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Predicting Failures of Banking and Financial Institutions in Nepal:
A Comparative Methodological Analysis

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Abstract: *Identification of the companies prone to various risks is important to regulators, investors, analysts and practitioners. It is imperative to identify early warning indications of impending financial problems and the potential subsequent failure of these companies. This study focuses on failures of Banking and Financial Institutions (BFIs) in Nepal. The main objective of this study is to examine the predictive power of CAMEL ratios to develop a Multivariate Discriminant Model (MDA) and Logistic Regression Model (LRA) in the context of Nepalese BFIs. To achieve this objective a descriptive and analytical research model was designed. The research applies secondary data to predict the predictive failure of the Nepalese BFIs with the support of MDA and LRA. The ratios of non-failed BFIs were relatively stable, contrary to those of failed BFIs under the study. The results indicate that, the overall accuracy in predicting bank failure using LRA is higher than with MDA. Therefore, LRA can be considered to be relatively more accurate than MDA. Finally, the relative contribution of return on assets and non-performing loans to total loans has been found to be a more reliable and predictable ratio with regard to banking failures for both MDA and LRA.*

I. INTRODUCTION

A firm is considered as failure when it is not likely to continue its operation, or pay dividends to its shareholders or wages to its employees (John, 1993). Bank failures do not necessarily result in the collapse and dissolution. Failure is eminent when cash and near cash assets are insufficient to meet its current ongoing obligations, or its total liabilities are greater that its total assets. It also means that its accumulated loss exceeds its capital equity.

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A general view of bank failures is the result of a mismatch between current available liquid assets and current obligations. This means its earnings' rate is less than its cost of capital (Weston & Copeland 1992). In other words, bank failures can be defined as the present value of its net cash flows is less than it net current obligations. Failure also can be classified as actual cash flows being below its expected cash flows and that its net cash flow projections have not or cannot be met. Signals of financial distress tend to start with short-term liquidity problems, followed by operating losses, excessive use of external debt and inability to meet obligations. Gradually, these signals will emerge into symptoms, which may be reflected in continuous decline in market price of shares, shortage of cash, default in payments of salaries and interests, decline in liquidity, profitability, turnover and other financial ratios.

This study aims to improve the prediction of confidence levels of future bank failures at their earliest stages in Banking and Financial Institutions (BFIs) of Nepal. In this study, a bank has been considered as per the classification of Bank and Financial Institution Act (BAFIA) of Nepal. According to BAFIA, Commercial banks, development banks and finance companies are classed as 'A', 'B' and 'C' respectively. According to the above analysis it is assumed that there is no evidence of failures yet in Class A commercial banks; therefore, only Class B and Class C financial institutions are considered as BFIs for this study. A BFI has been considered as stressed, if it suffered from continuous losses, increase in non-performing loan, insufficient capital adequacy and negative net worth.

The major objective of this study is to examine the prediction of bank failures in Nepal through both MDA and LRA models. Other specific objectives of this study are:

- To examine the CAMEL ratios' usefulness for predicting a tendency for bank failures in Nepal.
- To assess the differences in CAMEL ratios of failed and non-failed BFIs.
- To analyze and compare Multiple Discriminant Analysis and Logistic Regression Analysis useful for predicting banks tending towards failure.

II. NATURE AND SOURCES OF DATA

This study is based on secondary data obtained through published annual reports of sample firms and data obtained from Nepal Rastra Bank (NRB), Security Board of Nepal (SEBON) and Nepal Stock Exchange (NEPSE). The selection procedure is performed on a paired sample basis to eliminate the effect of asset size differences. Banking firms, which have the same financial ratios but with different asset sizes, may have different probabilities of failure. In this study, a firm is regarded as a failed firm when it is unable to cover and service its liabilities with its liquid assets, and therefore, it is technically in a bankrupt status. Some of the failed BFIs in Nepal were liquidated, while a few of them were either acquired by other companies or merged with others. Meanwhile, some of them were restricted by the Central Bank of Nepal from accepting deposits, thereby indicating their failed status as a full-fledged and healthy bank. Those financial institutions that failed during observation period of 2007-2010, are taken as Samples of failed firms. Non-failed banking firms are selected on the basis of the similar asset sizes within the same group of failed banking firms.

Table 1: Sample Banking and Financial Institutions

(In millions NRS)

Sr. No.	Failed banking and financial institutions	Class	Asset Size	Sr. No.	Non-failed banking and financial institutions	Class	Asset Size
1.	Nepal Development Bank	B	1412.90*	1.	Malika Development Bank	B	1456.60
2.	Gorkha Bikash Bank	B	5450.30	2.	Ace Development Bank	B	4556.80
3.	United Development Bank	B	254	3.	Uddyam Development Bank	B	188.10
4.	CSI Development Bank	B	879.40*	4.	Shubhechha Bikas Bank	B	839.50
5.	Nepal Industrial Development Corp.	B	2709.21	5.	NDEP Development Bank	B	2975.60
6.	Nepal Shreelanka Merchant Bank	C	744.67	6.	Yeti Finance	C	760.65
7.	Samjhana Finance Co.	C	483.53	7.	Shikhar Finance	C	517.52
8.	Arun Finance & Saving Co.	C	127.81	8.	Shrijana Finance	C	137.58

Sources: *Banking and Financial Statistics, No. 53, Mid-July 2009
Banking and Financial Statistics, No. 54, Mid-January 2010
www.nrb.org.np

III. METHODS OF ANALYSIS

Secondary data analysis is used such as descriptive analysis, significance test of CAMEL ratios, multivariate discriminant analysis and logistic regression analysis.

Descriptive Statistics

Average ratio of failure and non-failure firms have computed to observe whether there is a difference between financial ratios of failure and non-failure firms. Mean value gives the results of the average of each ratio within group presents the deviation of each ratio within group.

Multivariate Discriminant Analysis

Multivariate Discriminant Analysis is a statistical technique used to classify failure and non failure firms. It refers to simultaneous consideration of several indicators in the prediction process. Altman (1968) conducted the pioneer study using discriminant analysis.

$$Z = a + a_1 X_1 + a_2 X_2 + a_3 X_3 + a_4 X_4 .... + a_n X_n$$

X_1, X_2, X_3, X_4...X_n are variables used to differentiate between the group of failure and non-failure firms. This function transforms the individual variable values to a single discriminant score or Z value, which is used to classify failure and non-failure firms.

Logistic Regression Analysis

Logistic regression (logit) analysis depends on assuming that the probability of a bank failure or financial health depends on a vector of independent variables. Martin (1977) is first user of logit model to predict bank failures taking 25 ratios representing capital adequacy, asset quality, earning and liquidity. Using the logit model, predicted outcomes are limited to lie within a given unit interval, and are construed as the probability of an event. The Logit model has the statistical property of not assuming multivariate normality among the independent variables. This can be seen as an advantage when analyzing banking data, as it generally does not conform to a normal distribution.

Probability (Financial Health),

$F(Z_i) = 1/\ 1+e^{-Zi}$

$Z_i = a_1 + a2X_{i1} + a3X_{i2} + \ldots\ldots\ldots + a_nX_{\ in}$

F (Zi) is the cumulative probability function that lays the value between 0 and 1. It makes easier to interpret the probability of failure since the probability of an event lied between 0 and 1.Where, a = a_1, a_2, … a_n is a vector of a regression coefficient for forecasting variables $X_{in.}$

IV. DATA ANALYSIS AND FINDINGS

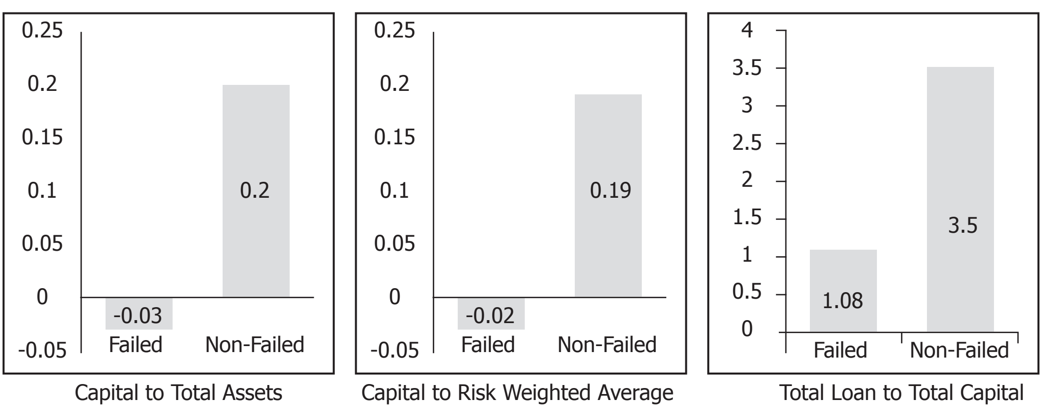
Descriptive Statistics

With the help of descriptive analysis, the mean ratio of CAMEL ratios is computed to examine the difference between the financial ratios of the failed and non-failed BFIs. Mean values yield the result of the average of each ratio within a group. Descriptive statistics are supported by a bar diagram, describing the financial position of failed and non-failed BFIs.

Capital Adequacy

Figure 1: Descriptive Statistics of Capital Adequacy Ratios

The figure provides descriptive statistics of the mean of the capital adequacy ratios of failed and non-failed BFIs that are obtained from pooled cross sectional data of 16 companies.

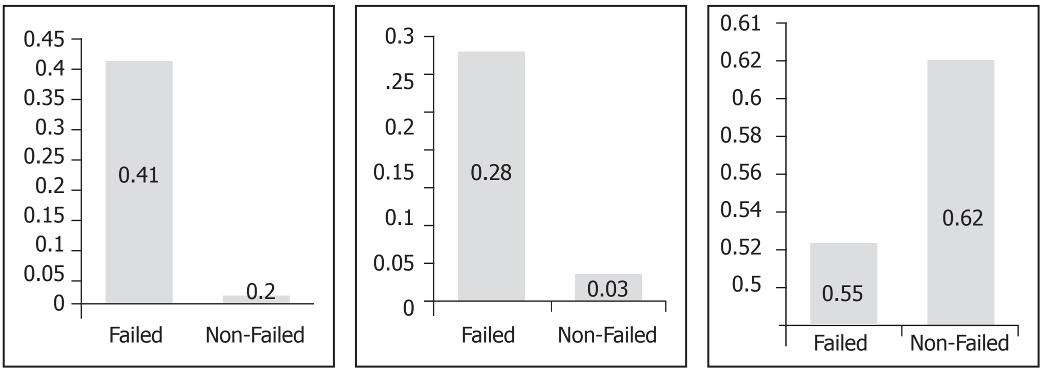


The figure 1 indicates the summary of average capital adequacy ratios of selected BFIs (failed and non-failed). It is observed that the capital adequacy ratios of failed BFIs are weaker than non-failed/healthy BFIs. The figures depict that the capital to total assets and capital to risk weighted average ratios of failed companies are poorly managed. It indicates that they are negative prior to their failure. In addition, the higher total loan to total capital ratio of non-failed companies indicates that these companies are collecting large amount of deposits, which enable them to provide large volumes in loans and advances.

Assets Quality

Figure 2: Descriptive Statistics of Assets Quality Ratios

The figure provides descriptive statistics for the mean of the asset quality ratios of failed and non-failed BFIs that are obtained from pooled cross sectional data of 16 companies.



Provision for Loan Loss to Net Loans

Non-Performing Loan to Total Loan

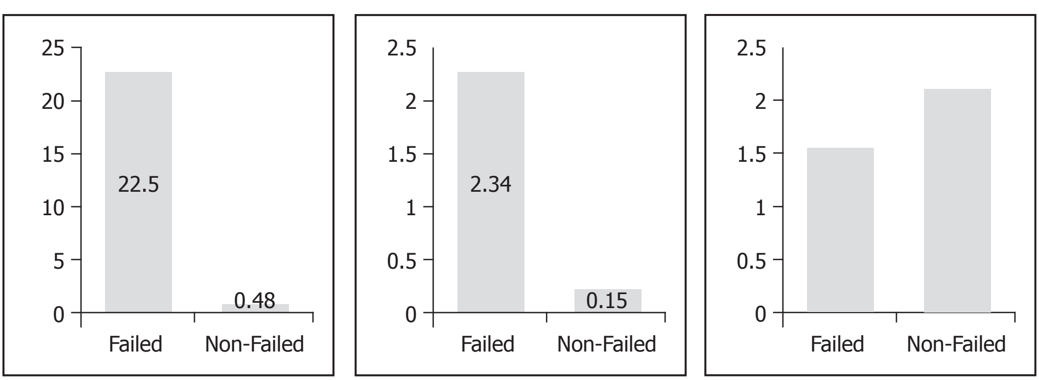
Loan to Total Assets

Figure-2 demonstrates that the provision for loan loss to net loan and non performing loans to total loans is significantly higher in failed companies than non-failed companies. It indicates that the asset quality of failed companies is weaker in comparison to the healthy companies. Otherwise, the loan to total assets ratio of non-failed companies are higher than failed companies. This demonstrates effective and efficient asset management by the non-failed BFIs to that of failed companies.

Management Capability

Figure 3: Descriptive Statistics of Management Capability Ratios

The figure provides descriptive statistics of mean of the management capability ratios of failed and non-failed BFIs that are obtained from pooled cross sectional data of 16 companies.



Total Operating Expenses to Operating Revenue

Loan Revenue/ Net Loan

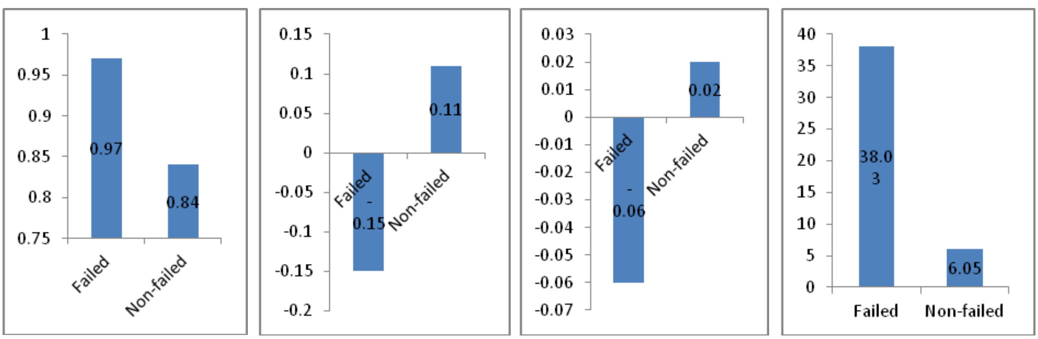
Interest Income/ Interest Expenses

From the Figure-3, it is evident that the total operating expenses to operating revenue of failed BFIs are higher for non-failed BFIs. It means that the failed BFIs' operating expenses are very high vis-à-vis operating income. Contrary to existing literature, it is observed that the loan revenue to net loan ratio of failed companies is higher than those non-failed companies. It also suggests that interest income to interest expenses of failed BFIs is lower. Correspondingly, the interest income to interest expenses ratio of non-failed BFIs is healthier than its failed counterparts.

Earnings

Figure 4: Descriptive Statistics of Earnings Ratios

The figure provides descriptive statistics of the mean of the earnings ratios of failed and non-failed BFIs that are obtained from pooled cross sectional data of 16 companies.



Loan to Total Sources of Funds | ROA | ROE | Loan Revenue to Total Operating Income

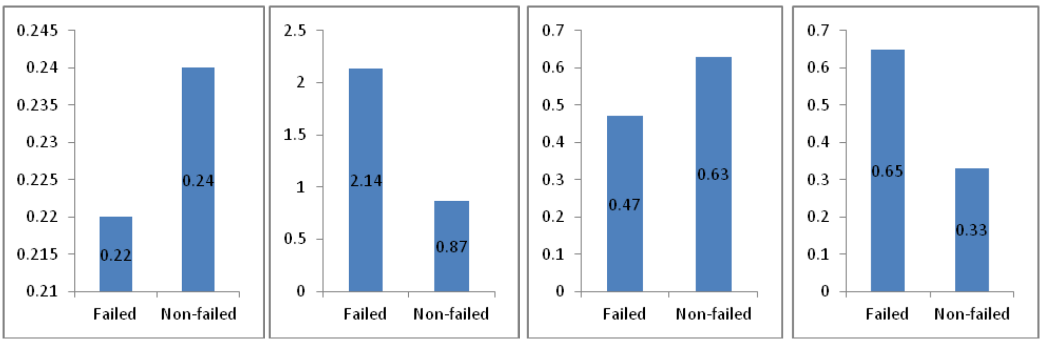
The figure 4 depicts that the total loan to total sources ratios of funds of failed companies are greater than their non-failed counterparts. This indicates that there is lesser amount of sources of fund of failed companies than the non-failed companies, which could be due to various reasons such as lack of management efficiency, mistrust by the depositors, etc. The return on assets and return on equity of failed companies are both negative indicating that the failed companies are operating at a loss prior to their failure, whereas the non-failed companies have an above average return on assets, as well as equity, indicating a healthy business. The total revenue to the operating income ratio of failed companies is higher than non-failed companies. This is due to the fact that their income generation from operating revenues of failed companies is low.

Liquidity

On the figure 5, the liquid assets to total assets ratio of failed BFIs is depicted to be lower than non-failed companies. This implies that the liquidity position is poorly managed by the failed companies. The higher total loan to total deposit ratio of failed companies indicates, either that they are unable to attract sufficient deposit, or to provide higher loan amounts to their customers. While the net loan to total assets ratio is higher in non-failed companies, which indicates that the non-failed companies manage their net loans over assets in an efficient manner. The liquid asset to total sources of fund is higher for failed companies due to the fact that they have lower amount of sources of fund as compared to non-failed companies.

Figure 5: Descriptive Statistics of Earnings Ratios

The figure provides descriptive statistics of mean of the liquidity ratios of failed and non-failed BFIs that are obtained from pooled cross sectional data of 16 companies



Liquid Assets to Total Assets | Total Loans to Total Deposits | Net loan to Total Assets | Liquid Assets to Total Source of Fund

Multivariate Discriminant Analysis

The financial ratios are considered to develop a multivariate discriminant function for the purpose of distinguishing firms into failed and non-failed BFIs based on selected CAMEL variables in the Nepalese context. There are total 48 observations including 24 observations from failed and non- failed companies equally. From the 48 observations, 39 were correctly classified, i.e. 81.3%. In 24 failed observations, 16 were correctly classified and 8 were misclassified as non- failed. Contrary to the failed observations, 23 were correctly classified as non-failed and one has been misclassified as failed. Therefore, the Type I error forms a ratio of 7:24 or 29.16% and Type II error forms a ratio of 1:24 or 4.16%. The Type I error occurs due to classification of failed, which has been predicted as non-failed and a Type II error occurs when a non-failed BFI is classified as failed. The Type II error is more serious because it predicts a non-failed as a failed company, ergo a false positive. The results indicate that the original classification is 81.3% accurate, while analyzing selected companies based on the seven-selected CAMEL financial ratios. Based on 48 observations prior to three years to failure, the MDA model for prediction and classification is developed. The model for practical use for discriminant function is:

$$Z = 0.56 X_1 + 0.64 X_2 - 0.25 X_3 - 0.96 X_4 + 0.13 X_5 + 0.75 X_6 + 0.03 X_7$$

Where, Z = Discriminant function of failed/non-failed company

X_1 = Capital to Total Assets (CTA)

X_2 = Capital Fund to Risk weighted Assets (RWA)

X_3 = Provision for Loan Loss to Net Loans (PLLNL)

X_4 = Non Performing Loan to Total Loan (NPLTL)

X_5 = Interest Income to Interest Expenses (IIIE)

X_6 = Return on Assets (ROA)

X_7 = Net Loan to Total Assets (NLTA)

In order to construct a range of failure prediction models, the study consider the 7 CAMEL ratios from a list of 17 ratios after significance test for differentiation of failed and non-failed BFIs. The ratios include the list are frequently used by previous researcher, which have proven to be relevant in earlier research on bank failure models. Most ratios are positively related to financial health while some high value ratios indicate a bad financial situation. Thus, these ratios have a negative 'expected sign'.

Ratios	Expected Sign	Observed Sign
Capital to Total Assets (CTA)	+	+
Capital Fund to Risk weighted Assets (RWA)	+	+
Provision for Loan Loss to Net Loans (PLLNL)	-	-
Non Performing Loan to Total Loan (NPLTL)	-	-
Interest Income to Interest Expenses (IIIE)	+	+
Return on Assets (ROA)	+	+
Net Loan to Total Assets (NLTA)	+	+

The above model implies that there is a strong positive impact of ROA and negative impact of NPLTL representing earnings and asset quality ratios respectively. The higher Z-score indicates good healthy company and vice-versa.

Logistic Regression Analysis

The Logistic Regression Analysis (LRA) model does not required normality among the independent variables. This can be seen as an advantage when analyzing banking data, as it generally does not confirm to a normal distribution.

The result shows that the overall correct percentage in predicting bank failure is 89.6%, which is marginally better than the MDA. In 24 failed observations, 20 were correctly classified and 4 were misclassified as non-failed. Correspondingly, 23 non -failed observations were correctly classified and one has been misclassified as failed. Therefore, the Type I error forms a ratio of 4:24 or 16.67%, and the Type II error forms a ratio of 1:24 or 4.16%. The Type I error occurs due to its failed classification, which has been predicted as non-failed and a Type II error occurs when the non-failed is classified as failed.

Based on 48 observations prior to three years to failure, the LRA method for prediction and classification is developed, which can be applied in practice. The model for prediction and classification is developed as shown below:

$Z = - 0.40 + 6.45\ X_1 – 3.59\ X_2 – 20.24\ X_3 – 8.75\ X_4 + 0.93\ X_5 - 21.77\ X_5 -1.74\ X_7$

X_1 = Capital to Total Assets (CTA)

X_2 = Capital Fund to Risk weighted Assets (RWA)
X_3 = Provision for Loan Loss to Net Loans (PLLNL)
X_4 = Non Performing Loan to Total Loan (NPLTL)
X_5 = Interest Income to Interest Expenses (IIIE)
X_6 = Return on Assets (ROA)
X_7 = Net Loan to Total Assets (NLTA)

The model implies that there is a higher impact of ROA and PLLNL representing earnings and asset quality ratios in predicting BFI failures. It was observed that the predicting power of LRA is marginally higher than the MDA.

V. CONCLUSION

Prediction failure of BFIs is important not only to analysts and practitioners. Countries throughout the world have been concerned with individual entity performance assessment. Developing countries and smaller economies, as well as the larger industrialized nations of the world, are vitally concerned with avoiding financial crises. Some policy makers in smaller nations are particularly concerned with financial panics resulting from failures. From the late 1960s to the present day, numerous studies were devoted to assessing one's ability to combine publicly available data with statistical classification techniques in order to predict failures. The most popular statistical classification techniques used to predict failure are multiple discriminant analysis (MDA) and logistic regression analysis (LRA). In this study, the ratios of non-failed BFIs were relatively stable, contrary to the failed BFIs. The results indicate that, the overall accuracy in predicting bank failure using logistic regression is higher than the MDA. Therefore, logistic regression can be considered to be relatively better than MDA.

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