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A LOGIT ANALYSIS

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ABSTRACT

Farm size, liquidity, solvency, profitability, capital efficiency, and operating efficiency measures are used to develop credit scoring models for dairy farm borrowers. Weighted logit models are used to discriminate between acceptable borrowers and borrowers who have defaulted. Also, methodological issues which pertain to classification models (identifying the naive model, selecting a classification cut-off point, and validating the model) are addressed. Results indicate that larger borrowers can be classified well using financial ratios. Ratios of importance were debt payments per dollar of milk sales, cash expenses before interest and taxes per dollar of gross income, and youngstock per cow.

Key words: borrower classification, credit scoring, dairy farm, financial ratios, loan default, logit

An important component of the total interest rate charged for a loan is the risk premium included to reflect the credit worthiness of the borrower (Federal Reserve Bank). A risk premium should be charged to borrowers with a relatively high default potential because they may: 1.) require above average servicing costs; 2.) reduce expected profits because of loan restructurings at terms less favorable to the lender (Chesser); and 3.) frequently cause loan losses stemming from total loan default (Federal Reserve Bank). Therefore, identifying borrowers who are more likely <u>not</u> to make timely payments is critical to loan pricing.

The purpose of this article is to present the results of an empirical study of factors related to borrower loan default and to discuss some methodological issues of importance in a credit assessment analysis. For this analysis, a logit probability model is used to relate loan default to financial ratios of dairy farm borrowers. The data for this analysis came from the short and intermediate term agricultural loan portfolio of a case study bank. As a part of this analysis, methodological considerations which have not received sufficient attention in previous agricultural credit assessment studies are addressed. These neglected issues may have biased prior results and caused misinterpretations of the effectiveness of models in correctly classifying borrowers.

Objective statistical methods for evaluating farm borrowers have been proposed since the mid 1960's. Agricultural credit assessment models have been used to evaluate potential borrowers (credit screening) or to evaluate existing borrowers (credit scoring). Credit screening and credit scoring require two different approaches. Credit screening relies on information from the initial loan application to discriminate between loans which have been successful and unsuccessful (Reinsel and Brake; Bauer and Jordan; Evans; Dunn and Frey). Credit scoring relies on recent financial information to identify variables which indicate the quality of unmatured loans (Johnson and Hagan; Hardy and Weed; Lufburrow, Barry, and Dixon). Credit scoring analyses are most suitable for periodic evaluations of loan quality and loan pricing.

THE DATA

The data for this project came from the short and intermediate term agricultural loan portfolio of a case study bank in upstate New York. Because precise statistical estimates required an overrepresented number of observations on lower quality and larger loans, a general nonproportional stratified sample was taken. The portfolio was stratified by loan size and loan quality. Large borrowers were defined as having an average loan balance of $90,000 or greater during 1984 and small borrowers had less than a $90,000 balance. Borrower loan contract compliance was used as the measure of loan quality. For this study, loan compliance was defined as paying the loan as scheduled without refinancing the loan. Borrowers who complied with the loan contract (made timely payments) were referred to as acceptable borrowers and those who did not as problem borrowers. Therefore, problem borrowers were in default of their loan contract at some time in 1984.

The definition of acceptable and problem borrowers used for this study is different than ones used in past agricultural credit scoring research. For this study, the definition of an acceptable and problem borrower is based on the observed payment performance of the loan and is thus objective. Typically, past agricultural studies have defined borrowers as acceptable or problem based on examiner classifications, which are subjective. Since an examiner's classification is subjective, measurement error may be encountered. In other words, an examiner's classification for a specific borrower would not necessarily be consistent between examiners, lenders, or time periods. Therefore, a loan defined as a problem loan for this study may have been classified an acceptable credit using the examiner's classification. Also, a loan classified as a problem by the lender because of past repayment history and inadequate security could be classified as an acceptable borrower for this study if the loan was paid as scheduled for the 1984 year.

With both definitions, some problem loans will ultimately be paid in full—including accrued interest. The full payment of a borrower's obligation may be accomplished by the lender foreclosing and applying proceeds (from the sale of the collateral) to the outstanding debt if the collateral is adequate. Or the lender may reschedule the outstanding principal and accrued interest in a manner which allows the borrower to payback the debt under new terms. Last, a problem borrower may "catch up" on delinquent payments and make future installments as originally scheduled.

The strength of this study's definition of acceptable and problem borrowers is the objective and logical method of identifying borrower quality via loan repayment. The weakness of this definition, as well as past ones, is that the definition does not distinguish well between the severity of default or the likelihood of the lender incurring a loan loss from a defaulted loan.

Using the afore mentioned definitions of loan size and quality—which specify four borrower groups—a nonproportional sample of 203 borrowers was drawn from the portfolio. The sample consisted of 52 large-acceptable borrowers, 24 large-problem borrowers, 71 small-acceptable borrowers, and 56 small-problem borrowers.

METHODOLOGICAL CONCERNS

Several methodological issues are important to address for a study which classifies borrowers based on their level of default risk. The first issue is the selection of an appropriate statistical procedure to estimate the classification model. The statistical method initially used to classify farm borrowers by their loan default risk was multiple linear discriminant analysis (Reinsel and Brake; Bauer and Jordon; Johnson and Hagan; Dunn and Frey; Hardy and Weed). However, linear discriminant analysis is acknowledged to be inappropriate when the explanatory variables are not normally distributed, which is typically the case with financial ratios. (Ohlson). Probit and logit are statistical methods which have superseded linear discriminant analysis. For this study, logit analysis was chosen because of software support.

The second methodological issue is the effect a nonrandom sample has on an estimated logit model and how to compensate for its effects. Manski and McFadden have proven that an unweighted choice-based sample will cause biased and inconsistent probability and parameter estimates in a classification model.[1] Zmijewski has shown that an unweighted outcome-based sample, which contains a disproportionately large number of financially distressed businesses, results in a model which overclassifies financially distressed firms and underclassifies nondistressed firms.

The sample used in this study is an outcome-based sample and must be weighted to correct for bias. The weighting scheme selected to correct for bias was the weighted exogenous sample maximum likelihood method. Thus, each borrower class is weighted by the ratio of their population proportion to their sample proportion.

The third issue is the method of reducing the number of financial measures which have been found significant in past studies, or are believed to influence borrower quality, to a manageable number of regressors for the final model. The list of potentially significant variables is frequently quite large because of the nature of ratio construction and financial distress analyses. Because no well specified underlying theory of financial distress exists, no well defined method for selecting variables for estimation is apparent (Marais, et al.). Thus, prior studies have used data-analytic procedures to cull a subset of explanatory variables from a list of candidates (Marais, et al.). However, overfitting to the data set is a problem with these data-analytic procedures (Marais, et al.). Thus, it appears data-analytic methods of selecting variables are necessary, but flawed.

To correct for the problem of overfitting to the data set, an independent data set (a hold out sample) should be used to validate results. For example, a classification model should be tested with a hold out sample to verify its correct classification rates and efficiency. In this study, a hold out sample of thirty borrowers was selected randomly from the full sample to test the classification ability of models.

To select an appropriate data-analytic method for this study, a tenet of financial distress theory was used. Because financial distress theory is based on the empirical evidence that the means of financial ratios are significantly different between financially distressed and nondistressed businesses, a method which analyzes differences between population means, analysis of variance (ANOVA), was used to select potential regressors.

The fourth methodological issue is the classification hypothesis. To optimally classify the observations based on their estimated probabilities, two items are considered. They are the prior probability of being in a class and the minimization of misclassification costs (Maddala). If one assumes a symmetrical misclassification loss function, then the cutoff point is equal to the prior probability of being in a class (Martin). Since the costs of misclassification were not estimated and are assumed to be equal for type I and type II error, the cutoff point for the portfolio is 83.8%.[2] Thus, a borrower with an estimated probability of being an acceptable loan that is greater than 83.8% would be classified as an acceptable borrower. A borrower with an estimated probability of less than 83.8% would be classified as problem borrower.

It is arguable that the costs of misclassifying a problem borrower as acceptable would be greater than misclassifying an acceptable borrower as a problem one. Thus, the misclassification loss function would not be symmetrical and the equal misclassification cost assumption would negate the usefulness of this classification model. However, the borrowers most likely to be misclassified are borderline cases and revenue (the interest paid on the loan) is treated as a negative cost, then the costs incurred for misclassifying a borderline borrower may not be great since the interest rate can be raised (the misclassification costs reduced) with dynamic differential loan pricing. Therefore, the assumption of equal misclassification costs is not inappropriate.

The last methodological consideration is the evaluation of the classification ability of a model. The classification efficiency rates of a model should be compared to the naive model rate. The naive model rate is the probability that one could correctly classify an item with no information available. Some studies have incorrectly interpreted the naive rate for a binary model as 50 percent. Actually, a conditional probability model which accounts for prior probabilities is the correct naive model specification (Beaver). For example, if a 10% failure rate for an industry was known, then the true naive model for predicting business failure in that industry would have a rate of [(0.1x0.1) + (.9x.9)]=82%.[3] Thus, a binary model which had an efficiency rate of less than 82% would be worse than the naive model.[4]

None of the past agricultural studies compared their efficiency rates to the correct naive model rate. To show the misleading interpretation of a model's classification ability based on the total correct classification rates, an example is presented. If the prior population proportion of acceptable borrowers for the past bi-classification models had been at least 90%, then the naive model efficiency rate would have been 82%.[5] Using the proposed prior proportion rate of 90%, the efficiency of two past bi-classification models is (0.9 x 0.9) + (0.1 x 0.6) =87% (Dunn and Frey) and (0.9 x 0.8) + (0.1 x 0.83) =80% (Weed and Hardy). The total correctly classified rates which were reported are 75% (Dunn and Frey) and 81% (Weed and Hardy). Thus, comparisons with the total correct classification rates are misleading.

EMPIRICAL APPLICATION

Seven prior agricultural credit assessment studies have identified various financial and non-financial factors as being important in assessing borrower quality (Table 1). However, no financial measure has consistently been identified as significant. Financial measures which have frequently appeared in agricultural credit assessment models are: 1.) a measure of solvency—significant in all but the first two analyses, 2.) a measure of repayment ability—material in all but two analyses, and 3.) a measure of liquidity or a ratio including short-term debts —important in five studies.

For this study, financial ratios of size, liquidity, solvency, profitability, capital efficiency, and operating efficiency were examined. A discussion of these measures follows. Business size measures describe the magnitude of resources a business controls. In the financial literature, it has been found that larger companies are less likely to fail (Ohlson). In agricultural research, farm size as measured by cow numbers was found to have either a positive effect or no influence on the success of dairy farms in New York state (Kauffman and Tauer). For this study, the measures of dollars of assets and cow numbers were included in the analysis.

Liquidity gauges the farm's ability to meet short term obligations. In past empirical studies, farms with more liquidity have been better risks (Table 1). For this study, the variables debt payments per dollar of milk sales and debt per cow were used in the analysis.

Solvency assesses a farm's ability to pay obligations in the case of liquidation or it can also indicate a firm's ability to withstand adverse conditions. Past agricultural studies have found that farms with higher levels of equity are better risks (Table 1). For this study, percent equity was used to measure solvency.

Profitability gauges the net dollars of income produced from investments. Logically, the more profitable a farm the better the risk it is. Researchers have found that an accrual measure of income better represents profitability (Lins, Ellinger, and Lattz). Thus, cash income ratios may only measure the farm's ability to make debt payments in that year. Since an accrual measure of farm income was not available for this research the measures studied were cash earnings before interest and taxes (EBIT) divided by assets and EBIT divided by equity.

Capital efficiency ratios assess the farm's ability to use assets optimally. For this study, the value of assets per cow was included as a variable. Higher values of investment per productive unit generally represents lower capital efficiency of a farm and thus, reduces the likelihood of timely payments.

The last group of factors incorporated into the study were those which measured operating efficiency. The measures which were included are: dollars of milk sold per cow (DPPMS), purchased feed cost per dollar of milk sales, operating expenses before interest divided by gross income and youngstock per cow (CEBIPGI). The more productive the farm or the more cost conscious it is, the better risk it is for a lender.

With the factors which may indicate borrower default risk identified, the borrower loan default risk model used for this study will be presented. Following Beaver's contention that with multiratio analysis each ratio should convey as much additional information as possible, only one financial variable which characterizes farm size, liquidity, solvency, profitability, or capital efficiency would be permitted in the general logit model. More than one variable from the operating efficiency group would be permitted in the model since these variables represent production as well as financial efficiency characteristics.

THE GENERAL MODEL SPECIFICATION

The general borrower loan default risk model can be stated as follows:

The predicted probability of Y is

$$\hat{Y}_{i,t+1} = 1 - \frac{1}{1 + \exp\left[b_o + W_i \sum_{k=1}^{6} [b_{ki} X_{ki,t}] \right]}$$

The predicted logit of Y is

$$Y^{*}_{i,t+1} = b_o + W_i \sum_{k=1}^{6} [b_{ki} X_{ki,t}]$$

where for the i th observation

$\hat{Y}_{i,t+1}$ is the predicted probability of being an acceptable borrower

$Y^{*}_{i,t+1}$ is the predected log of the odds ratio of being an acceptable borrower

W_i is the weight (weighted exogenous sample maximum likelihood method)

b_0 is the intercept

b_{1-6} are the logistic regression coefficients

$X_{1,t}$ is a farm size measure from year $_t$ financial statements

$X_{2,t}$ is a liquidity measure from year $_t$ financial statements

$X_{3,t}$ is a solvency measure from year $_t$ financial statements

$X_{4,t}$ is a profitability measure from year $_t$ financial statements

$X_{5,t}$ is a capital efficiency measure from year $_t$ financial statements

$X_{6,t}$ are operating efficiency measures from year $_t$ financial statements

INITIAL FINANCIAL VARIABLE ANALYSIS

Since many ratios can be constructed to measure or represent farm size, liquidity, solvency, profitability, capital efficiency, and operating efficiency, ANOVA was used to select the most important ratios which would be used in the logit models as explanatory variables. ANOVA was used to identify financial variables with significantly different means between the four borrower groups and to determine whether the group differences were due to loan size, loan quality, or the interaction of the two. The Statistical Analysis System (SAS) general linear models procedure was used to analyze the unbalanced two-way ANOVA.

Financial variables with means that were different only between borrower groups of unmatched loan sizes would not be considered of value for the logit analysis. These variables would have similar values for high and low quality borrowers. Thus, the best financial measures would have overall F statistics that were significant and have significantly different means between loan quality groups. The ANOVA F statistics are reported in Table 2.

The results of the initial analysis indicate that only DPPMS, percent equity, CEBIPGI, and youngstock per cow have significantly different means for the loan quality groups, but not the size groups. The measures debt per cow, value of equity, EBIT per dollar of assets, and milk sales per cow were significantly different between all groups. The variables value of assets, cow numbers, EBIT per dollar of equity, value of assets per cow, and purchased feed cost per dollar of milk sales were found to either have different means between borrower size groups or to have no apparent difference between all the groups. Thus, eight financial measures—DPPMS, percent equity, CEBIPGI, youngstock per cow, debt per cow, value of equity, EBIT per dollar of assets, and milk sales per cow—would be included in the logit probability analysis.

LOGIT RESULTS

To examine the relative importance of the eight financial measures in indicating potential borrower default, loan default probability models were estimated using the full sample; however, a hold out sample was randomly selected from the full sample to verify the classification ability of the models. Also, because the ANOVA results indicated that the larger and smaller borrower groups had significantly different levels for some ratios, the full sample was partitioned and models were estimated for the large and small borrower groups.

Although the objective of the estimation using the full sample was to find the best predictive model, two models, referred to as model one and model two, were found to be important for classifying borrowers as acceptable or problem. The only difference between model one and model two is that model one includes the variable, EBIT per dollar of assets, and model two replaces EBIT per dollar of assets with the variable, CEBIPGI. Thus the difference represents whether profitability or cost control is more important in determining the quality of borrower. The results of the estimated models for the portfolio are contained in Tables 3 and 4. The variables which were found to indicate borrower loan quality are: EBIT per dollar of assets, CEBIPGI, DPPMS, and youngstock per cow.

The variables found to be unimportant in indicating borrower quality by the logit analysis are: percent equity, dollars of equity, milk sales per cow and debt per cow. These independent variables, when added to the portfolio models one and two, did not have parameters which were significantly different from zero at the 30% level of confidence. Thus, these variables did not increase the explanatory power of the model and were dropped to improve the efficiency of the estimates.

Model one (Table 3) contains financial measures representing profitability, liquidity, and operating efficiency. The independent variables are EBIT per dollar of assets, DPPMS, and youngstock per cow respectively. Model one has a Chi Square statistic of 23.45 with 3 degrees of freedom and is significant at the one percent level of confidence. The "R" for this model was 0.338 which is low, but not unreasonable for a logit classification model using farm data.[6] Marais, et al., concluded that small firms have worse statistical fits than large publicly traded firms in classification models because of inconsistencies in financial statements. Since these farms are small businesses and the cash income statements and market value balance sheets, that farmers use, do not have the consistency that would be found with audited accrual statements, measurement error was expected. Thus, the lack of complete explanation of the loglikelihood function was expected. The "C" statistic for this model is 0.764.[7] All the independent variables have the correct sign and are not highly correlated. DPPMS is significant at the 1% level and EBIT per dollar of assets is significant at the 5% level. These results imply that a higher quality borrower has a lower DPPMS, a higher EBIT per dollar of assets, and a higher youngstock to cows ratio. Therefore, a higher quality borrower will be more liquid, more profitable, and have a higher operating efficiency.

Within the estimating sample, the model classified 71.1% of the borrowers correctly with 73.1% of the acceptable borrowers and 68.1% of the problem borrowers being correctly placed. Using the hold out sample, the model classified 73.3% of the borrowers correctly with 94.7% of acceptable borrowers and 36.4% of problem borrowers being correctly classified. Under the assumption that borrowers can be classified at the same rate as the population proportion, the naive model rate is 72.8%. By substituting in the model's correct rates, the efficiency of the model classifying borrowers with the estimating sample is 72.3% and with the hold out sample it is 85.3%. Thus, this model performed as well as the naive model with the estimating sample and better with the hold out sample.

Model two (Table 4) contains two measures of operating efficiency, and a measure of liquidity. The independent variables are CEBIPGI, youngstock per cow, and DPPMS respectively. Model two has a Chi Square statistic of 22.00 with 3 degrees of freedom and is significant at the one percent level of confidence. Model two has a lower Chi Square statistic than model one, but the Chi Square statistic is significant at the same level. The calculated "R" for the model is 0.324 which is slightly lower than the first estimated model. The "C" statistic for this model is 0.763 which is not substantially different from the first model.

With model two, the independent variables have the correct signs and are not highly correlated. DPPMS is significant at the 5% level and CEBIPGI is significant at the 10% level. For this model, a higher quality borrower will have a lower DPPMS, a higher youngstock to cow ratio, and a lower CEBIPGI ratio. Thus, a higher quality borrower will be more liquid and operate more efficiently.

Within the estimating sample, this model classified 68.8% of the borrowers correctly with 71.1 % of the acceptable borrowers and 65.2% of the problem borrowers being correctly placed. Using the hold out sample, the model classified 73.3% of the borrowers correctly with 84.2% of acceptable borrowers and 54.5% of problem borrowers being correctly identified. The efficiency of the model with the estimating sample is 70.1% and with the hold out sample it is 79.4%. Thus, this model performed less well with the estimating sample and better with the hold out sample when compared to the naive model.

To summarize, it appears that model two is equivalent to model one statistically, but that model two is a superior model because of its ability to classify problem borrowers with the full sample. Thus, it appears that cost control may be a better determinant of borrower loan default probability than profitability for dairy farmers in this portfolio. Also, it appears that higher liquidity is desirable. However, neither model was greatly different from the naive model with respect to classification ability. Because the models did not greatly improve the probability of correctly identifying acceptable and problem borrowers and because of the ANOVA results which indicated borrower loan size groups had unique ratio levels, model one and model two were fit to the large and smaller borrower groups to determine if separating the borrowers by loan size would improve the classification ability of the models.

LOGIT RESULTS FOR THE LARGE BORROWER GROUP

Model one and two were fit to the large borrower group to examine whether the loan size range of the portfolio was too large for the ratios to be effective predictors. The results of this estimation are presented in Tables 5 and 6.

Model one fit to the large borrower group (Table 5), referred to as model one-large, has a Chi Square statistic of 14.23 with 3 degrees of freedom. Its Chi Square is lower than the population model's, but is also significant at the one percent level of confidence. The R for model one-large is 0.336 and the C statistic is 0.758. Both are only slightly lower than found for the population model. For model one-large, all the independent variables have the correct sign, but the value of the coefficients differ from the portfolio model. For model one-large, DPPMS is significant at the 1% level, but EBIT per dollar of assets and youngstock per cow are not significant at the 10% level.

For model one-large, 71.0% of the borrowers were correctly classified with 76.2% of the acceptable borrowers and 60.0% of the problem borrowers being correctly placed within the estimating sample. Using the hold out sample, model one-large classified 71.4% of the borrowers correctly with 80.0% of acceptable borrowers and

50.0% of problem borrowers being correctly placed. The classification rates differ between the model one and one-large, but not substantially.

To judge the classification ability of model one-large with the efficiency test, its naive model rate must be calculated. For the large group, a borrower has a prior probability of being an acceptable borrower of 72.5% and thus the naive model rate is 60.1%. The efficiency of model one-large with the estimating sample is 71.7% and with the hold out sample it is 71.8%. Thus, model one-large performed better than the naive model with the estimating sample and with the hold out of sample. Compared to the portfolio model, model one-large predicted worse by raw percentage but did better when the gain in efficiency is considered.

The results of model two estimated for the large borrower group, referred to as model two-large, are presented in Table 6. Model two-large has a Chi Square statistic of 15.03 with 3 degrees of freedom. This statistic is lower than the population model's, but is significant at the one percent level of confidence. The "R" for model two-large is 0.352 and the "C" statistic is 0.773. Both are slightly greater than the population model. All the independent variables have the correct sign, but the values of the coefficients differ from the results of the portfolio model. DPPMS is significant at the 5% level while CEBIPGI and youngstock per cow are not significant.

Within the estimating sample, model two-large classified 75.8% of the borrowers correctly with 78.6 % of the acceptable borrowers and 70.0% of the problem borrowers being correctly indicated. Using the hold out sample, model two-large classified 85.7% of the borrowers correctly with 80.0% of acceptable borrowers and 100% of the problem borrowers being correctly placed. The classification rates are substantially greater for model two-large as compared to model two. The efficiency of model two-large with the estimating sample is 76.2% and with the hold out sample it is 85.5%. Thus, model two-large performed better than its naive model. Compared to model two, model two-large has better total correct classification rates. Therefore, the unrespecified models appear to classify large borrowers at a higher efficiency rate than the portfolio models classify all borrowers.

In summarizing this section, it appears that the preferred model for this study is model two-large. Statistically, it is superior to the other three models and it is also the best classifying model. Again, it appears that liquid dairy farmers which manage their costs well are better quality borrowers. Also, cost control appears to be a better determinant of borrower quality than profitability.

LOGIT RESULTS FOR THE SMALL BORROWER GROUP

As was noted before, models one and two were fit to the small borrower group; however, the results were disappointing. The results are not presented in this paper. Apparently, financial ratios based on farm financial records are not good determinants of borrower quality for small borrowers. Because off farm income was not available in this study and it directly affects a small borrower's ability to make timely payments, a possible explanation to the poor results with the smaller borrower group is that non-farming information may be important in indicating small borrower loan quality.

LOGIT RESULTS SUMMARY

In assessing the relative classification ability of this study's preferred model, model two-large, a comparison to models in past studies is made. However, direct comparisons of this study's results to past agricultural borrower classification results do have limitations. First, the definition for acceptable and problem borrowers for this analysis was different from those of past agricultural studies. Second, past agricultural studies which used linear discriminant analysis likely violated statistical assumptions or did not offer proof that these assumptions were not violated. Third, the only agricultural loan study which used a method other than discriminant analysis failed to weight their outcome-based sample. Fourth, past studies did not evaluate or report the efficiency of their models. Thus, the interpretation of past results is difficult because of the inappropriateness of the past models.

With the major differences between this and past studies recognized, an indirect comparison of predictive ability of this study's models can be made. For this study's preferred model which is model two-large, the total correct classification rate using the the hold out sample was 85.7%. Past studies had total correct classification rates of 79% (Lufburrow, Barry, and Dixon), 75% (Dunn and Frey), 62% (Johnson and Hagan), 81% (Weed and Hard), and 85%(Bauer and Jordan). It appears that model two-large is more effective in classifying acceptable and problem borrowers than models developed in previous studies.

CONCLUSIONS

From the empirical analysis using logit models, financial measures of liquidity, profitability, and operating efficiency were found to indicate borrower quality. Furthermore, the logit models developed in this research classify borrowers better than the naive model and better than past models. The models appear to be an effective and an objective way of evaluating borrower default risk for differential loan pricing.

One methodological issue for agricultural credit classification models which has received limited attention is the true cost of misclassifying a borrower or potential borrower. The costs of misclassifying a future problem borrower as acceptable are the costs associated with loan defaults. However, the severity of these costs are not truly known for agricultural borrowers. The costs of misclassifying a future acceptable borrower as a problem are the opportunity costs of lost profits from the proposed loan and future loans. Again, the true opportunity costs are unavailable. Until more is known about misclassification costs, researchers will not be able to minimize a misclassification cost function. Without this cost information, the expected savings or earnings from different classification models can not be estimated. However, measuring the costs associated with the misclassification of farm loans is a major limiting factor to including this information into the classification hypothesis.

NOTES

1. In choice-based sampling, the classification of the population into subsets is based on the outcomes: for each outcome a random sample is drawn. This is an endogenous sampling process, as opposed to an exogenous stratification on the independent variables used as predictors (Cosslett).

2. By convention, type I error is misclassifying a problem borrower as acceptable and type II error is misclassifying an acceptable borrower as a problem.

3. The naive model assumes that observations can be classified at the same rate as their population proportion.

4. To obtain the efficiency rate of a model for this example, the model's correct classification rate for failed businesses would be multiplied by 0.1 and that result would be added to the product of 0.9 and the model's correct classification rate for nonfailed businesses.

5. An acceptable borrower population proportion of 90% does not seem out of line since in 1982 and 1983, the national proportion of acceptable borrowers was 88.4% and 87.0% respectively for P.C.A.'s (Irwin) and these years could not be considered ones of high borrower quality for P.C.A.'s.

6. The calculated "R" for the model is analogous to the multiple correlation statistic in a standard regression setting. The range of the statistic is from 0 to 1 and a larger value implies that the model explains more of the loglikelihood variation.

7. A statistic calculated by the LOGIST procedure is with the classification statistic, "C". With a binary model, the "C" statistic is equivalent to the area under a receiver operating characteristic curve (Hanley and McNeil). Thus, the statistic has a range of 0.5 to 1 with 0.5 indicating no apparent discriminatory power and 1 indicating perfect discriminatory power. In this study, the "C" statistic represents the probability that a randomly chosen acceptable borrower will be correctly rated with greater probability to comply with loan terms than a randomly chosen problem borrower.

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TABLE 1 FACTORS INFLUENCING BORROWER QUALITY
PRIOR AGRICULTURAL STUDIES

FACTOR[a]	STUDY[b]								
	A	B	C	D	E	F	G	H	I
1. FARM SIZE	x						x		
2. LIQUIDITY			x			x			x
3. RATIO OF SHORT TERM TO TOTAL DEBT	x	x			x				
4. NONREAL ESTATE DEBT TO NONREAL ESTATE ASSETS					x				
5. SOLVENCY			x	x	x	x	x	x	x
6. LIABILITIES			x						
7. COLLATERAL									x
8. PREVIOUS INCREASE IN NET WORTH	x	x							
9. FARM OWNERSHIP	x								
10. NUMBER OF CREDITORS	x								
11. FARMING EXPERIENCE	x								
12. POOR PRODUCTION RECORDS				x	x				
13. REPAYMENT ABILITY		x				x			x
14. NOTE AMOUNT TO CASH FLOW							x		
15. LOAN REPAYMENT TO ASSETS								x	
16. REPAYMENT HISTORY									x
17. COSTS OF OPERATION				x	x				
18. LIVING EXPENSES		x		x	x				
19. REASONABLE FARM VALUE			x						
20. EXPECTED INCOME AS A PERCENT OF LAST YEARS				x					
21. MARITAL STATUS			x						
22 LIFE INSURANCE		x					x		
23. HEALTH INSURANCE		x							

a Some like financial measures were grouped together, i. e., solvency, liquidity, living expenses, repayment ability.

b A=Reinsel and Brake PCA; B=Reinsel and Brake FmHA; C=Bauer and Jordan; D=Evans PCA; E=Evans FmHA; F=Johnson and Hagan; G=Dunn and Frey; H=Hardy and Weed; I=Lufburrow, Barry, Dixon.

TABLE 2 ANOVA F STATISTICS FOR FINANCIAL MEASURES
173 Borrowers, 1984

FACTOR	OVERALL	LOAN QUALITY	LOAN SIZE	INTERACTION
FARM SIZE				
ASSETS	28.12[a]	3.55[c]	80.79[a]	0.04[c]
COWS	25.11[a]	2.28[c]	72.01[a]	1.03[c]
LIQUIDITY				
DPPMS[d]	10.20[a]	28.48[a]	0.42[c]	1.70[c]
DEBT PER COW	6.82[a]	9.75[a]	10.44[a]	0.28[c]
SOLVENCY				
% EQUITY	4.58[a]	10.19[a]	2.88[c]	0.69[c]
EQUITY	16.09[a]	9.32[a]	37.15[a]	1.81[c]
PROFITABILITY				
EBIT/ASSETS[e]	6.59[a]	11.83[a]	5.31[b]	2.63[c]
EBIT/EQUITY[f]	2.06[c]	1.09[c]	0.72[c]	4.36[b]
CAPITAL EFFICIENCY				
ASSETS PER COW	2.18[c]	0.00[c]	4.54[b]	2.02[c]
OPERATING EFFICIENCY				
PFCPMS[g]	2.85[b]	0.11[c]	8.42[a]	0.02[c]
CEBIPGI[h]	8.76[a]	21.81[a]	3.62[c]	0.85[c]
MILKS SALES PER COW	7.44[a]	13.96[a]	8.26[a]	0.10
YOUNGSTOCK PER COW	2.70[b]	7.09[a]	0.52[c]	0.51[c]

[a]Significant at the 1% level
[b]Significant at the 5% level
[c]Not significantly different from zero
[d]Debt payments per dollar of milk sales
[e]Earnings before interest and taxes per dollar of assets
[f]Earnings before interest and taxes per dollar of equity
[g]Purchased feed costs per dollar of milk sales
[h]Cash expenses before interest and taxes per dollar of gross cash income

TABLE 3 STATISTICS OF LOAN DEFAULT PROBABILITY MODEL ONE
173 BORROWERS, 1984

VARIABLE	COEFFICIENT	CHI SQUARE	P VALUE
INTERCEPT	1.335	1.70	0.1920
EBIT/ASSETS[a]	11.199	4.25	0.0393
DPPMS[b]	-4.503	8.82	0.0030
Y.STOCK/COW[c]	1.319	1.69	0.1936

MODEL STATISTICS

CHI SQUARE WITH 3 D.F.	23.45
P VALUE	0.000
R	0.338
C STAT	0.764

CORRECT CLASSIFICATION PERCENTAGES

TOTAL WITHIN SAMPLE	71.1%
ACCEPTABLE BORROWERS WITHIN SAMPLE	73.1%
PROBLEM BORROWERS WITHIN SAMPLE	68.1%
CLASSIFICATION EFFICIENCY WITHIN SAMPLE	72.3%
TOTAL HOLD OUT SAMPLE	73.3%
ACCEPTABLE BORROWERS HOLD OUT SAMPLE	94.7%
PROBLEM BORROWERS HOLD OUT SAMPLE	36.4%
CLASSIFICATION EFFICIENCY HOLD OUT SAMPLE	85.3%

[a] Earnings before interest and taxes per dollar of assets

[b] Debt payments per dollar of milk sales

[c] Youngstock per cow

TABLE 4 STATISTICS OF LOAN DEFAULT PROBABILITY MODEL TWO
173 BORROWERS, 1984

VARIABLE	COEFFICIENT	CHI SQUARE	P VALUE
INTERCEPT	4.553	7.75	0.0054
CEBIPGI[a]	-3.060	3.33	0.0682
DPPMS[b]	-3.670	4.86	0.0275
Y.STOCK/COW[c]	1.489	2.11	0.1467

MODEL STATISTICS

CHI SQUARE WITH 3 D.F.	22.00
P VALUE	0.001
R	0.324
C STAT	0.763

CORRECT CLASSIFICATION PERCENTAGES

TOTAL WITHIN SAMPLE	68.8%
ACCEPTABLE BORROWERS WITHIN SAMPLE	71.1%
PROBLEM BORROWERS WITHIN SAMPLE	65.2%
CLASSIFICATION EFFICIENCY WITHIN SAMPLE	70.1%
TOTAL HOLD OUT	73.3%
ACCEPTABLE BORROWERS HOLD OUT	84.2%
PROBLEM BORROWERS HOLD OUT	54.5%
CLASSIFICATION EFFICIENCY HOLD OUT	79.4%

a Cash expenses before interest and taxes per dollar of gross cash income
b Debt payments per dollar of milk sales
c Youngstock per cow

TABLE 5 STATISTICS OF LOAN DEFAULT PROBABILITY MODEL ONE-LARGE
62 BORROWERS, 1984

VARIABLE	COEFFICIENT	CHI SQUARE	P VALUE
INTERCEPT	2.260	1.55	0.2129
EBIT/ASSETS[a]	12.007	0.94	0.3314
DPPMS[b]	-10.199	6.67	0.0098
YOUNGSTOCK/COW[c]	1.528	1.58	0.2092

MODEL STATISTICS

CHI SQUARE WITH 3 D.F.	14.23
P VALUE	0.003
R	0.336
C STAT	0.758

CORRECT CLASSIFICATION PERCENTAGES

TOTAL WITHIN SAMPLE	71.0%
ACCEPTABLE BORROWERS WITHIN SAMPLE	76.2%
PROBLEM BORROWERS WITHIN SAMPLE	60.0%
CLASSIFICATION EFFICIENCY WITHIN SAMPLE	71.7%
TOTAL HOLD OUT	71.4%
ACCEPTABLE BORROWERS HOLD OUT	80.0%
PROBLEM BORROWERS HOLD OUT	50.0%
CLASSIFICATION EFFICIENCY HOLD OUT	71.8%

[a] Earnings before interest and taxes per dollar of assets

[b] Debt payments per dollar of milk sales

[c] Youngstock per cow

TABLE 6 STATISTICS OF LOAN DEFAULT PROBABILITY MODEL TWO-LARGE
62 BORROWERS, 1984

VARIABLE	COEFFICIENT	CHI SQUARE	P VALUE
INTERCEPT	6.941	4.34	0.0372
CEBIPGI[a]	-4.517	1.67	0.1957
DPPMS[b]	-8.720	4.42	0.0355
Y.STOCK/COW[c]	1.403	1.31	0.2528

MODEL STATISTICS

CHI SQUARE WITH 3 D.F.	15.03
P VALUE	0.002
R	0.352
C STAT	0.773

CORRECT CLASSIFICATION PERCENTAGES

TOTAL WITHIN SAMPLE	75.8%
ACCEPTABLE BORROWERS WITHIN SAMPLE	78.6%
PROBLEM BORROWERS WITHIN SAMPLE	70.0%
CLASSIFICATION EFFICIENCY WITHIN SAMPLE	76.2%
TOTAL HOLD OUT	85.7%
ACCEPTABLE BORROWERS HOLD OUT	80.0%
PROBLEM BORROWERS HOLD OUT	100 %
CLASSIFICATION EFFICIENCY HOLD OUT	85.5%

a Cash expenses before interest and taxes per dollar of gross cash income
b Debt payments per dollar of milk sales
c Youngstock per cow

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