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A Review of Agricultural Credit Assessment Research & an Annotated Bibliography

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A Review of Agricultural Credit Assessment Research and an Annotated Bibliography

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Introduction

Credit assessment (scoring) models are experience-based or statistical-based management tools used by lenders to forecast the outcome of existing loans and potential loans (loan applications). A credit score is essentially a forecast of what will happen to various classes of loans. Credit assessment models can be grouped into three categories: (1) credit-scoring models that are associated with the decision whether or not to grant credit, (2) loan review models that monitor the risk levels of existing loans, (3) 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.

As early as 1941, Durand recognized the importance of credit assessment models but also issued a warning:

> 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).

Similary, Batt and Fowkes (1972) said the following:

> 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).

Credit assessment in agriculture has historically been made by personal examination of individual credit applications and past performance records combined with personal knowledge of an applicant and his or her operation (Dunn and Frey 1976). However, recent declines in commodity prices and land prices coupled with high interest rates have led to an increased frequency of farm failures and defaulted loans, thus increasing the need for more sophisticated and objective credit assessment techniques.

Credit assessment models can be an important tool to manage loan risk. For example, the models can be used to identify loan applications with a high likelihood of default, to identify existing loans that need to be monitored closely, to price loans according to the level of risk, and to standardize loan criteria. The standardization of loan criteria will become especially important as secondary markets for agricultural loans develop. It is important to recognize, however, that credit assessment models are only an input into the overall credit environment.

This report provides a review of credit assessment and scoring models reported in the agricultural economics literature. First, the steps in developing credit assessment models and a discussion of the strengths and weaknesses of the commonly used credit assessment methods are presented. Second, applications of credit assessment models are reported. Third, past credit assessment studies in agriculture are reviewed. Fourth, areas of further research are identified, and finally, concluding remarks are made.

Development of Credit Assessment Models

Six basic steps can be used to describe the development process of a credit assessment model (Alcott 1985; Batt and Fowkes 1972; and Lufburrow et al. 1984): (1) choose the credit classifications, (2) collect information of past good and bad borrowers, (3) identify credit (discriminating) factors, (4) determine the weights given the discriminating factor 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

Choosing the credit classification establishes a point of reference. The classification scheme chosen is typically tied to a bank's existing loan classification scheme. The following are classification schemes that have been used in the past: (1) vulnerable or loss problem, and acceptable, (2) problem and acceptable, (3) prime, base, and premium, (4) poor risk and good risk, (5) good and bad, and (6) successful and unsuccessful (Table 1).

Collect Information on Past Good and Bad Borrowers

A reservoir of past lending experience is essential to developing a credible credit assessment model. Theoretical approaches may identify some factors that may be important when classifying loans; however, assigning weights to these discriminating factors requires experience. This reservoir may originate from credit experts or from the collection of relevant information on past borrowers. Data should include financial, production, market/external conditions, and subjective information. Production information, however, has frequently been omitted in credit-scoring schemes. Subjective information includes considerations of applicant's character, management ability, marital status, age, and loan repayment record.

Identify Discriminating Factors

Credit risk can be traced to many factors. These factors can be grouped into broad categories such as liquidity, solvency and collateral position, profitability, economic efficiency, repayment capacity, and borrower characteristics, including borrower's management ability. Table 1 shows the credit factors within each group that have been used in past studies.

Weigh Credit Factors and Correspond to Loan Classification

Concurrent with identifying credit factors, credit scores are determined by assigning weights to credit factors. The correspondence between credit scores and credit classifications is then determined. These weights can be assigned according to experience or statistical procedures. Useful statistical methods are discriminate analysis and qualitative choice models like linear probability, Logit, and Probit models. The procedures for estimating credit scores in past studies are reported in Table 1.

Experience

The choice and weights attached to credit factors can be based on the experience of the developer or the consensus of opinion of loan officers and executive officers of the lending institution.[1] Weights are established by eliciting the participating individuals' ranking of each credit factor. The average rank for each credit factor is used as the weight. The credit score for each loan is the credit factor value times the weight summed over all credit factors. Weighted scores are assigned to credit classifications. An individual application is classified by computing a total weighted score and identifying the category in which it falls.

The experience-based credit assessment models are validated by comparing the classifications of existing loans with the loan classifications based on credit scores. The weights are modified until the model classifies loans accurately. The credit scores are also compared with actual loan outcomes over time.

The strength of this procedure is that it incorporates the past experiences of the developers, thus increasing its chances of applicability and success. Furthermore, the users of the model can be included in the development process, thus increasing credibility and acceptance. The weakness of this procedure is that it is highly subjective, and little statistical theory is employed in its generation. The statistical significance of the credit score cannot be determined.

Discriminate Analysis

The basic objective of linear discriminate analysis, which was introduced by Fisher in 1936 and first used on credit data (used cars) in 1941 by Durand, is to form a linear combination of the discriminating variables with associated weights that will require the groups of data (acceptable and unacceptable borrowers) to be as statistically different as possible.

In its general form, a discriminate function can be expressed as

(1) $Y = \gamma_1 X_1 + \gamma_2 X_2 + ... + \gamma_k X_k$

where

Y = discriminate value,

X_i = quantifiable and observable characteristics ($i = 1, ..., k$),

γ_i = discriminate coefficients, ($i = 1, ..., k$).

The objective is to find a set of γ's so that for the two populations under consideration (good and bad loans), the calculated Y's are as far apart as possible. The γ's are then estimated using a least squares technique. Briefly, the procedure entails the following:[2]

(i) With matrix notation and the subscript G denoting good loans and B denoting bad or problem loans, the sums of squares and cross products for the two groups are

(2) $X'_G X_G$ and $X'_B X_B$

where

X_G is of dimension n_g x k,
X_B is of dimension n_b x k,
n_g is the sample size of good loans,
n_b is the sample size of bad loans, and
k is the number of variables.

To get the total sums of squares and the cross products, the two matrices are added:

(3) $X'_G X_G + X'_B X_B = X'X$

(ii) Next, generate a k x 1 vector M of differences between the means of the explanatory variables for the two groups:

(4) $$\begin{aligned} \overline{X}_{1g} - \overline{X}_{1b} &= X_1^* \\ &\vdots \\ \overline{X}_{kg} - \overline{X}_{kb} &= X_k^*. \end{aligned}$$

(iii) Then compute the γ's:

(5) $\gamma = (X'X)^{-1}M$

where γ is a k x 1 vector of γ_i (i = 1, ..., k).

By substituting these estimates into the general function, we get

(6) $Y = \hat{\gamma}_1 X_1 + \hat{\gamma}_2 X_2 + ... + \hat{\gamma}_k X_k$.

The average discriminate value of a good loan is given by

(7) $\overline{Y}_g = \hat{\gamma}_1 \overline{X}_{1g} + ... + \hat{\gamma}_k \overline{X}_{kg}$.

Similarly the average discriminate value of a bad loan is given by

(8) $\overline{Y}_b = \hat{\gamma}_1 \overline{X}_{1b} + ... + \hat{\gamma}_k \overline{X}_{kb}$.

In both cases, $\overline{X}_i$'s are mean values. A Z statistic can then be computed for $\overline{Y}_g$ and $\overline{Y}_b$ to determine a cutoff point between good and bad loans. Let the cutoff point be an arbitrary value Y_c. For good loans

(9) $Z_g = (Y_c - \overline{Y}_g)/Sd_g$

where:

Z_g = the Z statistic for good loans, and

Sd_g = the standard deviation of $\overline{Y}_g$.

Similarly, for bad loans,

(10) $Z_b = (Y_c - \overline{Y}_b)/Sd_b$

where:

Z_b = the Z statistic for bad loans, and
Sd_b = the standard deviation of $\overline{Y}_b$.

Let us assume that the probability of rejecting a good loan and the probability of accepting a bad loan are of equal significance. By setting $Z_g = -Z_b$, Y_c can be solved for as[3]

(11) $Y_c = (Sd_g \overline{Y}_b + Sd_b Y_g)/(Sd_g + Sd_b)$.

Using past records about good and bad loans, a financial institution can then estimate the γ coefficients with equation 5. Similarly, a cutoff value that discriminates between the good and bad loans can be computed using equation 11. To evaluate loan applications, relevant variables (i.e., those that correspond to the variables that were used during estimation) are used to generate the discriminant value for this particular borrower according to equation 6. This value is to be compared with the cutoff value that was computed using past records as discussed previously. If the borrower's computed discriminant value is less than the cutoff value, the loan will probably be a bad one, and if it falls above the cutoff value, then that loan will probably be a good one.

In the aforementioned formulation, the error of turning down a good loan and the error of accepting a bad loan are assumed to be of equal significance, which may not be true. This assumption is a simplification that assists in computing a cutoff value. Such an assumption, however, may not be legitimate because it may be less costly to reject a good loan, thinking it is bad, than to accept a bad loan, thinking it is good. Many costs may be involved in trying to recover a bad loan. The sample means $\overline{Y}_g$ and $\overline{Y}_b$ are assumed to be the true mean discriminant values. However, these values may be data specific. Leatham's (1987) comparison of explanatory variables used to develop agricultural credit-scoring models seems to suggest the same conclusion. This is a strong assumption, given that they are merely sample means. Results generated using these values should be used with caution.

Linear programming can also be used to solve discriminant-type problems. The logic followed in constructing a linear-programming model to solve the credit-scoring problem is similar to that used for discriminant analysis. Weights must be derived for the measurement variables that will separate scores computed for the two groups as much as possible. This is accomplished by first establishing a critical value or cutoff point as the boundary between the two groups of data. Next, through a system of constraints (each constraint representing an observation), weights for the variables are established that will maximize the deviation of an individual score from the critical cutoff value.[4]

Hardy and Adrian (1985) used a linear-programming formulation. They, however, noted that the lack of statistical measures creates a problem because options such as using the F-value to determine which variables should enter the scoring equation are not available. The selection of variables to enter is controlled by the intuitive logic of the analyst and varified through testing. Even though coefficients from linear-programming models cannot be tested statistically, the overall measure of a "good" model, i.e., the portion of observations correctly classified, is still present. Another problem with credit-scoring models generated with linear programming is that they do not have an intercept term; thus coefficients assigned to each variable must account for all variation in classification. Because of this, algebraic signs of the coefficients in the function will not always be as expected.

A major advantage noted by Hardy and Adrian (1985) is that the user does not need a high level of statistical knowledge to interpret and analyze the results. In addition, restrictive statistical assumptions are not required. Another advantage of the linear-programming approach is that the weights or penalties associated with incorrect classification can be changed. Conservative lending programs would attach relatively higher costs for misclassifying problem accounts during formulation of the linear program by judiciously attaching higher weights.

Qualitative Choice Models

In many situations, the dependent variable in a regression equation is not continuous but represents a discrete choice, such as purchasing or not purchasing a car, voting yes or no on a referendum, or participating or not participating in the labor force. Models involving dependent variables of this kind are called qualitative response models. The observed occurrence of a given choice is considered to be an indicator of an underlying, unobservable continuous variable, which is characterized by the existence of a threshold (or thresholds); crossing a threshold means switching from one alternative to another. As Kmenta (1986) notes, the complexity of estimation and testing of models with qualitive dependent variables increases with the number of alternative choices. The simplest models are those with only two alternatives involving a binary or dichotomous dependent variable. In the context of credit scoring, one wishes to find a relationship between a set of attributes describing a loan applicant and the probability that the loan will turn out to be a good or a bad loan. The dependent variable is given the value of 1 (when the loan is good) or 0 (when the loan is bad). The estimation procedure may be taken one of three ways: as a linear probability model, as a Probit model, or as a Logit model. Each of these estimation procedures is discussed as follows.

Linear Probability Model

The regression form of the model is

(12) $Y_i = \alpha + \beta X_i + \epsilon_i$

where

Y_i = 1 if loan is classified as good and 0 if loan is classified as bad;

α = constant;

β = change in probability of Y_i occuring, when X_i changes by 1 unit;

X_i = value of the attribute, i = 1, ..., n;

ϵ_i = error term.

The regression equation, which can be estimated using ordinary least squares, describes the probability that an individual's loan will turn out to be good (i.e., the individual will not default). When X_i is fixed, the probability distribution of ϵ_i must be equivalent to the (binomial) probability distribution of Y_i. Classical statistical tests cannot be applied to the estimated parameters because the tests depend on the normality of the errors.

The variance of the error term is given by

(13) $E(\epsilon_i^2) = \sigma^2_i = E(Y_i)[1 - E(Y_i)]$,

which suggests that the error term is heteroscedastic (i.e., the variance of the error term is not constant for all observations). Observations for which P_i (which is equal to $E(Y_i)$) is close to 0 or close to 1 will have relatively low variances, whereas observations with P_i closer to 0.5 will have higher variances. The presence of heteroscedasticity results in a loss of efficiency but does not in itself result in either biased or inconsistent parameter estimates (Pindyck and Rubinfeld 1981). Using weighted least squares to correct for heteroscedasticity does not guarantee that the estimated probabilities will fall between 0 and 1. Adjusting for such an anomaly by dropping out the responsible variables or by arbitrarily setting these probabilities that fall outside the 0 to 1 interval to numbers like 0.01 for a lower limit and 0.99 for an upper limit may result in inefficient estimates, particularly for small samples.

As previously noted, because the linear-probability model involves the interpretation of predicted values of Y_i as probabilities, a problem arises when a predicted value of Y_i lies outside the 0 to 1 interval. Constraining the model to this interval might yield unbiased estimates, but the predictions obtained from the estimation process are clearly biased.

To overcome the 0 to 1 interval problem, a cumulative probability function is used to transform the values of the attribute X_i, which may range in value over the entire real line, to a probability that ranges in value from 0 to 1. The resulting probability distribution may be presented as

(14) $P_i = F(\alpha + \beta X_i) = F(Z_i)$

where F is a cumulative probability function and X is stochastic. The two most commonly used cumulative probability functions are the normal and the logistic functions.

The cumultaive normal probability function is used in the Probit model, whereas the cumulative logistic probability function is used in the Logit model.

Probit Model

The Probit probability model is associated with the cumulative normal probability function. The standardized cumulative normal function is written as

(15) $P_i = F(Z_i) = \int_{-\infty}^{Z_i} (2\pi)^{-1/2} \, EXP\,(-S^{-2/2})\, ds \quad -\infty \langle Z_i \langle$

where s is a random variable that is normally distributed with mean zero and unit variance.

EXP represents the base of natural logarithms, which is approximately equal to 2.718. The variable P_i will lie in the 0 to 1 interval. P_i represents the probability that a loan will turn out to be good. To obtain an estimate of the index Z_i, the inverse of the aforementioned cumulative normal function is taken as

(16) $Z_i = F^{-1}(P_i) = \alpha + \beta X_i$.

Another similar probabilistic model is the Logit model discussed next.

Logit Model

The Logit model is based on the cumulative logistic probability function and is specified as

(17) $P_i = F(Z_i) = \mathrm{EXP}\,(Z_i) / \left\{1 + \mathrm{EXP}(Z_i)\right\}$,
$-\infty < Z_i < \infty$.

The logistic and Probit formulations are similar, the only difference being that the Probit function is similar in form to the cumulative normal function. The Logit Model, however, is easier to use computationally and is often substituted for the Probit model.

For grouped data, a Logit model can be estimated using OLS as the following formulation:

(18) $Z_i = \log\,(\hat{P}_i/(1 - \hat{P}_i)) = X_i^T\beta$

where $\hat{P}_i$ is the fraction of good loans in each class or grouping. However, for both Probit and Logit, the estimator of choice is a maximum likelihood estimation because this procedure does not require that the data be grouped and thus allows for each observation within the sample to be associated with a distinct probability. For large samples, all parameter estimates are consistent and efficient asymptotically. In addition, all the parameter estimates are known to be (asymptotically) normal so that the analog of the regression t test can be applied. In this case, the ratio of the estimated coefficient to its estimated standard error follows a normal distribution. To use a maximum-likelihood estimation, a log-likelihood function is formulated as

(19) $\log L = \sum_{i=1}^{n_1} \log P_i + \sum_{i=1}^{n_2} \log\,(1-P_i)$

where n_1 refers to the number of observations when $Y_i = 1$, and n_2 refers to the number of observations when $Y_i = 0$. Furthermore,

(20) $P_i = 1/\left\{1 + \mathrm{EXP}\,(-X^T\beta)\right\}$ and

(21) $1\text{-}P_i = 1/\left\{1 + \mathrm{EXP}\,(X^T\beta)\right\}$.

To obtain the slope estimators $\hat{\beta}$, the log-likelihood function is differentiated with respect to β, the result is set at zero, and the parameters are solved for. To test for the significance of all or a subset of the coefficients in the Logit or Probit model when maximum likelihood is used, a test using chi-square distribution replaces the usual F test.

Typically, if the estimated probability is greater than 0.5, then the first alternative is selected (Amemiya 1981); that is, the loan will be good. On the other hand, if the estimated probability is less than 0.5, the second alternative is selected; that is, the loan will be defaulted. With the current easy accessibility to computer software, qualitative choice models are easy to estimate.

Comparison of Discriminant and Qualitative Choice Models

As noted earlier, a discriminant function helps classify a loan as good or bad according to borrower characteristics. The Probit model, which uses a cumulative normal distribution function, and the Logit model, which used a logistic function, can also classify loans using a qualitative dependent variable.

There are other limitations of discriminate analysis. Amemiya (1981) concedes that the literature on discriminate analysis is typically more concerned with the art of discrimination or classification than with the estimation of the parameters that characterize the right-hand side of the discriminate function. Thus, it is not discernible how statistically significant these variables really are. On the other hand, the major interest of the analysis of qualitative models lies in estimation. Another distinction between a discriminate analysis model and a qualitative choice model is the fact that the former model specifies a joint distribution of Y_i's and X_i's. Amemiya (1981) further notes that in the discriminate analysis model, the statement that the loan will turn out to be good logically precedes the determination of X. Therefore it is more natural to specify the conditional distribution of X given Y. This assumption is formally stated as

(22) $X_i \mid Y_i = 1 \sim N(\mu_1, \Sigma_1)$

$X_i \mid Y_i = 0 \sim N(\mu_2, \Sigma_2)$

where $Y_i = 1$ refers to the fact that a loan will be good and $Y_i = 0$ refers to the fact that the loan will be bad or unacceptable. The means of the two populations are given by μ_1 and μ_2, whereas the variances are given by Σ_1 and Σ_2. During estimation, Σ_1 and Σ_2 are equated. That is, it is assumed that two populations of multivariate normal random variables exist where the variables of the two populations have different means but a common variance-covariance matrix.

First, the distribution of some of the credit factors used are not normal (Collins and Green, 1982), and second, the variances of acceptable (good) and nonacceptable (bad) loan applications may differ considerably (i.e., $\Sigma_1 \neq \Sigma_2$). This may then create inefficiency in the statistical estimates. Amemiya (1981) notes that if normality is not assumed, the discriminate analysis estimator loses its consistency in general, whereas the Logit maximum-likelihood estimator (one of the qualitative analysis techniques previously discussed) retains its consistency. Thus, one would expect the Logit maximum-likelihood estimator to be more robust. Amemiya concludes, however, that normal discriminate analysis (i.e., discriminate analysis that assumes the joint normal distribution of X_1 and Y_i) seems to be more robust against non-normality than one would intuitively expect. He points out, though, that this robustness may be conditioned to binary independent variables that characterized the work he reviewed.

In addition to being able to classify loans, therefore, qualitative models render themselves to statistical tests of significance, which makes them the most preferred models of choice.

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 loans. An outcome of a high percentage of successful classifications of loans is the first step in validation. The second step in validation is to score credit applicants for a time even though the scores are not used in credit decisions. These scores are compared with the credit manager's decisions. If differences exist, 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 data collection must be implemented and maintained. Without uniform data, credit scores will not be consistent. Second, an agreement by bank management, credit managers, and loan officers about a viable credit-scoring scheme must be reached. Opinions may vary, 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 in 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.

Applications of Credit Assessment Models

Credit assessment models can be applied in a number of ways (Alcott 1985; Batt and Fowkes 1972; Leatham 1987). The primary application is to screen loan applications. Loan applications can be grouped into categories such as weak, strong, and those that require special attention. The applications with a high likelihood of being problem loans (high loan-servicing cost, delinquency, or default) should be rejected or priced to reflect the additional risk and servicing costs. Immediately rejecting the weak loan applications avoids incurring additional costs of credit checks for unacceptable loan applications. The applications with a medium rating can be given special attention. This may prevent rejection of loans that have an acceptable likelihood of being of good loan (low loan-servicing costs and timely payments of principal and interest).

The categorization of loan applications according to credit scores can be used to allocate farm accounts among loan officers. Credit applications with strong scores and those with 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.

Credit assessment scores can provide a basis for pricing loans. The loan price would relate to credit risks and servicing costs. Credit scores would also provide more uniform loan-pricing criteria.

Credit assessment models can be used to manage loan portfolios. First, credit scores can flag existing loans that need special attention. Second, the overall level and distribution of risk in a loan portfolio can be monitored by observing the changes in the level and distribution of credit scores. This provides a means by which lenders can monitor the trend in the soundness of their existing farm loan portfolio. It also helps monitor competition and changes in the farm economy as these changes are reflected in the creditworthiness of loan applications. Third, credit scores provide a preferential basis for reduction of bad loans during times of credit restrictions. The volume of weak loans can be reduced by adjusting the cutoff score. Fourth, credit assessment models used over time may be used to determine the most appropriate credit limits for the various classes of loan applicants. Finally, credit scores can be used to measure 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. An improvement in credit scores provides evidence that promotional policies effectively increase loan portfolio quality, and conversely.

Credit assessment models are educational tools. First, credit assessment models can be used to teach inexperienced loan officers important credit factors and the relationships to consider when making a loan. Moreover, credit scores can be used as a lending control measure by comparing a trainee's credit decision with the credit scores. This comparison can also lead to some constructive self-examination and help identify where additional training is needed to improve credit analysis. Trainees can also be given applications having favorable credit scores early in their training and thus be provided with training in making potentially good loans. Of course, as their training progresses, they can be given loans with only marginally favorable scores and unfavorable scores to round out their training. In all cases, the credit models should be used only as input to the decision process. The decisionmaker must ultimately decide whether or not to make the loan. Second, agricultural credit assessment models can be used as a means of communicating to bank officers unfamiliar with agriculture and the status of their farm loan portfolio. Finally, the credit assessment model can be used as a counseling tool, helping to explain to borrowers the credit decisions.

Credit assessment models can help determine the loan information that should be collected and reported. Information collection is costly; therefore, only the relevant information should be collected. Furthermore, computers can print out reams of data, too much to assimilate; thus, only the relevant information should be reported.

Annotated Bibliography

An annotated bibliography that represents a literature review of credit assessment (scoring) models relating specifically to agriculture is presented in the appendix. Table 1 provides a summary of this review.

The loan classification most frequently used has been problem loans or acceptable loans (Johnson and Hagan 1978; Dunn and Frey 1976; Hardy and Weed 1980; Hardy and Adrian 1985; and Dunn 1974). Other similar two-category classifications were poor risk versus good risk (Bauer and Jordan 1972; and Hardy and Patterson 1983), good versus bad loans (Morris et al. 1980), and successful versus unsuccessful (Reinsel 1963). However, a four-category classification was proposed by Kohl (1987), and a five-category classification by Alcott (1985) (Table 1).

A number of credit factors have been used in estimating credit-scoring models. However, almost every study has used the ratio of total debt to total assets (Table 1) and has found it significant in credit scoring. About half the studies found the ratio of current assets to current liabilities to be a good predictor of loan quality. Several measures of farm profitability, such as the return on investment (Alcott 1985), have been suggested as an important credit factor, but there has been little agreement on the most suitable measure. Qualitative variables like marital status (Bauer and Jordan 1972) and meanagement ability (Kohl 1987 and Reinsel 1963) are beginning to be incorporated in credit assessment models, but so far, few studies have made use of them.

More than 90% of the studies conducted used data from Production Credit Associations and Farmers Home Administrations because of the extensive detail of the data that they carry (Bauer and Jordan 1972). Only two studies used data from the Federal Land Bank (Hardy and Adrian 1985 and Hardy and Patterson 1983), whereas Alcott's (1985) paper is based upon her experience at Oneida National Bank, New York, and Tongate's (1984) paper is based upon his experience at the Federal Intermediate Credit Bank of Louisville, Kentucky. The term *simulation* in Table 1 refers to credit-scoring propositions that are based on hypothetical data.

Discriminate analysis was the approach most frequently used (Johnson and Hagan 1978; Dunn and Frey 1976; Hardy and Weed 1980; Bauer and Jordan 1972; Hardy and Patterson 1983; and Daniel 1974). Hardy and Adrian (1985) used a linear-programming form of discriminate analysis and reported little difference in performance from the "mainstream" discriminate model. Qualitative choice models have not yet received widespread use. However, both Park (1986) and Lufburrow et al. (1984) have used Probit.

The number of observations used in the studies ranged from 99 (Dunn and Frey 1976 and Dunn 1974) to 2200 (Hardy and Patterson 1983) (Table 1). The percentage of observations successfully classified after model estimation have ranged from a low of 62 (Johnston and Hagan 1983) to a high of

85 (Bauer and Jordan 1972). To our knowledge, only two credit-scoring models were institutionalized: St. Louis FICB (Johnson and Hagan 1978) and Oneida National Bank, New York (Alcott 1985).

Areas of Further Research

Gustafson (1987) observed that agricultural lenders make only limited use of formal credit-scoring models because they believe that such models quickly become outdated, are difficult to reestimate, lack general robustness, and have less than 100% accuracy. He argues that more educational programs need to be developed to help lenders implement methods of credit scoring.

In addition to more educational programs, a need exists for more research that improves the usefulness of credit-scoring models for lender decisionmaking. Gustafson suggests five areas of needed research. First, existing models can be validated. Second, models can be fine-tuned. This calls for developing more adequate measures of loan quality such as production variables and qualitative variables including character, management ability, and financial goals. Third, procedures for incorporating the loan portfolio effects in the credit decision should be developed. The correlation of a new loan with the existing loan portfolio will affect systematic risk and the level of loan portfolio risk. Finally, loan dynamics should be considered. A loan may be profitable over several years but may incur losses in the short run. The trade-off between short-run losses and long-run profitable customers should be considered in the credit-granting decision. In addition to the areas of research suggested by Gustafson, procedures need to be investigated that incorporate general economic conditions and specific industry/commodity outlook and cycles into the credit assessment models. This is especially important for term loans.

Credit assessment models can also be used as input into other credit decision models. First, more work is needed in developing bootstrapping models that filter loan officers' credit decisions. Others have reported superior performance by models of the decisionmaker over performance of the decisionmaker himself or herself (Dawes and Corrigan 1974). Credit-scoring models can serve as the basis for developing and testing bootstrapping models. Second, with the prospect of secondary markets being developed for agricultural loans, effective loan standardization is needed. An important aspect of loan standardization is the identification of loans that exceed a minimum credit quality. Credit assessment models can be used to help identify credit factors that are good predictors of credit quality and the critical values of each credit factor. Finally, in recent years, much activity has been directed toward developing expert systems for financial analysis. A major role of an expert system is to evaluate the financial condition of a firm, which can be measured by a set of financial criteria and the weight given to those criteria. Credit-scoring models can be used to define the relative importance of different financial factors for analysis and to test these criteria in the lending and borrowing activity. A need exists to link more carefully the current work in expert systems and the credit-scoring models.

Conclusions

A number of credit-scoring models have been developed for agriculture. Credit assessment (scoring) models can be used as a tool to help bank management (1) screen loan applications, (2) allocate loan accounts among loan officers according to qualifications, (3) price loans equitably, (4) manage loan portfolios, (5) educate bank personnel and farm customers, and (6) determine the loan information that should be collected and reported. However, even with the strong arguments for the development and use of credit assessment models, only a few have been implemented by financial institutions. Perhaps better educational programs are needed to substantiate the usefulness of credit assessment models. Better data also needs to be collected, and existing models need further validation and fine-tuning. Finally, further research is needed to identify credit factors and appropriate credit factor weights that maximize the likelihood of correctly predicting the outcome of potential and existing loans.

Footnotes

[1]Credit scoring by experience refers to a collection of nonstatistical methods of loan rating; development is largely based upon the developers' own past experience. No common procedure of assigning weights to credit factors exists. Alcott (1985), for example, suggested conducting an opinion poll among the account officers about their perception of the importance of each credit factor. Weights were then assigned to each factor according to its perceived importance.

[2]This development follows Bauer and Jordan (1972).

[3]The negative sign in the equality $Z_g = -Z_b$ is just a mathematical relation to account for the fact that Z_g and Z_b fall on opposite sides of their respective distributions.

[4]A linear-programming problem can be expressed as follows:

$$\text{Maximize} \quad \sum_{i=1}^{n} \alpha_i D_i^+ - \sum_{i=1}^{n} \beta_i D_i^-$$

$$\text{Subject to} \quad \sum_{j=1}^{m} W_j V_{ji} - D_i^+ + D_i^- \geq C_i$$

j = number of variables for each acceptable borrower i,

$$\sum_{j=1}^{m} W_j V_{ji} + D_i^+ - D_i^- \leq C_i$$

for each unacceptable borrower i, and

$$\sum_{i=1}^{n} D_i^+ \leq \sum_{i=1}^{n} C_i$$

for V_1, V_2 being unrestricted in sign; $D_i^+, D_i^- \geq 0$ where

α_i, β_i = constants associated with deviational variables,

D_i^+ = positive deviational variable;

D_i^- = negative ("shortfall") deviational variable;

W_j = constant associated with jth borrower characteristic;

V_{ji} = jth borrower characteristic associated with ith borrower;

C_i = cutoff value for the ith borrower.

The objective function attempts to maximize the summed deviations from the established cutoff score. The weights assigned to deviational variables, α_i and β_i, are arbitrary. Hardy and Adrian (1985) note, however, that β_j values should always be greater than α_j values to indicate the penalty for not satisfying a constraint and to prevent the system from being unbounded. They further note that although the cutoff score C is also arbitrary, it should be the same for all observations.

[5]For a more rigorous discussion, refer to Pindyck and Rubinfeld (1981, pp. 273-315).

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Appendix

Alcott, Kathleen W. "An Agricultural Loan Rating System." *The Journal of Commercial Bank Lending* 65(1985):29-38.

The author discusses the importance of establishing a loan-rating system by agricultural lenders. Such a system could help management in pricing loans, monitoring adherence to internal policies, drawing budgets, as well as forecasting loan losses and net bank yields. This system makes it easier to review loans and monitor trends within the industry or a geographical region.

She recommends that lending institutions should classify borrower accounts into different classes. In her dairy farm example, she suggests the following performance criteria: liquidity (debt structure ratio, debt/dollar sales, debt/cow, debt/income, and cashflow coverage), solvency (leverage ratio and percentage of equity), and efficiency (pounds of milk sold per cow, replacement stock ratio, feed costs per milk income, machinery and real estate investment per cow, total investment per cow, total investment per man, and capital turnover).

These ratios are then weighted according to their perceived importance.* After the scores are totaled, the borrower is placed in one of the five relevant categories. The lending institution then takes any necessary action. Alcott concludes that a rating system forces agricultural lenders to look beyond their instincts to a more objective and complete analysis of farm credits.

Refer to the section on "Experience" for information on how these weights are established.

Bauer, L. Larry, and John P. Jordan. "A Statistical Technique for Classifying Loan Applications." University of Tennessee Agricultural Experiment Station, Bul. 476(1972):1-16.

The authors sampled 43 problem loans and 41 good loans from a group of east Tennessee farmers who were borrowers at Production Credit Associations. Using stepwise regression, the authors narrowed the number of independent variables down to (1) debt-to-asset ratio, (2) farm value, (3) total liabilities, (4) marital status, (5) family expenses as a percentage of total expenses, (6) current ratio, (7) number of dependents, and (8) expected income as a percentage of the previous year's. The statistical analysis indicated, after application of discriminant techniques, that the discriminant function could, with 99% probability, discriminate between the two groups of data. The analysis further indicates that the function correctly classified 85% of the loans included in the two groups, implying that discretion and further subjective analysis should be applied when the discriminant value is near the cutoff point because there is a 15% chance in this case of misclassifying an applicant. The authors caution that this, coupled with the limitation that qualitative variables like managerial ability were not included in the model, serves as a tool to supplement but not to replace the subjective analysis of the loan officer.

Dunn, Daniel J., and Thomas L. Frey. "Discriminate Analysis of Loans for Cash-Grain Farms." *Agricultural Finance Review* 36(1976):60-66.

The goal of the study was to determine which characteristics could be used to distinguish between loans that become problems and those that remain acceptable several years after the original loan is granted. Acceptable loans are defined by the Production Credit Association (PCA) as loans that are highest in quality ranging down to and including loans that have significant credit weaknesses. "Problem" loans are defined by PCA as those that have serious credit weaknesses and need more than normal supervision, but are believed to be collectible in full. Loans classified as "vulnerable" or "loss" were not included in the study. The study concentrated on predicting successful loans from data available on the original application.

Study data were from loans made to PCA cash-grain farmers in central Illinois. These farmers obtained their first PCA loans during 1964-68 and were still members in 1971, when the study was conducted. Sixteen financial ratio characteristics and six nonratio characteristics that are potentially significant measures for classifying "acceptable" and "problem" loans were used. Multiple discriminant analysis was used to determine which groups of ratios best discriminated between loans that remain acceptable and those that become problems. Stepwise discriminant analysis was first applied to the original 22 characteristics to cut down on the number of variables to be used in the final analysis. Only four characteristics met the 95% significance level for being included in the discriminant function: (1) the ratio of total liabilities to total assets, (2) the amount of credit life on the applicant, (3) the amount of note (original PCA loan) as a proportion of net cash farm income, and (4) the number of acres owned. The joint significance level exceeded 99%. The ratio of total liabilities to total assets was by far the most important. The correlation matrix for the four characteristics showed a low level of correlation among the characteristics, reflecting the additional discriminatory information added to the function by each of the characteristics. In the test, the model correctly classified 75% of the loans. Lenders without the model correctly classified 50% of the test loans.

Dunn, Daniel J. "Evaluating Potential Loan Outcomes Based on New Loan Applications for Illinois Cash-Grain Farms." Unpublished Master's Thesis, University of Illinois at Urbana-Champaign, Urbana, Illinois, 1974.

The purpose of this study was to analyze financial and nonfinancial data from the borrower's original loan applications to see what information available at that time could be used to discriminate between potentially acceptable and unacceptable loans. The data were collected from four central Illinois PCAs: Bloomington, Champaign, Charleston, and Decatur. Sixty acceptable loans and 39 problem loans were selected randomly to be studied. Information was collected from the original loan application of new members in 1964-1968.

Sixteen financial ratio characteristics and six nonratio characteristics were used. By using multiple discriminant analysis, it was found that data coming from different years did not matter. When the data were analyzed using stepwise discriminant analysis, only two ratios were significant: (1) the ratio of total assets to total liabilities and (2) the amount of note-to-net-cash farm income. This model classified 65% of the acceptable loans and 55% of the problem loans correctly. It correctly classified 50% of all loans.

Stepwise discriminant analysis was again carried out, this time on all the 22 ratio and nonratio characteristics. Only four were found significant: (1) total liabilities-to-total assets, (2) amount of loan insurance, (3) amount of note-to-net-cash farm income, and (4) acres owned. This model classified 90% of the acceptable loans and 60% of the problem loans correctly. It correctly classified 75% of all loans. Hence, this four-variable model performed better than the original two-variable model.

Evans, Carson D. "An Analysis of Successful and Unsuccessful Farm Loans in South Dakota." Economic Research Service, U.S.D.A., Feb. 1971.

Evans reported on successful and unsuccessful farm loans in South Dakota. He concentrated on existing farm operating loans and tried to identify borrower characteristics that showed developing unsatisfactory loan situations. He studied the differences between successful and unsuccessful loans of 100 PCA members and 100 Farmers Home Administration (FmHA) borrowers. All the farmers were creditworthy at the time of their original applications between 1955 and 1964. By 1964-65, however, half of the loans were unsatisfactory in terms of repayment. The study was concerned with developments after the first loan was made but not with the correct evaluation of available data by the lender at the time of the first loan application. The loans had to be successful or unsuccessful for at least 2 years before the study date. No distinctions were made among farm types, which differed from 5,000-acre ranches to 80-acre crop farms. The data used for analysis came from original loan applications and from the last year's loan applications.

Evans used discriminant analysis to test 15 characteristics from the last year's loan applications and 23 characteristics from the first year's applications. He found that the 23 characteristics of the first year's loan applications were not significant. He, however, did find significant differences in the characteristics of the last year's loan applications.

This study was concerned mainly with the loan characteristics that determine the deterioration of a loan. The five most significant characteristics of unsuccessful PCA loans were (1) the high ratio of debt to assets owned, (2) high cost of operations, (3) poor production record, (4) high ratio of debt to net worth, and (5) the large size of the borrower's household. The five most significant characteristics of unsuccessful FmHA loans were (1) the ratio of FmHA loans to poor production record, (2) the high cost of operation, (3) the high ratio of nonreal estate debt to total debt, (4) the high ratio of non-real estate debt to value of non-real estate assets, and (5) a low ratio of net worth to total assets owned.

Hardy, E. William, and James E. Patterson. "An Objective Evaluation of Federal Land Bank Borrowers Farm Real Estate Debt, Credit Scoring Techniques, Alabama, Louisiana, Mississippi." *Highlights in Agricultural Research.* Alabama Agricultural Experiment Station, Auburn, 30(1983):3-i11.

To analyze characteristics of real estate borrowers in the Fifth Farm Credit District (Alabama, Louisiana, and Mississippi), data were collected from the Federal Land Bank of New Orleans by Alabama Agricultural Experiment Station researchers. Data provided for the analysis included more than 22,000 loans made during the 5-year period from 1974 to 1978. A 10% sample was drawn from the data for use in the statistical model.

Of all variables considered, two appeared to possess significant discriminating power to distinguish between good and bad loans. These variables were total debt divided by total assets and loan commitment divided by net worth. Approximately 71% of the loans in the sample were classified correctly. In addition, 68% of the loans in a separate test sample were classified correctly.

Hardy, E. William, and John L. Adrian. "A Linear Programming Alternative to Discriminate Analysis in Credit Scoring." *Agribusiness* 1(1985):285-282.

The purpose of the study was to present a linear-programming formulation for solving discriminant type problems. Through a system of constraints (each constraint representing an observation), weights for the variables are established that will maximize the deviation of any individual score from the discriminant critical cutoff value. A sample of 1984 loan accounts from the Federal Land Bank of New Orleans was used as the basis for the analysis. The sample included 1764 accounts that were classified as acceptable and 216 that had problems in meeting repayment obligations. Two variables were used: a ratio of total debt to total assets and a ratio of loan commitment to net worth. The linear-programming model correctly classified 82.4% of the total borrower sample. The ordinary discriminant model correctly classified 70.6% of the total borrower sample. As the weight given to misclassifying problem borrowers is increased relative to that given to acceptable loans, the portion of acceptable loans classified correctly declines and the portion of problem loans classified correctly increases. Increasing the weight associated with misclassifying problem loans would yield a more conservative credit-scoring model.

Hardy, E. William, Jr., Stanley R. Spurlock, Donnie R. Parish, and Lee A. Benoist. "An Analysis of Factors that Affect the Quality of Federal Land Bank Loans." *Southern Journal of Agricultural Economics* 19(1987):175-182.

The purpose of the research presented in this paper was to examine the agricultural real estate credit market and determine which loan, borrower, and farm business characteristics are most important in discriminating between loans that are good (borrowers are able to meet repayment obligations) and those that have deteriorated to the level of foreclosure. It was hypothesized that certain borrowers' loan and farm business characteristics would be significantly different between borrowers who are making their payments and those who had suffered foreclosure. An additional justification for the analysis was the need to determine if the most important discriminating characteristics in the current (i.e., at the time the research was done) financial market for agriculture was different from that existing in the past.

Data for the analysis were taken from the loan files of the Federal Land Bank (FLB) in the Fifth Farm Credit District, Jackson, Mississippi, in spring 1985. The data represented a sample of loans closed between January 1, 1979, and December 31, 1981, in Alabama, Louisiana, and Mississippi. Data from those years were selected because they represented relatively recent history. Furthermore, the loans were of sufficient age to provide some indication of whether the borrower would be able to meet loan payment obligations.

A stratified random sample of loan accounts was taken so that observations would lie at both extremes of the performance scale. Good loans were those that were having no problems with repayment (not classified as problem, vulnerable, or loss), and bad loans were those that had already suffered foreclosure. A total of 68 observations were classified as good, and 76 were from foreclosed accounts.

Discriminant analysis was used to estimate a credit assessment model. Four variables proved to be important in discriminating between good loans and those that had been foreclosed. The variables were the ratio of total debt service to total income, the ratio of acres on security to acres owned, the ratio of loan amount to appraised value, and the ratio of debts to assets.

The model correctly classified 82.6% of the sample data. To statistically verify the validity of the discriminant function, the U-method was preferred on grounds that it is a particularly appropriate technique when sample sizes are relatively small, as was the case in their analysis. With this method, one observation at a time is deleted from the sample, and the discriminant classification function is derived using the remaining observations. The deleted observation is then classified with the new function. This process is continued until n classification functions, each using n-1 observations, have been derived where n is the number of observations. The "test of goodness" is the measure of the portion of the individual observations that are classified correctly. For the data used in this research, the U-method correctly classified 79.9% of the observations. Since this level of correct classification is relatively close to that achieved by the initial function, 82.6%, it could be assumed that the estimation error rate of about 17.4% in the original model was valid. This error rate would be associated with the classification of extreme cases (good and foreclosed accounts). Variables found to be important in the study are similar to those found by previous researchers.

Johnson, R. Bruce. "Agricultural Loan Evaluation with Discriminate Analysis." Unpublished Ph.D Dissertation, University of Missouri, 1970.

This study was conducted in pursuit of the following objectives: (1) identify factors that influence the financial success of selected agricultural borrowers; (2) develop a credit-scoring model for evaluating loan applications for selected Missouri farm operators; and (3) test the accuracy of the credit-scoring model on loan data from several PCAs.

The study's major concern was to develop a computer model for classifying PCA loans into two categories: acceptable loans and problem loans. Data for the study were acquired from loan applications in three Missouri PCAs. Twenty-four counties were represented by the 389 loan examples selected for the analysis. A representative sample of loan applicants was taken from each category of borrowers.

Four discriminant models were developed for testing on the relevant financial data. Models 1 and 2 were composed of three variables. Both models included the repayment index and the ratio of current assets to current debt. The third variable for Model 1 was the ratio of total debt to total assets. The final ratio in Model 2 was the ratio of net worth to total debt. The coefficients of these two models were applied to the relevant financial data of both the secured and unsecured loans.

Models 3 and 4 were developed for application to the secured loans only. These two models were analogous to Models 1 and 2 but included a fourth variable, namely, the ratio of total underlying security to the total PCA commitment.

Following considerable testing of the discriminant functions on data from the original sample and on data selected from loans of the Pittsfield, Illinois, PCA, Model 1 was selected as the most effective classification function for all production credit loans. More than 60% of the loans were correctly classified by Model 1. Moreover, none of the problem or loss loans were classified as acceptable loans. Thus, the study indicates that a function can be developed that will discriminate effectively between acceptable and problem production credit loans on the basis of data taken from loan application forms.

Johnson, R. Bruce, and Albert R. Hagan. "Agricultural Loan Evaluation with Discriminate Analysis." *Southern Journal of Agricultural Economics* 10(1978):57-62.

In this study, the authors classified loans into acceptable loans and problem loans by using discriminant analysis techniques. Data were collected from loan applications of borrowers at three PCAs in central and northwestern Missouri. The variables selected for use in the model were (1) repayment index: the amount of loans actually repaid each year plus the value of the marketable crops and livestock not sold during the year, expressed as a percentage of the amount expected to be repaid; (2) current ratio: current assets to current liabilities; and (3) debt-to-asset ratio: total debts to total assets. The discriminant function correctly classified 92% of the borrowers. This method of loan classification would be suitable if the consequences of the two possible classification errors were of equal significance.

To reduce the probability of misclassifying problem loans into the acceptable loan group, a new cutoff score that had a 0.1 probability for misclassifying problem loans was calculated. Using the tabulated Z value that corresponds to a 1% misclassification, Bruce and Hagan solved for a new critical cutoff value. When data from the Mississippi Valley PCA were used for verification, 61.6% of the 378 loans were correctly classified.

Kohl, David M. "Credit Analysis Scorecard." *Journal of Agricultural Lending* 1(1987):14-22.

The author proposes a classification of agricultural financial analysis criteria by considering repayment ability, credit management, financial position, level of management performance and profitability, and farm resources and individuals. The analysis centered on an illustration of a farmer who desired to add an enterprise that required additional capital. The author presents an agricultural credit scorecard format, guidelines, and yardsticks based upon previous research and experience in the agricultural credit analysis area.

Repayment ability was measured by (1) cash flow coverage ratio (cash earnings to annual debt payment), (2) debt service ratio (total annual debt payments to earnings), and (3) operating-expenses-to-earning ratio. Financial condition measures included (1) current ratio, (2) percentage of equity (net worth to total assets), and (3) borrowing capacity and reserve (collateral). Credit management was measured by (1) credit lines (number of credit sources) and (2) supplier and creditor accounts (bill payment status). Production management and profitability measures were (1) high production and efficiency in the top 20% of managers and (2) returns to investment. The last category concerned individual characteristics and farm goals.

A score of 0 to 3 was given to each subcategory, and a total score was computed from a possible 36. A score of 28-36 points implied that the loan was very serviceable and would most likely require minimal supervision, whereas a 22-27 score implied that the loan was serviceable, requiring regular supervision. A questionable loan scored 16-21 points, and if made, the loan would require close supervision. A score below 16 implied that the loan application should be rejected, or if the loan was already out, a special supervision plan should be made. The author concludes that the scorecard could act as a guide by removing some of the subjectivity that frequents lending analysis, but the author warns that this technique should not replace the agricultural lender's judgement.

Lufburrow, Jean, Peter J. Barry, and Bruce L. Dixon. "Credit Scoring for Farm Loan Pricing." *Agricultural Finance Review* 44(1984):8-14.

This study reports the results of a credit-scoring technique for pricing loans to individual farm borrowers. The credit-scoring model was developed using 1982 data for a sample of borrowers from five PCAs in Illinois that classify their borrowers into three risk categories for pricing purposes: Class I, prime (lowest risk); Class II, base (intermediate risk); and Class III, premium (highest risk).

To estimate and validate the model, a testing procedure was used that divided the sample of 241 borrowers into a model-generating sample of 202 and a test sample of 39. The test sample was chosen randomly from the complete sample. The coefficients of the credit-scoring model were estimated from the model-generating sample and tested for predictive accuracy using the test sample. Additional tests also occurred on the model-generating sample itself, as well as on coefficients estimated from the total sample.

The Probit model with an ordinarily ranked limited dependent variable (OLDV) representing the risk classes was used. The independent variables used were liquidity, leverage, profitability, collateral, tenure, repayment ability, and repayment history. Profitability and tenure were insignificant and thus omitted from the model.

A comparison of the model's classification of borrowers to the PCAs classification based on probabilities of being in the respective classes indicated that 66% of the model-generating sample had been classified correctly. The greatest accuracy occurred for Class I (94%) and Class III (91%). The accuracy was only 13% for Class II. According to comparisons of credit scores and threshold values, 79% of the test sample was classified correctly: 100% of Class I, 62% of Class II, and 77% of Class III. The authors suggest that the estimation procedure could be tailored to the characteristics of specific lenders, locations, and types of borrowers.

Morris, C. David, R. Lynn Harwell, and Eddie H. Kaiser. "Agricultural Loan Analysis and Agricultural Investment Analysis for the South Carolina Farmers Home Administration." *Agricultural Economics and Rural Sociology Report*, South Carolina Agricultural Experiment Station, Clemson University, Clemson, South Carolina, Feb. 1980 (411).

This handbook is designed to assist FmHA county officers in making consistent loan decisions. Loan analysis is discussed in terms of general borrower characteristics, financial ratios, and credit scores using these ratios and danger signals. The methods of credit scoring presented were developed from an analysis of FmHA loans in five counties of South Carolina.

Three financial ratios were used to develop a credit-scoring system: (1) annual debt payment to net income, (2) net worth to FmHA operating credit, (3) total debt to net worth. These ratios are categorized into three ranges: low, medium, and high, each range having a specific score. A debt-payment-to-net-income ratio more than 2.44 has a score of 0, whereas a ratio of 2.44-1.76 has a score of 166, and a ratio less than 1.76 has a score of 333. However, a net-worth-to-FmHA-credit ratio greater than 2.78 has a score of 166; 2.78-1.73 scores 83, and a ratio less than 1.73 scores 0. A total debt-to-net-worth ratio more than 2.56 scores 0; 2.56-1.13 scores 249, and a ratio less than 1.13 scores 499. When this system was applied to a five-county sample of South Carolina FmHA loans (actual sample size not given), the average score of bad loans was 793, and the average good loan score was 855. The midpoint between these scores, 824, was then considered as the dividing point between good and bad loans. Using this system, a loan officer can classify each loan application.

Park, N. William. "Analysis of Repayment Ability for Agricultural Loans in Virginia Using a Qualitative Choice Model. Unpublished Master's Thesis, Virginia Polytechnic Institute and State University, May 1986.

The primary objective of this research was to determine which factors most significantly predict delinquency of agricultural loan accounts. The study analyzed 382 loans issued by various commercial banks, FmHAs, and PCAs throughout Virginia for agricultural production operations during the years 1980-1985. Approximately 20% of 73 loan accounts had become delinquent, whereas the remaining 209 had not. The study examined the probability that a loan applicant, given a particular set of financial ratio and operation characteristics, will become delinquent in repayment of the loan. The dependent variable for the model was a 0-1 dummy variable, with a value of 1 given for a case of delinquency, and 0 otherwise.

The author used a Probit model, which was estimated according to maximum likelihood techniques. With a 90% level of confidence, the following variables were found significant: (1) current debt ratio measured as the ratio of current debt to total debt, (2) percentage of equity, measured as the ratio of net worth to total assets, (3) cash flow coverage ratio, measured as the ratio of cash available for risk, uncertainty, and new investment to total annual debt payment, principal and interest on them, and operating debt, (4) cash-expense-to-receipt ratio, computed as the ratio of cash expenses (excluding interest) to cash receipts, (5) credit lines (number of creditors applicant has), (6) diversification level, (7) whether or not loan is secured by Farm Credit System, (8) whether or not loan is secured by FmHA, and (9) gross farm income.

Efron's R^2 and McFadden's R^2 procedures were used as measures of goodness of fit. The former is the squared correlation coefficient between the binary dependent variable and the predicted probabilities and was 0.23 for the model. McFadden's R^2 was calculated as $1-[\text{Log } L(\hat{\beta})/\text{Log } L(\hat{\beta}_0)]$, where the second term is the likelihood ratio index and was 0.25 for the model. The two measures indicated that a significant amount of variation in the dependent variable was explained by the independent variables in the model. These two measures were considered excellent indicators of goodness of fit for the model because the maximum R^2 possible for uniform distribution (number of delinquent accounts = number of nondelinquent accounts) would be 0.33. The model correctly classified 83% of the loan accounts.

Reinsel, Ignatius Edward. "Discrimination of Agricultural Credit Risks from Loan Application Data." Unpublished Ph.D. Dissertation, Michigan State University, 1963.

This study was conducted to accomplish the following objectives: (1) to evaluate the importance of various borrower characteristics in discriminating "successful" from "unsuccessful" loan applicants, (2) to develop a model that can aid in discriminating "successful" from "unsuccessful" loan applicants based on information available at the time the loan is under consideration, and (3) to evaluate the effectiveness of present loan applications as sources of data for predicting the outcome of loans.

Three offices of agricultural lenders provided data. The lenders were asked to select a dichotomous sample of "successful" and "unsuccessful" borrowers. The FmHA and a PCA were used as data sources because these lenders had more complete information on their borrowers than did other agricultural lenders. Prediction models were developed independently for each of the samples used in the analysis. The form of these functions was much alike although the importance of the different variables did change.

Factors that seemed to be important for the PCA borrowers were farm ownership, experience on the particular farm, and the relationship between non-real estate debts and total debts. Individuals who were able to make annual gains in their net worth by taking risks appeared to be discriminated against by the PCA.

Analysis of the Ingham County FmHA sample produced evidence that the relationship between the firm and the household needs to be given more consideration for these borrowers. Other factors that seemed important were the attitudes toward insurance, the relationship between non-real estate and total debts, and the planned debt repayment. The ability to make annual increases in net worth before the loan seemed, in the case of these borrowers, to be an indicator that the borrower would succeed.

For the Eaton County FmHA sample, the past level of living was an indicator of potential future capacity of the farm to generate needed income. Factors such as the relationship between debt repayment and income, non-real estate debts, and total debts and the intensity of the farmer's crop program also appeared to be important.

Tongate, Ron. "Risk Indexing: A Valuable Tool for Today's Lender." *Agri Finance* (March 1984):12.

In October 1983, PCA's in the Louisville District began using a risk index to identify the level of risk in a particular loan. Tongate's article summarizes the background and use of the program. Within the Farm Credit System, annual credit reviews classify a loan as acceptable, problem, vulnerable, or as a loss. However, this is an after-the-fact rather than an early warning procedure. Tongate and his colleagues were concerned that several institutions were using loan-scoring or loan-indexing systems to aid in classifying loans, not to identify risk; i.e., they were developed to determine where a loan or portfolio was rather than where it might go. They then identified some 60 to 70 factors contributing to risk. These factors were further sorted into two groups: those related to the environment and those unique to the loan.

The researchers tested their formula using as much as 6 years of historical data on both a sample of active loans and loans charged off during 1982. Five factors were used in the evaluation: (1) owner's equity, (2) collateral, (3) repayment capacity, (4) value of farm production to debt, and (5) loan size. Owner's equity was assigned a maximum score of 40 points; collateral, 20 points; repayment capacity, 15 points; value of farm production to debt, 15 points; and loan size, 10 points. Three categories were established: low risk, moderate risk, and high risk. For example, for owner's equity, a ratio of 60% or more was categorized as low risk (assigned a score of 0), a ratio of 40%-60% as moderate risk (assigned a score of 20), and a ratio of 40% or less as high risk (assigned a score of 40). Different but similar ranges were established for the other four variables.

When using this model, data from an applicant are subjected to this analysis, and if his/her total score falls in the range of 0-29, he/she is classified as a low risk; 30-50 is a moderate risk; and 50-100 is a high risk. Researchers propose that this indexing could be used to (1) sort loans for diferential handling, (2) help the loan officer avoid the "good man = good loan" syndrome, (3) point out specific areas of weaknesses in the loan where the loan officer can reduce the level of risk, (4) make sure the loan remains within the lender's risk/return criteria on an ongoing basis, (5) determine how the loan fits into the lender's overall portfolio objectives, and (6) aid as a counseling tool with borrowers. Tongate warns, however, that loan indexing should not replace personal judgment.

Weed, B. Johno, and William E. Hardy, Jr. "Objective Credit Scoring of Alabama Borrowers." Circular, Agricultural Experiment Station, Auburn University, Auburn, Alabama, 249(1980):26.

The specific objective of the research presented in this report was to develop a quantitative financial analysis system that would aid Alabama PCAs and the Federal Intermediate Credit Bank of New Orleans in discriminating between loan applicants that would be acceptable and those that would be weak or have problems in repayment. Data used in this study were obtained from loan applications or borrowers at the eight PCAs in Alabama. All eight associations in the state were sampled because their locations serve every county in Alabama and thus provided a cross-sectional sample of the Alabama farm borrower. Data on 220 loan accounts were received from participating PCAs. A subsample of 25 problem loans and 25 acceptable loans was randomly drawn from 220 operable accounts to be used as a test sample for verifying the classification function developed in the analysis. The remaining sample of 170 loan applications contained 52 problem loans and 118 acceptable loans.

Financial and nonfinancial borrower characteristics from original loan applications were used to identify ratio and nonratio variables. By using stepwise discriminant analysis, total liabilities divided by total assets and annual anticipated loan repayment divided by total assets were found to be the variables most significant in the study and were hence used to construct a credit-scoring function. Total liabilities divided by total assets was found to be the most significant and was three times as important in the function as was the other variable.

The developed discriminating function was tested against a holdout of 25 acceptable loan and 25 problem loans. The function correctly classified 88% of the loan applications. It classified 84% of the acceptable loans correctly and 92% of the problem loans correctly. It also correctly classified 81% of the original sample.

By modifying the original function, an application technique was developed that could be used by Alabama PCAs and the Federal Intermediate Credit Bank of New Orleans for classification of loan applications and existing loans. Through the application of the derived table of cutoff values for different acceptable percentages of problem loan misclassification, a cutoff value could be selected that meets management requirements for correct classification of problem and acceptable loans.

TABLE 1. A summary of credit assessment models in agriculture.

Item	Johnson and Hagan	Dunn and Frey	Hardy and Weed	Lufburrow, Barry, and Dixon	Hardy Spurlock et al.	Alcott	Kohl	Bauer and Jordan
A. Classification:								
1. Vulnerable or loss, problem, and acceptable								
2. Problem and acceptable	X	X	X					
3. Prime, base, and premium				X				
4. I-V						X		
5. I-IV							X	
6. Poor risk and good risk								X
7. Good and bad								
8. Successful and unsuccessful								
B. Performance criteria								
1. Liquidity								
a. Current assets/current liabilities	X			X		X	X	X
b. Current debt/total debt								
c. Note-to-net-cash income								
d. Cash expenses/cash receipts								
e. Number of credit sources							X	
2. Solvency and collateral position								
a. Total debt/total assets	X	X	X	X	X	X	X	X
b. Net worth/total assets							X	
c. Net worth/FmHA credit								
d. Total debt/net worth								
e. Non-real estate debt/total debt								
f. Total liabilities								X
g. Loan commitment/net worth			X					
h. Collateral				X	X		X	
i. Loan secured by farm credit system								
j. Loan secured by FmHA								
k. Loan amount/appraised value					X			
l. Supplier and creditor accounts							X	

TABLE 1. (continued)

Item	Johnson and Hagan	Dunn and Frey	Hardy and Weed	Lufburrow, Barry, and Dixon	Hardy Spurlock et al.	Alcott	Kohl	Bauer and Jordan
3. Profitability								
a. Return on investment						X	X	
b. Return on equity						X		
c. Expected income as % of previous year								X
d. Gross farm income								
4. Economic efficiency								
a. Operating expenses/earnings							X	
5. Repayment capacity								
a. Actual loan payment/expected loan payment	X							
b. Debt payment/net income								
c. Planned debt repayment								
d. Total cash/total debt								
e. Total debt/total income					X			
f. Cash earnings/annual debt payment							X	
g. Repayment history				X			X	
6. Borrower's characteristics								
a. Size of family								X
b. Marital status								X
c. Number of dependents								X
d. Attitude toward insurance								
e. Credit insurance		X						
7. Management ability								
a. Management ability							X	
b. Tenure		X						
c. Diversification level								
C. Data								
1. Commercial banks						X		
2. FICB, PCAs/FmHA	X	X	X	X	X		X	
3. Simulation							X	
4. Federal land bank								

TABLE 1. (continued)

Item	Johnson and Hagan	Dunn and Frey	Hardy and Weed	Lufburrow, Barry, and Dixon	Hardy Spurlock et al.	Alcott	Kohl	Bauer and Jordan
D. Estimate of weights								
1. Based on experience						X	X	
2. Discriminate analysis	X	X	X		X			X
3. Qualitative choice models								
a. Linear probability models								
b. Logit								
c. Probit				X				
4. Linear programming								
5. Number of observations	272	99	220	241	144	—	—	84
E. Validate percentage successfully classified (%)	62	75	81	71	82.6	—	—	85
F. Institutionalized	St. Louis FICB	—	—	—	—	Oneida Nat'l. Bank, N.Y.	—	—

Item	Morris, Harwell, and Kaiser	Hardy and Adrian	Tongate	Reinsel	Hardy and Patterson	Dunn	Park
A. Classification:							
1. Vulnerable or loss, problem, and acceptable			X				
2. Problem and acceptable		X				X	X
3. Prime, base, and premium							
4. I-V							
5. I-IV							
6. Poor risk and good risk							
7. Good and bad	X				X		
8. Successful and unsuccessful				X			
B. Performance criteria							
1. Liquidity							
a. Current assets/ current liabilities			X				
b. Current debt/ total debt							X
c. Note-to-net-cash income						X	
d. Cash expenses/ cash receipts							X
e. Number of credit sources							

TABLE 1. (continued)

Item	Morris, Harwell, and Kaiser	Hardy and Adrian	Tongate	Reinsel	Hardy and Patterson	Dunn	Park
2. Solvency and collateral position							
a. Total debt/total assets		X	X		X	X	
b. Net worth/total assets							
c. Net worth/FmHA credit	X						
d. Total debt/net worth	X						
e. Non-real estate debt/total debt				X			
f. Total liabilities							
g. Loan commitment/net worth							
h. Collateral							
i. Loan secured by farm credit system							X
j. Loan secured by FmHA							X
k. Loan amount/appraised value							
l. Supplier and creditor accounts							
3. Profitability							
a. Return on investment							
b. Return on equity							
4. Economic efficiency							
a. Operating expenses/earnings							
5. Repayment capacity							
a. Actual loan payment/expected loan payment							
b. Debt payment/net income	X						
c. Planned debt repayment				X			
d. Total cash/total debt							X
e. Total debt/total income							
f. Cash earnings/annual debt payment							
g. Repayment history							

TABLE 1. (continued)

Item	Morris, Harwell, and Kaiser	Hardy and Adrian	Tongate	Reinsel	Hardy and Patterson	Dunn	Park
6. Borrower's characteristics							
a. Size of family							
b. Marital status							
c. Number of dependents							
d. Attitude toward insurance				X			
e. Credit insurance						X	
7. Management ability							
a. Management ability				X			
b. Tenure						X	
c. Diversification level							X
C. Data							
1. Commercial banks							
2. FICB, PCAs/FmHA	X		X	X		X	
3. Simulation							
4. Federal land bank			X		X		
D. Estimate of weights							
1. Based on experience	X		X				
2. Discriminate analysis					X	X	
3. Qualitative choice models							
a. Linear probability models				X			
b. Logit							
c. Probit							X
4. Linear programming		X					
5. Number of observations	—	9180	—	—	2200	99	382
E. Validate percentage successfully classified (%)	—	82.4	—	—	68	75	83
F. Institutionalized	—	—	—	—	—	—	—

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