AN OVERVIEW OF CREDIT ASSESSMENT MODELS

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AN OVERVIEW OF CREDIT ASSESSMENT MODELS

David J. Leatham *

This paper provides an overview of the purpose, application and development of credit assessment models. Specifically, the paper focuses on credit scoring schemes that have been developed for agriculture and serves as an introduction to the following paper by Gustafson. In addition, a selected bibliography of credit assessment models is presented.

Definition and Purpose of Credit Assessment Models

Lending requires loan portfolio risk management. Bank policies can be instituted to attract borrowers with good character and strong loan repayment ability. In addition, lenders can strive to increase loan volume. However, lenders face a tradeoff between increased volume and increased risk. Greater volume increases expected profit but the increased risk requires greater loan servicing costs and increases the likelihood of losses from delinquent and default loans. Loan portfolio risk management is important in agriculture especially in view of the current financial stress. Recent declines in commodity prices, and land prices coupled with high interest rates has lead to an increased frequency of farm failures and defaulted loans. These events have lead to an increase in the riskiness of farm loan portfolios held by many agricultural lenders.

Credit assessment models can be an important tool to manage loan portfolio risk. They can be thought of statistical or experience based management tools for forecasting the outcome of a particular loan application or an existing loan. Credit Assessment models can be grouped into three categories:

- Credit scoring models that are associated with the decision whether or not to grant credit.

- Loan review models that monitor the risk levels of existing loans.

- Bankruptcy-prediction models that can be used for preliminary credit screening or loan review but are not credit scoring or loan review models per se.

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As early as 1941, Durrand recognized the importance of credit assessment models but also issued a warning. He said:

A credit formula is ordinarily regarded as a supplement to, rather than a substitute for, judgement and experience. It may enable a loan officer to appraise an ordinary applicant fairly quickly and easily; and in large operations, it may be of service in standardizing procedure, thus enabling most of the routine work of investigation to be handled by rather inexperienced and relatively low-salaried personnel. A credit formula may not be satisfactory, however, in the investigation of extraordinary cases (p. 84).

Similarly, Batt and Fowkes said:

Credit scores, used in the hands of experienced lending officers, can provide a more accurate and consistent control of lending than is possible either by using scores alone or by relying entirely on experience and judgement (p. 194).

Applications of Credit Assessment Models

Credit assessment models can be applied in a number of ways (Alcott; and Batt and Fowkes). Applications of most significance to agricultural lenders include:

(A) Screening Loan Applicants.
   - Screen loan applications into categories, weak, strong and those that require special attention.
   - Avoid incurring additional costs of credit checks for unacceptable loan applications.

(B) Loan Pricing.
   - Relate price to credit risks
   - Provide a more uniform loan pricing criteria. This is particularly important for the Farm Credit System and large banks.

(C) Monitor Adherence to Internal Policies.

(D) Portfolio Management.
   - Flag existing loans that need special attention.
   - Monitor the overall level and distribution of risk in a loan portfolio.
   - Forecast loan losses -- A credit score is essentially a forecast of what will happen to various classes of loans.
Monitor the trend in the soundness of farm loan portfolio.

Provide preferential reduction of bad debts during time of credit restriction -- The volume of weak loans can be reduced by increasing the cutoff score.

Detect changes in creditworthiness of applicants -- Helps monitor competition and changes in the farm economy.

Determine the optimum credit limits -- A credit scoring model used over time may be used to determine the most appropriate credit limits for various classes of loan applicants.

Measurement of the effect of promotional and advertising policies -- The effects of advertisement programs on the quality of loan applicants can be assessed by monitoring the average credit scores of all applicants over a period of time.

(E) Educational Purposes

Teaching young loan officers important credit factors and their relationship to consider when making a loan

Comparison of a trainee's credit decisions and credit scores can be used as a control measure.

A trainee could use credit scores to compare with his credit decisions which should lead to some constructive self-examination.

Credit scoring could improve on-the-job training. Trainees could be given the applications with high credit scores. This would provide training to new loan officers without increasing the risk of a high default rate.

Identification of where additional training is needed to improve credit analysis.

Used as a means of communicating to bank officers unfamiliar with agriculture the status of the farm loan portfolio.

Used as a counseling tool with borrowers

(F) Allocating Farm Accounts

Credit applications with high scores and weak scores could be given to a less experienced loan officer. Credit applications with medium scores could be given to a more experienced officer.
Credit scores could be used to separate loans that require a minimum of servicing and those that need careful attention. The loans could be assigned to the officers according to their experience and capacity.

A credit officer's decisions could be compared to credit scores and loan outcomes.

(G) Data Collection and Reporting

Helps determine the information that should be collected and reported. Information collection is costly and only the relevant information should be collected. Also, computers can print out reams of data, too much to assimilate, thus only the relevant information should be reported.

Development of Credit Assessment Models

There are six basic steps that can be used to describe the development process of a credit assessment model (Alcott; Eilon and Fowkes; and Lufburrow, Barry and Dixon). These steps are (1) choose the credit classifications, (2) collect information of past good and bad borrowers, (3) identify discriminating factors, (4) determine the weights given the discriminating factors in assigning credit scores and correspond the credit scores to the loan classification scheme, (5) validate the model, and (6) institutionalize the model.

Choose Credit Classification

This step is just to establish a point of reference. The classification scheme chosen is usually tied to a bank's existing loan classification scheme. The following are classification schemes that have been used in the past:

- Good, fair, and poor;
- Low, moderate, high, and excessive;
- Vulnerable or loss, problem, and acceptable;
- Problem, and acceptable;
- Prime, base, and premium;
- I, II, III, IV, and V; and
- Successful and failure.
Collect information of past good and bad borrowers

A reservoir of past lending experience is essential to developing a credible credit assessment model. Theory may give some indication which factors may be important when classifying loans, however, assigning weights to these discriminating factors requires experience. This reservoir may come from credit experts or the collection of relevant information on past good and bad borrowers. Information should include financial, production, and subjective information. Production information has frequently been omitted in credit scoring schemes. However, Leatham has shown that the inclusion of production information can improve the predictability of problem loans. Subjective information includes such things as character, management ability, marital status, age, and loan repayment record.

Identify Discriminating Factors

Credit risk can be traced to a host of factors. These factors can be grouped into broad categories such as liquidity, solvency and collateral position, profitability, economic efficiency, repayment capacity, borrower's characteristic, and borrower's management ability. I will not attempt to provide an exhaustive list of factors that can be included in each group. However, the following provides a few to give a flavor of the factors that have been used in previous studies:

(A) Liquidity.
   - Current ratio -- Current assets-to-current liabilities
   - Working capital

(B) Solvency and Collateral Position
   - Debt-to-Asset ratio (and other combinations of this ratio)
   - Collateral-to-total line of credit

(C) Profitability
   - Rate of return-to-assets
   - Rate of return-to-equity

(D) Economic Efficiency
   - Turnover ratio -- Gross revenue-to-total farm productive assets
   - Gross ratio -- Total operating expense-to-total operating revenues
(E) Repayment Capacity
   o Projected net cash flow plus projected inventory-to-total line of credit
   o Debt exposure -- Value of farm production-to-total debt
   o Coverage ratio -- Income from farming operations before interest-to-total interest charges
   o Repayment history -- Average of loan principal repaid-to-principal due over the past three years

(F) Borrower's Character (This is a subjective factor)

(G) Borrower's Management Ability
   o Quality of production records
   o Milk per cow
   o Yield per acre

(H) Borrower Stability
   o Marital status
   o Tenure arrangement -- Percent of land owned
   o Age
   o Insurance

Weight Discriminating Factors and Correspond to Loan Classifications

Concurrent with the identification of discriminating factors, credit scores are determined by assigning weights to credit factors. Then the correspondence between credit scores and credit classifications are determined. These weights can be assigned based on experience or statistical procedures. A credit expert can indicate which credit factors he uses and how much weight he gives to each one when making credit decisions (Kohls; Tongate). An alternative would be to have a group of individuals that have experience making credit decisions assign weights to selected credit factors. These weights could be averaged or revised until a group consensus is reached (Alcott).

Several statistical techniques have been used to assign weights to credit factors based on historical data. Multiple discriminate analysis (MDA) has been the most widely used (Johnson and Hagan; Dunn and Frey; Hardy and Weed; Bauer and Jordan). Meyer and Pifer used a linear probability model (LPM) to predict bank failures. The LPM has the disadvantage that there is no basis for
tests of significance. Recently, qualitative choice models (LOGIT and PROBIT) have been used (Lufburrow, Barry and Dixon; Park: Leatham). The development of qualitative choice models has out dated the use of MDA models. They can provide the same information as MDA plus additional probability information. For further comparisons of these statistical techniques see Collins and Green.

Validate the Model

A credit scoring scheme has to be validated before it can be implemented with confidence. In the initial development of a credit scoring model, the model can be used to predict the outcome of out-of-sample historical loan observations. A high percentage of successful classifications of loans would be the first step in validation. The second step in validation would be to score credit applicants for a period of time even though the scores were not used in credit decisions. These scores could be compared with the credit manager’s decisions. If there are differences, additional evaluation is needed to determine if the credit manager’s decisions are out of line or if the credit scoring scheme needs to be revised. After the credit scoring scheme is implemented, continual validation is needed to assure that it is correctly classifying loans.

Institutionalize the Model

Successfully implementing a credit scoring scheme in a large lending institution can be a tremendous undertaking. First, a uniform system of collection of data has to be implemented and maintained. Without uniform data, credit scores would not be consistent. Second, an agreement by bank management, credit managers and loan officers as to a viable credit scoring scheme must be reached. There can be different opinions but in the end, a general acceptance must be reached or the discord could undermine the effectiveness of the program. Third, bank personnel involved in the use and evaluation of the credit scoring scheme must be well trained in its purpose and how it can be used as an aid in credit decisions. Finally, continual updating of the credit scoring program is required as economic conditions change and additional information is obtained.

Credit Scoring in Agriculture

Credit scoring models are not new to agriculture. Reinsel used discriminate analysis to determine the contribution of several factors in distinguishing between successful and unsuccessful loan applicants. The work by Reinsel, Bauer and Jordan, Johnson, and Evans are summarized by Dunn and Frey along with a credit scoring model they developed to analyze PCA loan applications. Since that time additional studies have been published (Allcott; Hardy and Weed; Kohl: Kohl and Forbes; Lufburrow, Barry and Dixon; Tongate; and Weed and Hardy). Several of these studies are summarized in Table 1.
Conclusions

A number of credit scoring models have been developed for agriculture. However, few have been implemented by financial institutions. The usefulness of credit scoring models has been substantiated. However, better data needs to be collected, and existing models need further validation and fine-tuning. Finally, further research, as discussed in the following paper by Gustafson, is needed to improve credit scoring models.
Table 1 -- Description of Credit Assessment Models in Agriculture

<table>
<thead>
<tr>
<th>Item</th>
<th>Johnson &amp; Hagan</th>
<th>Dunn &amp; Frey</th>
<th>Hardy &amp; Weed</th>
<th>Lufburrow, Barry &amp; Dixon</th>
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<td>A. Classification:</td>
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<td>3. Vulnerable or loss, problem, and acceptable</td>
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<td>4. Problem and acceptable.</td>
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<td>6. I-V.</td>
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<td>7. Poor Risk or Good Risk</td>
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<td>B. Performance Criteria</td>
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C. Data

1. Commercial Banks

2. FICB and PCAs  X  X  X  X

D. Estimate of Weights

1. Based on experience

2. Discriminate Analysis  X  X  X

3. Linear Probability Models

4. Qualitative Choice Models
   a. Logit
   b. Probit  X

5. Number of Observations  272  99  220  241

E. Validate

Percent Successfully Classified (%)  62  75  81  71

F. Institutionalized
   St. Louis
   FICB  --  --  --
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<thead>
<tr>
<th>Item</th>
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<th>Tongate</th>
<th>St. Louis FICB</th>
<th>Kohl</th>
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REFERENCES


Leatham, David J. "Statistical Relationship Between Financial and Production Variables, and Dairy Failure." Presented at the Semiannual Meeting between the Farm Credit Banks of Texas and Agricultural Finance Workgroup. Texas A&M University, May 1987.


