Lending Decision Model for Agricultural Sector in Thailand

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EXTENDED ABSTRACT

Loan contracts performance determines the profitability and stability of the financial institutions, and screening the loan applications is a key process in minimizing credit risk. Before making any credit decisions, credit analysis (the assessment of the financial history and financial backgrounds of the borrowers) should be completed as part of the screening process. Good borrowers with low credit risk would be granted a loan, while a high risk borrower would be denied. A good credit risk assessment assists financial institutions on loan pricing, determining the amount of credit, credit risk management, reduction of default risk and increase in debt repayment.

The purpose of this paper is to develop a lending decision model (credit scoring) for the agricultural sector in Thailand. The data used in this study is from Bank of Agriculture and Agricultural Cooperative (BAAC), a major lender in Thailand agricultural sector. During the period of 2001 to 2003 a total of 16,560 agricultural loans were made available. The logistic regression and artificial neural networks (ANN) were used to identify critical factors in lending decision process in the agricultural sector and to predict the borrower's creditworthiness (probability of a good loan).

The results of the logistic regression verify the importance of total farm asset value, capital turnover ratio (efficiency), and the length of bank-borrower relationship (duration) as important factors in determining the creditworthiness of the borrowers. The results show that a higher value of farm assets implies a higher creditworthiness, which lead to a higher probability of a good loan. However, the negative signs found on both capital turnover ratio and the length of bank-borrower relationship (duration), which contradict with the hypothesized signs, suggest that the borrower with a longer relationship with the bank and a higher gross income to total assets has a higher probability to default on debt repayment.

The overall prediction accuracy of the logistic lending decision models is above 85% on both in-sample and out-of-sample forecast, and is higher than the probabilistic neural network (PNN) model on out-of-sample forecast. However, the neural network models can detect Type I error (accepting a bad loan as a good loan) more accurately than the logistic models. The costs of classifying a bad loan as a good loan (Type I error) are more significant than the costs of misclassifying a good loan as a bad loan (Type II error). The overall prediction accuracy is not completely reliable since it ignores the relative cost difference between Type I and Type II errors. Thus, when the expected loss of misclassification is computed and compared, the results indicate that the misclassification cost of the PNN model is the best model with the lowest misclassification costs. In summary, the empirical results found in this study support the use of PNN model in classifying and screening agricultural loan applications in Thailand.

1. INTRODUCTION

The performance of loan contracts determines the profitability and stability of financial institutions, and screening the loan applications is a key process in minimizing credit risk. Before making any credit decisions, credit analysis (the assessment of the financial history and financial backgrounds of the borrowers) should be completed as part of the screening process. Good borrowers with low credit risk would be granted a loan, while a high risk borrower would be denied. A good credit risk assessment assists financial institutions on loan pricing, determining amount of credit, credit risk management, reduction of default risk and increase in debt repayment.

Credit analysis is the primary method in reducing the credit risk on a loan request. This includes determining the financial strength of the borrowers, estimating the probability of default, and reducing the risk of nonpayment to an acceptable level (Plata and Nartea, 1998). In general, credit evaluations are based on the loan officer's subjective assessment (or judgmental assessment technique). However, this technique seems to be inefficient, inconsistent and non-uniform (Crook, 1996; Glassman and Wilkins, 1997).

A major evolution in the credit evaluation practices has been the risk assessment (or credit scoring) of borrowers based on sophisticated statistical analysis of the borrower's financial data and other information related to creditworthiness. Credit scoring models have the potential in reducing the variability of credit decisions and adding efficiencies to credit risk assessment process. Furthermore, the models not only assist financial institutions on loan approval, but also on loan pricing, loan monitoring, determining amount of credit, credit risk management, and assessment of loan portfolio risks (Turvey and Brown, 1990).

Credit scoring is broadly applied in consumer lending, especially in credit cards, and it is becoming more commonly used in mortgage lending. Credit scoring has not been widely used for business lending because business loans substantially differ across borrowers and make it more difficult to construct an accurate scoring method. However, the complexity and flexibility of statistical models and computing technology have made such scoring method possible. Several financial institutions are currently using credit scoring models to assess loan applications, making these models a cost effective credit management tool (Mester, 1997).

The overall idea of credit scoring model is quite straightforward. A large historical loan sample, consisting of similar loan types, is divided into two categories, good loans and bad loans. Based on statistical probabilities, the combination of borrowers' characteristics differentiating "good" from "bad" loans is used to generate a score (or probability) serving as an estimate of the riskiness of each new loan (Crook, 1996) when lenders decide whether to make loans or not.

Several statistical methods have been used to estimate credit scoring models, such as discriminant analysis (Dunn and Frey, 1976; Turvey, 1991; Altman et al., 1994), linear probability models (Turvey, 1991; Barney et al., 1999), logit models (Turvey and Brown, 1990; Turvey, 1991; Altman et al., 1994; Turvey and Weersink, 1997; Lee and Jung, 1999) and probit models (Lufburrow et al., 1984; Turvey, 1991). The logit model has dominated the literature and has been widely used because of its simplicity. Recently, there has been an increase in using the artificial neural networks (ANN) to make a lending decision process (see Altman et al., 1994; Lee and Jung, 1999; Barney et al., 1999; Wu and Wang, 2000).

The primary purpose of this paper is to develop a credit scoring model (lending decision) for the agricultural sector in Thailand. In this paper, a special class of artificial neural networks called "probabilistic neural network (PNN)" is employed to estimate the credit scoring model together with the logit model and a widely used artificial neural networks called "multi-layer feed-forward neural network (MLFN)". The paper also empirically compares the predictive power among the three different estimation methods.

The paper is organized as follows. The key variables used in lending decision models are described in section 2. Section 3 discusses the data and methodology. Section 4 and 5 present the empirical results and conclusion, respectively.

2. FACTORS USED IN LENDING DECISION MODELS

The major factors used in lending decision models include borrowers' liquidity (i.e. current ratio, quick ratio, and net working capital), profitability (i.e. return on assets and return on equity), solvency (i.e. leverage ratio and debt-to-equity ratio), efficiency (i.e. gross ratio and capital turnover ratio) and repayment capacity (i.e. interest expense ratio, interest coverage ratio, and debt repayment ratio).

The variables can be easily calculated from a borrower's financial statements. Thus, lenders always use these financial criteria in combination with other factors, such as the borrower's personal attributes, enterprise type, region, and etc., in the credit decision model. Since it has been found that the relationship between bank (lender) and borrower has an influence on the availability of credit and the cost of credit (Petersen and Rajan, 1994; Berger and Udell, 1995), the lender-borrower relationship should have an influence on the lending decision. Therefore, the relationship indicators will be included in the lending decision model to further enhance the analysis.

3. DATA AND METHODOLOGY

The data in this study are obtained from the Bank of Agriculture and Agricultural Cooperative (BAAC), Thailand. BAAC is considered a major lender in Thailand agricultural sector with a high significant share in the agricultural financing market (more than 55 percent of the total loan, in 2003). The credit files were retrieved from the "Credit BPR" (Credit Business Process Reengineering) database in June 2004. During the period of 2001 to 2003, a total of 16,560 agricultural loans were made available. The data set comprises of 14,383 good loans (GL) and 2,177 bad (or default) loans (BL). All loans are under the normal loan scheme (excluding the government loans for specific projects). Unfortunately, information about borrowers' current assets, current liabilities, and debt repayment were not available on the database. As a result, the borrower's liquidity and repayment capacity can not be estimated.

3.1 Logistic model

We assume that the probability of a good loan follows the logistic distribution and is a function of the borrower characteristics, credit risk proxies, relationship indicators, and dummy variables. The lending decision model for the agricultural sector in Thailand can be written as follows:

Lending Decision = f(Borrower characteristics, Credit risk proxies, Relationship indicators, Dummy variables) (1)

where Lending Decision = 1 if there is no default on the loan (good loan) and 0 if there is a default (bad loan); Borrower characteristics include: Assets (+) = total assets value, Age (+) = age of borrower, Education (+) = 0 if the qualification of the borrower is primary school or lower, and 1 otherwise; Credit risk proxies include: Collateral (+) = value of collateral, Return on assets (+) = net return / total assets, Leverage ratio (-) = total liabilities / total assets, Capital turnover ratio (+) = gross income / total assets; Relationship indicators include: Borrowing from others (-) = 1 if the borrower has an outstanding debt with other financial sources and 0 if the borrower has a loan from BAAC only, Duration (+) = the number of years of banking relationship between the bank and the borrower; Dummy variables include: Province (Province 1 to 17), Farm type (Horticulture, Orchard/Vegetable, Livestock/ Aquaculture, and others), Loan type (Cash credit loan, Short-term loan, Medium-term loan, and Long-term loan), Loan size (Small loan, Medium loan, and Large loan), and Lending year (2001 to 2003) dummies.

Priori hypotheses are indicated by (+) or (-) in the above specification. For example, assets, age, education, collateral, return on assets, capital turnover ratio, and duration are positively related to the probability of a good loan. In contrast, leverage ratio and borrowing from others are negatively related to the probability of a good loan.

Dummy variables such as province, farm type, loan type, loan size, and lending year dummies are included to describe the systematic effects relating to the type of borrower and the type of contract, and are hypothesized to influence the borrower's credit risk and the probability of loan repayment. For example, borrowers who have cash crop (horticulture) as the major production would require a smaller amount of credit than the other farm types, and the contract term for the cash crop production is short-term contract. Thus, this group of borrowers would have a higher probability to obtain a loan than the others. This is because a short-term loan is less risky than a medium-term or a long-term loan, and the lending risk is relatively low. In contrast, if the major production of the borrowers is either orchard or livestock, which may need a large and long-term loan, they would be expected to have a higher credit risk and would have a higher probability to default.

3.2 MLFN 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 2).

$$U_j = F_j\left(\sum W_{ij} X_i\right) \quad (2)$$

where F_j is a transfer function which can take many different functional forms.

The multi-layer feed-forward neural network (MLFN) computational units are grouped into 3 main layers – input layer, hidden layer(s), and output layer. If the network has only one hidden layer, and one output (Z) in the output layer, the output of the network can be algebraically as shown in equation 3 (see Figure 1).

$$Z = F\left(\sum_{j=1}^{J} W_j^{(2)} . F_j\left(\sum_{i=1}^{i} W_{ij}^{(1)} X_i\right)\right) \quad (3)$$

where Z is the output of the network, F is the transfer function in the output node, $W_{ij}^{(1)}$ and $W_j^{(2)}$ are connection weights from input layer (node i) to hidden layer (node j) and from hidden layer (node j) to output layer, respectively (West et al, 1997).

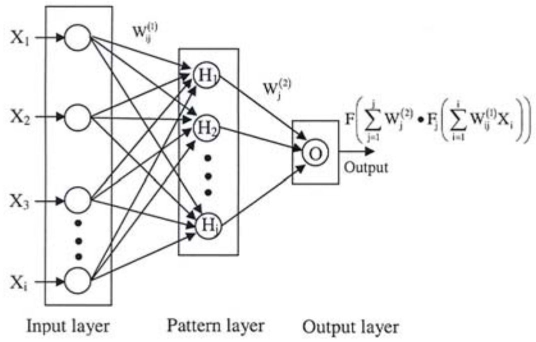

Figure 1: MLFN structure with one hidden layer

The calculation of the neural network weights is known as training process. The process starts by randomly initializing connection weights and introduces 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 and 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.

3.3 PNN model

The PNN model proposed by Specht (1990) is basically a classification network. Its general structure consists of 4 layers - an input layer, a pattern layer, a summation layer, and an output layer (see Figure 2). The PNN model is conceptually based on the Bayesian classifier statistical principle. According to the Bayesian classification theorem, X will be classified into class A, if the inequality in equation 4 holds:

$$h_A c_A f_A(X) > h_B c_B f_B(X) \quad (4)$$

where X is the input vector to be classified, h_A and h_B are prior probabilities for class A and B, c_A and c_B are costs of misclassification for class A and B, $f_A(X)$ and $f_B(X)$ are probabilities of X given the density function of class A and B, respectively (Albanis and Batchelor, 1999)

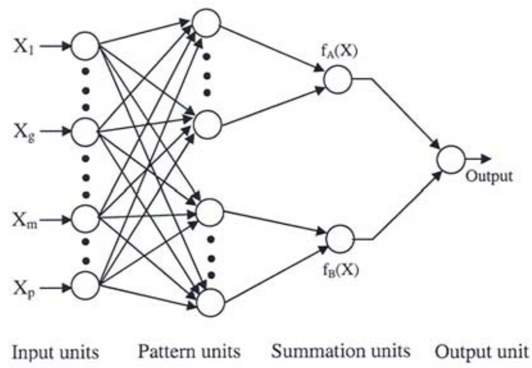

Figure 2: The PNN architecture

To determine the class, the probability density function is estimated by a non-parametric estimation method developed by Parzen (1962) and extended afterwards by Cacoulos (1966). The joint probability density function for a set of p variables can be expressed as:

$$f_A(X) = \frac{1}{(2\pi)^{p/2}\sigma^p n_A} \sum_{j=1}^{n_A} e^{\frac{-(X-Y_{Aj})'(X-Y_{Aj})}{2\sigma^2}} \quad (5)$$

where p is the number of variables in the input vector X, n_A is the number of training samples which belongs to class A, Y_{Aj} is the j^{th} training sample in class A and σ is a smoothing parameter.

To construct the artificial neural network models, NeuroShell2 package was used, while the logistic model was estimated by the maximum likelihood method used in the LIMDEP software. To examine the predictive power of the models, the out-of-sample forecasting technique was applied. The sample was randomly divided into two sub-samples: an estimation sample and a forecasting sample. The estimation sample and the forecast sample contain 80 and 20 percent of the total observations, respectively. All models were re-estimated by using only the estimation samples and the out-of-sample forecasting were conducted over the forecasting samples. To evaluate the forecast accuracy of the model, the classification rates and the expected misclassification loss of each model were computed and compared.

4. EMPIRICAL RESULTS AND DISCUSSION

The estimated results of the logistic lending decision models are shown in Table 1. In general, model I and model II (without and with duration, respectively) fit the data quite well. The chi-square statistics fail to accept the null hypothesis that the parameter estimates for the models are equal to zero. Both models correctly predict the lending decision 87.19 and 85.30 percent, respectively. However, model I and II have produced 93.98 and 90.70 percent of Type I error (wrongly reject H_0 or accepting a bad loan as a good loan), respectively. Although model I has a higher overall percentage correct, model II can predict the bad loan better than model I (see Table 2).

Table 1: Logistic models

Variables	Coefficients	
	Model I	Model II
Log (Assets)	0.3197*	0.3719*
Age	-0.0009	-0.0016
Education	0.1686*	0.1769
Log(Collateral)	-0.0339	-0.0689
Return on assets	0.0383	0.005
Leverage ratio	-0.9629*	-0.8326
Capital turnover ratio	-0.0634*	-0.0596*
Borrowing from others	0.1081	0.0329
Duration		-0.1915*
Province, Farm type, Loan type, Loan size, Lending year dummies	yes	yes
Constant	yes	yes
No. of observation	16,560	3,965[1/]
LR statistic (χ^2)	1,446.85*	398.97*
Degree of freedom	34	35
Log likelihood	-5,720.45	-1,489.09
McFadden R^2	0.1123	0.1182

Note: 1/ Due to recent implementation of Credit BPR database, there is no available information to estimate the duration for all samples.
* represent 5% significant level.

Table 2: In-sample prediction classification

	Model I			Model II		
	BL	GL	Overall	BL	GL	Overall
LOGIT						
% Correct	6.02	99.48	87.19	9.30	98.90	85.30
% Incorrect	93.98	0.52	12.81	90.70	1.10	14.70
MLFN						
% Correct	14.47	98.89	87.80	8.47	99.29	85.50
% Incorrect	85.53	1.11	12.20	91.53	0.71	14.50
PNN						
% Correct	87.51	98.92	97.42	88.37	97.98	96.52
% Incorrect	12.49	1.08	2.58	11.63	2.02	3.48

In model I, the estimated coefficients of assets, education, leverage ratio, and capital turnover ratio are found to be significant at 5 percent level (see Table 1). As expected, the probability of a good loan increases with increased total assets value and education. On the other hand, the probability does not decrease with only increased leverage ratio (solvency), but also with capital turnover ratio (efficiency). This contradictory result with the hypothesis on capital turnover ratio illustrates that the borrower who has a higher gross income to total assets has a higher probability to default on debt repayment. In general, it implies that when the borrower earned more, they prefer to spend their money on other activities or purposes rather than repaying their debt.

When the duration is included in the model (model II), the estimated results show that assets and capital turnover ratio are significant at 5 percent level, while education and leverage ratio are insignificant. Furthermore, the estimated coefficient on capital turnover ratio is negative, which is consistent with the estimated result in model I. However, the relationship between duration and lending decision contradicts the postulated hypothesis. The estimated coefficient is negative and significant at 5 percent level. Thus, it suggests that the borrower who has a longer relationship with the bank has a higher probability to default on debt repayment and the bank should cautiously deal with this group of borrowers.

The estimated coefficients of province, farm type, loan type, loan size, and lending year dummy variables are not presented here, but the estimated results show that horticultural production, short-term loan, and small borrowing have a lower credit risk than others. Therefore, the loan repayment probability of the borrower who is in this group is relatively higher than the other groups. Furthermore, the estimated coefficients of the provinces show that the credit risk differs according to the residential province.

Since the ANN model is usually nonlinear and their training process is always regarded as a black-box, it is very difficult to write out the algebraic relationship between a dependent variable and an independent variable, unlike traditional econometric models such as logistic models. Furthermore, the learned outputs, connection weights or coefficients, can not be interpreted and tested. Therefore, only the classification results of the models are presented in Table 2.

The classification results in Table 2 show that the PNN models (both model I and II) exhibit a superior ability to learn and memorize the patterns corresponding to the borrower's default risk. The overall percentage correct of PNN for both models I and II are 97.42 and 96.52 percent, respectively.

Thus, the PNN models offer better classification results than the logistic models, whereas the MLFN models yield almost the same level of accuracy as the logistic models. However, the results do not provide strong and conclusive evidence of superiority in term of prediction capability among the models, as shown by the in-sample results.

The classification rates on the out-of-sample prediction for the logistic, MLFN, and PNN models are presented in Table 3. The results show that the prediction accuracy of the three models is similar to each other in model I, but in model II, the logistic and MLFN models are slightly better than the PNN model. However, a closer examination indicates that the logistic model can predict well only on the good loan. The Type I error rate shows that the logistic model is unable to predict the bad loan, as it has more than 90 percent of Type I error. In contrast, the Type I error of the PNN model is smaller than the logistic and MLFN models, especially when the length of bank-borrower relationship (duration) is introduced into the lending decision model (model II).

Table 3: Out-of-sample prediction classification

	Model I			Model II		
	BL	GL	Overall	BL	GL	Overall
LOGIT						
% Correct	4.05	99.41	86.62	5.13	99.11	85.25
% Incorrect	95.95	0.59	13.38	94.87	0.89	14.75
MLFN						
% Correct	10.59	99.13	87.26	4.27	99.26	85.25
% Incorrect	89.41	0.87	12.74	95.73	0.74	14.75
PNN						
% Correct	11.04	99.23	87.41	40.17	91.57	83.98
% Incorrect	88.96	0.77	12.59	59.83	8.43	16.02

It is generally accepted that the misclassification cost of Type I error is more costly than Type II error. For Type I error, the lender may lose not only the principal but also the interest on the principal. On the other hand, for Type II error, the lender loses only the interest and expected profit from the loan. Therefore, the overall percentage correct may be misleading in this case, as it is calculated under the assumption that the misclassification costs of both types of errors are identical. Thus, to interpret the model performance in a meaningful way, the misclassification costs of both types of errors must be differentiated and taken into the account. The expected loss of misclassification on out-of-sample forecasting must be estimated. The lending decision model that offers the smallest expected loss is considered as the most preferable model.

According to Koh (1992), the expected misclassification loss (EL) of the model can be calculated as follows:

$$EL = (PB)(PI)(CI) + (PG)(PII)(CII) \qquad (6)$$

where PB and PG = prior probability of being bad and good loans, PI and PII = conditional probability of Type I and Type II errors, CI and CII = misclassification costs of Type I and Type II errors, respectively.

As the PB and PG are unobserved, they are estimated by dividing the total number of bad and good loans by the total number of samples, respectively. Since the consequences of incorrect classification are intangible and immeasurable (such as loss of existing and potential clients, loss of depositor's trustworthy, etc), it is not easy to quantify CI and CII. Therefore, the relative misclassification costs of Type I and Type II errors are used. The relative cost ratios are assumed to vary accordingly from 1:1, 2:1, 3:1, 4:1 and 5:1, with the relatively higher misclassification cost on Type I error where a bad loan is classified as a good loan.

Table 4 summarizes the models expected misclassification loss on out-of-sample forecasting at the different relative cost ratios. The PNN model without duration (model I) has the lowest expected loss when the relative cost ratio is 1:1. Although the PNN model with duration (model II) has lower overall percentage correct than the logistic and MLFN models (model II) on out-of-sample forecasting, when the cost ratio is 2:1 or higher, the PNN model becomes the top performer since it has the lowest expected loss. Therefore, the PNN model can be considered as the superior model in predicting the lending decision.

Table 4: Expected loss (out-of-sample prediction)

CI : CII	1:1	2:1	3:1	4:1	5:1
LOGIT					
Model I	0.1313	0.2574	0.3835	0.5097	0.6358
Model II	0.1324	0.2571	0.3819	0.5066	0.6313
MLFN					
Model I	0.1251	0.2427	0.3602	0.4778	0.5953
Model II	0.1323	0.2581	0.3840	0.5098	0.6356
PNN					
Model I	***0.1236***	0.2406	0.3575	0.4745	0.5914
Model II	0.1519	***0.2305***	***0.3092***	***0.3878***	***0.4665***

Note: Bold and italic indicate the minimum expected loss.

5. CONCLUSION

The estimated results of the logistic regression show the significance of total farm assets value, capital turnover ratio (efficiency) and the length of bank-borrower relationship (duration) in determining the creditworthiness of borrowers.

The results show that a higher asset values implies a higher creditworthiness and a higher probability of a good loan. However, the negative signs in both capital turnover ratio and duration, which contradict the hypothesized signs, suggest that the borrower who has a longer relationship with the bank and who has a higher gross income to total assets has a higher probability to default on debt repayment.

The overall prediction accuracy of the logistic lending decision models is above 85% on both in-sample and out-of-sample forecast, and is higher than the PNN model II on out-of-sample forecast. In most cases, the logistic models performances are quite similar to the MLFN model. Therefore, in terms of precision, the ANN model might not necessarily predict the lending decision better than the logistic regression. However, most of the ANN models can detect Type I error much better than the logistic regression models. Since it is generally accepted that the costs of classifying a bad loan as a good loan (Type I error) are significantly greater than the costs of misclassifying a good loan as a bad loan (Type II error), the overall prediction accuracy is not completely reliable, since it ignores the relative cost difference between Type I and Type II errors. Thus, when the expected loss of misclassification are computed and compared, the results indicate that the misclassification cost of the PNN model is the best model with the lowest misclassification costs. In summary, the empirical results in this study support the use of the PNN model in classifying and screening agricultural loan applications in Thailand.

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