Debt status		Percentage of accuracy
		Good debt	Bad debt		Good debt	Bad debt	
Debt status	Good debt	7,032	31	99.56	7,040	23	99.67
	Bad debt	894	43	4.59	904	33	3.52
Percentage of overall accuracy				$\boxed{88.44}$			$\boxed{88.41}$

Source: Author's calculations.

Note: The cut-off point used in the prediction classification was 0.50.

Table 3: Comparison of performance issues of prediction error between the logit model and the artificial neural network (ANN) model by the statistical classification

Comparison items	The logit model (# 8,000 samples)	The ANN model (# 8,000 samples)
1. Percentage of the Type I error	11.17	11.30
2. Percentage of the Type II error	0.39	0.29
3. Percentage of the Type I and Type II errors[1]	$\boxed{11.56}$	$\boxed{11.59}$

Source: Author's calculations.

Note: The cut-off point used in the prediction classification was 0.50.

[1] The first type of wrong decision (Type I error) was the opportunity that the BAAC thought was good debt and does not cut-off, but actually becomes overdue, causing the BAAC to incur additional debt collection expenses or an additional provision for doubtful accounts expenses, or (Probability (G/B) = Loss of Given Default (LGD)). The second type of wrong decision (Type II error) was the opportunity that BAAC thought was overdue and cut-off, but actually returned to good debt, causing the BAAC to lose the income that should be received from losing customers to other banks or (Probability(B/G) = Interest received from losing customers to other banks)

Comparison of efficiency in predicting and classifying debtors between the logit model and the artificial neural network model using the Receiver Operating Characteristic Curve (ROC Curve) technique based on the area under the model accuracy curve. It was found that the logit model had higher accuracy than the artificial neural network model. The result is shown in Figure 4.

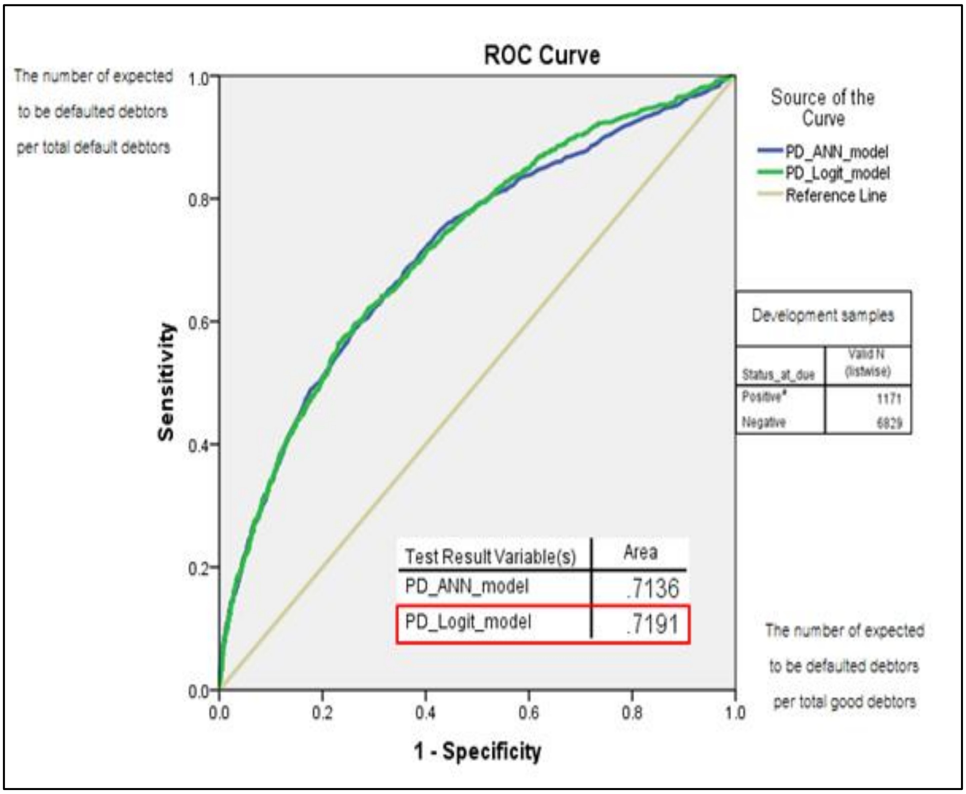


Figure 4: Comparison of performance issues of predictive accuracy between the logit model and the artificial neural network model by the Receiver Operating Characteristic Curve (ROC Curve) technique

Source: Author's calculations.

The comparison of the efficiency in predicting the probability of default and debtor classification above supports the use of the logit model to develop the front-end's lending decision system for the agricultural bank in Thailand because the logit model gives more accuracy than the artificial neural network model.

5.2 The variables affecting the probability of default, the equation for predicting the probability of default in the next 12 months, and the application scoring model

The author developed the logit model for forecasting the probability of default from a set of 8,000 development samples. Use the analysis of the relationship between the independent variables and the probability of default to explaining the change of probability of default of BAAC's new borrowers (see Table 4).

Table 4: Independent variables affecting the probability of default of BAAC's new borrowers

Marginal Effects	Coefficients	Independent variables	Sig.
-	-4.8453**	Constant	0.0000
0.0010*	0.0131*	(X_1) Age of farmers applying for loans (years)	0.0142
-0.0056*	-0.0758*	(X_2) Total income to total expenditure ratio (times)	0.0275
0.0719**	0.9655**	(X_3) Loan to collateral value ratio (times)	0.0000
-0.0302**	-0.4803**	(X_4) Savings with BAAC 5,001 to 10,000.99 baht	0.0051
-0.0351**	-0.5841**	(X_5) Savings with BAAC 10,001 to 20,000.99 baht	0.0040
-0.0507**	-0.8978**	(X_6) Savings with BAAC equal to or more than 20,001 baht	0.0000
0.0939**	1.1069**	(X_7) Land mortgages	0.0000
0.1060**	1.1365**	(X_8) Person guarantees	0.0000
0.0274**	0.3678**	(X_9) Debt service ratio [times]	0.0000
0.0167**	0.2247**	(X_{10}) The number of dependents in the household [man]	0.0007
0.0296*	0.3938*	(X_{11}) Facing agricultural price decreases and/ or highly fluctuating	0.0113
-0.0195**	-0.2705**	(X_{12}) Farmed land not located in an area experiencing recurring drought or recurring flood with a high severity level	0.0014
0.0370*	0.4925*	(X_{13}) Farmed land not located in an irrigated area	0.0406
-0.0370**	-0.4920**	(X_{14}) Soil suitability for growing crops	0.0091
-0.0231*	-0.2852*	(X_{15}) Farmed land not located in an area suffering from the epidemic of diseases or pests	0.0181

Source: Author's estimations.

Note: ** Significant at 1 percent level * Significant at 5 percent level

The independent variables presented in Table 4 describe the statistically significant change in the probability of default of BAAC's new borrowers. The marginal effects indicate the influence of independent variables on the probability of default on debt repayment. The sign and estimated coefficients in front of each variable describe the directions and weights to the probability of default on debt repayment which is based on the hypothesized sign. The meaning of the signs and coefficients in front of each variable can be described as follows:

These variables include the age of farmers applying for loans (variable X1), loan to collateral value ratio (variable X3), debt service ratio (variable X9), and the number of dependents in the household (variable X10) preceded by a positive coefficient, explai ning that the borrower who has the probability of default increase with increased these variables. Loan collateral types are land mortgages (variable X7), person guarantees (variable X8) preceded by a positive coefficient, explaining that the borrower who has only land mortgages applying for loans or who has only person guarantees applying for loans has a higher probability of default compared with borrowing using both land mortgages and person guarantees. These variables include facing agricultural price decreases and/ or highly fluctuating (variable X11), farmed land not located in an irrigated area (variable X13) preceded by a positive coefficient, reflecting that the debtor has been exposed to agricultural risks, the probability of default h as higher compared to the debtor who has not been exposed to agricultural risks.

Total income to total expenditure ratio (variable X_2), the estimated coefficient is negative, the probability of default decreases with an increased total income to total expenditure ratio. Savings variables are savings with BAAC 5,001 to 10,000.99 baht (variable X4), savings with BAAC 10,001 to 20,000.99 baht (variable X5), savings with BAAC equal to or more than 20,001 baht (variable X6) preceded by a negative coefficient, ex plaining that the borrower who has savings with BAAC on the deposit classes mentioned above has a lower probability of default compared with the borrower who does not has savings or has savings with BAAC 1 to 5,000 baht. These variables include farmed land not located in an area experiencing recurring drought or recurring flood with a high severity level (variable X12), soil suitability for growing crops (variable X14), farmed land not located in an area suffering from the epidemic of diseases or pests (variable X15) preceded by a negative coefficient, reflecting that the debtor has not exposed to agricultural risks, the probability of default has lower compared to the debtor who has been exposed to agricultural risks.

By using the constant and coefficients in front of the 15 variables (see Table 4) to create the equation for predicting the probability of default in the next 12 months for each BAAC's new borrower (PD_i) that follows the form of the logit equation can be written as shown in equation 3.

$$PD_i = \frac{\exp(-4.8453 + 0.0131X_1 - 0.0758X_2 + ...- 0.4920X_{14} - 0.2852X_{15})}{1 + \exp(-4.8453 + 0.0131X_1 - 0.0758X_2 + ...- 0.4920X_{14} - 0.2852X_{15})} \quad (3)$$

After obtaining PD_i , the author developed "the application scoring (front-end) model" by converting the probability of default for each debtor to each debtor's credit score. A debtor with a high probability of default will receive a low credit score. On the other hand, a debtor with a low probability of default will receive a high credit score. In this study, the credit score is assigned a value of 0 to 100 points.

5.3 The internal rating model and the loan interest rate structure

The internal rating model

After obtaining the front-end model, the author developed the internal rating model according to the BOT guidelines. The internal rating model must be able to distinguish between high-risk and low-risk debtors. The author determined each risk rating using a statistical randomization method (see Appendix B), with each risk rating has different width of the probability of default (PD), but the total of PD in all risk ratings must be equal to 1 (100 percent). The results show that the debtor with a low probability of default (PD near 0), the debtor will be in a high grade, For example, 1(AAA) 2(AA+), the credit score earned will be high (score approaching or equal to 100), but if the probability of default of the debtor is high (PD is far from 0), the debtor will be in a low grade, such as 9(BBB) 10(BBB-), the debtor will get a low credit score (scores far from 100 or closer to 0). The risk ranks obtained also indicate the proportion of debtors and capital required to maintain risk for each rating, which can provide information for BAAC credit risk management to diversify and reduce the concentration risk (see Table 5).

Table 5: The internal rating model

Probability of default (PD) for each rating	Credit (risk) ratings	Credit score ranges for each rating (0 to 100 points)	Proportion of debtors in each rating	Proportion of capital required to maintain risk for each rating
0.0000 to 0.0170	1(AAA)	81 to 100	0.0438	0.0532
0.0171 to 0.0252	2(AA+)	77 to 80	0.0775	0.0647
0.0253 to 0.0344	3(AA)	73 to 76	0.1066	0.0722
0.0345 to 0.0511	4(AA-)	69 to 72	0.1220	0.0816
0.0512 to 0.0841	5(A+)	64 to 68	0.1764	0.0981
0.0842 to 0.1087	6(A)	61 to 63	0.1191	0.1139
0.1088 to 0.1400	7(A-)	58 to 60	0.0966	0.1257
0.1401 to 0.1969	8(BBB+)	54 to 57	0.0794	0.1396
0.1970 to 0.2753	9(BBB)	50 to 53	0.0615	0.1521
0.2754 to 1.0000	10(BBB-)	0 to 49	0.1171	0.1535

Source: Author's calculations.

By creating optimization of the portfolio returns equation to measure the expected profits before risk cost to calculate "the PD cut-off point" to determine the minimum credit approval score (see Appendix B). The calculation of the PD cut-off point is a reference to a marginal analysis of the economic principle of what level of PD of the last good borrower will be selected to borrow. The result shows that the level of PD at the intersection must be 14.00 percent, which is the level of expected profits before risk costs from the investment in the credit portfolio are the highest. The result indicates that the last good debtor to be borrowed must have a PD, not more than 14.00 percent, the credit score receives 58 points, as the minimum credit approval score (total credit score equal to 100 points). This is from the forecast of the new loan amount throughout the year as of March 31, 2021, of the BAAC, there will be approximately 20,000 million baht, resulting in BAAC's expected profits before risk cost of approximately 622 million baht (see Appendix A).

The loan interest rate structure

After obtaining the internal rating model and setting the cut-off score at a minimum credit approval score of 58 points (PD cut-off of 14 percent), it achieved the BAAC credit approval rating, namely: tier 1(AAA) to tier 7(A-), however, as the BAAC is not the most profitable organization, but an organization with a mission to help farmers gain access to funding. Therefore, the author relaxes the minimum credit approval score from 58 to 50 and assigns a rating with these 50 to 58 credit scores range as "Low-side overrides[2]", which are tier 8(BBB+) and tier 9(BBB). The new minimum credit approval score of 50 is used as a credit score criterion for rejecting loans on a scale that has a credit score of less than 50, which is, tier 10(BBB-). The author used these results to determine the rate structure. Loan interest is designed to be applied in practice following current data of BAAC's credit settlement activities, with 88.29 percent of approved borrowers or good debtors and 11.71 percent of bad debtors (see Table 6).

Table 6: The loan interest rate structure

Probability of default (PD) for each rating	Credit score ranges for each rating (points)	Proportion of debtors in each rating	Credit (risk) ratings	Loan interest rate	Assessing debt quality levels according to the credit score obtained
0.0000 to 0.0170	81 to 100	0.0438	1(AAA)	4.50%	Particularly excellent.
0.0171 to 0.0252	77 to 80	0.0775	2(AA+)	5.25%	Excellent
0.0253 to 0.0344	73 to 76	0.1066	3(AA)	6.00%	Very good
0.0345 to 0.0511	69 to 72	0.1220	4(AA-)	6.75%	Good
0.0512 to 0.0841	64 to 68	0.1764	5(A+)	7.50%	Quite good
0.0842 to 0.1087	61 to 63	0.1191	6(A)	8.25%	Normal
0.1088 to 0.1400	**58 to 60**	**0.0966**	**7(A-)**	**9.00%**	**Normal, the bank should take care**
0.1401 to 0.1969	54 to 57	0.0794	8(BBB+)	9.75%	Low-side Override Level 1
0.1970 to 0.2753	50 to 53	0.0615	9(BBB)	10.50%	Low-side Override Level 2
0.2754 to 1.0000	0 to 49	0.1171	10(BBB-)	-	Loan not approved

Source: Author's calculations.

After obtaining the loan interest rate structure, tier 1(AAA) to tier 9(BBB) in Table 6, The author analyzes the relationship between the probability of default (PD), credit score, and the loan interest rate, which determined that the structured interest rate covers the overall risk

[2] Low-side overrides are decisions to approve an applicant whose credit score falls below the cut-off score

profile of the credit portfolio. Based on the calculations, the credit portfolio risk premium is approximately 6% (see Appendix A), so the author sets the loan interest rate to increase according to the risk premium of each tier increasing by 0.75%. Each debtor charged a loan interest rate covering the cost of deposits, operating costs, and BAAC's desired profit at the rates of 1.50, 2.00, and 1.00 percent respectively for all debtors, but will vary according to the risk premium of individual risks. Therefore, the initial loan interest rate that the BAAC charges from the debtor, which is the minimum retail rate, is 4.50 percent per annum, that is, the debtor in tier 1(AAA) has a PD value between 0.0000 and 0.0170 (PD value is very low, which may be considered risk-free and therefore no risk premium). While the debtor in tier 9(BBB) has a risk premium of 6%, so the debtor will be charged interest at a rate of 10.50% per annum (see Table 6).

5.4 The evaluation of the accuracy of the rank order and the accuracy in estimating defaults in each grade of the internal rating model by Cumulative Accuracy Profiles Curve (CAP Curve)

The results showed that the evaluation of the accuracy of the rank order and the accuracy in estimating defaults in each grade by Cumulative Accuracy Profiles Curve (CAP Curve). The accuracy is measured by the "Accuracy ratio" or "Area under CAP Curve" which is the area below the concave curve and it is 0.6332 which means it has a CAP predictive power of 63.32% which is quite good (see Figure 5).

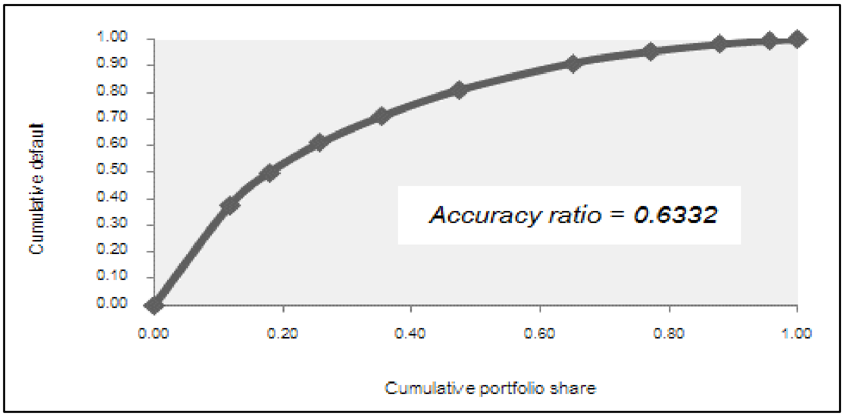


Figure 5: The accuracy of the rank order and the accuracy in estimating defaults in each grade of the internal rating model by Cumulative Accuracy Profile Curve (CAP Curve)

Source: Author's calculations.

5.5 The front-end's lending decision system

After obtaining the front-end model, the internal rating model, and the loan interest rate structure, the author developed "the front-end's lending decision system" according to BOT guidelines. The front-end's lending decision system is used to manage credit risk and affordability risk in agricultural lending activities of the BAAC and support the implementation of appropriate credit policies in handling agricultural household's excess debt and promote financial discipline building for agricultural households in the rural sector of Thailand (see Figure 6).

Criteria for the loan based on the ability to repay and have enough money left after paying the debt for a living (Affordability risk)

Loan applicant	[1]	[2] = 0.63× [1]	[3] = [2] × [7]	[4] = [2]+[3] (≈ 0.70 × [1])	[5] = [4] ÷ [1]	[6] = [1] – [4]
Borrower A	Expected the total annual income (baht)	The amount of credit Loan principal due [loan amount approval] (baht)	Interest expense per annum (baht)	Expected the total debts full-year payment amount (baht)	Debt Service Ratio: DSR* (times)	Expected the residual income after deducting the total debt repayment burden for living and saving (baht)
	200,000	126,000	11,340	137,340	0.6867	62,660

Loan payment criteria by considering the risks of credit receivables (Credit risk)

[7]	[8]	[9]	[10]	[11]	[12]
Loan interest rates based on the risk (Pricing) [% per annum]	Internal credit rating	Credit score [0 to 100 points]	Probability of Default: PD [0 to 1]	Criterion assessment with the application scoring model	Level assessment credit quality according to credit score received
9.00%	7(A-)	60	0.1163	Pass	Normal, the bank should take care

F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
AGE	INC	LTV	SAV	COL	DSR	DEH	PDF	EDF	FLI	SGC	FSE
50	1.20	1.00	1	2	0.69	3	0	0	0	1	1

Figure 6: The front-end's lending decision system

Source: Author's calculations.

Where:

AGE (F1) is an abbreviation used to represent the variable name, Age of farmers applying for loans [Years] (X_1)

INC (F2) is an abbreviation used to represent the variable name, Total income to total expenditure ratio [Times] (X_2)

Total income = Agricultural income + Non-agricultural income

Total expenditure = Agricultural expenditure + Non-agricultural expenditure + Household expenditure

LTV (F3) is an abbreviation used to represent the variable name, Loan to collateral value ratio {Value in range ($0 < LTV <= 1$)} [Times] (X_3)

SAV (F4) is an abbreviation used to represent the variable name, Savings according to the deposit class

1 Does not saving with BAAC or savings with BAAC less than or equal to 5,000.99 baht (Reference)

2 Savings with BAAC 5,001 to 10,000.99 baht (X_4)

3 Savings with BAAC 10,001 to 20,000.99 baht (X_5)

4 Savings with BAAC equal to or more than 20,001 baht (X_6)

COL (F5) is an abbreviation used to represent the variable name, Loan collateral

1 Land mortgages (X_7)

2 Person guarantees (X_8)

3 Person guarantees and land mortgages (Reference)

DSR (F6) is an abbreviation used to represent the variable name, Debt service ratio [Times] (X_9)

DEH (F7) is an abbreviation used to represent the variable name, the number of dependents in the household [man] (X_{10})

PDF (F8) is an abbreviation used to represent the variable name, Facing/not facing agricultural prices decrease and/ or highly fluctuating

0 the borrower who is not facing agricultural prices decrease and/ or highly fluctuating (Reference)

1 the borrower who is facing agricultural prices decrease and/ or highly fluctuating (X_{11})

EDF (F9) is an abbreviation used to represent the variable name, Farmed land located in/out of an area experiencing recurring drought or recurring flood with a high severity level.

0 the borrower who has farmed land located in an area experiencing recurring drought or recurring flood with a high severity level (Reference)

1 the borrower who has farmed land not located in an area experiencing recurring drought or recurring flood with a high severity level (X_{12})

FLI (F10) is an abbreviation used to represent the variable name, Farmed land located in /out of an irrigated area

0 the borrower who has farmed land located in an irrigated area (Reference)

1 the borrower who has farmed land not located in an irrigated area (X_{13})

SGC (F11) is an abbreviation used to represent the variable name, Soil suitability/ unsuitability for growing crops

0 the borrower who has soil unsuitability for growing crops (Reference)

1 the borrower who has soil suitability for growing crops (X_{14})

FSE (F12) is an abbreviation used to represent the variable name, Farmed land located in /out of an area suffering from the epidemic of diseases or pests

0 the borrower who has farmed land located in an area suffering from the epidemic of diseases or pests (Reference)

1 the borrower who has farmed land not located in an area suffering from the epidemic of diseases or pests (X_{15})

The working process of the front-end's lending decision system is classified into two sections as follows:

Section1: Credit risk management, the process of screening the loan applications, and setting the credit approval or rejection criteria. For example, if borrower A applies for a loan with a risk profile based on risk factors 1 to 12 (X_1 to X_{15}), the front-end's lending decision system including, the probability of default equation, the application scoring model, the internal rating model, and the system of the loan pricing will be processed and displayed. The results showed that borrower A had an 11.63% probability of default, a credit score of 60 points, the risk rating was level 7(A-), which passed the application scoring model, in debt quality class "Normal, the bank should take care". BAAC charges borrower A at a rate of 9.00% per annum (see Figure 6).

Section 2: Affordability risk management, which is an ongoing process of credit risk management. This is a process of determining the maximum loan amount for the debtor who has passed the credit approval criteria with the application scoring model. The author caps the debt service ratio (DSR) as a threshold for determining the amount of credit (the loan amount approval and interest expense) at 70 percent and determines that the maximum loan principal is 63 percent of the debtor's total annual income. For example, if borrower A is expected to have a total annual income of 200,000 baht, the system will show the maximum amount that borrower A can borrow is 126,000 baht (63%), plus the interest burden payable approximately 11,340 baht per year (loan interest rate is 9.00%). The system will show borrower A's full-year payment amount of 137,340 baht or about 70 percent of the total annual income or DSR is about 0.70 times. Borrower A still has money left after paying the debt for living and saving 62,660 baht or about 30 percent of the annual income (see Figure 6).

The front-end's lending decision system will be used as an instrument for credit activities in response to access to finance for small farmers. It is also used as an instrument to support the implementation of appropriate credit policies in handling agricultural household's excess debt and promote financial discipline building for agricultural households in the rural sector of Thailand.

6. Conclusions and policy implications

The main objective of this study is to develop the front-end's lending decision system of the Bank for Agriculture and Agricultural Cooperatives, a major lender in Thailand's agricultural sector. The logit model and the artificial neural network model have been developed to reflect risk factors to identify the probability of default in each of new borrowers. The study supports the use of the logit model to develop the system because it gives more accuracy in predicting the probability of default and debtor classification than the artificial neural network model.

The working process of the system is classified into two sections including, credit risk management, the process of screening the loan applications and setting the credit approval or rejection criteria, and affordability risk management, the process of determining the maximum loan amount for the debtor who has passed the credit approval criteria. In this study, the author caps the debt service ratio as a threshold for determining the amount of credit (the loan amount approval and interest expense) at 70 percent and determines that the maximum loan principal is 63 percent of the debtor's total annual income.

The system is also used as an instrument to support the implementation of appropriate credit policies in handling agricultural household's excess debt and promote financial discipline building for agricultural households in the rural sector of Thailand.

References

Altman, E. I., Glancario, M., & Varetto, F. (1994). Corporate distress diagnosis: comparisons using linear discriminant analysis and neural networks (The Italian experience). *Journal of Banking and Finance*, *18*(3), 505-529.

Bandyopadhyay, A. (2007). Credit risk models for managing bank's agricultural loan portfolio. *ICFAI Journal of Financial Risk Management*, *5*(4), 86-102.

Barney, D. K., Graves, O. F., & Johnson, J. D. (1999). The farmers home administration and farm debt failure prediction. *Journal of Accounting and Public Policy*, *18*(2), 99-139.

Bank of Thailand. (2005). Circulated letter No.: ThorPorTor. SorGorSor. (03) Wor. 227/2548 Re: Guidelines for Risk Management Practices. Retrieved from https://www.bot.or.th/Thai/FIPCS/Documents/FPG/2548/EngPDF/25480006.pdf

Bank of Thailand. (2019). Policy guidelines for appropriate retail credit to take care of the problem of excessive debt of the household sector. Retrieved from https://www.bot.or.th/Thai/FinancialInstitutions/Publications/Pages/ConsultationPaperLoan.aspx

Chen, W. S., & Du, Y. K. (2009). Using neural networks and data mining techniques for the financial distress prediction model. *Expert Systems with Applications*, *36*(2), 4075-4086.

Coakley, J. R., & Brown, C. E. (2000). Artificial neural networks in accounting and finance: modeling issues. *International Journal of Intelligent Systems in Accounting, Finance & Management*, 9, 119-144.

Hu, Y. (2008). Incorporating a non-additive decision making method into multi-layer neural networks and its application to financial distress analysis. *Knowledge-Based Systems*, *21*(5), 383-390.

Lee, T. H., & Jung, S. C. (2000). Forecasting creditworthiness: Logistic vs. artificial neural network. *The Journal of Business Forecasting Methods and Systems*, *18*(4), 28-30.

Limsombunchai, V., Christopher, G., & Minsoo, L. (2005). An analysis of credit scoring for agricultural loans in Thailand. *American Journal of Applied Sciences*, *2*(8), 1198-1205.

Somboon, S. (2015a). Credit risk portfolio management system for agricultural lending of the rural financial market in Thailand. *Thammasat Economic Journal*, *33*(1), 76-122.

Somboon, S. (2015b). Credit scoring system for managing risk in agricultural loan portfolio of the Thai rural financial market. *Applied Economics Journal*, *22*(1), 27-50.

Somboon, S. (2017). Credit risk management system for managing risk in farmer loan portfolio of the agricultural financial institution in Thailand. *NIDA Development Journal*, *57*(3), 100-130. (in Thai)

Turvey, C. G. (1991). Credit scoring for agricultural loans: A review with application. *Agricultural Finance Review*, 51, 43-54.

Turvey, C. G., & Brown, R. (1990). Credit scoring for a federal lending institution: The case of Canada's farm credit corporation. *Agricultural Finance Review*, *50*, 47-57.

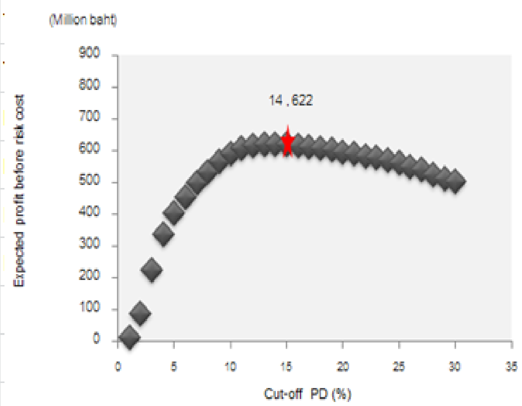
Turvey, C. G., & Weersink, A. (1997). Credit risk and the demand for agricultural loans. *Canadian Journal of Agricultural Economics*, *45*(3), 201-217.

Wu, C. & Wang, X.M. (2000). A neural network approach for analyzing small business lending decision. *Review of Quantitative Finance and Accounting*, *15*, 259-276.

Appendix A: Estimation results

The result from Optimize the portfolio returns (Maximize the expected profit before risk cost)

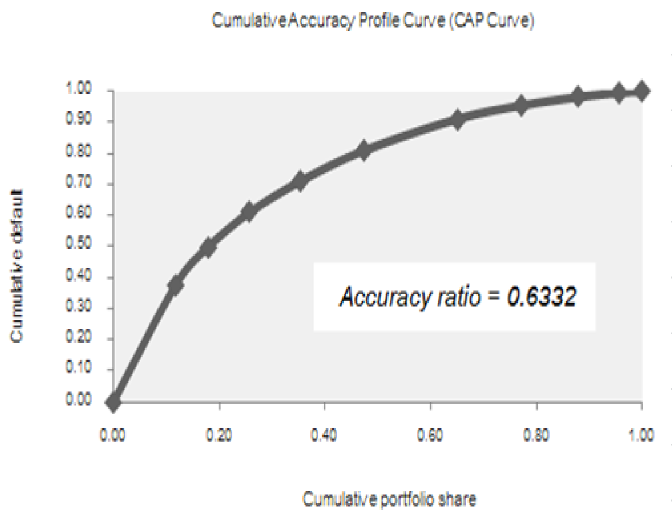
Summary statistics for specified grading structure			
Capital requirements: CR(K%)	Grading structure		
10.64%	0-0.0171-0.0253-0.0345-0.0512-0.0842-0.1088-0.1401-0.197-0.2754		
		Risk premium in portfolio	6.36%
Cutoff PD	0.14	PD	Profit before risk cost
Exposure at default (EAD)	20,000	1	12.73
Capital requirement in portfolio	2,129	2	89.55
Average PD	6.15%	3	227.57
LGD	35.00%	4	337.78
ROE	2.96%	5	405.57
COD	1.50%	6	456.71
Expected yield* – COD	6.00%	7	500.51
COD(1.50%) (Amount)	300	8	535.82
Operating cost: OC (2.00%) (Amount)	400	9	566.57
Expected profit before risk cost	622	10	590.12
		11	606.76
		12	616.90
		13	621.22
		14	622.32
		15	621.09
		16	618.48
		17	614.00
		18	608.72
		19	603.92
		30	502.77
		Max	622.32



The result from the determination of credit risk ratings

Grading structure and calculations								
Lower PD bound	Grade	Portfolio Share	Grade CR	Area under CAP	%Default	CumPortshare	Cum%Default	Score
0.0000	1	0.0438	0.0532	0.0436	0.0047	1.0000	1.0000	81-100
0.0171	2	0.0775	0.0647	0.0766	0.0142	0.9563	0.9953	77-80
0.0253	3	0.1066	0.0722	0.1032	0.0271	0.8788	0.9811	73-76
0.0345	4	0.1220	0.0816	0.1137	0.0440	0.7721	0.9540	69-72
0.0512	5	0.1764	0.0981	0.1516	0.1014	0.6501	0.9101	64-68
0.0842	6	0.1191	0.1139	0.0905	0.0976	0.4738	0.8086	61-63
0.1088	7	0.0966	0.1257	0.0638	0.1010	0.3546	0.7111	58-60
0.1401	8	0.0794	0.1396	0.0440	0.1121	0.2580	0.6101	54-57
0.1970	9	0.0615	0.1521	0.0268	0.1240	0.1786	0.4980	50-53
0.2754	10	0.1171	0.1535	0.0657	0.3740	0.1171	0.3740	0-49
						0	0	
CR	AR	Grading structure						
0.1064385	0.6332	0-0.0171-0.0253-0.0345-0.0512-0.0842-0.1088-0.1401-0.197-0.2754						

Random search optimization results		
CR	AR	Grading structure
0.0906834	0.604	0-0.0015-0.0099-
0.0907472	0.593	0-0.0016-0.0031-
0.0907497	0.597	0-0.0007-0.0013-
0.0907651	0.617	0-0.0012-0.0036-
0.0907659	0.589	0-0.0011-0.0077-
0.0907715	0.595	0-0.0021-0.0095-
0.0907750	0.618	0-0.0023-0.0089-
0.0907860	0.597	0-0.0014-0.0047-0.0148-0.0399-0.0509-0.0676-0.1367-0.2393-0.4091



Appendix B: Portfolio optimization commands

Optimize the portfolio returns (Maximize the expected profit before risk cost)

= {{[(1- PD) × (Expected yield*– COD) × (EAD)] – [(PD) × (LGD) × (EAD)] + [(ROE – COD) × (K%)]}+COD – OC}

PD	=	Probability of default
Expected yield*	=	Expected yield in agricultural loan portfolio (7.50%)
COD	=	Cost of deposit (1.50%)
EAD	=	Exposure at default (20,000 million baht)
LGD	=	Loss of given default (35.00%)
ROE	=	Return on equity (2.96%)
K%	=	Capital requirements rate (CR; K%)
OC	=	Operation cost (2.00%)

Capital requirements (K%) in portfolio equation

```
Function CAPREQ(PD, LGD, M)
Dim rpd As Double, bpd As Double
rpd = 0.12 * (1 - Exp(-50 * PD)) / (1 - Exp(-50)) _
    + 0.24 * (1 - (1 - Exp(-50 * PD)) / (1 - Exp(-50)))
bpd = (0.11852 - 0.05478 * Log(PD)) ^ 2
CAPREQ = (LGD * Application.WorksheetFunction.NormSDist( _
      (Application.WorksheetFunction.NormSInv(PD) _
      + rpd ^ 0.5 * Application.WorksheetFunction.NormSInv(0.999)) _
      / (1 - rpd) ^ 0.5) _
      - PD * LGD) _
      * ((1 + (M - 2.5) * bpd) / (1 - 1.5 * bpd)) * 1.06
End Function
```

```
Sub cutoffproc()
  Application.ScreenUpdating = True
  Application.Calculation = xlCalculationAutomatic
  For i = 1 To 100
    cutoff = i * 0.01
    Range("cutoffpd").Value = cutoff
    Range("startout").Offset(i, 0).Value = cutoff
    Range("startout").Offset(i, 1).Value = Range("portreturn").Value
  Next i
End Sub
```

Determination of credit risk ratings by statistical randomization

A Row	B Probability of default (PD) for each borrower	C Upper boundary of the PD for each rating	D Lower boundary of the PD for each rating	E Credit risk ratings
1	0.0036		0	1(AAA)
2	0.0344	0.0050	= D1+ROUND(RAND()×(C2-D1),4)	2(AA+)
3	0.0578	0.0250	= D2+ROUND(RAND()× (C3-D2),4)	3(AA)
4	0.1326	:	= D3+ROUND(RAND()× (C4-D3),4)	4(AA-)
5	0.0234	:	= D4+ROUND(RAND()× (C5-D4),4)	5(A+)
6	0.1234	:	= D5+ROUND(RAND()× (C6-D5),4)	6(A)
7	0.2567	:	= D6+ROUND(RAND()× (C7-D6),4)	7(A-)
8	0.0123	:	= D7+ROUND(RAND()× (C8-D7),4)	8(BBB+)
9	0.0987	:	= D8+ROUND(RAND()× (C9-D8),4)	9(BBB)
10	0.7012	1.0000	= D9+ROUND(RAND()× (C10-D9),4)	10(BBB-)
n	N			

```
Sub RandomSearchRating()
    Application.ScreenUpdating = True
    Application.Calculation = xlCalculationAutomatic
    Dim imax As Long, i As Long

    imax = 100
    For i = 1 To imax
        Application.StatusBar = i
    Range("startOutRange").Offset(i, 0).Value = Range("objective").Value
    Next i

    Range(Range("startOut").Offset(1, 0), Range("startOut").Offset(imax, 3)).Sort
Key1:=Range("F31"), Order1:=xlAscending
End Sub
```

Loan pricing

Loan interest	= Cost of deposit + Operating cost + Margin + Risk premium						
YY	=	(1.50%)	+	(2.00%)	+ (1.00%) +		XX

Risk premium (XX)

$$= (PD \times LGD) + \{(k\%) \times \{riskfreerate + \{\beta_{unlevered} \times (marketrisk - riskfreerate)\}\}\}$$

$$= (PD \times LGD) + \{(k\%) \times \{2.96\%\}\}$$

$\beta_{unlevered}$	=	0.28
$marketrisk$	=	7.83%
$riskfreerate$	=	1.06%

Appendix C: The determination of the dummy variable

The determination of the dummy variable of the facing/not facing agricultural price decreases and/or highly fluctuating can be written as shown below

Volatility in agricultural price	The direction of agricultural price (trend analysis)		
	Increases	Not change	Decreases
Low volatility (CV. <= 0.50)	0	0	1
Moderate volatility (0.51< CV. <= 1.00)	0	0	1
High volatility (CV. > 1.00)	0	1	1

The facing/not facing with agricultural price (rice, maize, cassava, sugarcane, longan, rubber, oil palm; prices for individual agricultural products follow the price in each region) decreases and/or highly fluctuating which is code = 1 for the borrower who is facing with agricultural price decreases and/ or highly fluctuating (The author determines 1 borrower = 1 agricultural product) and code = 0 for the borrower who is not facing with agricultural price decreases and/or highly fluctuating.

The price direction of the agricultural product can be determined from the analysis of the trend in agricultural price over the past 5 years. The agricultural price volatility is measured by the coefficient of variation (CV.) calculated by using the standard deviation of the agricultural price (over the past five years) divided by the average of the agricultural price (over the past five years). The author determines the criteria that if the CV value is greater than 1, the agricultural price is highly volatile, if the CV value is in the range of 0.51 to 1.00, the agricultural price is moderately volatile and if the CV is less than or equal to 0.50, the agricultural price is low volatility.