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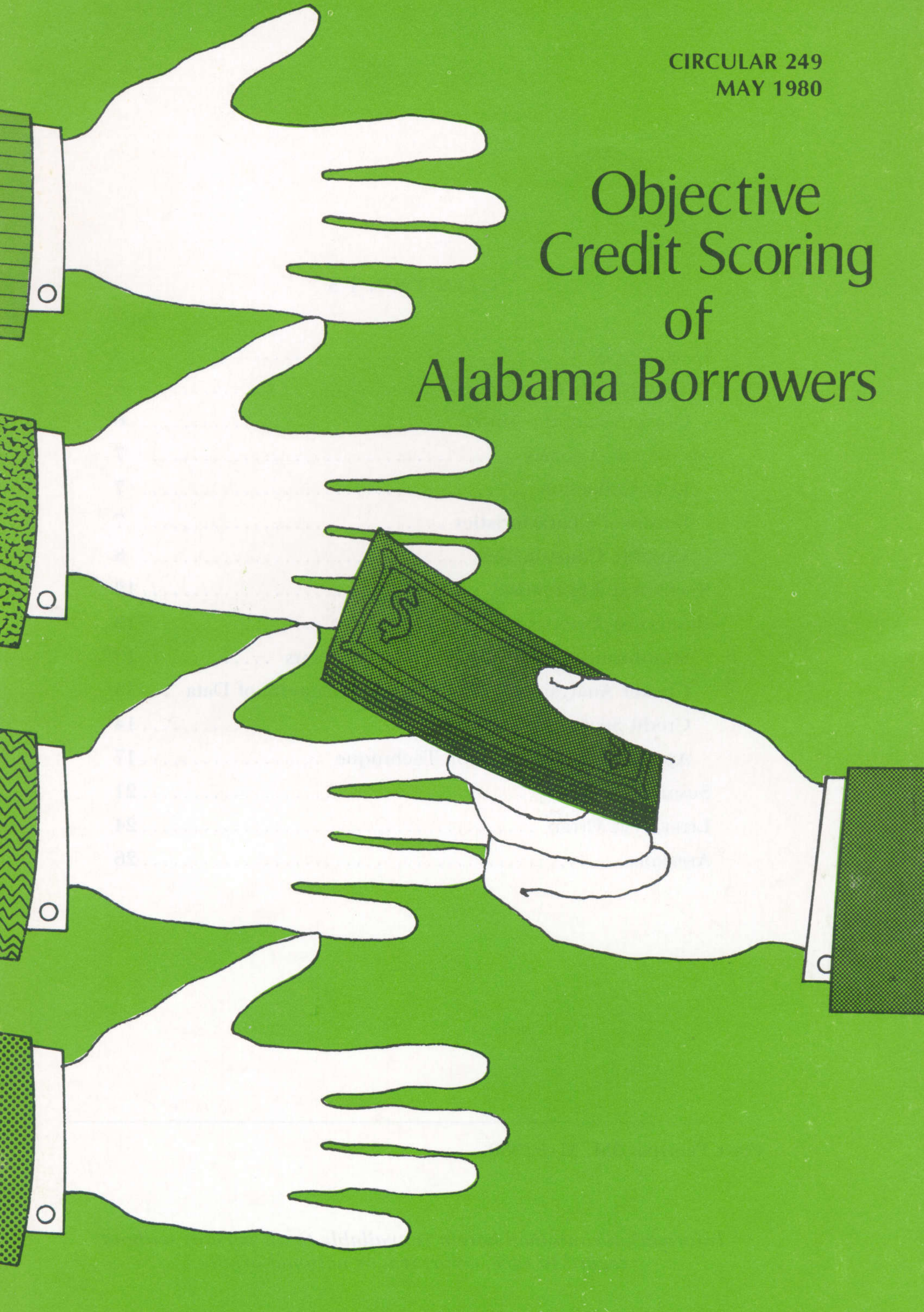
# Objective Credit Scoring of Alabama Borrowers



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CONTENTS



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# Objective Credit Scoring of Alabama Borrowers[1]

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## INTRODUCTION

AGRICULTURE is a capital intensive industry having two to three times the investment capital per man as most nonagricultural industries *(19)*. High levels of capital investment and specialization increase the financial risk involved in farming and make a higher level of managerial capability of the farm operator a necessity.

The use of borrowed capital is becoming increasingly important for the proper functioning of American agriculture. Total outstanding farm debt of $132.2 billion at the end of 1979 was more than double the 1970 value. During this period, the real estate component increased by 147 percent to a level of $72.2 billion, while the non-real estate part increased by 183 percent to $60.0 billion. Non-real estate debt has also increased in proportion to real estate debt, accounting for 45 percent of the total in 1979, the largest percentage since the beginning of the farm land price boom in the early 1970's, figure 1 *(14)*.

Increased agricultural productivity, mounting pressures for non-farm use of rural land, and inflation have had a direct effect on the value of farm land. The increase in land value has served as a major loan security in the farming sector. Some lenders anticipate a slowing in the increase in land prices and a few anticipate declines *(21)*. If slower gains become reality,

[1]Research on which this report is based was supported by Federal and State research funds under Hatch Project—Ala-476.

[2]Former Graduate Research Assistant and Associate Professor, Department of Agricultural Economics and Rural Sociology, respectively.

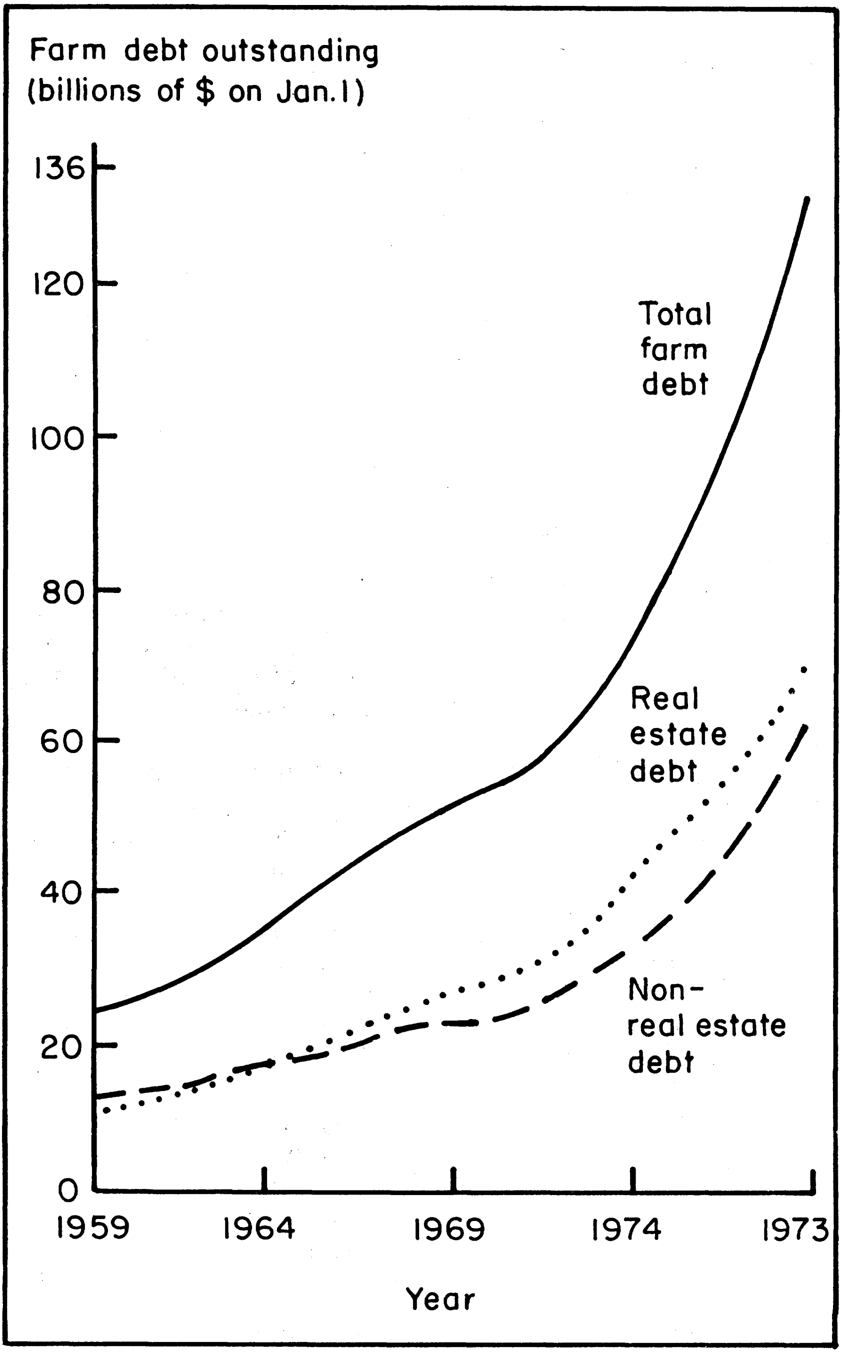


**FIG. 1. Farm debt outstanding on January 1, 1959-1978** (22).

poorly secured farm loans may result in losses for lenders rather than being offset by gains in land values.

The ratio of outstanding debt to total net cash income is a measure of the relative burden of debt against income. For 1979, total debt was 1.52 times as great as net cash income, increasing from the level of 1.34 which existed in 1970 *(14)*. This change indicates a less liquid position for farm operators and potential loan repayment difficulties.

### Statement of the Problem

Structural changes in agriculture and the associated increase in debt load carried by farmers have made farm financing more difficult for the agricultural lender. Narrow income to expense margins, increased average size of loans, and increased numbers of loans have made the agricultural lender more aware of the need to determine how borrower and agricultural business characteristics are related to debt repayment ability and the quality of loans.

Financial organizations want to lend money to solvent, profitable, and growing businesses. The lender's problem involves deciding which loan applications meet these criteria. In determining the merits of a loan application, lenders normally consider at least five basic factors.

**The individual or entity.** The individual's honesty, integrity, experience, performance record, and management ability.

**Purpose of the loan.** The loan should be for a constructive purpose and practical as to repayment terms.

**Financial position and progress.** Total assets, equity position, liabilities, and a history of how these factors have changed over the years are considered in evaluating the financial responsibility of a borrower.

**Repayment capacity.** Cash flow histories and projections are used to supplement statements of financial condition to determine repayment capacity.

**Collateral available to protect the loan.** The amount of collateral should be enough to protect the lender, and should be based on the strengths and weaknesses of the other credit factors.

As risks involved in lending increase, agricultural lenders have to be more cautious in making new loans and in supervising loans already made. Lenders need to acquire greater expertise in farm financing through a better understanding of characteristics of the farm business which affect potential risks involved with a loan. Therefore, these characteristics must be identified and their relative effect on credit risk determined.

Many analyses of borrower's repayment ability are conducted through personal examination of individual credit files by credit analysts and loan officers. Considerable time may be required to determine the risk associated with particular loans. As this risk increases, so does the necessity to better recognize a borrower's potential for long-run success as well as current debt repayment ability.

## Objectives of the Study

The specific objective of the research presented in this report was to develop a quantitative financial analysis system that would aid Alabama Production Credit Associations 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.

In addition to providing assistance to PCA and FICB loan officers and credit administrators, the research results should be useful to other agricultural lenders as well as borrowers by indicating which borrower characteristics are important in predicting repayment success.

More specific potential benefits of the research are: first, a more quantitative and objective system would be available to discriminate between acceptable loans and those that are weak and would need close supervision. Second, there could be more frequent checks on the borrower by reexamining a few key characteristics. Third, such a quantitative system would be helpful in training credit employees. Fourth, current credit indexes and trends, as well as outstanding loan classifications, could be analyzed through computer services to help in management and administrative decisions. Finally, current and potential borrowers would possibly receive the greatest benefit since credit analysts should be able to do a more thorough job of analyzing credit needs and hopefully prevent borrowers from getting too deeply in debt.

## METHOD OF ANALYSIS

### Data Collection

Data used in this study were obtained from loan applications of borrowers at the eight Production Credit Associations located in Alabama. All eight associations in the State were sampled because their locations serve every county in Alabama and thus would give a cross-sectional sample of the Alabama farm borrower. A questionnaire was used to collect sample information from the original loan applications of borrowers who were PCA members in 1974-1978. A questionnaire was necessary to preserve the confidentiality of borrower records, Appendix 1.

Each association president was requested to select a random sample of 40 loans including both acceptable and problem accounts. Acceptable loans are of such high quality that they require only normal supervision. In some cases, even loans with significant credit weaknesses, backed up by adequate member equity to assure repayment performance are classified as acceptable.

Problem loans are weak loans in that they possess serious credit deficiencies and require more than normal supervision either to improve repayment standards or to liquidate on schedule. These loan accounts may contain factors such as low equity position, unwise use of credit, adverse trends in financial conditions, or faulty management.

Data on a total of 220 loan accounts were received from the participating PCAs. A subsample of 25 problem loans and 25 acceptable loans was randomly drawn from the 220 usable 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.

### Borrower Characteristics

Data collected from loan applications contained the following borrower characteristics: (1) age of operator; (2) full-time or part-time farmer; (3) major farm enterprise; (4) acres owned; (5) acres rented; (6) current assets; (7) current liabilities; (8) total assets; (9) total liabilities; (10) net worth; (11) net farm income; (12) gross farm income; (13) gross non-farm income; (14) underlying security value; (15) total loan commitment; (16) loan repayment anticipated; (17) loan repayment made; and (18) marketable inventory.

Selected borrower characteristics by major enterprises and for the total sample are given in table 1. Borrower characteristics may be compared and contrasted by nine major enterprise categories. The mean age was 46 years, with a range of 37 to 52 years. The mean number of acres owned by those represented in the sample was 320 acres, with the two cattle enterprises containing the highest average acreage. Total sample mean for rented acres was 363, with soybean and cotton farmers dominating.

Sixty-one percent of the sample of borrowers were full-time farmers. The cotton, peanuts, and dairy cattle categories contained the highest percentages of full-time farmers, whereas the lowest percentage was those borrowers who were predominantly beef cattle farmers.

Dairy cattle borrowers had the highest mean current assets, while cotton producers had the highest mean current liabilities as well as total liabilities. Borrowers in the row crops category had the highest mean of total assets, but were near the middle with total liabilities. The mean net worth for the total sample was $224,781 with row crops and dairy cattle categories both having values greater than $300,000.

Mean net farm income for the total sample was nearly $15,000, with the highest net farm income being obtained by dairy cattle farmers and the lowest by cotton farmers. Mean gross farm income for the total sample was over $90,000 with dairy cattle and beef cattle operators receiving the highest and lowest incomes, respectively. Beef cattle and the "other" category represented the highest gross non-farm incomes. These were also the enterprises with the highest percentages of part-time farmers.

The ratio of net to gross farm income indicates the profitability of the enterprise in terms of profit retained from total receipts. Operators in the livestock, poultry, and "other" categories retained the highest percentage of gross farm income. Cotton operators retained the least amount.

**Variable Construction**

Borrower characteristics from the sample questionnaires provided raw data necessary for construction of the fifteen

TABLE 1. SAMPLE MEANS FOR BORROWER CHARACTERISTICS BY MAJOR ENTERPRISES

| Borrower characteristics | Major enterprises | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Row crops | Soybeans | Cotton | Peanuts | Beef cattle | Dairy cattle | Swine | Poultry | Other[2] | Total |
| Number in sample | 29 | 31 | 31 | 16 | 59 | 12 | 11 | 34 | 7 | 220 |
| Age (years) | 47 | 43 | 48 | 42 | 48 | 52 | 43 | 45 | 37 | 46 |
| Acres owned (acres) | 400 | 347 | 316 | 270 | 405 | 410 | 202 | 141 | 133 | 320 |
| Acres rented (acres) | 478 | 634 | 759 | 351 | 232 | 205 | 297 | 35 | 0 | 363 |
| Percent of borrowers full-time farmers | 72 | 74 | 90 | 94 | 32 | 83 | 55 | 55 | 50 | 61 |
| Current assets (dollars) | 185,937 | 254,409 | 223,873 | 100,426 | 154,208 | 263,849 | 188,339 | 169,440 | 97,163 | 189,639 |
| Current liabilities (dollars) | 61,944 | 119,051 | 126,218 | 72,935 | 65,754 | 89,828 | 112,842 | 100,183 | 41,410 | 90,009 |
| Total assets (dollars) | 462,949 | 427,198 | 420,977 | 195,279 | 285,925 | 428,868 | 336,065 | 295,880 | 217,074 | 355,995 |
| Total liabilities (dollars) | 131,474 | 161,615 | 174,094 | 90,552 | 101,651 | 122,210 | 149,637 | 128,539 | 66,536 | 130,486 |
| Net worth (dollars) | 331,130 | 265,582 | 247,857 | 104,737 | 176,150 | 315,853 | 200,418 | 168,335 | 150,672 | 224,781 |
| Net farm income[3] (dollars) | 8,815 | 10,358 | 4,813 | N/A | 12,524 | 42,209 | 15,847 | 16,643 | 20,472 | 14,684 |
| Gross farm income[3] (dollars) | 116,400 | 117,309 | 145,199 | 71,507 | 36,432 | 155,043 | 76,846 | 95,201 | 51,238 | 93,251 |
| Gross non-farm income[3] (dollars) | 10,132 | 8,289 | 2,303 | 4,169 | 16,832 | 2,208 | 12,118 | 4,317 | 17,010 | 9,400 |
| Percent of gross farm[4] income retained | 8 | 9 | 3 | N/A | 34 | 27 | 21 | 18 | 40 | 16 |

[1]Row crops catagory implies that no single crop enterprise supplies the majority of farm income.
[2]Other catagory includes nursery, produce, timber products, pecans, and catfish.
[3]Means computed from data represent 60 percent of total sample.
[4]Mean net farm income divided by mean gross farm income for each enterprise.

variables to be used in the statistical analysis of this study. Three non-ratio variables were drawn directly from the raw data and twelve ratios were constructed. Variables containing farm and non-farm income information could not be constructed because only 60 percent of the data contained such information.

The three non-ratio borrower characteristics were: (1) age of operator; (2) acres owned; and (3) acres rented. The twelve financial ratios were: (1) current assets divided by current liabilities; (2) current liabilities divided by total liabilities; (3) total assets divided by net worth; (4) current liabilities divided by net worth; (5) total liabilities divided by total assets; (6) Underlying security value divided by total loan commitment; (7) total loan commitment divided by net worth; (8) total loan commitment divided by current assets; (9) total liabilities divided by net worth; (10) loan repayment made divided by loan repayment anticipated; (11) loan repayment made plus marketable inventory divided by loan repayment anticipated; and (12) loan repayment anticipated divided by total assets.

The operator's age was assumed to reflect the current life stage of a farmer and possibly how he views the use of credit. Acres owned and acres rented were important because they reflect the size of the farming operation.

Current assets divided by current liabilities is the current ratio which indicates whether current assets are adequate to meet current indebtedness. This liquidity ratio reflects the ability of a farmer to meet cash obligations as they come due.

Current liabilities divided by total liabilities reflects the proportion of the total farm debt that will fall due within the current year. The ratio of total assets divided by net worth shows the structure of the assets indicating the proportion of the owner's equity in the assets.

The ratio of current liabilities divided by net worth reflects the amount of current indebtedness relative to the farmer's equity. Total liabilities divided by total assets is another measure of solvency. This ratio shows the proportion of total assets against which lending institutions hold claim.

The ratio of underlying security value divided by total loan commitment indicates the safeness of the loan commitment in terms of total liquidation, while total commitment divided by net worth is a ratio of capital that has been borrowed from the association to farmer-owned capital. Total loan commitment divided by current assets reflects the proportion of the total loan that could be repaid within the year. The ratio of total liabilities divided by net worth is a measure of solvency showing the amount of leverage of the farmer. As the use of borrowed capital increases in relation to equity capital, the lender's risk increases.

The ratio of the amount of annual principal debt actually repaid, divided by the amount of annual principal debt repayment anticipated from the previous year's loan, is a credit performance measure. The amount of annual principal debt actually repaid, plus the value of any marketable inventory held by the farmer, divided by the amount of annual principal debt repayment anticipated from the previous year loan is another credit performance measure. This ratio takes into consideration any marketable inventory that could have been used for debt repayment.

The ratio of the amount of annual principal debt repayment anticipated divided by total assets is a repayment capacity measure. It shows the proportion of the assets that the farm must generate for debt repayment.

The means and standard deviations of the financial ratio variables for problem loans and for acceptable loans are presented in table 2. The current ratio of the acceptable loans is 25

TABLE 2. SAMPLE MEANS AND STANDARD DEVIATIONS FOR FINANCIAL RATIO VARIABLES

| | Problem loans | | Acceptable loans | |
|---|---|---|---|---|
| Variable | Mean | Standard deviation | Mean | Standard deviation |
| 1. Current assets/current liabilities | 1.94 | 1.12 | 52.16 | 494.90 |
| 2. Current liabilities/total liabilities | 0.74 | 0.30 | 0.77 | 0.47 |
| 3. Total assets/net worth | 2.10 | 1.77 | 1.44 | 0.36 |
| 4. Current liabilities/net worth | 0.93 | 1.45 | 0.32 | 0.29 |
| 5. Total liabilities/total assets | 0.50 | 0.18 | 0.27 | 0.15 |
| 6. Underlying security value/ total loan commitment | 1.76 | 1.33 | 2.05 | 1.57 |
| 7. Total Loan commitment/ net worth | 1.00 | 1.06 | 0.42 | 0.40 |
| 8. Total loan commitment/ current assets | 0.85 | 0.44 | 0.72 | 0.89 |
| 9. Total liabilities/ net worth | 1.12 | 1.72 | 0.45 | 0.36 |
| 10. Loan repayment made/loan repayment anticipated | 1.08 | 2.42 | 1.17 | 1.10 |
| 11. (Loan repayment made + marketable inventory)/loan repayment anticipated | 1.73 | 2.85 | 2.43 | 3.87 |
| 12. Loan repayment anticipated/ total assets | 0.25 | 0.22 | 0.14 | 0.13 |

times larger than for problem loans, but the standard deviation for acceptable loans was 400 times as great as for problem loans. This suggests that even though the current ratio is higher for acceptable loans, it is subject to a greater degree of variability.

The means and standard deviations of current liabilities divided by total liabilities, total loan commitment divided by current assets, and loan repayment made divided by loan repayment anticipated were similar for both problem and acceptable loans.

The values of total assets divided by net worth, current liabilities divided by net worth, total loan commitment divided by net worth, and total liabilities divided by net worth were larger for problem loans. This is a reflection of the smaller net worth of farmers for problem loans.

Acceptable loans had a higher value for underlying security value divided by total loan commitment and loan repayment made, plus marketable inventory divided by loan repayment anticipated. These ratios reflect the greater security held by acceptable loans and the greater amount of marketable inventory held for higher receipts by acceptable loan farmers.

Total liabilities divided by total assets and loan repayment anticipated divided by total assets were both greater for problem loans than for acceptable loans. The most interesting aspect of these two ratios was that they had the lowest standard deviations of the 12 ratios, which indicates that these two ratios were close about their means within groups and, therefore, greatly separated between groups. Such characteristics make them good discriminating variables for classifying between groups.

## STATISTICAL FRAMEWORK

Previous research has indicated that discriminant analysis is a useful tool for constructing objective credit evaluation criteria. It has been indicated that cluster analysis could be used to supplement discriminant analysis by aiding in determining the homogeneity of a dataset and thus how many credit scoring functions should be developed for maximum predictive power. The nature and characteristics of both discriminant and cluster analysis are described in detail in numerous publications *(1, 7, 8, 9, 13, 16, 17, 18)*.

## RESULTS OF ANALYSIS

Before actual analysis and construction of the credit scoring model could begin, two preliminary steps were required. The first involved a test to determine whether the data drawn from different years were significantly different. The second involved testing the homogeneity of the data to determine if more than one discriminant function would be necessary for optimum classification in the analysis.

### Significance of Data From Different Years

Discriminant analysis was used to determine if there were significant statistical differences among data from 5 different years, 1974-1978. The 12 financial ratio variables and the three non-ratio variables were used in this analysis. The F-ratio for this analysis was not significant above the 70 percent confidence level. With this, it could be assumed that the data from different years were not statistically different for discriminating purposes with the variables used in this study. An earlier study by Dunn *(4)* found the same to be true for a similar analysis.

### Cluster Analysis to Examine Homogeneity of Data

A cluster analysis was performed to determine if there were any natural groupings within the data that would bias the discriminant function. The results of this analysis were used to determine for classification purposes, if full-time and part-time farm borrowers were separate natural groupings and if borrowers with different types of farms were separate natural groupings.

The variables included in the cluster analysis were the 12 financial ratio variables, the three non-ratio variables, and the variable indicating membership in either the acceptable loan category or the problem loan category. The results indicated that there was no significant difference between full-time and part-time farm borrowers for classification purposes with the variables used in this analysis. It was also shown that there was no significant difference between borrowers with different types of farms.

**Credit Scoring Model**

Numerous variations of the 15 financial ratio and non-ratio variables were examined to determine which combination would give the best discriminating equation for use in classifying acceptable and problem loan accounts. Only two of the variables were found to be significant at the 95 percent confidence level, total liabilities divided by total assets and the amount of annual loan repayment anticipated divided by total assets. Both variables combined had a F-ratio that significant above the 99 percent level, and correlation between the two variables was not significant. The equation was as follows:

$Y_s = 1.85995 - 4.60761X_1 - 1.61209X_2$ (1)

where:

$Y_s$ = the calculated discriminant score which distinguishes between acceptable and problem loans.

$X_1$ = the original value of total liabilities divided by total assets.

$X_2$ = the original value of loan repayment anticipated divided by total assets.

Standardized coefficients were calculated by subtracting the corresponding mean from each variable and then dividing the results by the variable's standard deviation, table 3. The standardized discriminant function was as follows:

$Y_s = -0.88118X_1 - 0.28254X_2$ (2)

where: The symbols are the same as in equation (1) except the $X_i$s are standardized.

TABLE 3. MEANS AND STANDARDIZED COEFFICIENTS FOR VARIABLES OF THE DISCRIMINANT FUNCTION

| | | Means | | |
|---|---|---|---|---|
| | | Loan classification group | | |
| Variable | Coefficient | Acceptable | Problem | Difference between means |
| Total liabilities/ total assets | −0.88118 | 0.2745 | 0.4998 | 0.2253 |
| Loan repayment anticipated/ total assets | −0.28254 | 0.1370 | 0.2521 | 0.1151 |

Each of these coefficients represents the relative contribution of its associated variable to the function, with the sign indicating whether the variable is making a positive or negative contribution. For this function, total liabilities divided by total assets was about three times as important as annual loan repayment anticipated divided by total assets, with both variables contributing negatively to the function.

The group means in table 3 indicate that the ratio of total liabilities to total assets is 50 percent for the problem loan group and only 27 percent for the acceptable loan group. This 23 percent difference indicates, as would be expected, a relatively stronger financial position for borrowers in the acceptable loan group than those in the problem loan group and helps explain the importance of the solvency ratio in discriminating between the two groups.

Annual loan repayment anticipated to total asset ratio is 25 percent for the problem loan group and only 14 percent for the acceptable loan group. This indicates that the problem loan group will have to generate more debt repayment from their assets than the acceptable loan group.

The difference between the repayment capacity ratios for each group is half of the difference between the solvency ratios for each group. This difference helps explain the lesser importance of the repayment capacity ratio in discriminating between the two groups.

The standardized discriminant function coefficients are not very useful for computational purposes with raw data. Therefore, the unstandardized coefficients were used to arrive at a discriminant score. The mean discriminant values for the two groups were computed by substituting the respective means for the variables as given in table 3 into the discriminant function. The result for the acceptable loan classification group was:

$$Y_a = 1.85995 - 4.60761\overline{X}_{a1} - 1.61209\overline{X}_{a2}$$

where:

$Y_a$ = mean discriminant score for acceptable loans.

$\overline{X}_{a1}$ = mean of total liabilities divided by total assets for acceptable loans.

$\overline{X}_{a2}$ = mean of loan repayment anticipated divided by total assets for acceptable loans.

By substitution,

$$\begin{aligned} Y_a &= 1.85995 - 4.60761\,(0.2745) - 1.61209\,(0.1370) \\ &= 0.37419 \end{aligned}$$

The mean discriminant value for the problem loan classification group was computed in the same way:

$$y_p = 1.85995 - 4.60761\overline{X}_{p1} - 1.61209\overline{X}_{p2}$$

where:

$Y_p$ = mean discriminant score for problem loans.

$\overline{X}_{p1}$ = mean of total liabilities divided by total assets for problem loans.

$\overline{X}_{p2}$ = mean of loan repayment anticipated divided by total assets for problem loans.

by substitution,

$$Y_p = 1.85995 - 4.60761\ (0.4998) - 1.61209\ (0.2521)$$
$$= -0.84919$$

These calculated mean discriminant scores and their corresponding variances and standard deviations are given in table 4. These estimated parameters were treated as population parameters for the establishment of a critical cutoff value of Y.

TABLE 4. MEAN DISCRIMINANT SCORES, CORRESPONDING VARIANCES, AND STANDARD DEVIATIONS FOR THE DISCRIMINANT FUNCTION; ACCEPTABLE AND PROBLEM LOANS

| Loan group | Sample size | Mean discriminant value | Variance | Standard deviation |
|---|---|---|---|---|
| Acceptable ............ | 118 | 0.37419 | 0.61984 | 0.78730 |
| Problem .............. | 52 | −0.84919 | 0.78324 | 0.88501 |

The critical cutoff value of Y is needed to classify agricultural loans with the developed discriminant function. If it is assumed that misclassification of acceptable and problem loans are of equal significance, the cutoff value can be calculated as follows:

$$Y_c = \frac{S_p\overline{Y}_a + S_a\overline{Y}_p}{S_p + S_a}$$

where:

$Y_c$ = the calculated cut-off Y value.

$S_p$ = the standard deviation of the Y-values for problem loans.

$S_a$ = the standard deviation of the Y-values for acceptable loan.

$\overline{Y}_p$ = the mean Y-value for problem loans.

$\overline{Y}_a$ = the mean Y-value for acceptable loans.

For the given analysis, this would be:

$$Y_c = \frac{(0.88501)\,(0.37419) + (0.78730)\,(-0.84919)}{(0.88501) + (0.78730)}$$

$$= -0.20176$$

Given this calculated cutoff score, those loans with computed Y values equal to or greater than −0.20176 would be classified as acceptable loans, while those with Y values less than −0.20176 would be classified as problem loans.

In order to verify how well the function could actually classify loans into either acceptable or problem loan groups, the computed discriminant function and critical cutoff value were applied to the hold-out sample of 50 loan applications. The results of this test are given in table 5. The function correctly classified 84 percent of the acceptable loans, 92 percent of the problem loans and 88 percent of the total.

TABLE 5. RESULTS OF CLASSIFICATION TEST OF THE DISCRIMINANT FUNCTION ON HOLDOUT SAMPLE

| | Classified as | | |
|---|---|---|---|
| Actual group | Problem | Acceptable | Total |
| Problem | 23 | 2 | 25 |
| Acceptable | 4 | 21 | 25 |
| Total | 27 | 23 | 50 |

**Application of Evaluation Technique**

To make the discriminating function easier to use, it can be modified by multiplying through by 100 giving:

$$SC = 186 - 460.8X_1 - 161.2X_2$$

where:

SC = the calculated classification score.

$X_1$ = total liabilities divided by total assets.

$X_2$ = loan repayment anticipated divided by total assets.

To demonstrate how this function could be used to evaluate loans, an example is presented for two typical loans. Values for the two example loan applications are:

| | Loan 1 | Loan 2 |
|---|---|---|
| | (000) | (000) |
| 1. Total assets .............. | \$370 | \$270 |
| 2. Total Liabilities ......... | 50 | 140 |
| 3. Loan repayment anticipated ............. | 30 | 18 |

The calculated value of variable $X_1$ for each loan would be:

$$\frac{\text{Total liabilities}}{\text{Total assets}} = \frac{50}{370} \quad \frac{140}{270}$$

$$= 0.135 \quad 0.52$$

Likewise, the calculated value of variable $X_2$ for each loan would be:

$$\frac{\text{Loan repayment anticipated}}{\text{Total assets}} = \frac{30}{370} \quad \frac{18}{270}$$

$$= 0.08 \quad 0.07$$

Given the two calculated variables for each loan, the function score can be determined by:

$$\text{SC (loan 1)} = 186 - 460.8\ (0.135) - 161.2\ (0.08)$$
$$= 110.896$$
$$\text{SC (loan 2)} = 186 - 460.8\ (0.52) - 161.2\ (0.07)$$
$$= -64.9$$

Thus, the loan can be classified as either an acceptable or problem loan by the criterion of the cutoff score. If the calculated score is equal to or greater than the cutoff score, then the loan is classified as an acceptable loan, but if the score is below the cutoff score the loan is classified as a problem loan. Using the cutoff score of −20.2, loan one would be classified as an acceptable loan and loan two would be classified as a problem loan.

In determining the cutoff score, the significance of the consequences of misclassifying both problem and acceptable loans has to be considered. If the consequences of the two possible classification errors are of equal significance then the Z statistic will be equal for both classification errors. However, since all problem loans need close supervision and the consequences of misclassifying a problem loan could possibly be more costly than misclassifying an acceptable loan, a more precise cutoff score is needed that will reflect the negative consequences of problem loan misclassification.

This could be accomplished by selecting the desired percentage of problem loan classification error that would be suitable, consulting a table of cummulative normal frequency distributions, and deriving the appropriate cutoff value through the following equation *(18)*.

$$Y_e = \overline{Y}_p + (Z)\, S_p$$

where:

$Y_e$ = problem loan classification error selected cutoff value.

$\overline{Y}_p$ = mean Y value for problem loan group.

Z = standard measure of normal distribution.

$S_p$ = standard deviation for problem loan group.

Calculated cutoff values for various selected percentages of misclassified problem loans and their effect on classification of the original sample collected are given in table 6.

TABLE 6. CUTOFF SCORES AND CLASSIFICATION RESULTS OF TOTAL SAMPLE FOR SELECTED PROBLEM LOAN MISCLASSIFICATION PERCENTAGES

| Problem loan misclassification percentage selected | Computed cutoff score | Percent correct classification | | |
|---|---|---|---|---|
| | | Problem | Acceptable | Total |
| 50 | −84.9 | 54.5 | 90.2 | 77.7 |
| 45 | −73.4 | 55.8 | 87.6 | 75.9 |
| 40 | −62.8 | 59.7 | 86.7 | 77.3 |
| 35 | −50.4 | 64.9 | 86.0 | 78.6 |
| 30 | −39.0 | 70.1 | 85.3 | 80.0 |
| 25 | −25.6 | 81.8 | 81.1 | 81.4 |
| 23.3 | −20.2 | 83.1 | 79.7 | 80.9 |
| 20 | −10.6 | 84.4 | 79.0 | 80.9 |
| 15 | 7.1 | 89.6 | 69.2 | 76.4 |
| 10 | 28.4 | 92.2 | 60.8 | 71.8 |
| 5 | 60.2 | 93.5 | 44.8 | 61.8 |
| 2.5 | 88.5 | 97.0 | 29.4 | 53.2 |
| 2 | 96.5 | 97.4 | 26.6 | 51.4 |
| 1 | 121.3 | 98.7 | 11.9 | 42.3 |

In order to use the table, an allowable percentage of problem loan misclassification has to be chosen. The corresponding computed cutoff value can then be used to classify loans with a probable assurance of misclassifying at most the chosen percentage of problem loans. An example would be to assume that only 1 percent of problem loans can be misclassified, then

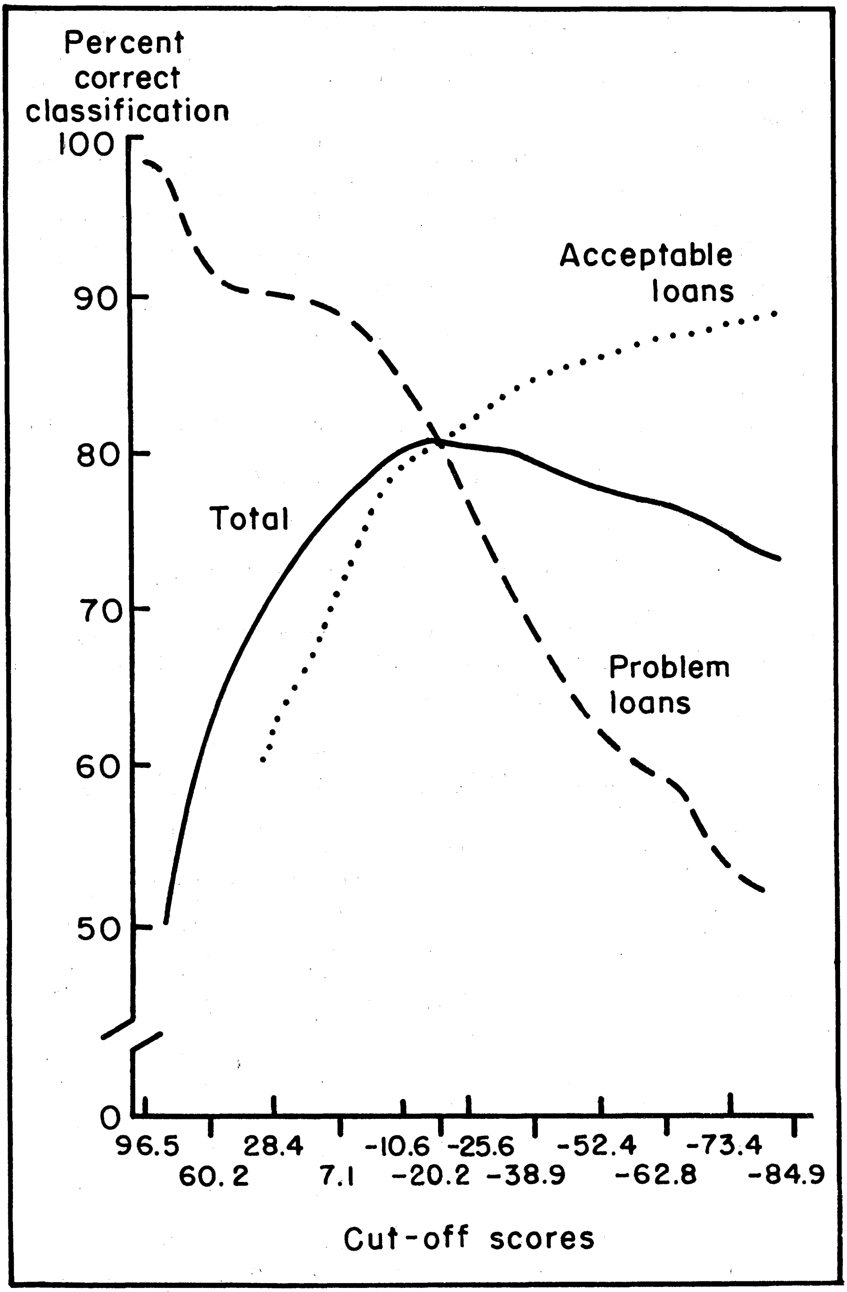


FIG. 2. Percentage of correct classification for acceptable, problem, and total loans at various cutoff scores

the corresponding cutoff value would be 121.3. Using this cutoff value, the discriminant function would misclassify at most 1 percent of the problem loans. However, as can be seen from the results of the classification test, if 99 percent of the problem loans are correctly classified, only 12 percent of the acceptable loans are correctly classified. There is a tradeoff between the correct classification of problem and acceptable loans. An increase in the percentage of misclassification of problem loans will cause a decrease in the percentage of misclassification of acceptable loans.

The tradeoff of correct classification can be better seen in figure 2. The X-axis is the cutoff value and the Y-axis is the actual percent of correct classification. As indicated earlier, the percent of acceptable loans correctly classified increases as the percent of problem loans correctly classified decreases. Also, as the problem loan misclassification percentage decreases, total correct classification increases, reaches a maximum, and then decreases. All three lines intersect at the point of maximum total correct classification. This point is the optimum cutoff value for maximizing total correct classification with the developed discriminant function.

By using the data in table 6, the discriminant function can be used to classify loans with any selected problem loan misclassification percentage. This selected problem loan misclassification percentage can be compared to the approximate acceptable loan correct classification percentage and total correct classification percentage in order for cutoff value decisions to me made. Misclassification costs for acceptable and problem accounts are important in determining the appropriate cutoff value.

## SUMMARY

The purpose of this study was to develop an objective loan evaluation technique that could be used in differentiating between acceptable and problem loans. Emphasis was directed toward evaluating agricultural loans made by the eight Production Credit Associations in Alabama; however, the overall results should also be interesting to and useful for other agricultural lenders and farm borrowers. Various objective methods that have been developed in the past and subjective and objective methods now in use by credit institutions were examined and evaluated.

Financial and non-financial borrower characteristics from original loan applications were used to identify ratio and non-ratio variables. These were used to determine which combination of borrower characteristics best discriminated between acceptable and problem loans.

Discriminant analysis was used to determine that there was no statistical significance in the data that came from different years. The homogeneity of the data was evaluated and verified through the use of cluster analysis. Stepwise discriminant analysis was used to determine which variables were most significant in the study and to construct a credit scoring function using these selected variables.

The analysis indicated that only two variables were significant; total liabilities divided by total assets and annual loan repayment anticipated divided by total assets. Total liabilities divided by total assets has been found to be significant in studies by Bauer and Jordan *(2)*, Dunn and Frey *(5)*, and Johnson and Hagan *(12)*. The amount of annual loan repayment anticipated, divided by total assets had not been included as a variable in other studies.

Total liabilities divided by total assets was found to be the most significant and was three times as important in the function as the other variable. It contributed negatively toward borrower classification indicating that as this ratio increased, the probability of a loan being classified as acceptable decreased. Using the calculated cutoff value for the evaluation technique (−20.2), total liabilities divided by total assets taken by itself could not be greater than 0.447 for a loan to be classified as acceptable.

The second variable, annual loan repayment anticipated divided by total assets, also had a negative effect on borrower classification. As this ratio increased, the probability of a loan being classified as acceptable decreased, indicating that higher values for this ratio placed more stress on the farmer's assets to generate repayment capital.

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

By modifying the original function, an application technique was developed that could be used by Alabama Production Credit Associations 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 percentage of problem loan misclassification, a cutoff value could be selected that meets management requirements for correct classification of problem and acceptable loans. Estimations of misclassification costs could be considered and a cutoff value selected that would minimize such objectives as the chance of misclassifying problem loans or maximize total loan volume.

The table of various cutoff values indicated the tradeoff between correct classification of problem loans and acceptable loans. As the percentage of correct classification of problem loans decreased, the percentage of correct classification of acceptable loans increased. Also, as the percentage of correct classification of problem loans decreased, the percentage of total loans correctly classified increased, reached a maximum where correct classification of both loan groups were equal, and then decreased.

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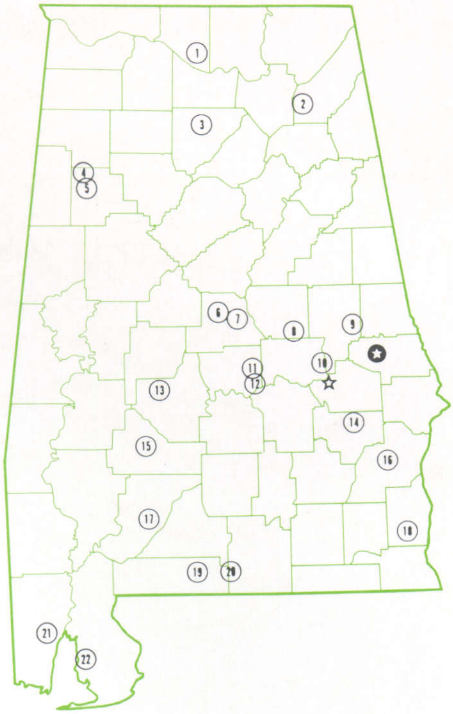
## APPENDIX

ALABAMA CREDIT STUDY
CONFIDENTIAL
**Agricultural Economics and Rural Sociology Department**
**Auburn University**

1. Year loan was made .................. ____________
2. Classification of loan ....... Acceptable __Problem__
3. Full-time farmer ...................... Yes__No____
4. Age of operator ........................ ____________
5. Major enterprise of farm ............... ____________
6. Acreage owned ......................... ____________
7. Acreage rented ........................ ____________
8. Current assets
   (Include both current and
   intermediate assets.) ................ ____________
9. Current liabilities
   (Include both current and
   intermediate liabilities.) ............ ____________
10. Total assets .......................... ____________
11. Total liabilities ..................... ____________
12. Net worth ............................. ____________
13. Net farm income ....................... ____________
14. Gross farm income ..................... ____________
15. Gross non-farm income ................. ____________
16. Value of underlying security .......... ____________
17. Total loan commitment to
    your organization ..................... ____________
18. Repayment of principal anticipated
    during prior loan year ................ ____________
19. Repayment actually made on principal
    during prior loan year ................ ____________
20. Marketable inventory on hand at loan
    renewal date .......................... ____________

## Alabama's Agricultural Experiment Station System
## AUBURN UNIVERSITY

With an agricultural research unit in every major soil area, Auburn University serves the needs of field crop, livestock, forestry, and horticultural producers in each region in Alabama. Every citizen of the State has a stake in this research program, since any advantage from new and more economical ways of producing and handling farm products directly benefits the consuming public.




## Research Unit Identification

⍟ Main Agricultural Experiment Station, Auburn.
☆ E. V. Smith Research Center, Shorter.

1. Tennessee Valley Substation, Belle Mina.
2. Sand Mountain Substation, Crossville.
3. North Alabama Horticulture Substation, Cullman.
4. Upper Coastal Plain Substation, Winfield.
5. Forestry Unit, Fayette County.
6. Foundation Seed Stocks Farm, Thorsby.
7. Chilton Area Horticulture Substation, Clanton.
8. Forestry Unit, Coosa County.
9. Piedmont Substation, Camp Hill.
10. Plant Breeding Unit, Tallassee.
11. Forestry Unit, Autauga County.
12. Prattville Experiment Field, Prattville.
13. Black Belt Substation, Marion Junction.
14. The Turnipseed-Ikenberry Place, Union Springs.
15. Lower Coastal Plain Substation, Camden.
16. Forestry Unit, Barbour County.
17. Monroeville Experiment Field, Monroeville.
18. Wiregrass Substation, Headland.
19. Brewton Experiment Field, Brewton.
20. Solon Dixon Forestry Education Center, Covington and Escambia counties.
21. Ornamental Horticulture Field Station, Spring Hill.
22. Gulf Coast Substation, Fairhope.