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TECHNICAL SUMMARY

PUBLICATION

An Analysis of Credit Scoring for Agricultural Loans in Thailand

By Visit Limsombunchai, Christopher Gan and Minsoo Lee, in the American Journal of Applied Sciences, New York: Science Publications, 2005.

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Introduction

The following is a summary of *An Analysis of Credit Scoring for Agricultural Loans in Thailand* written by Visit Limsombunchai, Christopher Gan and Minsoo Lee, published by Science Publications in 2005.

Loan performance significantly affects the profitability and stability of financial institutions. Therefore, careful screening of loan applications is key to minimizing risk. A credit analysis, or the assessment of a potential borrower's financial history, should be completed as part of the screening process. This includes evaluating the financial strength of a borrower and estimating their probability of default. Good borrowers with low credit risk should be granted loans, while high credit risk borrowers should be denied loans. Traditionally, credit evaluations are based on a loan officer's subjective assessment, leading to inefficient and inconsistent lending decisions.

Increasingly, credit scoring models are used to reduce variability in credit decisions and add efficiencies to the credit risk assessment process. The models not only assist financial institutions on loan approval, but also on loan pricing, loan monitoring, determining the amount of credit, credit risk management and assessment of loan portfolio risks.

The purpose of this study is to determine the optimal credit-scoring model for agricultural loans in Thailand. Three credit scoring models are tested to predict a borrower's creditworthiness and default risk. For this study, the models include a logistic model and two special classes of Artificial Neural Networks (ANN): a Probabilistic Neural Network (PNN) model and a Multi-Layer Feed-Forward Neural Network (MLFN) model (see Box 1).

BOX 1

Logistic Model: Because of its simplicity, the logistic model has been traditionally used to estimate credit scoring. Logistic regression models the relationship between a dependent variable (e.g. credit worthiness) and one or more independent variables (e.g. borrower characteristics and credit risk proxies). Logistic regression estimates the probability of an event occurring, such as the probability of a borrower being creditworthy.

ANN Models: While computers are great at solving algorithmic and math problems, not all data can be translated or defined with a mathematical algorithm. Recently, there has been an increase in the use of the Artificial Neural Networks (ANN) in the lending decision process. ANNs essentially model the way human brain processes information.

- **PNN:** The model structure consists of 3 layers: an input layer, a hidden layer and the output layer.

- **MLFN:** The model structure consists of 4 layers: an input layer, a pattern layer (the first hidden layer), a summation layer (the second hidden layer) and an output layer.

Source: Box compiled using information from Gan, C., Limsombunchai, V., Clemes, M. and Weng, A. (2005).

Credit Scoring Models

In general, credit scoring models use a large sample of historical loans divided into two categories: good loans and bad loans. Based on statistical probabilities, the combinations of borrower characteristics differentiating "good" from "bad" loans are used to generate a credit score. The credit score serves as an estimate of risk for each new loan.

Lending institutions use data from a borrower's financial statements in a lending decision model, including:

- **Profitability** — return on assets and return on equity

- **Solvency** — leverage ratio and debt-to-equity ratio

- **Efficiency** — gross ratio and capital turnover ratio

- **Liquidity** — current ratio, quick ratio and net working capital

- **Repayment Capacity** — interest expense ratio, interest coverage ratio and debt repayment ratio

In addition to these variables, the **borrower's personal attributes, enterprise type, region, and the lender-borrower relationship** are also included in the credit scoring models.

The data for the study was obtained from the Bank of Agriculture and Agricultural Cooperative (BAAC), which is a major lender in the agricultural sector of Thailand.

The data set includes 14,383 good loans and 2,177 bad (or default) loans.

BOX 2

Type I Error: Also known as a "false positive." A Type I error incorrectly rejects a true null hypothesis. In lending, a Type I error occurs when a borrower is incorrectly deemed creditworthy, when in fact, the institution should not give the borrower a loan.

Type II Error: Also known as a "false negative." A Type II error is the failure to reject a false null hypothesis. In lending, a Type II error occurs when a financial institution denies a loan to a creditworthy borrower.

The misclassification cost of a Type I error is more costly for lending institutions than a Type II error. For a Type I error, the lender will likely lose not only the principal but also the interest on the principal. On the other hand, for a Type II error, the lender loses only the interest and expected profit from the loan.

Model Results

A logistic model, a PNN model and a MLFN model were generated and evaluated for loan performance accuracy.

The results of the logistic regression confirm the importance of total asset value, capital turnover ratio (efficiency), and the duration of bank-borrower relationship as important factors in determining the creditworthiness of a borrower. The results also show that a higher value of assets implies a higher creditworthiness and a higher probability of a good loan. Conversely, the logistic model results suggest that the borrower with a long term relationship with a bank and a higher gross income to total assets has a higher probability for loan default.

The overall prediction accuracy of the PNN model is superior to both the logistic model and the MLFN model, with a 97.42 % accuracy rate. Both ANN models predict Type I errors (bad loans) better than the logistic model, however, the PNN model is far superior to both other models. In summary, the empirical results in this study support the use of the PNN model in classifying and screening agricultural loan applications in Thailand.

	% Of time a loan is correctly predicted (i.e. good loan vs. bad loan)	% of time a Type I error is made
Logistic Model	87.19	93.98
MLFN Model	87.8	85.53
PNN Model	**97.42**	**12.49**

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