SELECTING THE "BEST" PREDICTION MODEL: AN APPLICATION TO AGRICULTURAL COOPERATIVES

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Abstract

A credit scoring function incorporating statistical selection criteria was proposed to evaluate the credit worthiness of agricultural cooperative loans in the Fifth Farm Credit District. In-sample (1981-1986) and out-of-sample (1988) prediction performance of the selected models were evaluated using rank transformation discriminant analysis, logit, and probit. Results indicate superior out-of-sample performance for the management oriented approach relative to classification of unacceptable loans, and poor performance of the rank transformation in out-of-sample prediction.

Key words: cooperatives, discriminant analysis, logit, probit, rank transformation

The economic and financial conditions in agriculture during the 1980s have brought on a major reorganization of the farm credit system and a new set of regulatory requirements by the Farm Credit Administration. Bank officials now seek new and improved ways to classify loan applications from potential borrowers. The Bank for Cooperatives, which serves the financial needs of agricultural cooperatives and other agribusinesses, could benefit from an objective and easy to use credit scoring function that is applicable to evaluating and pricing loans. Prior to the new regulatory environment, cooperative bank officials subjectively employed ratio analysis on a case by case (and group by group) basis to evaluate an agricultural cooperative's loans.

Considerable research effort has been devoted in the economics and finance literature to predicting business financial performance. The methodological focus on most of these applications has been to present, first, the conceptual framework for studying a firm's financial performance, and second, the selection of a predictive model based on purely statistical criteria. One limitation of previous procedures is that they do not take into account prior information about the relative importance of vari-

ables suggested by the theory. Stepwise procedures, for instance, have been used for variable selection in bankruptcy prediction. These procedures, however, examine variables in a sequence usually determined by the data. The purpose of this study is to introduce a procedure that supplements previous studies by giving further consideration to the specification of a statistical model within a management oriented framework and the evaluation of predictive performance of that model. Four specific objectives were associated with the classification and prediction of agricultural cooperatives into two groups (acceptable and unacceptable) according to the performance criteria provided by the Bank for Cooperatives. These four criteria are: (1) to define financial variables that reflect the ability of the cooperative firm to repay its loan, (2) to propose a procedure for grouping financial variables prior to statistical evaluation, (3) to identify a cooperative financial model (credit scoring function) through the application of statistical selection criteria that measure the amount of information provided by each explanatory variable, and (4) to determine the in-sample and out-of-sample predictive accuracy of the model.

A four stage procedure was followed for identifying a credit scoring function useful in evaluating cooperative loans. A statistical ordering procedure, which is based upon finance theory, and two statistical selection criteria were used to determine the final model. These two statistical selection criteria are based upon the "non-additional information hypothesis," i.e., they measure the amount of information that each variable is adding to the explanatory power of the model. The empirical findings of these models are presented in the next section.

PROCEDURES

The classification of firms into one of two groups, acceptable or unacceptable, determines a dependent variable that is discrete (it can only take two values, 1 or 0). Techniques applied to this type of problem

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are categorized as qualitative response models and commonly include Discriminant Analysis (DA), Logit (L), and Probit (P). Some studies have used Linear Probability models (LP) (see Collins and Green, Johnson and Hagan, and Fischer and Moore for additional applications). The theoretical assumptions of these models are extensively discussed by Amemiya (1981), and Maddala (1983). However, the effects of these underlying assumptions have provided much debate among applied economists due to inconsistent or mixed results (Johnson, Wang, and Ramberg 1982). In the past decade, a tremendous amount of literature, particularly in multivariate analysis, has been developed that provides procedures and techniques applied researchers can use to test available data and alternative model specifications.

In applying these new procedures, four stages are followed: First, group business characteristics of a cooperative and measures of financial performance in sets of variables that reflect the different financial aspects of the cooperative; second, apply two statistical selection criteria to obtain the "best" subset of variables to include in the model; third, evaluate the multivariate statistical properties of the selected models to determine the most appropriate estimation technique; and fourth, evaluate the predictive performance of the selected models.

Stage One

Based on the generally accepted financial categories, obtained from theory (namely liquidity, debt utilization, asset utilization, and profitability), previous studies, and the experience of the officials of the Bank for Cooperatives-Jackson Mississippi (a subjective evaluation of some financial ratios is used by the bank's officials when deciding to make a loan), five business characteristics were defined containing at least one financial ratio in each category. These characteristics are as follows:

1. *Liquidity* refers to the ability of a cooperative to meet its short run commitments. The current ratio, current assets to current liabilities (CA/CL), and a measure of absolute liquidity, working capital (WC), represent this category. Liquidity reflects the financial strength of the business and is expected to be highly associated with firms that are classified as acceptable.

2. *Debt Utilization* is operationalized by a measure based on the firm's asset base and earning potential, the debt to asset ratio (D/A), and a measure of interest payments on borrowed capital, interest expenses to sales (IE/S). The debt

to asset ratio is a measure of solvency. Large debt to asset ratios are positively related to businesses that would be classified unacceptable. Interest expenses to sales bears no *a priori* relationship to a cooperative financial performance.

3. *Profitability*, or the ability to generate net margins in a cooperative, includes the mean return on local assets (local assets = total assets minus investment in other cooperatives). This ratio was first introduced by Fischer and Moore (1986). It is expected that cooperatives with higher rates of return on local assets would be classified as acceptable.

4. *Assets Utilization* includes two ratios, sales to assets, (S/A) and accounts receivables to sales (AR/S); and an absolute measure, accounts receivables older than ninety days (R-L). Total accounts receivables is related to large sales volume of the cooperatives' goods and services. Thus, total accounts receivables, particularly among farmer supply cooperatives, are likely associated with the group of cooperatives classified as acceptable. However, if these accounts are not recent (more than 30 days), it may suggest that cooperatives are having problems collecting debt from their member-users. In this case, older accounts receivables are associated with poor financial performance. A larger sales-to-asset ratio is likely associated with an acceptable cooperative business.

5. *Operational Efficiency* is measured by the income to expenses (I/E) ratio. This ratio has been used in agribusiness finance before (Fischer and Moore; Mortensen et al.), and bank officials have also defined it as an important component when analyzing financial performance of cooperatives. Larger income to expense ratios are expected to be positively associated with firms that are acceptable.

Therefore, we propose an information set containing financial ratios grouped in five business characteristics derived from theory and practice to predict cooperative financial performance (Rambaldi 1988).

Stage Two

One of the most difficult problems applied researchers encounter is the selection of the "best" subset of variables to include in a statistical model given the information set. Conventional practice is to, first, decide which model selection criteria to use, and second, define how the criteria will be imple-

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mented. Fujikoshi (1985) evaluated two methods, Akaike's information criterion (AIC) and natural risk (NR),[1] for selecting the "best" subset of variables in two-group discriminant analysis. While these statistical selection criteria are very useful in finding statistical models that best fit the data, the selected variable(s) may not necessarily represent key variables that management use in making financial decisions. In an effort to develop a model compatible with their decision apparatus, a restriction was imposed such that at least one variable from every financial category appears in the final model (restricted final model, RFM hereafter), i.e., the RFM would at least be a five variable model. This approach can be perceived as casting purely statistical models into a more management-oriented framework; but given that the forecasting performance of a model is basically an empirical issue, the purely statistical model was used, SFM hereafter, as a benchmark for evaluation (Scott 1981).

Hsiao (1979) introduced a sequential procedure for identifying and fitting multivariate processes. The procedure as applied to this study consists of three main steps. Step one selects a category and calculates the selection criteria (i.e., AIC and NR) and the model that minimizes the selection criteria is retained, step two sequentially applies step one to all remaining categories, and step three identifies the final model by putting together all single-equation specifications from each category.

An illustrative example: first, select liquidity, and calculate AIC and NR for the following models,

(1) $y = c + \beta (CA/CL) + e$,
(2) $y = c + \beta WC + e$, and
(3) $y = c + \beta_1 CA/CL + \beta_2 WC + e$,

where c is a constant, CA/CL is the current assets to current liabilities ratio, WC is working capital, and e is an error term; then choose the model that minimizes the AIC and NR criteria. Second, respecify models (1)-(3) for debt utilization, asset utilization, profitability, and operational efficiency, and apply the previous procedure; then, put together all single specifications. As a final step, Hsiao recommends diagnostic checks to examine the adequacy of the model specification because the sequential procedure may bias the joint nature of the process. For

the statistical case, which is used as a benchmark for predictive evaluation, AIC and NR must be calculated for all possible combinations from a one-variable model to a full-variable model and the objective is to find the model that minimizes the value of the criteria AIC and NR.

Stage Three

It is well known that linear discriminant analysis (DA) assumes that the data have a multivariate normal distribution and that the covariance matrices between the two groups (acceptable and unacceptable in our case) are equal. Probit assumes also an underlying normal distribution. Box's M test is applied in this study to test equality of covariance matrices and Lagrange Multiplier (Jarque-Bera) and Mardia's measures of skewness and kurtosis are applied to test for multivariate normality.[2]

Stage Four

The evaluation of the in-sample and out-of-sample predictive performance of the model(s) selected is measured by the application of DA, L, and P. The data for this study were provided by the Jackson Bank for Cooperatives' Credit Information System. They consisted of audited financial statements. The in-sample data included 64 marketing cooperatives and 115 supply cooperatives operating in the Fifth Farm Credit District (Louisiana, Alabama, Mississippi) from 1981 to 1986.[3] The out-of-sample data included 95 supply cooperatives and 42 marketing cooperatives for the year 1988. In both cases, the number of marketing cooperatives classified as unacceptable was very small and many of the financial data needed to calculate the ratios were missing. Therefore, we decided to concentrate on the supply group.[4]

RESULTS AND DISCUSSION

The application of the AIC and NR criteria within the RFM approach yielded the following equation:

(4) $y = c + \beta_1 CA/CL + \beta_2 D/A + \beta_3 I/E + \beta_4 S/A + \beta_5 MROLA + e$

where CA/CL is Current Assets/Current Liabilities, D/A is the Debt/Asset ratio, I/E is Total Operating Income/Total Expenses, S/A is Sales to Assets,

[1] The reader is referred to Fujikoshi's original paper for a formal presentation of the properties of these selection criteria.

[2] The derivation of the LM3 test is provided in Bera, Ch. 10. Based on this Monte Carlo experiment, this omnibus form of the test has superior power when compared to alternative tests of normality in both small and large samples.

[3] Approximately 68 percent of the total number of cooperatives operating in that area for the year 1986.

[4] In this study, supply cooperatives were defined as those whose farm supply business accounted for more than 50 percent of total dollar volume.

MROLA is the Mean Rate of Returns on Local Assets, where return on local assets equals Net Margins/(Total Assets-Investment in other cooperatives), and e is an error component. We have included in the Appendix the tabulated results of the application of AIC and NR, within the RFM approach, to the supply cooperative data.

The benchmark model (SFM) selected by applying the AIC, NR criteria is

$$(5) \quad y = c + ß_1 \, CA/CL + e,$$

that is, the application of both statistical selection criteria to the 1981-1986 data selected the same model, and for the unrestricted case, both were minimized when acceptability (unacceptability) is explained only by CA/CL plus the error component. Notice that this one variable model is nested (i.e., included) into the RFM model by construction. It is worth noting that the empirical results corroborate Fujikoshi's theoretical results. That is, AIC and NR, the two selection criteria applied in this study, select the same subset of variables.

The null hypothesis that the covariance matrices between the successful and the unsuccessful group are equal was rejected (Box's M test value is 157.21, and the chi-square critical value at .05 is 24.995). Multivariate normality was rejected (LM3 test for unacceptable was 779.85 and 14046.5 for acceptable, chi-square at .05, 10 is 18.307). Mardia's measures of skewness and kurtosis also confirmed deviations from normality.[5] Discriminant analysis is known to be sensitive to deviation from normality, therefore, a transformation technique was needed to correct for deviations. Conover and Iman (1980) proposed a transformation technique called rank transformation (variables' values are replaced by ranks). This mathematical transformation of the samples is expected to yield an approximately normal distribution.[6] The application of this procedure allows the use of DA (linear or quadratic)[7] and P, since both assume an underlying multivariate normal distribution.

Rank transformation was applied to the ratio variables data and the resulting transformed data was tested for multivariate normality and equality of covariance matrices. The null hypothesis that the transformed samples (acceptable and unacceptable) had a multivariate normal distribution could not be rejected by either the Lagrange Multiplier (LM3) or Mardia's measures. Box's M showed that covariance matrices for the transformed data were also unequal.[8]

The prediction ability of the RFM and SFM models was tested using quadratic DA, probit, and logit. Quadratic DA and probit were used with transformed data (referred to as RQDA and P), logit was used with raw data, and quadratic DA was also used on raw data as the control technique (referred to as QDA). Results for the RFM and the SFM for in-sample and out-of-sample data are shown in Table 1.[9]

The results indicate that the five variable model (RFM) performs better in-sample and out-of-sample prediction than does the one-variable model (SFM). The RFM out-of-sample prediction of acceptable loans (A) is higher for probit, but lower for RQDA and logit than are those of SFM. The percentage of right predictions for unacceptable loans (U) in out-of-sample is higher for RFM in two cases, RQDA and probit and the same as that of SFM for logit (80 percent). The predictive power of the models out-of-sample remained over 60 percent of total right predictions (T) for the restricted final model. The unrestricted final model (SFM) out-of-sample prediction was also good. The total of right predictions was over 50 percent in all cases, with logit (81 percent), slightly higher than that of RFM (80 percent). Therefore, Akaike's information criterion (AIC) and natural risk (NR) seem to be useful not only for descriptive purposes, but also for predictive purposes based on the results of this study.

From a banker's perspective, the cost of classifying an unacceptable loan as acceptable is higher than the reverse case. The results from this perspective confirm earlier expectations that a more management-oriented statistical model should be a more reliable

[5] Due to space constraints, the results of Mardia's tests are not shown, however, tabulated results are available from the authors.

[6] The interested reader should be able to replicate the procedure by reading Conover and Iman's original paper.

[7] Quadratic DA is applied when the covariance matrices between the two groups are not equal.

[8] This result is absolutely expected, since the transformation is a correction for normality and should not affect the relative dispersion of the data.

[9] The corresponding estimates of the 16 models in Table 1 are available from the authors. They are not presented since the objective of the methodology is to compare prediction ability across models. It is important to note, however, that the rank transformation technique creates a source of multicollinearity. When the actual value of the variable is replaced by a rank, the range of variation within each variable is considerably reduced. However, as it is pointed out in the literature (see Judge et. al., Chapter 22), multicollinearity causes imprecise parameter estimates, and when estimates are not where interest centers, the best solution is to proceed as if multicollinearity were not present.

Table 1. In-Sample and Out-of-Sample Prediction Results of the Selected Models Percentage of Right Predictions

	RFM[a]						SFM[b]					
	I-S[c]			O-O-S[c]			I-S			O-O-S		
	A	U	T[d]	A	U	T	A	U	T	A	U	T
QDA[e]	86	72	81	92	22	62	6	97	37	85	49	69
RQDA[f]	82	100	88	31	100	61	76	47	67	83	22	57
L[g]	88	64	80	80	80	80	83	52	73	83	80	81
P[h]	99	92	97	91	71	82	80	39	67	72	36	57

[a]RFM = restricted final model.

[b]SFM = purely statistical model.

[c]I-S = in-sample; O-O-S = out-of-sample.

[d]A = acceptable; U = unacceptable; T = total percent of right predictions.

[e]QDA = quadratic discriminant analysis.

[f]RQDA = quadratic discriminant analysis with transformed data.

[g]L = logit with new data.

[h]P = probit with transformed data.

predictor of financial performance. The out-of-sample performance for the RFM is equal or superior to that of the SFM (with exception of the control technique). This is clear by comparing RQDA, logit, and probit with 100 percent, 80 percent, and 71 percent, respectively, for RFM (U) to 22 percent, 80 percent, and 36 percent, respectively, for SFM (U).

In terms of techniques, probit outperforms logit and RQDA for the in-sample restricted final model. However, it is interesting to note that logit shows the least prediction variability (comparison between restricted versus unrestricted models and in-sample versus out-of-sample). When comparing the restricted five-variable model (RFM) with the unrestricted one-variable model (SFM), in-sample total percentage of right predictions (T) were 80 percent and 73 percent and out-of-sample were 80 percent and 81 percent, respectively. On the other hand, if in-sample is compared to out-of-sample prediction, logit maintained the percentage of right predictions (T) for the restricted final model (RFM) at 80 percent, and for the unrestricted final model (SFM), logit had a higher percentage of right predictions in out-of-sample than in in-sample (81 percent versus 73 percent).

A fairly large amount of discussion on the performance of DA versus logit can be found in the literature (Collins and Green; Amemiya; Maddala; Press and Wilson). Violation of the normality assumption has been alluded to as one of the main reasons why DA performs poorly relative to other models. Rank transformation offered a way of solving that particular problem. However, the findings indicated that the transformation works well within sample for the

restricted final model (especially for detecting unacceptable loans), but its performance changes drastically with the unrestricted final model. Both—RFM and SFM—perform poorly out-of-sample. Note that in out-of-sample, QDA does a better job than RQDA. These results seem to indicate that this technique may not be reliable, since it seems to be very sensitive to changes in the content of the information.

CONCLUSIONS

This paper has introduced a theory-based procedure for ordering financial variables before statistical evaluation. Explanatory variables were selected through the use of two selection criteria that account for the amount of information provided by each explanatory variable. A decision-oriented restriction, based on the theoretical information set, was imposed such that five financial aspects of the firm had to be represented in the model. An unrestricted model was selected on purely statistical grounds by applying the same model selection criteria. The data were tested for multivariate normality, and a transformation was applied to correct for deviations from normality. The in-sample and out-of-sample performance of both (restricted and unrestricted) models was evaluated.

Probit in a decision-oriented restricted model had the superior performance in-sample; however, logit showed less prediction susceptibility to changes in the data (in-sample and out-of-sample) and to model specification (five-variable or one-variable model). Rank transformation discriminant analysis performs poorly in out-of-sample prediction of acceptability

for both restricted and unrestricted models. In all cases, careful evaluation of model assumptions and application of methodologies that allow for departures from ideal conditions proved predictively useful.

The methodology suggested in this paper, i.e., a decision-oriented methodology for model selection, is expected to yield a model that would prove more robust to structural changes in the industry particularly when there is more specific prior information about the relative importance of variables. It seems plausible that management would be less skeptical about using prediction results from a model that allows for variables which are important in making financial decisions under uncertainty.

APPENDIX

Application of AIC and NC to Supply Cooperative Data

Variable	NR	AIC	Rank NR	Rank AIC
(L1)	-1.4E-05	104.83	10	6
(L2)	-4.7E-07	104.83	11	6
(L3)	-1.2E-07	104.83	12	6
(L4)	-.0695*	104.32*	1	1
(L1) (L4)	.0675	106.31		
(L2) (L4)	.0692	106.30		
(L3) (L4)	.0670	106.30		
(D1) (D2)	.5245	106.80		
(D1)	-.0169*	104.80*	5	5
(D2)	.1324	104.83	13	6
(O1)	-.0211*	104.87*	4	4
(A1) (A2)	46.6096	106.83		
(A1) (A3)	5.2625	106.83		
(A2) (A3)	9.2577	106.83		
(A1)	-.0011*	104.833*	7	7
(A2)	-.0004	104.834	9	8
(A3)	-.0005	104.834	8	8
(A1) (A2) (A3)	8.9011	110.27		
(P1)	-.0405*	104.658*	2	2
(P2)	-.0394	104.66	3	3

* Indicates the smallest value within categories.

L1: WC for the most current year operations
L1: WC average of the last three years of operation
L3: WC averages of the last six years of operation
L4: CA / CL
D1: D / A
D2: IE / S

O1: I / E
A1: S / A
A2: AR / S
A3: R - L
P1: MROLA (Average of the last six years of operation)
P2: SMROLA (Average of the last three years of operation)

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