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The Back-end's Lending Decision System for Managing risks in the Agricultural Bank in Thailand

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Abstract

The main objective of this study is to develop the back-end's lending decision system of the Bank for Agriculture and Agricultural Cooperatives, a major lender in Thailand's agricultural sector. The study highlights the application of the system to help the Bank to manage credit risk and affordability risk in agricultural credits. The Logit model and the Artificial Neural Network (ANN) model have been developed in this study to reflect risk factors/variables of the Thai agricultural sector to identify the probability of default in each obligor. The development of the models and the model validations complied to be consistent with the advanced internal rating-based approach in the Basel capital accord. The study shows how back-end agricultural loan exposure is typical and can be managed on a portfolio basis which will enable the bank to set the credit approval or rejection criteria, diversify the risk in each of the portfolio shares, determine the risk-based pricing in each of borrowers, determine the amount of credit, optimize the portfolio returns, calculate the capital adequacy in the portfolio. The back-end's lending decision system is also used as an instrument to support the implementation of appropriate credit policies in handling agricultural household's excess debt, as well as, promoting and supporting financial discipline building for agricultural households in the rural sector of the country.

Keywords: Lending decision system, Credit risk, Affordability risk, Agricultural credits, Logit model, Artificial Neural Network model, Model validations, Financial discipline, Agricultural households
JEL Classifications: G21, Q14, C53, C52, G51

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1. Introduction

The Bank for Agriculture and Agricultural Cooperatives (BAAC), a state enterprise under the jurisdiction of the Ministry of Finance in Thailand, was established under the BAAC act of 1966. Its primary objective is to provide financial services to farmers and farmers' associations. Following the amendment of the BAAC act in 2006, it was authorized to provide financial services to persons, groups of persons, entrepreneurs, villages or community funds, related organizations, and all kinds of cooperatives. The BAAC maintains its role in rural development in facilitating farmers to access financial services at fair lending rates and providing a reasonable amount of credit necessary for career persons so that they are able to live properly. Moreover, The BAAC strongly supports government policies that benefit farmers. The significant performances are, for example, the scheme to informal debt resolution scheme, the supporting credit scheme farmer who registered "Government Welfare", Debt suspension project for the BAAC's clients, the scheme reduces debt for supporting agriculture reform, and etc.

Currently, the BAAC credit assessment system uses only the history of default as a risk factor in the assessment process, together with the credit staff's judgment. However, such a system and approach appear to be ineffective, inconsistent, and non-uniform, and it lead 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.

A new pattern in the agricultural credit assessment process has been the risk assessment of borrowers based on sophisticated statistical and mathematical analysis of the economic risk factor, financial risk factor, geographic risk factor, and other risk factors related to the creditworthiness or credit delinquency of the borrowers. The back-end lending decision system will be the BAAC's new credit assessment system that integrates such risk factors into the debtor's credit assessment process. It can reduce the prejudice of credit decisions and add efficiencies to the credit risk and affordability risk assessment process. Moreover, the system not only assists the BAAC on loan approval, but also on loan pricing, determining the amount of credit, loan monitoring, optimizing the portfolio returns, and capital adequacy in the portfolio.

This research article is to study "the back-end's lending decision system for managing risks in the agricultural bank in Thailand" with the following primary objectives.

1. To investigate the risk factors/variables of the Thai agricultural sector to identify the probability of default in each of the borrowers.
2. To develop the back-end's lending decision system to manage credit risk and affordability risk in the back-end agricultural loan portfolio of the agricultural bank in Thailand.
3. To implement the back-end's lending decision system as an instrument to support the implementation of appropriate credit policies in handling agricultural households' excess debt, as well as, promoting and supporting financial discipline building for agricultural households in the rural sector of the country.

2. Theoretical Frameworks

2.1 Credit Risk Management

Credit risk management is a process or system which a financial institution uses to specify, monitor, and control risks arising 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, herewith, focus on loan portfolio management (Bank of Thailand, 2005).

2.1.1 The behavioral scoring model and the internal rating model

The behavioral scoring (back-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 behavior of a borrower is the same as the past behavior of a debtor with a similar profile. The back-end model studies risks according to the profile of the population, geography, and financial information of the old credit applicants to be used for the credit approval, manages credit portfolio by ongoing monitoring the debtors' behavior such as increasing or decreasing the credit limit, debt collection, renewal of limit, calculating capital adequacy ratio, and 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. According to Basel Committee on Banking Supervision guidelines, 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 normal loans (good debts) into at least 7 grades and defaulted loans (bad debts) into at least 1 grade. Additionally, the definition of each grade must be clearly established to enable the classification of normal loans, watch lists, and default loans to enable appropriate risk management (Basel Committee on Banking Supervision, 2005a; Bank of Thailand, 2005).

2.1.2 The guidelines for the calculation of risk-weighted assets and the capital requirement for credit losses

Basel Committee on Banking Supervision (BCBS) has a role to oversee the central bank's monetary policy of each country. The BCBS has proposed the concept of credit risk assessment criteria of Basel, which has set the guidelines for the calculation of risk-weighted assets and the capital requirement for credit losses to the advanced internal ratings-based approach (AIRB approach). The AIRB is a method by which commercial banks and specialized banks use their internal data to calculate credit risk-weighted assets. The principle of calculating credit risk-weighted assets, The Basel provides a formula for translating probability of default (PD), loss of given default (LGD), exposure at default (EAD), and effective maturity (M) into a risk weight (Basel Committee on Banking Supervision, 2005b; 2011).

While the capital requirement for credit losses, BCBS determined the formula for each credit capital requirement and the central banks of each country to provide a basis for banking supervision in their countries (Basel Committee on Banking Supervision, 2005b; 2011). Based on the type of debtor under the Bank of Thailand debtor classification criteria (Bank of Thailand, 2012), BAAC debtors are classified as sovereign, bank, and corporate exposures (see Equation 1).

$$K\% = LGD \times ((N[\frac{G(PD) + \sqrt{R} \times G(0.999)}{\sqrt{1-R}}]) - PD) \times (\frac{1+(M-2.5)\times b}{1-1.5\times b}) \times 1.06 \qquad (1)$$

$$R = 0.12 \times \frac{1-\exp(-50\times PD)}{1-\exp(-50)} + 0.24 \times \left[1 - \frac{(1-\exp(-50\times PD)}{1-\exp(-50)}\right]$$

$$b = [0.11852 - 0.05478 \times \ln(PD)]^2$$

b = Adjustment with maturity times of the debtor. b depends on the probability of default (PD) of debtors; b will increase with the credit quality level of the debtor (low PD debtor) as high credit quality debtor has more potential for down-grading than low credit quality debtor (high PD debtor)

ln (x) = The natural logarithm

exp = Exponential function (value is approximately 2.71828)

N(x) = The cumulative distribution function for a standard normal random variable (that is the probability that the value of the normally distributed random variable is less than or equal to x, where such random variable has mean = 0 and variance = 1)

G(z) = The inverse cumulative distribution function for a standard normal random variable (that is the value of x that makes N(x) = z)

R = The default correlation (sovereign exposure), Correlation is assets correlation that reflects the PD of each debtor and the systematic risk factor e.g. overall economic conditions. The value of the systematic risk factors ranges between 0.12 and 0.24 depending on the PD of the debtor. If the debtor is of low credit quality (high PD), the probability of default will depend more on the debtor's own idiosyncratic risk factor rather than systematic risk factor; if the debtor is of high credit quality, the probability of default will depend more on the systematic risk factor. Therefore, a debtor with high (low) PD is likely to have low (high) R.

1.06 = Adjusting the scaling factor to 1.06 to compensate for the calculated reduction in capital requirement.

2.2 The Policy Guidelines for Appropriate Retail Credit to Take Care of the Problem of Excessive Debt of the Household Sector

The Bank of Thailand (BOT) has set the policy guidelines for appropriate retail credits 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, and 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.

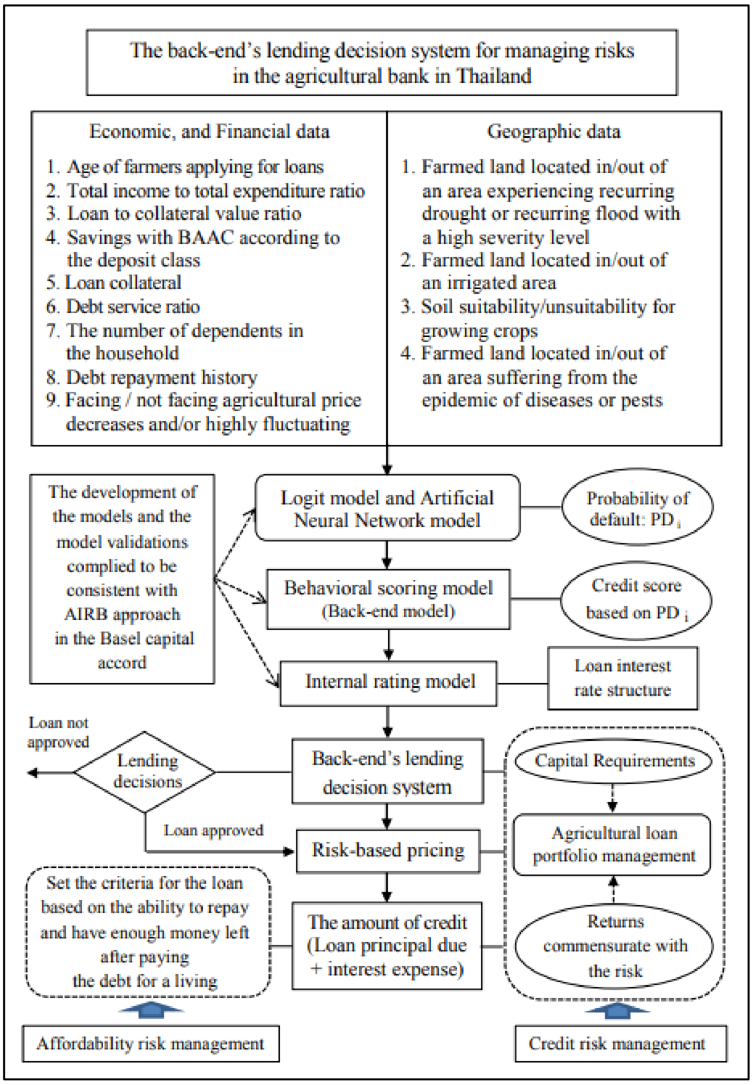
Banks in Asia, such as Malaysia and Singapore, have adopted DSR configuration measures to tackle household debts or economic bubble issues. For example, Malaysia imposes a DSR of 60 percent on all types of loans lending with vulnerable borrowers, and Singapore has set a limit of the DSR level at 60 percent with mortgage loans, and 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).

2.3 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 back-end's lending decision system for managing risks in the agricultural bank in Thailand. The conceptual framework of this study is presented in Figure 1.

Figure 1: Conceptual Framework



Source: Author's explanations.

3. Methodology and Data

3.1 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; Kammoun & Triki, 2016; Somboon, 2017; Römer & Mußhoff, 2017; Bennouna & Tkiouat, 2019), artificial neural network (ANN) model (Altman, Glancario, & Varetto, 1994; Coakley, & Brown, 2000; Lee & Jung, 2000; Wu & Wang, 2000; Limsombunchai, Christopher, & Minsoo, 2005; Hu, 2008; Kammoun & Triki, 2016; Somboon, 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:

3.1.1 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 2).

$$prob(Y_i = 1) = \frac{\exp(Z_i)}{1 + \exp(Z_i)} \qquad (2)$$

$Y_i = 0$ 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)

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

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

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

X_{ij} = The characteristic of debtor i

In this study, the author uses the Logit model to analyze the relationship between the independent variables and the probability of default to explain the change of probability of default of BAAC borrowers. The results from the Logit model are subsequently employed to formulate the equation for predicting the probability of default, the behavioral scoring (back-end) model, and the internal rating model, respectively.

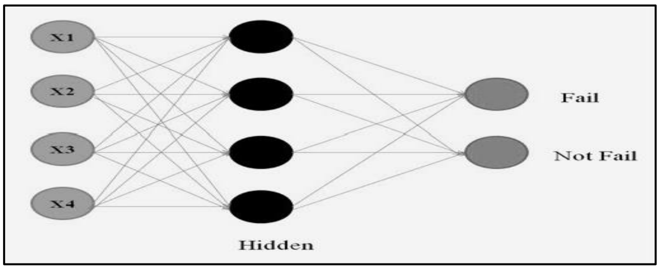
3.1.2 Artificial Neural Network (ANN) model

The 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 3).

$$U_j = F_j(\sum W_{ij} X_i) \qquad (3)$$

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 (Limsombunchai, Christopher, & Minsoo, 2005). 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. If the network has only one hidden layer and two outputs (fail, not fail) in the output layer, the network is shown in Figure 2 (Chen & Du, 2009).

Figure 2: ANN Structure with One Hidden Layer and Two Outputs



Source: Chen & Du (2009).

In this study, the author uses the ANN model to analyze the risk factors that are affecting and influencing the probability of default of BAAC borrowers.

3.2 Data and Data Preparation Used to Develop the Back-end's Lending Decision System

The data in this study are obtained from the BAAC. The credit files were retrieved from the core banking system database in August 2020. During the period of 2017 to 2020 (April 2017 to July 2020), a total of 13,500 agricultural loans were credit for manufacturing expenses (loan repayable not exceeding 1 year) including rice, maize, cassava, sugarcane, longan, rubber, and oil palm. The data set comprises 11,812 good debts[1] and 1,688 bad debts[2] (corresponding to the population default rate of 12.50%). All loans are under the normal loan

[1] Good debt refers to a debtor who 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
[2] Bad debt refers to a debtor who owes interest or principal payment more than 90 days from the due date

scheme (excluding the government loan for specific projects). The author collected the data, which were distributed according to the population proportion in each region and covers operating areas of BAAC throughout the country including specifying risk factors/variables to test the given hypothesis as follows:

1. Age of farmers applying for loans; as people get older, they tend to be unhealthy, resulting in a decrease in their career potential. The loan received may not be able to increase production for the purpose of the loan and when the debt is due it cannot be repaid. The author hypothesizes that the age of farmers applying for loans is positively correlated with the probability of default. As expected, the probability of default increases as credit applicants gets older. This variable is measured in the ratio scale.

2. Total income to total expenditure ratio; this ratio indicates the repayment ability of loan applicants from income covering expenses, and sufficient to repay debt. The author hypothesizes that the total income to total expenditure ratio is negatively related to the probability of default. As expected, the probability of default decreases with increased total income to total expenditure ratio. This variable is measured in the ratio scale.

3. Loan to collateral value ratio; this ratio represents the collateral value of the applicant to accommodate the loan amount. The author hypothesizes that the loan to collateral value ratio is positively related to the probability of default. As expected, the probability of default increases with an increased loan to collateral value ratio. This variable is measured in the ratio scale.

4. Savings according to the deposit class; Savings with BAAC is used to measure debt repayment potential. The author hypothesizes that borrower who has savings with BAAC (5,001 to 10,000.99 baht or 10,001-20,000.99 baht or equal to or more than 20,001 baht) has a lower probability of default compared with the borrower who does not has savings or has savings with BAAC 1-5,000 baht. Savings with BAAC according to the deposit class can be measured on the ordinal scale.

5. Loan collateral; Collateral gives confidence to the lender. Each type of collateral has a different level of risk. The author hypothesizes that a borrower who has only land mortgages or only personal guarantees has a higher probability of default compared with a borrower who has both land mortgages and personal guarantees. Loan collateral types can be measured on a nominal scale.

6. Debt service ratio; Debt service ratio measures debt burden which is an important indicator of household stability. The author hypothesizes that the debt service ratio is positively related to the probability of default. As expected, the probability of default increases with an increased debt service ratio. This variable is measured in the ratio scale. The debt service ratio can be written as shown in equation 4.

$$\text{Debt Service Ratio} = (\text{principal due} + \text{interest expense}) / \text{household income} \quad (4)$$

7. The number of dependents in the household; Debt repayment capacity is limited by spending schemes. For example, agricultural households with multiple children have higher expenses than agricultural households with the same income level but have fewer children. As a result, there is a greater risk of default on debt repayment. The author hypothesizes that the number of dependents in the household is positively related to the probability of default. As expected, the probability of default increases with increased the number of dependents in the household. This variable is measured in the ratio scale.

8. Debt repayment history; The debt repayment history variable is used to measure the potential of the debtor in terms of the intention to repay the debt, such as during the past 3 years if the borrower has never defaulted on the debt repayment at all, the lender will be confident that the borrower is a good debtor. On the other hand, if in the past, the borrower has ever defaulted on repayment of the debt, the confidence that the lender will receive

payment from the borrower is less. Therefore, the author hypothesizes that if in the past 3 years, the borrower who has ever defaulted on debt repayment is a higher probability of default compared with the borrower who has never defaulted on debt repayment. The borrower who has ever defaulted on debt repayment is positively related to the probability of default. The debt repayment history variable can be measured on a nominal scale.

9. Facing/not facing agricultural price decreases and/or highly fluctuating; Facing agricultural price (rice, maize, cassava, sugarcane, longan, rubber, oil palm) decreases and/or highly fluctuating will affect farmers' income. The author hypothesizes that the borrower who is facing agricultural price decreases and/or highly fluctuating (in this study, 1 borrower = 1 agricultural product) is a higher probability of default compared with the borrower who is not facing agricultural price decreases and/or highly fluctuating. Facing with agricultural price decreases and/or highly fluctuating is positively related to the probability of default. The facing/not facing agricultural price decreases and highly fluctuating can be written in the dummy variable as shown in the Appendix and measured on a nominal scale.

10. Farmed land located in/out of an area experiencing recurring drought or recurring flood with a high severity level; Farmed land located in an area experiencing recurring drought or recurring flood with a high severity level, the output has been damaged affecting farmers' income and causing insufficient income to repay debt. The author hypothesizes that the borrower who has farmed land not located in an area experiencing recurring drought or recurring flood with a high severity level has a lower probability of default compared with the borrower who has farmed land located in an area experiencing recurring drought or recurring flood with a high severity level. Farmed land not located in an area experiencing recurring drought or recurring flood with a high severity level is negatively related to the probability of default. The farmed land located in/out of an area experiencing recurring drought or recurring flood with a high severity level can be written in the dummy variable as shown in the Appendix and measured on a nominal scale.

11. Farmed land located in /out of an irrigated area; Water scarcity in agriculture will affect agricultural productivity and farmers' income and will continue to affect debt default. The author hypothesizes that the borrower who has farmed land not located in an irrigated area has a higher probability of default compared with the borrower who has farmed land located in an irrigated area. Farmed land not located in an irrigated area is positively related to the probability of default. The farmed land located in /out of an irrigated area can be measured on a nominal scale.

12. Soil suitability/unsuitability for growing crops; when cultivated soil is suitable for plant growth, farmers will get the full product according to the production potential. This resulted in a higher income of farmers and enough income to pay their debts. The author hypothesizes that the borrower who has soil suitability for growing crops has a lower probability of default compared with the borrower who has soil unsuitability for growing crops. Soil suitability is negatively related to the probability of default. Soil suitability/unsuitability for growing crops can be measured on a nominal scale.

13. Farmed land located in/out of an area suffering from the epidemic of diseases or pests; experiencing the epidemic of diseases or pests is one of the natural disaster variables that damage agricultural products. Farmers have additional production costs for eliminating diseases or pests, low yield, affecting the income and expenses of farmers' households. This causes farmers to have insufficient income to repay their debts. The author hypothesizes that the borrower who has farmed land not located in an area suffering from the epidemic of diseases or pests has a lower probability of default compared with the borrower who has farmed land located in an area suffering from the epidemic of diseases or pests. Farmed land not located in an area suffering from the epidemic of diseases or pests is negatively related to the probability of default. Farmed land located in/out of an area suffering from the epidemic of diseases or pests can be measured on a nominal scale.

From the 13,500 data sets, the author classified them into two groups, with 80% of the data (10,800 samples) used to develop the model (development samples) and 20% of the data (2,700 samples) used to test the reliability and validity of the model (Hold-out samples). However, the dependent and independent variables are specified. It also describes the characteristics of each variable in the group used to develop the model and the group used to test the reliability and validity of the model, which can be shown in Table 1.

Table 1: Characteristics of variables

Variables	Development samples (10,800 samples)	Hold-out samples (2,700 samples)
Dependent variable		
Debt status (Y; 0,1)	10,800 (100.00%)	2,700 (100.00%)
Good debt (Y= 0)	9,450 (87.50%)	2,362 (87.48%)
Bad debt (Y=1)	1,350 (12.50%)	338 (12.52%)
Independent variables		
1. Average of the age of farmers applying for loans (years)	51.28	51.47
2. Average of the total income to total expenditure ratio (times)	1.88	1.88
3. Average of the loan to collateral value ratio (times)	0.69	0.70
4. Savings according to the deposit class	10,800 (100.00%)	2,700 (100.00%)
(4.1) Does not saving with BAAC or savings with BAAC less than or equal to 5,000.99 baht	8,158 (75.54%)	2,010 (74.44%)
(4.2) Savings with BAAC 5,001 to 10,000.99 baht	839 (7.77%)	213 (7.89%)
(4.3) Savings with BAAC 10,001 to 20,000.99 baht	577 (5.34%)	142 (5.26%)
(4.4) Savings with BAAC equal to or more than 20,001 baht	1,226 (11.35%)	335 (12.41%)
5. Loan collateral	10,800 (100.00%)	2,700 (100.00%)
(5.1) Land mortgages	4,477 (41.45%)	1,092 (40.44%)
(5.2) Person guarantees	2,903 (26.88%)	719 (26.63%)
(5.3) Person guarantees and land mortgages	3,420 (31.67%)	889 (32.93%)
6. Average of the debt service ratio (times)	0.73	0.72
7. Average of the number of dependents in the household (man)	2.59	2.58

Table 1: (Continued)

Variables	Development samples (10,800 samples)	Hold-out samples (2,700 samples)
8. Debt repayment history	10,800 (100.00%)	2,700 (100.00%)
(8.1) the borrower who has never defaulted on debt repayment	9,314 (86.24%)	2,322 (86.00%)
(8.2) the borrower who has ever defaulted on debt repayment	1,486 (13.76%)	378 (14.00%)
9. Facing/not facing agricultural prices decrease and/or highly fluctuating	10,800 (100.00%)	2,700 (100.00%)
(9.1) the borrower who is not facing agricultural prices decrease and/ or highly fluctuating	5,537 (51.27%)	1,371 (50.78%)
(9.2) the borrower who is facing agricultural prices decrease and/ or highly fluctuating	5,263 (48.73%)	1,329 (49.22%)
10. Farmed land located in/out of an area experiencing recurring drought or recurring flood with a high severity level	10,800 (100.00%)	2,700 (100.00%)
(10.1) the borrower who has farmed land located in an area experiencing recurring drought or recurring flood with a high severity level	6,830 (63.24%)	1,774 (65.70%)
(10.2) the borrower who has farmed land not located in an area experiencing recurring drought or recurring flood with a high severity level	3,970 (36.76%)	926 (34.30%)
11. Farmed land located in /out of an irrigated area	10,800 (100.00%)	2,700 (100.00%)
(11.1) the borrower who has farmed land located in an irrigated area	5,414 (50.13%)	1,342 (49.70%)
(11.2) the borrower who has farmed land not located in an irrigated area	5,386 (49.87%)	1,358 (50.30%)
12. Soil suitability/unsuitability for growing crops	10,800 (100.00%)	2,700 (100.00%)
(12.1) the borrower who has soil unsuitability for growing crops	5,351 (49.55%)	1,354 (50.15%)
(12.2) the borrower who has soil suitability for growing crops	5,449 (50.45%)	1,346 (49.85%)
13. Farmed land located in/ out of an area suffering from the epidemic of diseases or pests	10,800 (100.00%)	2,700 (100.00%)
(13.1) the borrower who has farmed land located in an area suffering from the epidemic of diseases or pests	1,481 (13.71%)	356 (13.19%)
(13.2) the borrower who has farmed land not located in an area suffering from the epidemic of diseases or pests	9,319 (86.29%)	2,344 (86.81%)

Source: Author’s calculations.

3.3 Data Analysis Methods

The risk factors/variables described above can be developed into the back-end's lending decision system to manage risks in the agricultural bank in Thailand as shown in the data analysis framework (see Figure 3).

Figure 3: Data Analysis Framework

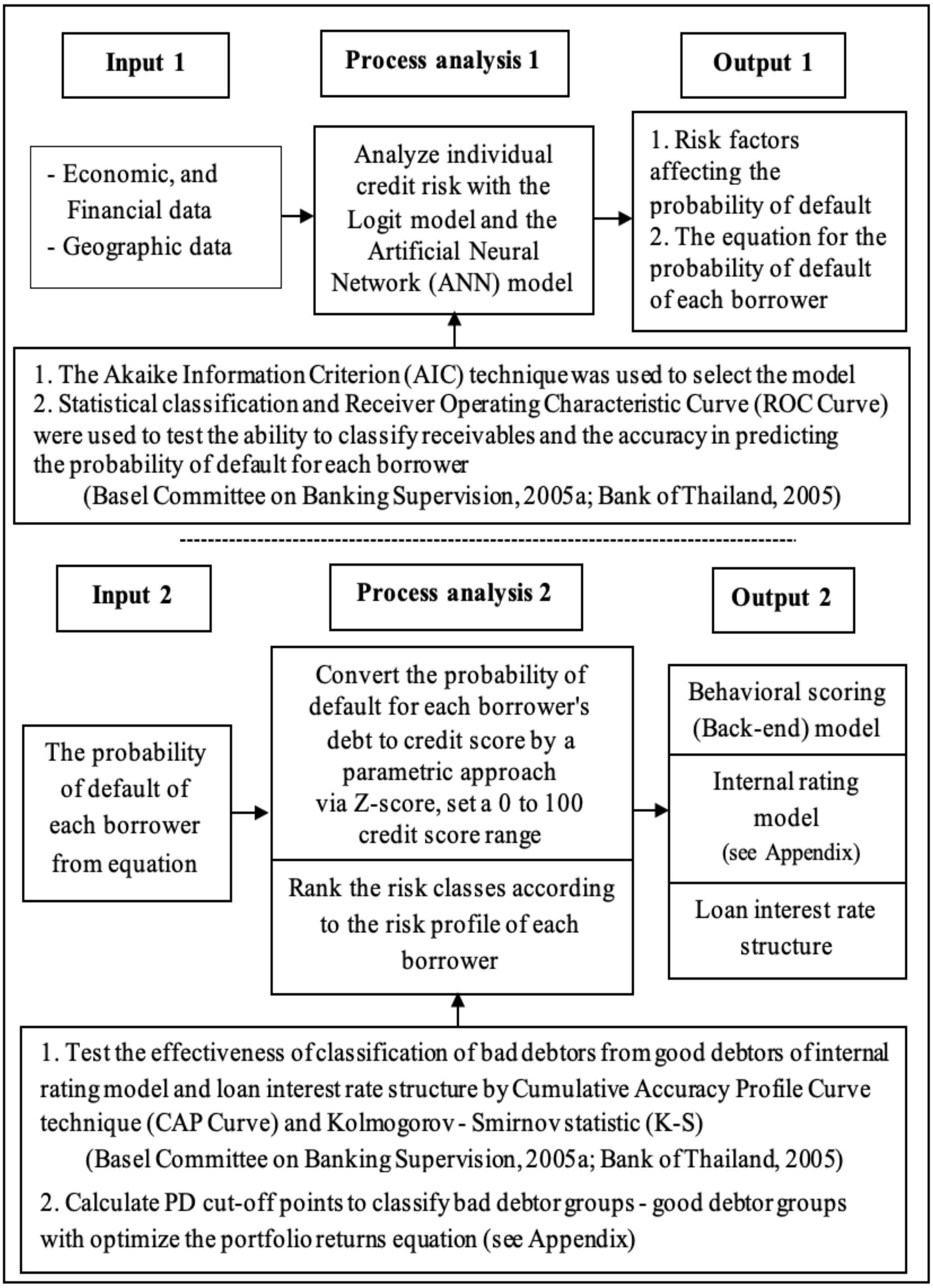
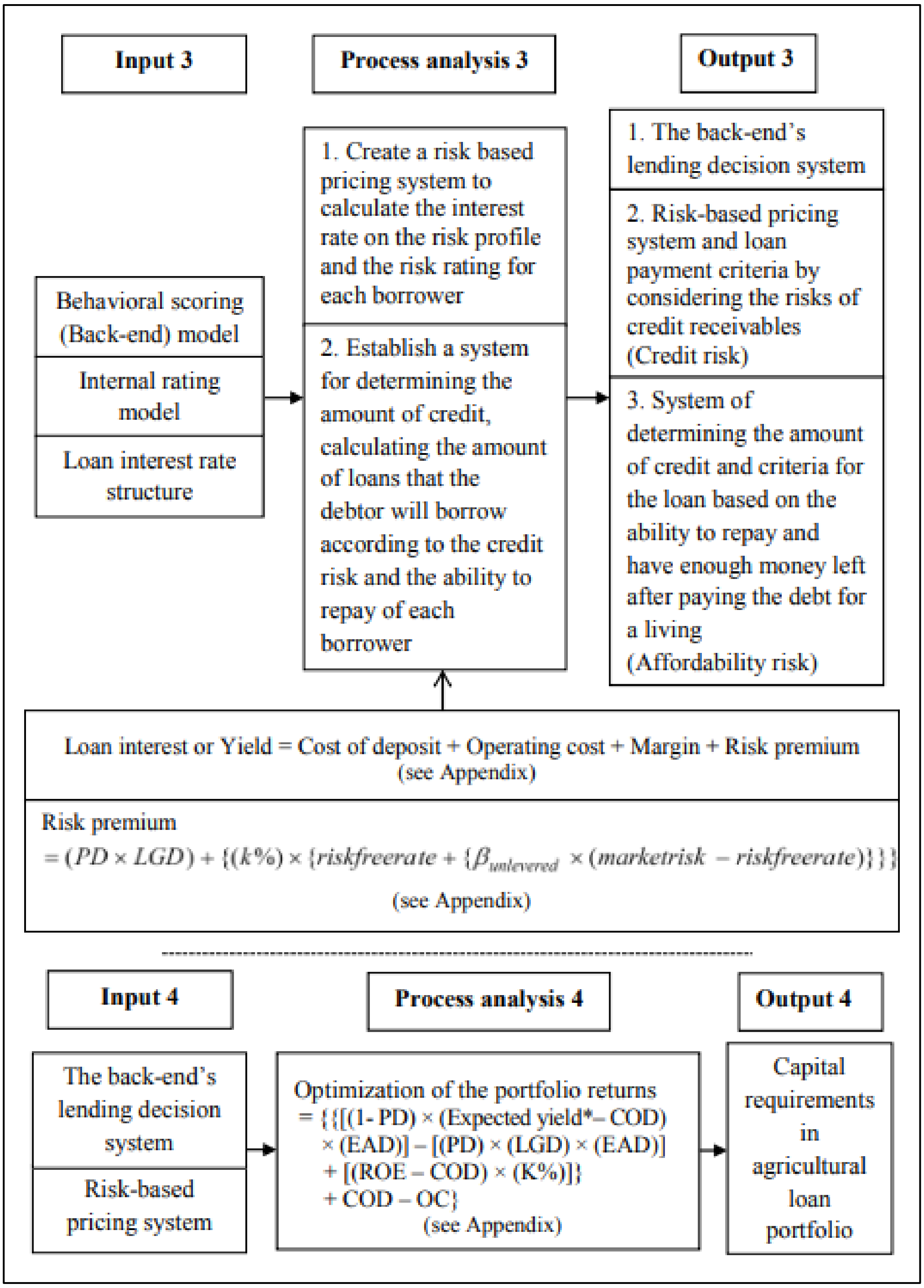


Figure 3: (Continued)



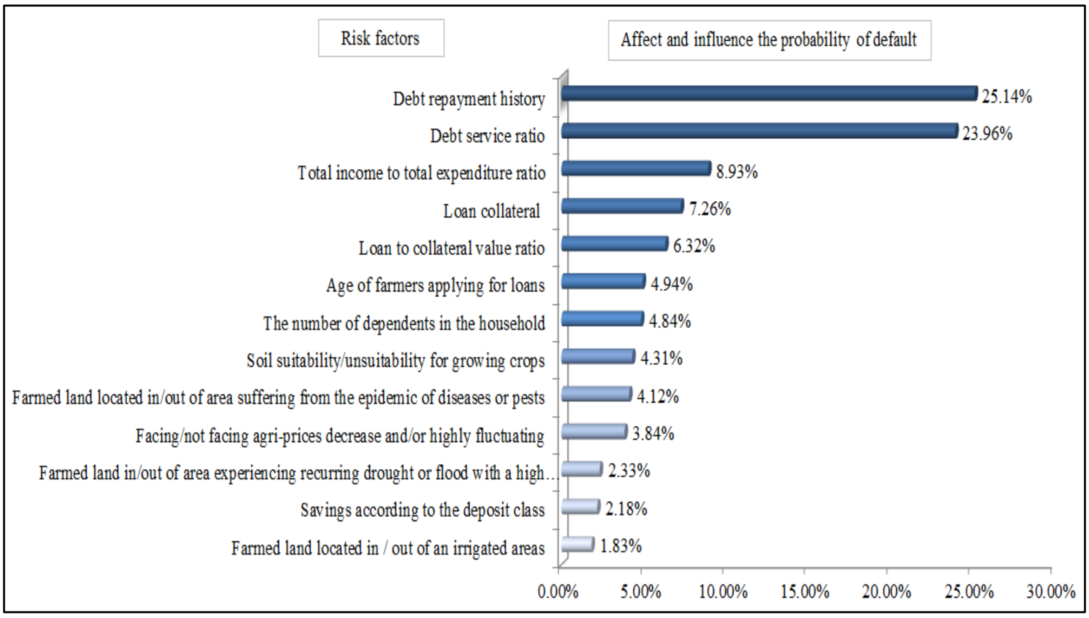
Source: Author's explanations.

4. Results

4.1 Relevant Risk Factors that have been identified as A Predictor of Default Risk in Agricultural Loan

The estimated results of the ANN model are shown in Figure 4. The risk factors are affecting and influencing the probability of default of BAAC borrowers including debt repayment history (25.14%), debt service ratio (23.96%), total income to total expenditure ratio (8.93%), loan collateral (7.26%), loan to collateral value ratio (6.32%), age of farmers applying for loans (4.94%), the number of dependents in the household (4.84%), soil suitability/unsuitability for growing crops (4.31%), farmed land located in/out of an area suffering from the epidemic of diseases or pests (4.12%), facing/not facing agricultural prices decrease and/or highly fluctuating (3.84%), farmed land located in/out of an area experiencing recurring drought or recurring flood with a high severity level (2.33%), savings according to the deposit class (2.18%), and farmed land located in /out of an irrigated area (1.83%).

Figure 4: Risk Factors that Affect and Influence the Probability of Default



Source: Author’s estimations.

4.2 The Model Selection, the Variables Affecting the Probability of Default, the Equation for Predicting the Probability of Default in the Next 12 Months, and the Back-end Model

The author developed the Logit model for forecasting the probability of default from a set of 10,800 development samples. The analysis of the relationship between the independent variables and the probability of default is used to explain the change of probability of default of BAAC borrowers and selected the model with the Akaike Information Criterion (AIC) technique.

As a result of AIC, 16 of the independent variables (Table 2) gave the AIC value of 6224.63, which is the lowest value compared to the case with 15 independent variables (AIC = 6225.93). 14 variables (AIC = 6231.97) in the case of 13 independent variables (AIC = 6288.17), and etc. (see Appendix), indicating that these 16 independent variables shown in Table 2 can be used to develop the equation for predicting the probability of default and the back-end model.

Table 2: Independent Variables Affecting the Probability of Default

Marginal Effects	Coefficients	Independent variables	Sig.
-	-5.3246***	Constant	0.0000
0.0008***	0.0117***	(X_1) Age of farmers applying for loans (years)	0.0003
-0.0098***	-0.1456***	(X_2) Total income to total expenditure ratio (times)	0.0000
0.0798***	1.1863***	(X_3) Loan to collateral value ratio (times)	0.0000
-0.0152*	-0.2468*	(X_4) Savings with BAAC 5,001 to 10,000.99 baht	0.0827
-0.0202**	-0.3407*	(X_5) Savings with BAAC 10,001 to 20,000.99 baht	0.0534
-0.0312***	-0.5536***	(X_6) Savings with BAAC equal to or more than 20,001 baht	0.0001
0.1108***	1.4214***	(X_7) Land mortgages	0.0000
0.1050***	1.2028***	(X_8) Person guarantees	0.0000
0.0124***	0.1841***	(X_9) Debt service ratio [times]	0.0000
0.0125***	0.1853***	(X_{10}) The number of dependents in the household [man]	0.0022
0.2319***	1.9089***	(X_{11}) The borrower has ever defaulted on repayment of the debt	0.0000
0.0243**	0.3589**	(X_{12}) Facing agricultural price decreases and/ or highly fluctuating	0.0113
-0.0236***	-0.3642***	(X_{13}) Farmed land not located in an area experiencing recurring drought or recurring flood with a high severity level	0.0000
0.0412***	0.6062***	(X_{14}) Farmed land not located in an irrigated area	0.0051
-0.0317***	-0.4683***	(X_{15}) Soil suitability for growing crops	0.0052
-0.0140*	-0.1960*	(X_{16}) Farmed land not located in an area suffering from the epidemic of diseases or pests	0.0692

Note: *** Significant at 1 percent level ** Significant at 5 percent level
* Significant at 10 percent level
Source: Author's estimations.

The independent variables presented in Table 2 describe the statistically significant change in the probability of default of borrowers. The marginal effects indicate the influence of independent variables on the probability of default on debt repayment. As a result, the marginal effects indicate that the borrower has ever defaulted on repayment of the debt, affecting and influencing the probability of default of BAAC borrowers is higher than other independent variables. 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:

1. Age of farmers applying for loans (variable X_1); the estimated coefficient is found to be significant at 1 percent level, a positive coefficient. As expected, the probability of default increases with older the loan applicant farmer.

2. Total income to total expenditure ratio (variable X_2); the estimated coefficient is negative and significant at 1 percent level. As expected, the probability of default decreases with an increased total income to total expenditure ratio.

3. Loan to collateral value ratio (variable X_3); the estimated coefficient is positive and significant at 1 percent level. As expected, the probability of default increases with an increased loan to collateral value ratio.

4. Savings with BAAC 5,001 to 10,000.99 baht (variable X_4); the estimated coefficient is negative and significant at 10 percent level. As expected, the borrower who has savings with BAAC 5,001 to 10,000.99 baht 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.

5. Savings with BAAC 10,001 to 20,000.99 baht (variable X_5); the estimated coefficient is negative and significant at 10 percent level. As expected, the borrower who has savings with BAAC 10,001 to 20,000.99 baht 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.

6. Savings with BAAC equal to or more than 20,001 baht (variable X_6); the estimated coefficient is negative and significant at 1 percent level. As expected, the borrower who has savings with BAAC equal to or more than 20,001 baht 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.

7. Land mortgages (variable X_7); the estimated coefficient is positive and significant at 1 percent level. As expected, the borrower who has only land mortgages applying for loans has a higher probability of default compared with borrowing using both land mortgages and personal guarantees.

8. Person guarantees (variable X_8); the estimated coefficient is positive and significant at 1 percent level. As expected, the borrower who has only personal guarantees applying for loans has a higher probability of default compared with borrowing using both land mortgages and personal guarantees.

9. Debt service ratio (variable X_9); the estimated coefficient is positive and significant at 1 percent level. As expected, the probability of default increases with an increased debt service ratio.

10. The number of dependents in the household (variable X_{10}); the estimated coefficient is positive and significant at 1 percent level. As expected, the probability of default increases with increased the number of dependents in the household.

11. The borrower has ever defaulted on repayment of the debt (variable X_{11}); the estimated coefficient is positive and significant at 1 percent level. As expected, the borrower who has ever defaulted on debt repayment has a higher probability of default compared with the borrower who has never defaulted on debt repayment.

12. Facing agricultural price decreases and/or highly fluctuating (variable X_{12}); the estimated coefficient is positive and significant at 5 percent level. As expected, the borrower who is facing agricultural price decreases and/or highly fluctuating is a higher probability of default compared with the borrower who is not facing agricultural price decreases and/or highly fluctuating.

13. Farmed land not located in an area experiencing recurring drought or recurring flood with a high severity level (variable X_{13}); the estimated coefficient is negative and significant at 1 percent level. As expected, the borrower who has farmed land not located in the area experiencing recurring drought or recurring flood with a high severity level has a lower probability of default compared with the borrower who has farmed land located in the area experiencing recurring drought or recurring flood with a high severity level.

14. Farmed land not located in an irrigated area (variable X_{14}); the estimated coefficient is positive and significant at 1 percent level. As expected, the borrower who has farmed land not located in an irrigated area has a higher probability of default compared with the borrower who has farmed land located in an irrigated area.

15. Soil suitability for growing crops (variable X_{15}); the estimated coefficient is negative and significant at 1 percent level. As expected, the borrower who has soil suitability for growing crops has a lower probability of default compared with the borrower who has soil unsuitability for growing crops.

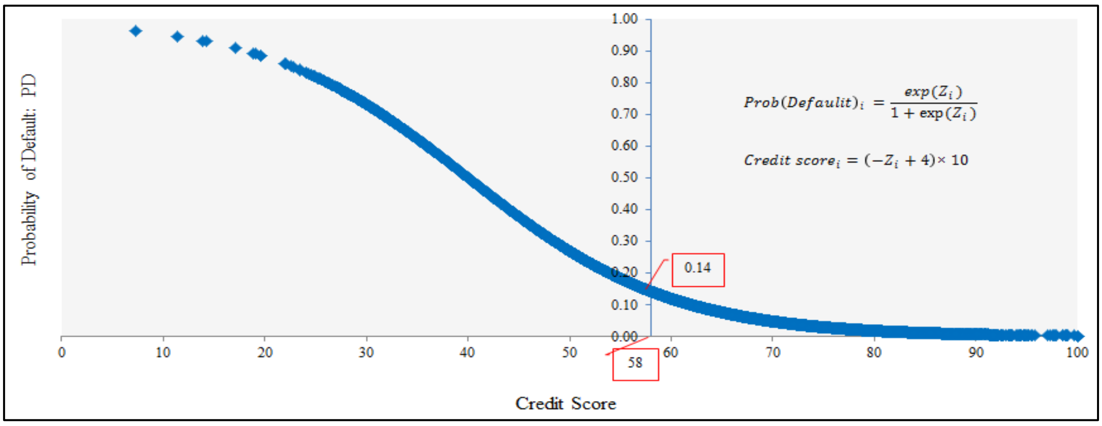
16. Farmed land not located in an area suffering from the epidemic of diseases or pests (variable X_{16}); the estimated coefficient is negative and significant at 10 percent level. As expected, the borrower who has farmed land not located in an area suffering from the epidemic of diseases or pests has a lower probability of default compared with the borrower who has farmed land located in an area suffering from the epidemic of disease or pest.

By using the constant and coefficients in front of the 16 variables (see Table 2) to create the equation for predicting the probability of default in the next 12 months for each BAAC borrower (PD_i) can be written as shown in equation 5.

$$PD_i = \frac{\exp(-5.3246+0.0117X_1-0.1456X_2+.........-0.4683X_{15}-0.1960X_{16})}{1+\exp(-5.3246+0.0117X_1-0.1456X_2+.........-0.4683X_{15}-0.1960X_{16})} \quad (5)$$

After obtaining PD_i, the author developed "the back-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 (see Figure 5).

Figure 5: Conversion of the Probability of Default for Each Debtor to Each Debtor's Credit Score



Source: Author's calculations.

4.3 The Validations (Accuracy) of the Equation for Predicting the Probability of Default in the Next 12 Months for Each BAAC Borrower

After obtaining the equation (Logit model) for predicting the probability of default in the next 12 months for each BAAC borrower from a set of 10,800 development samples (see Equation5). The author tested the model's validity by assessing the model's predictive performance and classification of the model's debtor groups from a set of 2,700 hold-out samples. The classification rate on the hold-out sample prediction for the Logit model is presented in Table 3 and Table 4. The overall prediction accuracy is 88.11% which is rather good (see Table 3), and the overall prediction misclassification is 11.89% (see Table 4). However, the Logit model can predict well only on the good debt but unable to predict the bad debt, which will give BAAC a cost arising from the wrong decision of Type I error in the form of debt collection expenses or provision for doubtful accounts expenses.

Table 3: Statistical Classification Measuring Prediction the Borrowers' Default and Discrimination between Bad debt and Good debt Accuracy

Observed		Forecasting results with the Logit model					
		Development samples (# 10,800 samples)			Hold-out samples (# 2,700 samples)		
		Debt status		Percentage of accuracy	Debt status		Percentage of accuracy
		Good debt	Bad debt		Good debt	Bad debt	
Debt status	Good debt	9,223	227	97.60	2,304	58	97.54
	Bad debt	999	351	26.00	263	75	22.19
Percentage of overall accuracy				88.65			88.11

Source: Author's calculations.

Table 4: Statistical Classification Measuring Misclassification Cost

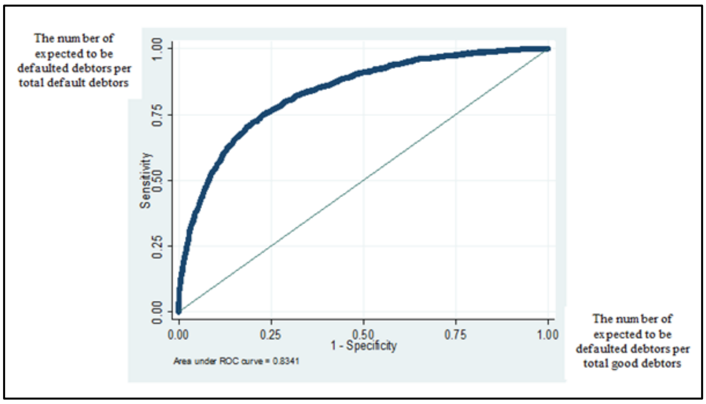
Type of errors	Percentage of error
1. Percentage of the Type I error	9.74
2. Percentage of the Type II error	2.15
3 Percentage of the Type I and Type II errors [3]	11.89

Source: Author's calculations.

The test results showed that the Logit model can discriminate between bad debt and good debt. The "Area measures the discriminatory power under ROC Curve" which is the area below the concave curve, and it is 0.8341 which means it has a ROC predictive power of 83.41% which is rather good (see Figure 6).

[3] 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)

Figure 6: Receiver Operating Characteristic Curve (ROC Curve) Measuring the Borrowers' Default and the Discriminatory Power



Source: Author's calculations.

4.4 The Internal Rating Model and the Loan Interest Rate Structure

4.4.1 The internal rating model

After obtaining the back-end model, the author developed "the internal rating model" according to BCBS guidelines. The internal rating model must be able to distinguish between high-risk and low-risk debtors, and the capital requirement for each level of risk is the lowest (Minimum K %). The author assigns each risk rating to be a different width of the probability of default (PD), but together they 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 (CC/C) 10 (D), 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 be used to provide information for BAAC credit risk management to risk diversify and reduce the concentration risk (see Table 5).

Table 5: The Internal Rating Model

Probability of default (PD) for each rating	Internal (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 0.0100	1(AAA)	86 to 100	0.0319	0.0419
0.0101 to 0.0162	2(AA)	81 to 85	0.0725	0.0546
0.0163 to 0.0244	3(A)	77 to 80	0.1093	0.0632
0.0245 to 0.0411	4(BBB)	71 to 76	0.1404	0.0745
0.0412 to 0.0656	5(BB)	67 to 70	0.1596	0.0887
0.0657 to 0.0938	6(B)	63 to 66	0.1207	0.1047
0.0939 to 0.1400	7(CCC)	58 to 62	0.1015	0.1228
0.1401 to 0.2007	8(CCC/CC)	54 to 57	0.0761	0.1404
0.2008 to 0.2668	9(CC/C)	50 to 53	0.0630	0.1516
0.2669 to 1.0000	**10(D)**	**0 to 49**	**0.1250**	**0.1415**

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). 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 loan amount throughout the year as of March 31, 2021of the BAAC. There will be approximately 1,198,050 million baht, resulting in BAAC's expected profits before risk cost of approximately 42,296 million baht (see Appendix).

4.4.2 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 (CCC). However, as the BAAC is not the most profitable organization, but an organization with a mission to help farmers gain access to funding. 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[4]", which are tier 8 (CCC / CC) and tier 9 (CC/C). 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(D). 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 87.50 percent of approved borrowers or good debtors and 12.50 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 0.0100	86 to 100	0.0319	1(AAA)	4.50%	Particularly excellent
0.0101 to 0.0162	81 to 85	0.0725	2(AA)	5.25%	Excellent
0.0163 to 0.0244	77 to 80	0.1093	3(A)	6.00%	Very good
0.0245 to 0.0411	71 to 76	0.1404	4(BBB)	6.75%	Good
0.0412 to 0.0656	67 to 70	0.1596	5(BB)	7.50%	Rather good
0.0657 to 0.0938	63 to 66	0.1207	6(B)	8.25%	Normal
0.0939 to 0.1400	**58 to 62**	**0.1015**	**7(CCC)**	**9.00%**	**Normal, the bank should take care**
0.1401 to 0.2007	54 to 57	0.0761	8(CCC/CC)	9.75%	Low-side Override Level 1(extra care)
0.2008 to 0.2668	50 to 53	0.0630	9(CC/C)	10.50%	Low-side Override Level 2 (extra care)
0.2669 to 1.0000	**0 to 49**	**0.1250**	**10(D)**	**-**	**Loan not approved**

Source: Author's calculations.

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

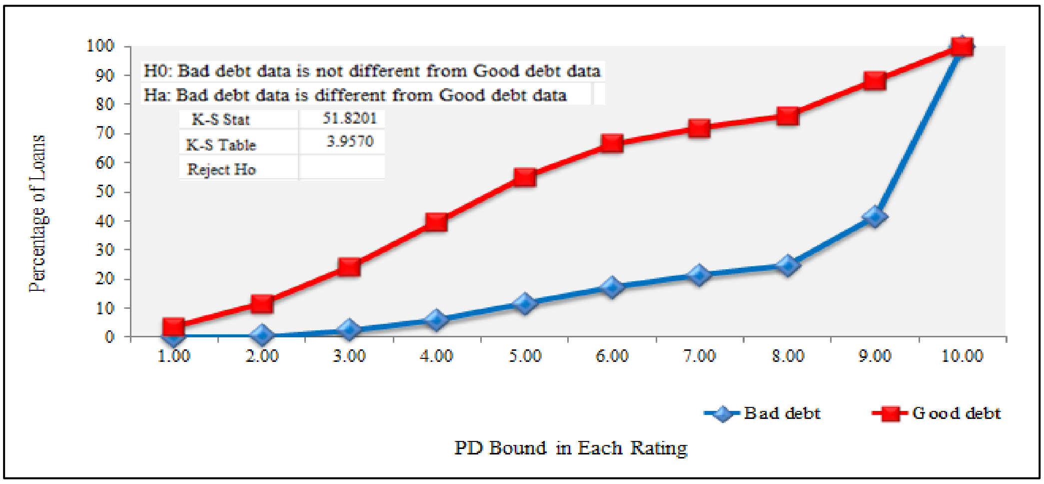
The author analyzes the relationship between the probability of default (PD), credit score, and the loan interest rate, which determined that the structured interest rate (4.50% to 10.50%) covers the overall risk profile of the credit portfolio. Each debtor charged a loan interest rate covering the cost 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 0.0100 (PD value is very low, which may be considered risk-free and therefore no risk premium). A credit score that the debtor receives is between 86 and 100 points, in debt quality class "Particularly excellent" (see Table 6).

4.5 The Validations (Accuracy and Confidence Testing) of the Internal Rating Model

4.5.1 The evaluation of the accuracy of the rank order and ability to discriminate between bad debt and good debt in each grade of the internal rating model by Kolmogorov-Smirnov (K-S) statistic

The results showed that the internal rating model is able to discriminate between bad debt and good debt. The results from the K-S statistic (K-S stat) were greater than the K-S value from the statistical table (51.8201 > 3.9570). Therefore, the author rejects the null hypothesis that the bad debt data is not different from the good debt data (rejects H_0), however, the author cannot reject the alternative hypothesis that the bad debt data is different from the good debt data (cannot reject H_a). The results are shown in Figure 7 and Table 7.

Figure 7: Kolmogorov–Smirnov (K-S) Statistic Measuring the Ability to Discriminate between Bad debt and Good debt



Source: Author’s calculations.

Table 7: Kolmogorov-Smirnov (K-S) Statistic Measuring the Ability to Discriminate between Bad debt and Good debt

Risk Ratings	Distribution		Cumulative distribution		Cumulative distribution		K-S test (%)
	Bad debt (#)	Good debt (#)	Bad debt (#)	Good debt (#)	Bad debt (%)	Good debt (%)	
1(AAA)	1	331	1	331	0.0741	3.5026	3.4286
2(AA)	7	735	8	1,066	0.5926	11.2804	10.6878
3(A)	23	1,199	31	2,265	2.2963	23.9683	21.6720
4(BBB)	45	1,474	76	3,739	5.6296	39.5661	33.9365
5(BB)	76	1,462	152	5,201	11.2593	55.0370	43.7778
6(B)	79	1,081	231	6,282	17.1111	66.4762	49.3651
7(CCC)	57	521	288	6,803	21.3333	71.9894	50.6561
8(CCC/CC)	41	397	329	7,200	24.3704	76.1905	51.8201
9(CC/C)	230	1,152	559	8,352	41.4074	88.3810	46.9735
10(D)	791	1,098	1,350	9,450	100.0000	100.0000	0.0000
	1,350	9,450					
				Max	51.8201		
	Total	10,800		K-S Stat	51.8201		
				K-S Stat tables	3.9570		
		(K-S Stat > K-S Stat tables)			rejects H_0		

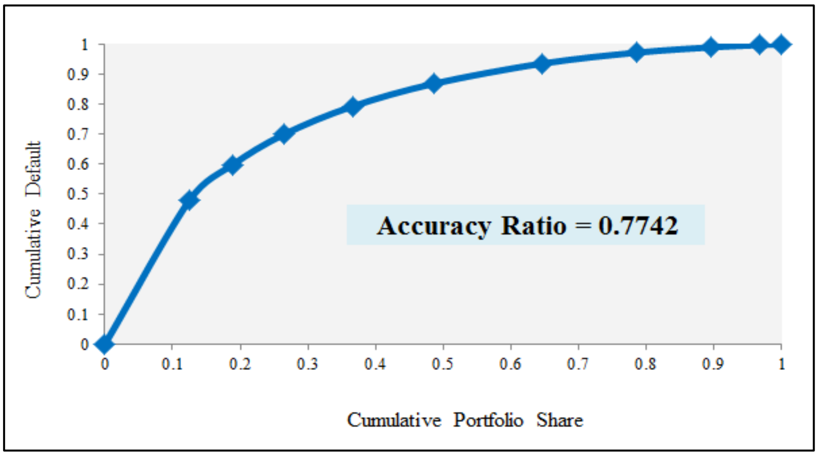
H_0: Bad debt data is not different from Good debt data.
H_a: Bad debt data is different from Good debt data.

Source: Author's calculations.

4.5.2 The evaluation of the accuracy of the rank order and the accuracy in estimating defaults in each grade (prediction) 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 0.7742 which means it has a CAP predictive power of 77.42% which is rather good (see Figure 8).

Figure 8: The Accuracy of the Rank Order and the Accuracy in Estimating Defaults in Each Grade by Cumulative Accuracy Profile Curve (CAP Curve)



Source: Author’s calculations.

4.6 The Back-end’s Lending Decision System

After obtaining the back-end model, the internal rating model, and the loan interest rate structure, the author developed “the back-end’s lending decision system” according to BCBS and BOT guidelines. The back-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 households' excess debt, as well as, promoting and supporting financial discipline building for agricultural households in the rural sector of the country (see Figure 9).

Figure 9: The Back-end's Lending Decision System

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		The amount of credit				
	Expected the total annual income (baht)	Loan principal due [loan amount] (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)
	400,000	252,000	22,680	274,680	0.6867	125,320

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 behavioral scoring model	Level assessment credit quality according to credit score received
9.00%	7(CCC)	58	0.1386	Pass	Normal, the bank should take care

F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13
AGE	INC	LTV	SAV	COL	DSR	DEH	DRH	PDF	EDF	FLI	SGC	FSE
46	1.48	0.85	3	1	0.69	3	0	1	1	1	0	1

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})

DRH (F8) is an abbreviation used to represent the variable name, Debt repayment history

0 the borrower who has never defaulted on debt repayment (Reference)

1 the borrower who has ever defaulted on debt repayment (X_{11})

PDF (F9) 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_{12})

EDF (F10) is an abbreviation used to represent the variable name, Farmed land located in/out 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_{13})

FLI (F11) is an abbreviation used to represent the variable name, Farmed land located in /out 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_{14})

SGC (F12) 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_{15})

FSE (F13) is an abbreviation used to represent the variable name, Farmed land located in/ out 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_{16})

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

Section1: Credit risk management, the process of 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 13 (X1 to X16), the back-end's lending decision system including, the probability of default equation, the behavioral scoring model, the internal rating model, and the system of the risk-based pricing will be processed and displayed. The results showed that borrower A had a 13.86% probability of default, a credit score of 58 points, the risk rating was level 7(CCC), which passed the behavioral 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 9).

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 behavioral scoring (back-end) model. The author caps the debt service ratio (DSR) as a threshold for determining the amount of credit (the loan amount and interest expense) at 70 percent (Bank of Thailand, 2019) and determines that the maximum loan principal is 63% of the debtor's total annual income. For example, if borrower A is expected to have a total annual income of 400,000 baht, the system will show the maximum amount that borrower A can borrow is 252,000 baht (63%), plus the interest burden payable approximately 22,680 baht per year (loan interest rate is 9.00% per annum). The system will show borrower A's full-year payment amount of 274,680 baht or about 70% of the annual income or DSR is about 0.70 times. Borrower A still has money left after paying the debt for living and saving 125,320 baht or about 30% of the annual income (see Figure 9).

The back-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 households' excess debt, as well as, promoting and supporting financial discipline building for agricultural households in the rural sector of the country.

4.7 Computing the Capital Requirement for Credit Losses

After obtaining the back-end's lending decision system, the author computed the amount of the capital requirement for credit losses in the agricultural loan portfolio according to the formula as equation 1, and the optimization of the portfolio returns equation. This is from the forecast of the cumulative agricultural loan amount as of March 31, 2021, which will be approximately 1,198,050 million baht and about 1,495,461 million baht in credit risk-weighted assets. The BAAC must have at least 100,832 million baht capital requirements for credit losses in this agricultural loan portfolio (see Table 8 and Appendix).

Table 8: The Amount of the Capital Requirement for Credit Losses

Items	Results
[1] Exposure at default (EAD)	1,198,050 million baht
[2] Risk-weighted assets $= K(\%) \times 12.5 \times EAD$ ($K\% = 9.99\%$)	1,495,461 million baht
[3] Capital requirement in agricultural loan portfolio	100,832 million baht

Source: Author's calculations.

5. Conclusions and Policy Inferences

The main objective of this study is to develop the back-end's lending decision system of the Bank for Agriculture and Agricultural Cooperatives, a major lender in Thailand's agricultural sector. The study highlights the application of the system to help the Bank to manage credit risk and affordability risk in agricultural lending activities. The Logit model and the Artificial Neural Network (ANN) model have been developed in this study to reflect risk factors/variables of the Thai agricultural sector to identify the probability of default in each obligor. The development of the models and the model validations complied to be consistent with the advanced internal rating-based approach in the Basel capital accord. The results from the logit model are subsequently employed to formulate the prediction equation of the probability of default, the behavioral scoring (back-end) model, the internal rating model, and the back-end's lending decision system. The models and the systems are tested for the validity of the prediction power in discriminating the debtors and applicability of the agricultural lending activities, the statistical classification (Hold-out samples), receiver operating characteristic curve (ROC curve), and cumulative accuracy profile curve (CAP curve) at the levels of 88.11%, 83.41%, and 77.42%, respectively.

The results verify the age of farmers applying for loans, total income to total expenditure ratio, loan to collateral value ratio, savings with BAAC 5,001 to 10,000.99 baht, savings with BAAC 10,001 to 20,000.99 baht, savings with BAAC equal to or more than 20,001 baht, land mortgages, personal guarantees, debt service ratio, the number of dependents in the household, whether the borrower has ever defaulted on repayment of the debt, facing agricultural prices decrease and/or highly fluctuating, farmed land not located in an area experiences recurring drought or recurring flood with a high severity level, farmed land not located in an irrigated area, soil suitability for growing crops and, farmed land not located in an area suffering from the epidemic of disease or pest are important variables in determining of the probability of default in the farmer lending.

The working process of the back-end's lending decision system is classified into two sections including credit risk management, the process of 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 with the behavioral scoring model and internal rating model. In this study, the author caps the debt service ratio (DSR) as a threshold for determining the amount of credit (the loan amount and interest expense) at 70 percent and determines that the maximum loan principal is 63% of the debtor's total annual income.

The study has shown how back-end agricultural loan exposure is typical and can be managed on a portfolio basis which will enable the bank to set the credit approval or rejection criteria, diversify the risk in each of the portfolio shares, risk-based pricing in each borrower, determining the amount of credit, optimize the portfolio returns, and capital adequacy in the portfolio. The back-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 households' excess debt, as well as, promoting and supporting financial discipline building for agricultural households in the rural sector of the country.

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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,* 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,* 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. (2012). Notification of the Bank of Thailand No. FPG. 16 / 2555 Re: Regulation on the Calculation of Credit Risk-Weighted Assets for Commercial Banks under Internal Ratings-Based Approach (IRB). Retrieved from https://www.bot.or.th/Thai/FIPCS/Documents/FPG/2555/EngPDF/25550334.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/ConsultationPaper_Loan.aspx

Basel Committee on Banking Supervision. (2005a). Studies on the validation of internal rating system, Working Paper No.14 (Revised version). Retrieved from www.bis.org/publ/bcbs_wp14.pdf

Basel Committee on Banking Supervision. (2005b). An explanatory note on the basel II IRB risk weight Functions. Bank for International Settlement. Retrieved from https://www.bis.org/bcbs/irbriskweight.pdf

Basel Committee on Banking Supervision. (2011). Basel III: A global regulatory framework for more resilient banks and banking systems. Retrieved from https://www.bis.org/publ/bcbs189.pdf

Bennouna, G. & Tkiouat, M. (2019). Scoring in microfinance: Credit risk management tool –case of Morocco-. Procedia Computer Science, *148*, 522-531.

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.

Kammoun, A., & Triki, I. (2016). Credit scoring models for a Tunisian microfinance institution: Comparison between artificial neural network and logistic regression. *Review of Economics & Finance*, *6,* 61-78.

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.

Römer, U., & Mußhoff, O. (2017). Can agricultural credit scoring for microfinance institutions be implemented and improved by weather data? *DARE Discussion Papers 1703,* Georg-August University of Gottingen, Department of Agricultural Economics and Rural Development (DARE).

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*, 100-130.

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

Turvey, C. G., & Weersink, A. (1997). Credit risk and the demand for agricultural loans. *Canadian Journal of Agricultural Economics*, *4,* 201-217.

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.

Appendix

The model selection with Akaike Information Criterion (AIC) Technique

estat ic

Model	Obs	ll(null)	ll(model)	df	AIC
.	10800	-4069.118	-3095.317	17	6224.633

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC
.	10800	-4069.118	-3096.965	16	6225.931

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC
.	10800	-4069.118	-3100.985	15	6231.97

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC
.	10800	-4069.118	-3130.083	14	6288.166

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC
.	10800	-4069.118	-3144.449	13	6314.898

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC
.	10800	-4069.118	-3329.178	12	6682.355

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC
.	10800	-4069.118	-3332.887	11	6687.774

. estat ic

Model	Obs	ll(null)	ll(model)	df	AIC
.	10800	-4069.118	-3362.818	10	6745.636

Logistic regression			
	Number of obs	=	10800
	LR chi2(16)	=	1947.60
	Prob > chi2	=	0.0000
Log likelihood = -3095.3166	Pseudo R2	=	0.2393

status_at_~e	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
age	.0116927	.0032417	3.61	0.000	.005339	.0180464
inc	-.1456208	.0328166	-4.44	0.000	-.2099401	-.0813015
ltv	1.186348	.1927771	6.15	0.000	.8085118	1.564184
sav2	-.2467982	.142249	-1.73	0.083	-.5256012	.0320048
sav3	-.3406957	.1763818	-1.93	0.053	-.6863976	.0050062
sav4	-.5536292	.138058	-4.01	0.000	-.8242178	-.2830406
col1	1.421437	.1421243	10.00	0.000	1.142879	1.699996
col2	1.202769	.114539	10.50	0.000	.978277	1.427262
dsr	.1841072	.0301993	6.10	0.000	.1249177	.2432966
deh	.1852733	.0606074	3.06	0.002	.066485	.3040617
drh	1.908859	.0725246	26.32	0.000	1.766714	2.051005
pdf	.3588988	.1416871	2.53	0.011	.0811972	.6366004
edf	-.3641901	.0753756	-4.83	0.000	-.5119236	-.2164566
fli	.6061966	.21647	2.80	0.005	.1819231	1.03047
sgc	-.4682946	.1675039	-2.80	0.005	-.7965963	-.139993
fse	-.1960294	.1078972	-1.82	0.069	-.4075041	.0154454
_cons	-5.324594	.4075161	-13.07	0.000	-6.123311	-4.525877

. mfx

Marginal effects after logit
y = Pr(status_at_due) (predict)
= .07252763

variable	dy/dx	Std. Err.	z	P>|z|	[95%	C.I.]	X
age	.0007865	.00022	3.60	0.000	.000358	.001215	51.2822
inc	-.0097955	.00216	-4.53	0.000	-.014038	-.005553	1.88172
ltv	.0798025	.01274	6.26	0.000	.054823	.104782	.69486
sav2*	-.0151997	.00798	-1.91	0.057	-.030835	.000435	.077685
sav3*	-.0201551	.00908	-2.22	0.026	-.037957	-.002353	.053426
sav4*	-.0311878	.00637	-4.90	0.000	-.043672	-.018704	.113519
col1*	.1107715	.0124	8.93	0.000	.086462	.13508	.414537
col2*	.1049885	.01198	8.77	0.000	.081516	.128461	.268796
dsr	.0123844	.00206	6.02	0.000	.008349	.016419	.727417
deh	.0124629	.00407	3.06	0.002	.004476	.02045	2.58722
drh*	.2318568	.01308	17.73	0.000	.206221	.257493	.137593
pdf*	.0243136	.0097	2.51	0.012	.005307	.04332	.487315
edf*	-.0235845	.00467	-5.05	0.000	-.032739	-.01443	.367593
fli*	.0411757	.01487	2.77	0.006	.012037	.070315	.498704
sgc*	-.0317296	.01149	-2.76	0.006	-.054253	-.009206	.504537
fse*	-.0140211	.00831	-1.69	0.091	-.030305	.002263	.86287

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Optimization of the portfolio returns

$$= \{\{[(1-PD) \times (\text{Expected yield*} - COD) \times (EAD)] - [(PD) \times (LGD) \times (EAD)] + [(ROE - COD) \times (K\%)]\} + COD - OC\}$$

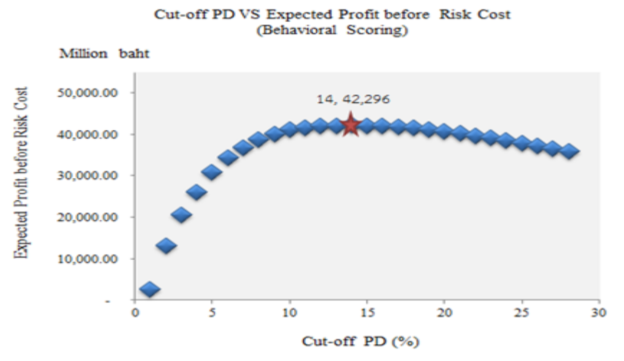
PD	=	Probability of default
Expected yield*	=	Expected yield in agricultural loan portfolio (7.50%)
COD	=	Cost of deposit (1.50%)
EAD	=	Exposure at default (1,198,050 million baht)
LGD	=	Loss of given default (35.00%)
ROE	=	Return on equity (2.96%)
K%	=	Capital requirements rate (9.99%)
OC	=	Operation cost (2.00%)

Summary statistics for specified grading structure

CR (K%)	Grading structure
9.99%	0-0.0101-0.0163-0.0245-0.0412-0.0657-0.0939-0.1401-0.2008-0.2668
RWA	1,495,461

Cutoff PD	0.14
Exposure at Default (EAD)	1,198,050
Minimum Capital Requirement(K)	100,832
Average PD	5.10%
LGD	35.00%
ROE	2.96%
COF	1.50%
Expected yield* – COF	6.00%
COF (1.50%) (Amount)	17,971
Operating Cost: OC (2.00%) (Amount)	23,961
Expected Profit before Risk cost	42,296
Yield (%)	7.03%
Yield (Amount)	84,228
Risk Cost (%)	1.79%
Risk Cost (Amount)	21,400
Expected profit after Risk Cost (%)	1.74%
Expected profit after Risk Cost (Amount)	20,896

PD	Profit before Risk Cost
1.00	2,697.12
2.00	13,165.25
3.00	20,730.81
4.00	26,256.92
5.00	30,878.44
6.00	34,439.90
7.00	36,950.55
8.00	38,970.74
9.00	40,303.41
10.00	41,206.06
11.00	41,726.95
12.00	42,075.06
13.00	42,250.59
14.00	42,296.14
15.00	42,233.31
16.00	42,103.43
17.00	41,893.26
18.00	41,642.09
19.00	41,223.98
20.00	40,831.15
21.00	40,324.27
22.00	39,855.88
23.00	39,273.24
24.00	38,678.71
25.00	38,034.00
26.00	37,385.24
27.00	36,693.90
28.00	35,963.38
29.00	35,324.75
30.00	34,686.60
Max	42,296.14



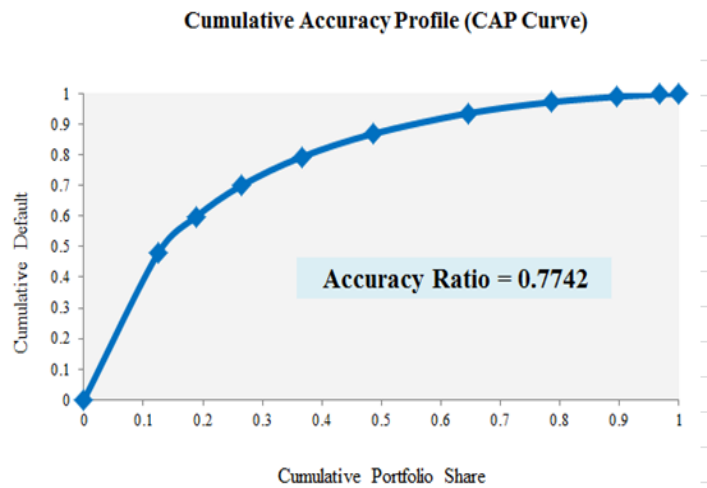
Internal rating model

Grading structure and calculations										
Lower PD bound	Grade	Portfolio Share	Grade PD	Grade CR	Exp. Share of defaults	Area under CAP	%Default	CumPortshare	Cum%Default	Credit Score
-	1	0.0319	0.0073	0.0419	0.0019	0.0319	0.0019	1.0000	1.0000	86 to 100
0.0101	2	0.0725	0.0135	0.0546	0.0078	0.0721	0.0078	0.9681	0.9981	81 to 85
0.0163	3	0.1093	0.0201	0.0632	0.0175	0.1072	0.0175	0.8956	0.9903	77 to 80
0.0245	4	0.1404	0.0326	0.0745	0.0366	0.1340	0.0366	0.7863	0.9728	71 to 76
0.0412	5	0.1596	0.0526	0.0887	0.0672	0.1441	0.0672	0.6459	0.9362	67 to 70
0.0657	6	0.1207	0.0786	0.1047	0.0759	0.1003	0.0759	0.4863	0.8690	63 to 66
0.0939	7	0.1015	0.1152	0.1228	0.0935	0.0757	0.0935	0.3656	0.7931	58 to 62
0.1401	8	0.0761	0.1685	0.1404	0.1026	0.0493	0.1026	0.2641	0.6996	54 to 57
0.2008	9	0.0630	0.2319	0.1516	0.1168	0.0339	0.1168	0.1880	0.5971	50 to 53
0.2669	10	0.1250	0.4805	0.1415	0.4803	0.0901	0.4803	0.1250	0.4803	0 to 49
		1.0000								

Average PD	0.12504	
CR (K%)	**AR**	**Grading structure**
9.99%	**0.7742**	**0-0.0101-0.0163-0**
Used		

Random Search Optimization Results

CR	AR	Grading structure
0.090683441	0.604207	0-0.0015-0.0099-0.0
0.090747217	0.593012	0-0.0016-0.0031-0.0
0.090749724	0.596886	0-0.0007-0.0013-0.0
0.090765057	0.616680	0-0.0012-0.0036-0.0107-0.0328-0.0595-0.0826-0.1174-0.2434-0.405



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

Risk premium (XX)

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

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

$$\beta_{unlevered} = 0.28$$

$$marketrisk = 7.83\%$$

$$riskfreerate = 1.06\%$$

....

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

The direction of agricultural price (trend analysis)

Volatility in agricultural price	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) decreases and/or highly fluctuating which is code = 1 for the borrower who is facing with agricultural price decreases and/ or highly fluctuating (in this study, 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.

The determination of the dummy variable of the farmed land located in/out an area experiencing recurring drought or recurring flood with a high severity level can be written as shown below.

Experiences recurring flood

Experiences recurring drought

Severity	High level	Medium level	Low level
High level	0	0	0
Medium level	0	1	1
Low level	0	1	1

The farmed land located in/out of an area experiencing recurring drought or recurring flood with a high severity level which is code = 1 for the borrower who has farmed land not located in an area experiencing recurring drought or recurring flood with a high severity level and code = 0 for the borrower who has farmed land located in an area experiencing recurring drought or recurring flood with a high severity level. The severity levels of recurring drought or recurring flood are measured by the Land Development Department, Thailand.