ASCERTAINING PERFORMING AND NON-PERFORMING LOAN POTENTIALS IN COOPERATIVE SOCIETIES USING DESCRIPTIVE DISCRIMINANT ANALYSIS.

[1]Fortune MEKA, [1]Jacob Chiedum Ehiwario, [2]John N. Igabari

Email: fortune.meka@unidel.edu.ng

[1]University of Delta, Agbor.

[2]Delta State University, Abraka.

Abstract

The issue of non-performance of loans (a situation by which a borrower fails to repay his collected loan) has become a concern to cooperative societies. In this study, methods and results of analyzing loan performance by borrowers was emphasized. Descriptive Discriminant Analysis was used to reveal variables that separate loan applicants who can pay back and those who may find it difficult to pay back. The data for this study was collected from cooperative societies of selected tertiary institutions for a period of 5 years, 2018 to 2022. 7 variables generated from information on the loan forms were used from a sample of 30 past applicants who paid well (performing loan) and 30 who did not pay well (non- performing loan). The 30 by 7 matrices for the two groups were analyzed using SPSS. The result shows that the variables with the highest discriminating powers were net salary, department of guarantor and accumulated fund of applicant.

Keywords: *Cooperative societies, Discriminant Analysis, Performing and Non-Performing Loans, Tertiary institutions.*

1. Introduction

Statistics involves the collection and analysis of data for the purpose of decision making. A good statistician therefore should act as a watch dog on societal issues. This he can do through rendering guided advice on issues as they arise from proper data analysis using appropriate statistical tools. The choice of statistical approaches to be employed in researches must be carefully made in order to avoid misleading conclusions that may be due to wrong choice of approach.

The issue of non-performing loans has become a major challenge facing cooperative societies today. This is because the dream behind every cooperative society hinges mainly on safety of cooperators' savings. Most public servants today depend on cooperative societies to carry out their financial projects. The increasing need for money by cooperators in cooperative societies has put the management of such cooperative societies in a state of confusion. It becomes an unfortunate occurrence for borrowers not to be able to pay back their loans as expected due to one reason or the other. The biggest problems arise when loans given to cooperators do not come back as expected. This kind of loan is captioned as non- performing loans by the cooperative societies. A major problem associated with it is that it reduces physical cash availability for loaning, and therefore affects profit generated at the end of the financial year. It also creates a negative image of the executive committee of such cooperative society. A number of factors can be responsible for such scenarios to arise. The application of statistical techniques to generate a model that will enable the management of cooperative societies to judge loan applicants and know whether to grant or decline loan requests is therefore needful.

The aim of this study therefore is to investigate and discriminate between good and bad borrowers using discriminant analysis with a view to advising cooperative societies on steps to avoid non-performing loans. This process has been described as credit scoring by a lot of researchers. A number of researches have been carried out on credit scoring by banks, (Srinvas et al, 2011 and Lobna et al, 2016). These researches focused on bank loans and mainly to business people. But attention has not been paid to civil servants borrowing from cooperative societies as this poses a different scenario. This forms the basis for this study.

2. Credit Scoring

Credit scoring can be defined as a systematic method for evaluating credit risk that provides a consistent psychotherapy of the factors that have been determined to cause or affect the level of risk (Fensterstock, 2005). According to Lobna et al (2016) while citing Thomas *et al.* (2002), credit scoring is described as a set of decision models having specific underlying techniques that are advocated to give support to lenders when providing credits to customers. From the above definitions, one can define credit scoring as a systematic model that could assist loan givers to ascertain the possibility of loan repayment by loan applicants. It is a tool that every financial institution should have at their disposal. It has advantages ranging from increasing the speed of processing loan applications and allowing the financial institutions to quantify the risks associated with giving loans to particular applicants in a shorter time.

Linear discriminant analysis (LDA) is a widely used Multivariate statistical method for the analysis of data with categorical outcome variables.

Discriminant analysis has various practical applications. Say, the loans department of a bank wants to find out the credit worthiness of applicants before disbursing loans. It may use discriminant analysis to find out whether an applicant is a good credit risk or not. This would serve as method of screening applicants in order to prevent bad debts.

3. METHODS

3.1. The Data

The data base of this study is constructed on the basis of information taken from a cooperative societies in tertiary institutions in Delta state and included a sample of 60 loans granted to cooperators over the period 2018 – 2022. This was carefully selected such that 30 was performing and 30 non-performing. The loan form of these cooperators was examined and key variables were rooted out. Areas of discrimination of the two groups by the variables were assessed using Descriptive discriminant analysis. The variables generated as filled in their loan forms are as shown in the table below.

Table 1 Variable Representation

Variable	Definition

X_1	Salary grade level
X_2	Net salary
X_3	Department of guarantor
X_4	Accumulated fund
X_5	Years left in service
X_6	Years spent in cooperative
X_7	Reason for borrowing

The net salary was categorized as

- Less than 30% of gross,
- between 30% and 50%, and
- above 50%.

Also, accumulated funds was categorized as

- less than 30% of loan requested,
- 30% to 50%,
- Above 50%.

3.2. Discriminant Analysis (DA)

DA is a powerful statistical method for characterizing the elements of society, and the data must be divided into two or more separate groups, to know the boundaries between the data, and to establish a specific rule to know that any new element belongs to the appropriate group (Hussain and Uraibi, 2023). The aim of the discriminant analysis is to find the discriminant function and to classify items into one of two or more groups having certain features describing those items. The main purpose of the discriminant analysis is to maximize the difference between two groups, whereas the differences among particular members of the same group are minimized. This implies maximizing the ratio

$$\tau = \max_{v \in R^{d \times t}} \frac{tr(V^T S_B V)}{tr(V^T S_W V)} \qquad (1)$$

Where S_B and S_W are the between class scatter matrix and within class scatter matrix respectively, defined by:

$$S_B = \frac{1}{N}\sum_{i=1}^{c} N_i(\bar{x}_i - \bar{x})^T(\bar{x}_i - \bar{x}) \qquad (2)$$

$$S_W = \frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{N_i}(x_{ij} - \bar{x}_i)^T\left(x_{ij_i} - \bar{x}_i\right) \qquad (3)$$

V represents the discriminant vector and $tr(.)$ represents the trace of the matrix. See Chun et al (2019) for clarifications.

Descriptive discriminant analysis DDA is designed to successfully identify the linear combination of attributes which contribute maximally to group separation (Osemwenkhae et al 2019). In the sphere of credit risk models, one group consists of good borrowers (non-defaulted – group A), while the other includes the bad ones (already defaulted – group B). The differences are measured by means of the discriminant variable – score Z. For a given borrower i, we calculate the score as follows:

$$Z_i = \sum_{j=1}^{n}\gamma_j x_j \qquad (4)$$

where x denotes a given characteristic, γ is its coefficient within the estimated model and n represents a number of indicators.

The Discriminant Analysis seeks to obtain a linear combination of the independent variables. The aim is to classify the observations into mutually exclusive groups as accurately as possible, by maximizing the variance of the ratio of among-groups to within-groups. The discriminant function has the following form:

$$Z = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n \qquad (5)$$

(see Lobna et al 2016)

Where x_j is the jth independent variable, b_j is the coefficient for the jth independent variable, and Z is the discriminant score that maximizes the distinction between the two groups.

Seven variables which are considered as the discriminant variables were used in this study. They were applied in the chosen sample in order to find out the fitted discriminant score which will represent the discriminant criterion allowing distinguishing between the default and the non-default borrowers.

4. Results

Table 2 Log Determinants

Groups	Rank	Log Determinant
1	3	-3.665
2	3	-3.909
Pooled within-groups	3	-3.601

One of the assumptions upon conducting Discriminant Analysis is that the covariance matrices for the groups should be identical. The closeness of the log determinants above suggests that the covariance matrices are identical. This is further confirmed from the Box M statistic value of 0.117 below that the covariance matrices for the two groups are identical.

Table 3: Box's M Test Result

Box's M		10.789
F	Approx.	1.697
	df1	6
	df2	24373.132
	Sig.	.117

Table 4: Wilk's Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1	.433	47.348	3	.000

The significance of the discriminant function has been established as shown in the Wilks Lambda table above as the p value is less than 0.05.

Table 5 Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	1.312a	100.0	100.0	.753

The discriminant function explained 75% of the total variance in the independent variable as revealed from the above table.

Table 6: Structure Matrix

		x_2	x_3	x_4	x_7	x_5	x_6	x_1
Function	1	.763	.550	.480	.264	.176	.135	.103

From the above structure matrix, the top three variables that discriminated most between performing loan borrowers and non-performing loan borrowers are

1. Variable x_2, which is Net Salary. It checked the percentage of the gross salary that was left as net pay for the applicant after the loan
2. Variable x_3, which is the department of Guarantor. It explains how trustworthy the applicant is. As a person who is trustworthy will easily have guarantors from his department. But in a situation when the guarantor is just a colleague from another department in the institution, then issues of lack of trust should be suspected.
3. Variable x_4, which is the accumulated fund of the applicant. Applicants with little funds but asking for huge loans should be feared.

Other variables did not discriminate much between the groups. Hence the construct that characterized group separation between the two groups can be named as Net salary, guarantor's department and accumulated fund.

5. Conclusion.

As revealed by this study, the management of cooperative societies should apply discretion when borrowing to the following, to avoid the risk of bad loans.

i. Applicants whose net salary is less than 30% of their gross. Such applicants can easily fall to a level whereby their salary fails to carry their deductions.

ii. Applicants whose guarantors are not in their department, as most of such can have some issues with trust. This is because a trustworthy person will easily have guarantors from his department. Because colleagues from the same department will easily know much about themselves.

iii. Applicants whose accumulated funds are less than 30% of the amount they are asking for. This is an indicator that such applicants are not worthy of the loan they are requesting for.

Declaration of Conflict of Interest

There was no conflict of interest in carrying out this work.

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