The Journal of University Grants Commission, Vol. 1, No. 1, 2012

Indicators of Banking and Financial Institutions Failures in Nepal

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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 know the early warnings of impending financial problems and subsequent failures of these companies. This study focuses on analyzing the causes and problems associated with the failure 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. The research applies to secondary data to predict the predictive failure of the Nepalese BFIs with the support of MDA and LRA. Some of the failed BFIs in Nepal were liquidated while a few of them were either acquired by other companies or merged with others. The study examines the causes of failure and subsequently predicts the genuine failure of the Nepalese BFIs. Further efforts are made to test the hypothesis through CAMEL variables to distinguish these companies based on their financial strength. The research findings demonstrate that the selected seven CAMEL financial ratios of these companies varied in their mean ratios three year prior to their actual failure. The ratios of non-failed BFIs were relatively stable throughout the three years, contrary to the failed BFIs under study. 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.*

Keywords: *Banking and financial institutions (BFIs), CAMEL variables, failures, bankruptcy, multivariate discriminant model, logistic regression model.*

Background

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 failure does not necessarily result in the collapse and dissolution. It means losing money and its liabilities are insufficient to meet its obligations. It also means its accumulated loss exceeds its capital equity. A general view of bank failure is the result of a mismatch between the current available liquid assets and current obligations. This means its earning rate is less than its cost of capital. In other words, bank failure can be defined as a present value of cash flows is less than obligations. It can be classified as actual cash flows being below its expected cash flows and its projections have not been met (Weston and Copeland, 1992).

There are different reasons for any banking firm moving towards bank failures. Some of these reasons include recessionary trends, natural calamities, lack of good management practice especially lack of corporate governance, poor implementation of policy, and inadequate risk management practice. These items signal financial distress

before a healthy banking firm turns into a failure. 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 payment of salaries and interests, decline in liquidity, profitability, turnover and other financial ratios (Sinkey, 1975).

Nepalese financial institutions are facing problems in the recent years. Political instability and conflicts have caused operating losses directly or indirectly to a number of small and large business firms. Not only political issues may be a reason of bank failures, moreover a lack of efficient management, resources, vision, technical knowledge, attitude of management, financial analysis, and lack of regulation and supervision related to risk management contribute to bank failures. Thus, this study attempts to assess the differences in financial ratios of failed and non-failed BFIs in the context of Nepal.

Significance of the study

Many studies have been carried out in developed countries in predicting bank failures. The emergences of different concepts have improved the literature in the subject of bank failure over time. However, no research has been conducted yet particularly in predicting bank failures of Nepal. Therefore, this study may prove beneficial to scholars, investors, managers, and policy makers to understand the early warning indicators of bank failures.

Research objectives

There has been much research conducted in the prediction of business failures in general such as Beaver (1966), Altman (1968), Deakin (1972) and Ohlson (1980). Similarly, several researches have been carried out in prediction of bank failures. Some of the most significant studies which influence this study are Meyar and Pifer (1970), Sinkey (1975), Altman (1977) and Martin (1977). The major objective of this study is to examine the indicators of banking and financial institutions failures in Nepal through 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 determine how financial ratios deteriorate when firms move toward the failure.

Litrature review

The review of this study has been carried out with assorted articles by different researchers and authors in the area of indicator of business failures and bank failures.

Beaver (1966) attempted a univariate prediction model to predict the financial ratios as predictors of failure on the basis of paired sample design of 79 failed and 79

non-failed firms of similar industries and same size. He used 30 ratios for every set of financial statement. Thirty ratios were divided into six major common element groups and only one ratio for each group was selected for the analysis. Three criteria used to select the ratio i) popularity based on the frequent appearance in the literature ii) the ratios performed well in one of the previous studies and iii) cash flow concept. In this study comparison of mean values, dichotomous classification test and likelihood ratios have been used to test predictive power of ratios for failure. The major findings of this study were the ratio distribution of failed firms began to deteriorate at least five year before failure, the ratios of non-failed firms were quite stable throughout the five year and the gap determines the difference in the mean ratios of failed and non-failed firms.

Altman (1968) applied the first multivariate discriminant analysis. The sample was composed of sixty six corporations with thirty three bankrupt and thirty three non-bankrupt firms. Twenty two potential ratios were chosen on the basis of popularity in the literature, potential relevance to the study and a few new ratios were initiated from the original list of ratios, five ratios were selected as doing the best overall job together in the prediction of corporate bankruptcy.

Deakin (1973) attempted to develop an alternative model to Beaver and Altman based on 32 failed and 32 non-failed firms. The study applied both univariate and multivariate statistical techniques to assess the predictive ability of large groups of ratios. The major outcome of this study were five ratios out of fourteen could best predict corporate failure in each of the five years prior to failure and the discriminant analysis was the best to predict business failure using ratios as prediction variable three years in advance with fairly high degree of accuracy.

Taffler and Trishaw (1977) study approached the corporate distress problem primarily from the viewpoint of security analysis and adaptations of their work. This model is also relevant for accounting firms to assess the growing concern in capability of clients and in their work as receivers and liquidators of firms that have already failed. To construct their solvency model, Taffler and Tisshaw (T&T) utilized linear discriminant analysis on a sample of 46 failed firms and 46 financially sound manufacturing companies. The latter sample was matched to the failed sample by size and industry, from period 1969 through 1975. Eighty different ratios were examined for the two samples with a resulting model utilizing only four measures.

Ohlson (1980) has studied on financial ratio and the probability of prediction of bankruptcy by using a sample of 105 bankrupt manufacturing companies which experienced bankruptcy during the period of 1970-1976. In this study the econometric methodology of conditional logit analysis has been applied to avoid some problems of multivariate analysis. The four factors derived from financial statement were statistically significant in assessing the probability of bankruptcy. They were: i) size ii) the financial structure as measured by leverage (total liabilities to total asset) iii) some performance measures (net income to total asset) iv) some measure of current liquidity (working capital to total asset, current liability to current asset).

Bhatia (1988) developed a discriminant analysis model for identifying "sick" companies. Sick companies in India refer to companies that continue to operate even after incurring losses. The sample consisted of 18 sick and 18 healthy companies all of which are publicly traded. Data used pertained to the period 1976-95. The healthy companies were paired with the sick ones based on the type of product and gross fixed assets. The companies were drawn from the cement, electrical, engineering, glass, paper and steel industries. The predictor model includes only seven variables in the final discriminant model.

Mayer and Piffer (1970) have studied on the prediction of bank failure by taking 39 paired failed banks and solvent banks. The failed banks were selected in the period of 1749-1965 and solvent banks for the same period. The study had attempted to discriminate between bankrupt and solvent banks facing similar local and national market condition. Thirty two financial ratios were used as the independent variables in stepwise linear regression model for prediction of bank failure. Financial ratios were computed for a period of six years prior to failure. The major findings of this study were: the financial measures can evaluate relative strength and weakness of firm, financial variables were unable to discriminate between viable and failing banks, when lead time is three years or more and the current financial position is needed to discriminate among bank groups.

Sinkey (1975) used linear multiple discriminant analysis (MDA) to evaluate data on 220 problems and non-problem commercial banks for the period 1969–1972. Half of the sample commercial banks were listed as problem banks by FDIC in 1972–1973. Each problem bank is matched with non-problem bank based on geographic market area, total deposit, number of banking office and Federal Reserve membership status. After testing more than 100 ratios designed to cover all CAMEL categories, ten financial variables were chosen. Among these, six ratios have significant discriminator in stepwise analysis. The study concluded that although different in the means of these variables are statistically significant, the classification accuracy of the model is low due to group overlap among the problem and non-problem banks.

Altman (1977) also used multiple discriminant analysis to analyze three groups of troubled saving and loan institutions. Improving on Sinkey's (1975) study, the study tests and rejects the equality of groups and uses a quadratic structure. The study examines data on 212 saving and loan association during the periods of 1966-1973. Altman tests 32 financial ratios that cover all CAMEL categories. Only seven variables seemed to be the best predictors for the model in the study. These variables reflect on profitability, capital adequacy and assets quality.

Martin (1977) used a logit probability model to evaluate commercial bank failure. The study analyzes data covering all commercial banks that are members of the Federal Reserve systems between 1970 and 1976. He analyzes 25 ratios which are chosen for their usefulness in previous study. The preferred model includes only four variables.

Avery and Hanweck (1984) studied commercial bank closure using semiannual data for 100 closed and 1190 non-closed commercial banks during the period of 1978 to 1983. The study analyzes using nine financial ratios on the basis of previous studies. Five financial ratios coefficient prove significant and receive signs expected a priory.

Barth *et al*. (1985) study thrift institutions closure using a logit probability model. They used semiannual data for 318 closed and 588 non-closed saving and loan associations covering the period of 1981-1984. The study mentioned that only 12 financial ratios were similar to the earlier studies. Five of these variables receive their expected sign and prove that these are statistically significant.

Table 1. Summary of significant independent variables of previous studies classified into CAMEL categories

Variables	**Sinkey (1975)**	**Altman (1977)**	**Martin (1977)**	**Avery and Hanweck (1984)**	**Barth *et al.* (1985)**
Capital Adequacy	LCR	NWTA HLBANW ESTA	GCARA	KTA LNTA	NWTA
Asset Quality	LRTR LA	RETA SRETA TLTS	GCONI CI2LM	NLTA CILNNL	
Management Competence	OEOI OETR				
Earnings	SLRTR	NOIGOI	NITA	NITA HERF PTD	NITA ISFTF
Liquidity					LATA LNTA

The description of independent variables which were used in previous study is given in Table 2.

Table 2. Description of independent variables of bank failures

Authors	**Variables**	**Definition**
Sinkey (1975)	LCR	Loan/Capital + Reserve
	LRTR	Loan Revenue/Total Revenue
	LA	Loan/Assets
	OEOI	Operating Expenses/Operating Income
	OETR	Other Expenses/Total Revenue
	SLRTR	Revenue from State and Local Obligations/Total Revenue

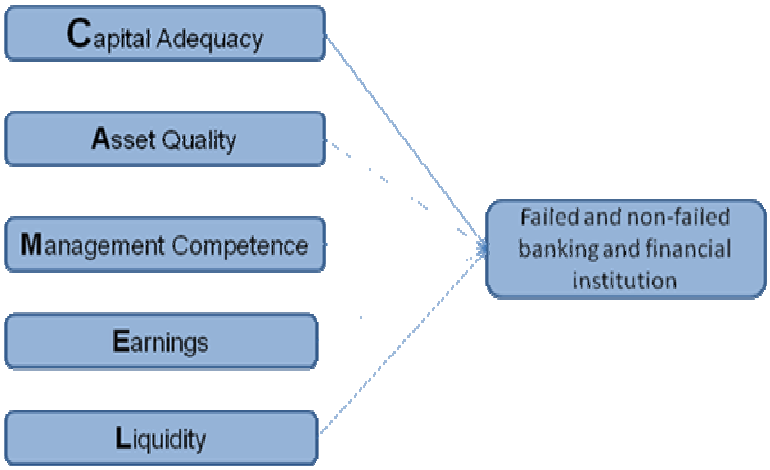
Altman (1977)	NWTA	Net Worth / Total Assets
	HLBANW	FHLB Advance/Net Worth
	ESTA	Earned Surplus/ Total Assets
	RETA	Real Estate Own/ Total Assets
	SRETA	Real Estate Own (SI)/Total Assets
	TLTS	Total Loans/Total Saving
	NOIGOI	Net Operating Income/Gross Operating Income
Martin (1977)	GCARA	Gross Capital/Adjusted Risk Assets
	GCONI	Gross Charge Offs/ (Net Operating + Loss Provision)
	CI2LN	(Commercial and Industrial Loan + Loans to REITS and Mortgage Bankers + Commercial Real Estate Loan + Construction Loan) / Total Assets
	NITA	Net Income / (Total Assets- Cash in Process)
Avery and Hanweck (1984)	KTA	(Equity Capita + Loan Loss Reserve Allowance)/ Total Assets
	LNTA	Natural Logarithm Total Bank Assets – Loan Loss Reserves
		Net Loans / Total Assets
	NLTA	Commercial and Industrial Loans/Net Loans
	CILNNL	Net After Tax Income / Total Assets
	NITA	Herfindahl Index for Banks Local Banking Market
	HERF	Semiannual Percentage Change in Total Deposits within each Banks Local Banking Market
	PTD	
Barth *et al*. (1985)	NWTA	Net Worth/ Total Assets
	NITA	Net Income /Total Assets
	ISFTF	Interest Sensitive Funds/Total Funds
	LATA	Liquid Assets/ Total Assets
	LNTA	Natural Logarithm of Total Assets

This study therefore uses some of above financial ratios to indicate bank failures in Nepal.

Conceptual framework

There are various reasons for banking firms to start down the slippery slope towards failure. The 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 emerge as symptoms, which may be reflected in a continuous decline in share market price, a shortage of cash, defaults in payroll and debt servicing, a decline in liquidity, profitability, turnover, and other financial ratios i.e. capital adequacy, assets quality and management competency.

Fig. 1. Conceptual framework



The "C.A.M.E.L." graphic above demonstrates the predictive ability of specific financial variables (Capita Adequacy, Asset Quality, Management Competence, Earnings, and Liquidity) on the future of banking and financial institutions in Nepal.

Research methodology

This study is based on secondary data obtained through published annual reports of sample firms and data obtained from Central Bank of Nepal, (Nepal Rastra Bank, NRB), Security Board of Nepal (SEBON) and Nepal Stock Exchange (NEPSE). It includes the balance sheets, income statements, and cash flow statements. All banking and financial institutions are required to submit their quarterly financial reports to Nepal Rastra Bank. Besides this, all listed companies are required to submit their annual report to SEBON and NEPSE including audited financial statement within specific period as prescribed by the Security Exchange Act and Regulation. The selection has been done on the basis of paired sample design to eliminate the effect of assets size differences. Banking firms which have same financial ratios with different asset sizes may have different probabilities of failures. Even though the ratios of two firms are identical, the larger banking firms with larger asset bases have a lower probability of failure than smaller banking firms. The BFIs that failed during observation period of 2007-2010 are taken as sample of failed firms. Non-failed banking firms are selected on the basis of the closest assets size within the same group of failed BFIs. In this study, significance test of CAMEL ratios, profile analysis is conducted.

Selection of the firms

All banking and financial institutions are required to submit their quarterly financial reports to the NRB. Besides this, all listed companies are required to submit

their annual report to SEBON and NEPSE, including audited financial statement within specific period as prescribed by Nepal's Security Exchange Act and Regulation. 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 different asset sizes, may have different probabilities of failure. Even when the ratios of two firms are identical, larger banking firms with larger asset bases have a lower probability of failure than smaller banking firms. Those financial institutions that failed during observation period of 2007-2010 are taken as samples of failure firms. Non-failed banking firms are selected on the basis of the similar asset sizes within the same group failed banking firms.

Table 3. Sample banking and financial institutions (In millions NRS)

SN	Failed banking and financial institutions	Class	Asset size	SN	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 and 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

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.

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 been 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.

$$Z = \alpha + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4 \ldots\ldots\ldots\ldots\ldots + \alpha_n X_n$$

X_1, X_2, X_3, $X_4 \ldots X_n$ 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 the 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),

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

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

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

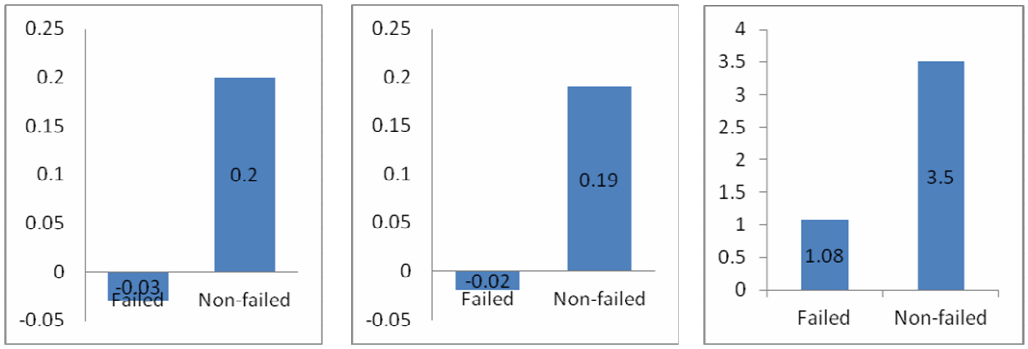
Data analysis and findings

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: 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.

Fig. 2. Descriptive statistics of capital adequacy ratios



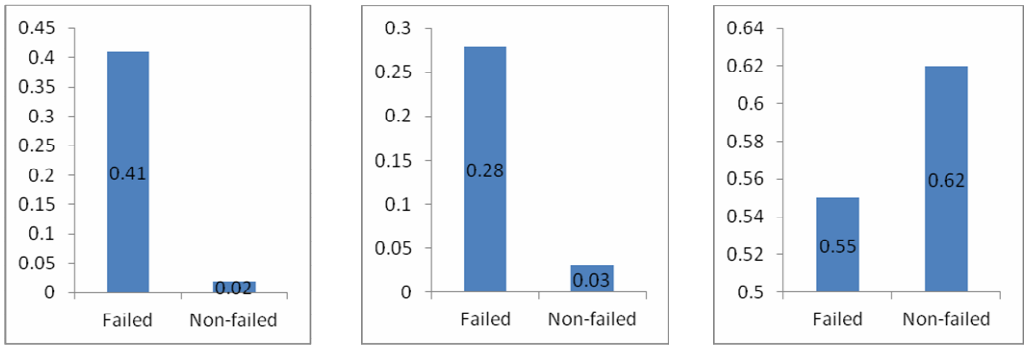
Capital to total assets | Capital to risk weighted average | Total loan to total capital

The figure-2 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: 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.

Figure-3 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 the effective and efficient asset management by the non-failed BFIs to that of failed companies.

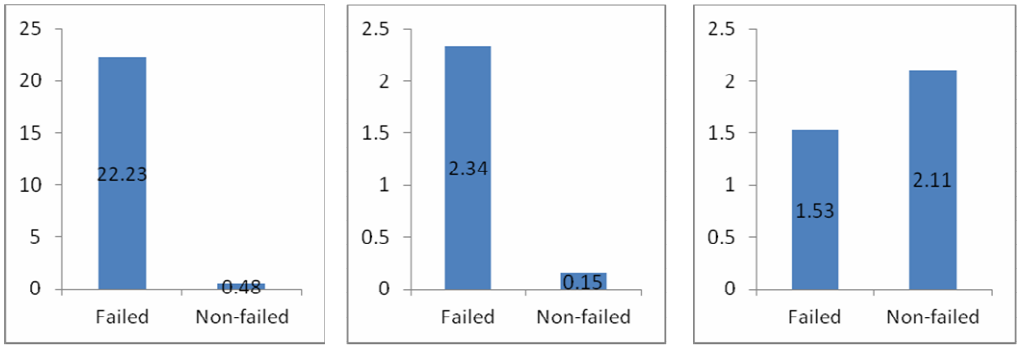
Fig. 3. Descriptive statistics of assets quality ratios



Provision for loan loss to net loans | Non-performing loan to total loan | Loan to total assets

Management capability: 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.

Fig. 4. Descriptive statistics of management capability ratios

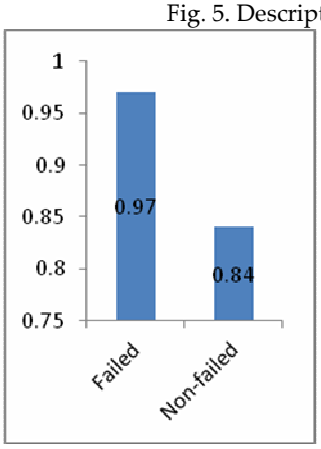


Total operating expenses to operating revenue | Loan revenue/net loan | Interest income/ interest expenses

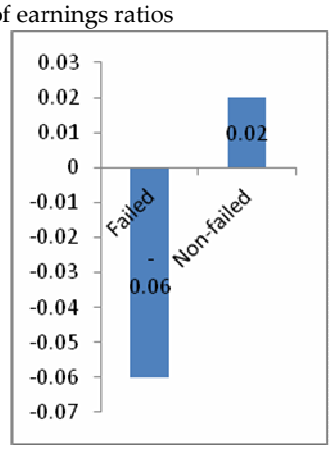
From Figure-4, it is evident that the total operating expenses to operating revenue of failed BFIs are higher for non-failed BFIs. It means that the failed BFIs' operating expenses are very high vis-à-vis operating income. Contrary to existing literature, it is observed that the loan revenue to net loan 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: 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.

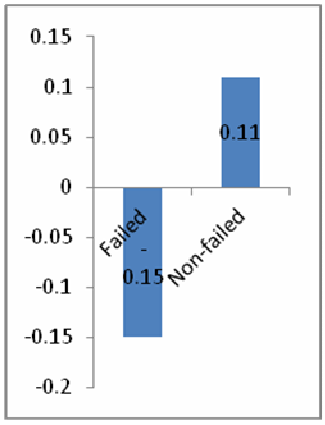
Fig. 5. Descriptive statistics of earnings ratios



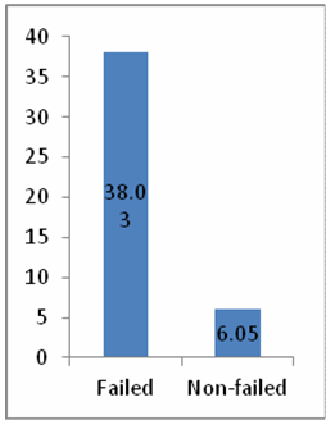
Loan to total sources of funds



ROA



ROE

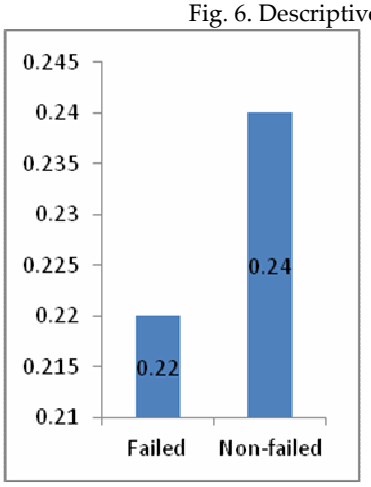


Loan revenue to total operating income

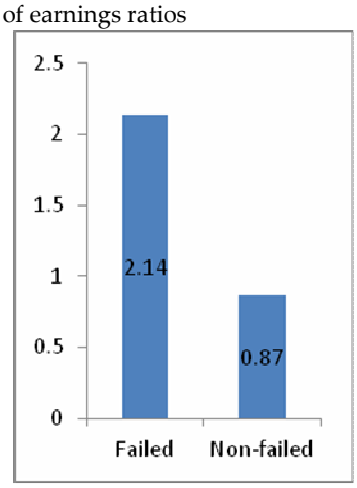
The above figure depicts that the total loan to total sources ratios of funds of failed companies are greater than their non-failed counterparts. This indicates that there is lesser amount of sources of fund of failed companies than the non-failed companies, which could be due to various reasons such 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 the income generation from operating revenues of failed companies is low.

Liquidity: 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.

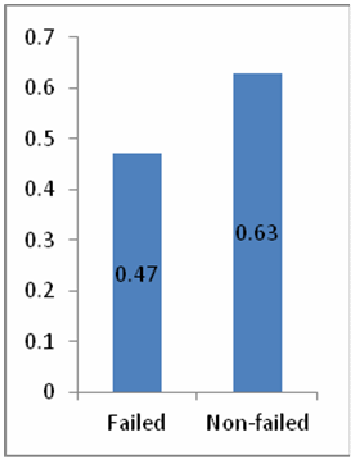
Fig. 6. Descriptive statistics of earnings ratios



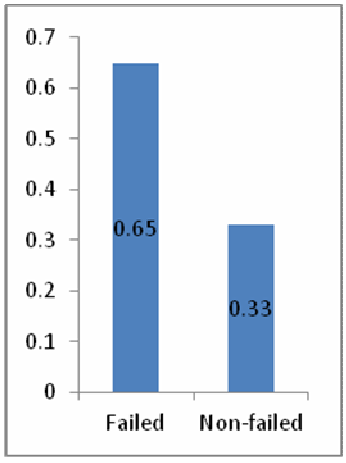
Liquid assets to total assets



Total loans to total deposit



Net loan to total assets



Liquid assets to total source of fund

In the above figure, 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.

Significance test of CAMEL ratios

The data related to sixteen BFIs have been evaluated for the significance test of CAMEL ratios. Out of sixteen BFIs, eight are healthier and still in operation. The

remaining eight BFIs were unable to cover and service their liabilities with their liquid assets, and therefore, are technically bankrupt. Some of the failed BFIs were liquidated. Some were either acquired by another company or merged with other companies. Meanwhile, some were restricted by the Central Bank of Nepal from accepting deposits, thereby indicating their failure status as full-fledged banks. In the classification of failed and non-failed BFIs, the ratios are categorized into five groups called CAMEL, which are capital adequacy, assets quality, management capability, and earning and liquidity ratios.

Table 4. Two-tailed T-test on CAMEL variables

The table provides significance tests for two-tailed T-tests of CAMEL: ratios of failed and non-failed BFIs.

CAMEL category	**Financial ratios**	**F**	**Sig.**	**t**	**df**	**Sig. (2-tailed)**
Capital adequacy	Capital / Total Assets	33.428	.000	-3.273	42	.002**
	Capital Fund / RWA	5.783	.021	-2.610	42	.012**
	Total Loans / Total Capital	5.919	.019	-1.302	42	.200
Assets quality	Provisions for Loan Loss / Net Loans	9.659	.003	1.863	42	.069*
	Non Performing Loan / Total Loan	74.749	.000	3.572	39	.001**
	Loan / Total Assets	.271	.605	-.990	42	.328
Management capability	Total Operating Expenses / Operating Revenue	5.447	.024	1.150	42	.257
	Loan Revenue/ Net Loans	5.240	.027	1.126	42	.266
	Interest Income/ Interest Expenses	3.625	.064	-1.682	42	.090*
Earnings	Loan/ Total Sources of Funds	3.836	.057	.977	42	.334
	ROA	14.977	.000	-2.700	42	.010**
	ROE	9.465	.004	.290	42	.773
	Loan Revenue /Total Operating Income	4.651	.037	1.143	42	.259
Liquidity	Liquid Assets/ Total Assets	4.881	.033	-.279	39	.782
	Total Loans/ Total Deposits	11.893	.001	1.690	39	.010
	Net Loan/ Total Assets	2.572	.117	-2.227	39	.032**
	Liquid Assets/ Total Source of Fund	5.389	.026	1.085	39	.285

** Significant at 5% level of significance * Significant at 10% level of significance

A pair sample t-test was conducted to examine whether the given 17 ratios (as per data assessable for CAMEL ratios) are significantly different between failed and non-failed BFIs. It has been found that out of 17 selected financial ratios, 7 are significantly different. The seven ratios which have distinguishing features between the failed and non-failed BFIs, are considered for profile analysis. The above mentioned 7 significant ratios support formulated research hypothesis that there is a significant relationship between a bank's probability of failure and its capital strength, asset quality, management quality, earnings and liquidity.

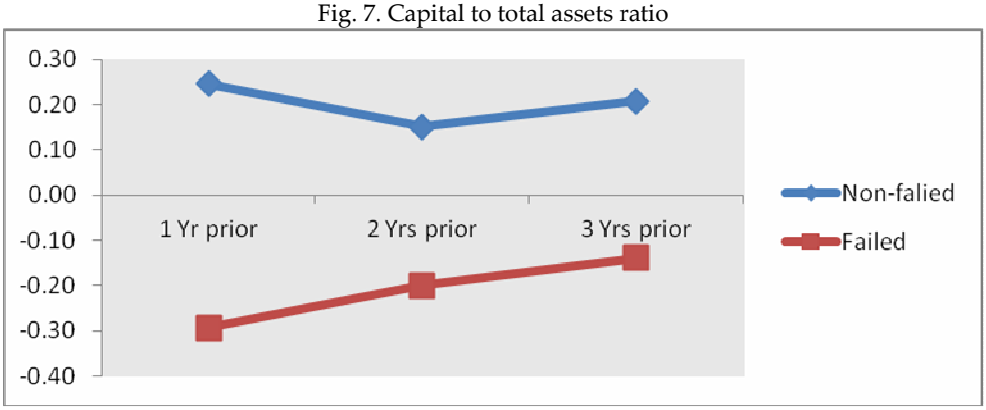
Profile of failed and non-failed BFIs

It is a way of outlining the general relationships between failed and non-failed BFIs. The results exhibit the differences between failed and non-failed BFIs. It concentrates upon a single point mean on the ratio distribution. If the mean values do not overlap, then it implies that the ratio would be an excellent predictor of failures. This analysis is entirely based upon the mean values. Therefore, the mean has been computed for failed and non-failed BFIs taking statistical data prior to three years of it failures, thereby comparing and contrasting with each other.

Capital to total assets ratio

The figure summarizes the ratio of capital to total assets of 16 sample firms including 8 failed and 8 non-failed BFIs from 44 observations in the three years prior to failure. Capital refers to total long term debt and equity capital. Total assets include currents assets, fixed assets and other assets.

Fig. 7. Capital to total assets ratio

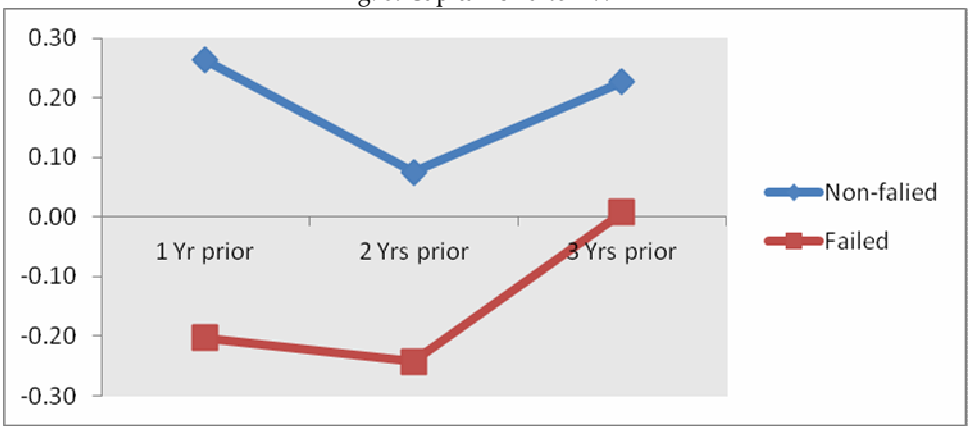


The above figure depicts that the capital to total assets ratio of failed BFIs is negative for the entire three years prior to failure. On the other hand, the capital to total assets ratio for non-failed BFIs is positive in all these three years. The deterioration in the mean value of capital to total assets ratio of failed BFIs is very pronounced in these three years. The data also shows the gap between the two groups in terms of mean value of capital to total assets ratio widening as they approach nearer to the verge of failure.

Capital fund to risk weighted assets (RWA)

The figure summarizes the ratio of capital fund to RWA of 16 sample firms including 8 failed and 8 non-failed BFIs from 44 observations of three years prior to failure.

Fig. 8. Capital fund to RWA

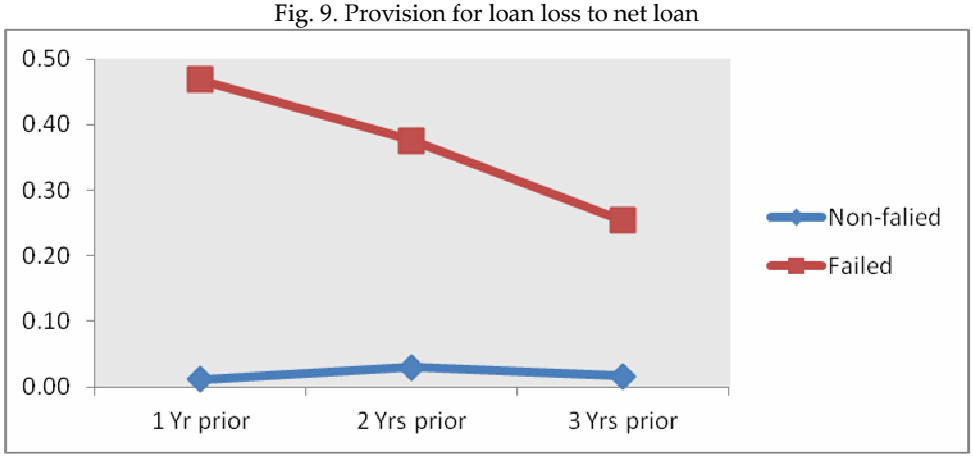


The above figure represents that the non-failed BFIs' capital fund to risk weighted assets ratio is positive and improving before the second year under study, while in the failed BFIs, it has been found to be deteriorating during the same period. The signal of downfall has been shown by the fact that it became negative prior to two years of its failure.

Provisions for loan loss to net loans

The figure summarizes the ratio of provision for loan loss to net loan of 16 sample firms including 8 failed and 8 non-failed BFIs from 44 observations of three years prior to failure.

Fig. 9. Provision for loan loss to net loan

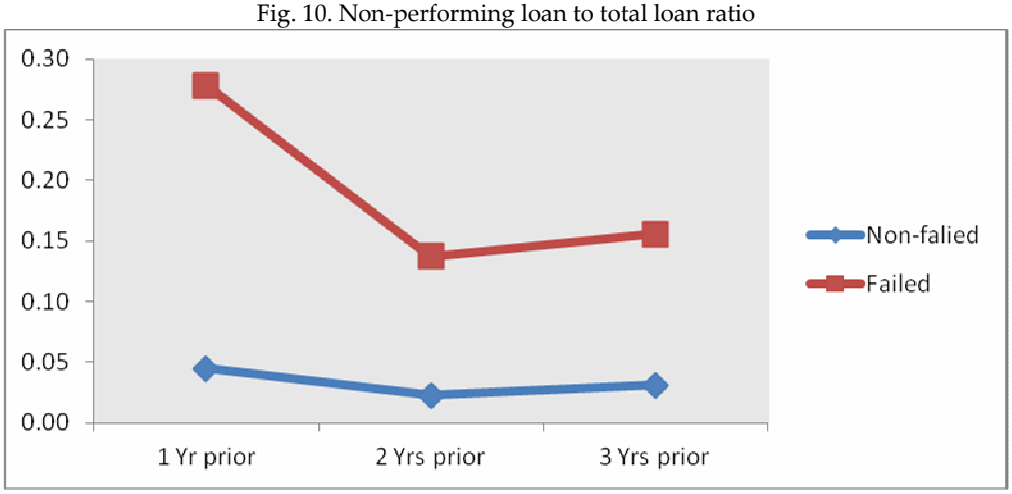


In the preceding diagram the proportion of provision for loan loss to net loan of the failed BFIs has been observed to be higher for non- failed BFIs. It shows that the failed BFIs' provision for loan loss to net loan is increasing, which is evidence of its downfall. The increase in provision for loan loss indicates that there is an increase in the huge amount of uncollectable or uncovered loans. On the contrary, the non-failed BFIs have very low bad debts or non-performing loans that indicate the robust financial health of these companies.

Non performing loan to total loan

The figure summarizes the ratio of non-performing loans to total loans of 16 sample firms including 8 failed and 8 non-failed BFIs from 44 observations over three years prior to failure.

Fig. 10. Non-performing loan to total loan ratio



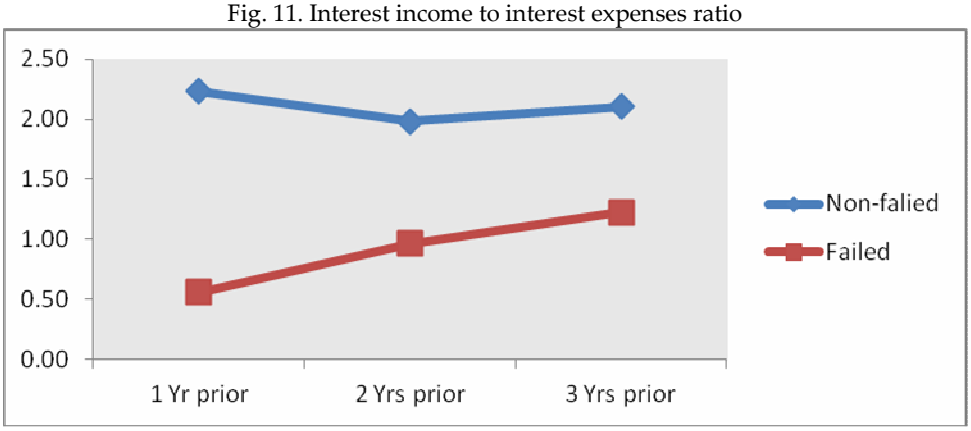
The trend in non-performing loans to total loans ratio for both failed and non-failed BFIs has been shown above. It is observed that the non-failed BFIs' non-performing loans to total loans ratio is stable as compared to its counterparts. It is below the 5% level, which is lower than the failed BFIs. It is also evident that the ratio for the failed companies is increasing and became very high just one year prior to its actual failure.

Interest income to interest expenses

The figure summarizes the ratio of interest income to interest expenses of 16 sample firms including 8 failed and 8 non-failed BFIs from 44 observations of three years prior to failure.

The figure on the next page denotes that the interest income to interest expenses of failed BFIs is deteriorating, as the time of failure approaches. The interest income to interest expense ratio of non-failed BFIs is encouraging and almost stable and sufficient to meet interest expenses in all years charted.

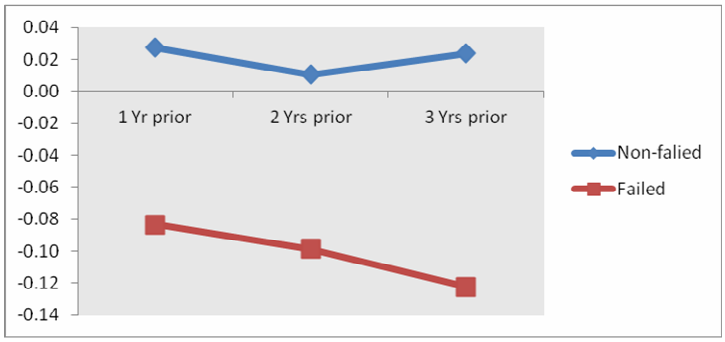
Fig. 11. Interest income to interest expenses ratio



Return on assets

The figure summarizes the ratio of net income to total assets of 16 sample firms including 8 failed and 8 non-failed BFIs from 44 observations of three years prior to failure.

Fig. 12. Return on assets ratio



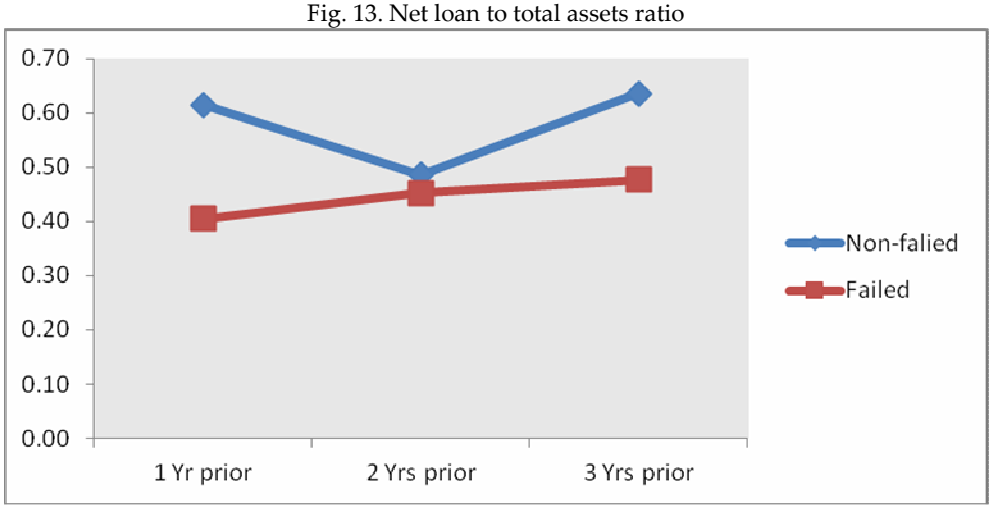
The figure explains that the Return on Assets (ROA) of non-failed BFIs is fluctuating, although it appears positive in all three years. The Return on Assets of failed BFIs is negative in all three years prior to failure. Hence, it can be concluded that the failed BFIs were operating under losses prior to their failure. The result is evident that net income to total assets ratio of non-failed BFIs is better in comparison to those failed companies.

Net loan to total assets

The next figure summarizes the ratio of net loan to total assets of 16 sample firms including 8 failed and 8 non-failed BFIs from 44 observations of three years prior to failure.

The figure below represents that the net loan to total assets of non-failed BFIs' is higher to failed BFIs. Thus, this is the proof of the non-failed BFIs utilizing the sources of funds efficiently.

Fig. 13. Net loan to total assets ratio



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.

Table 5. Accuracy of discriminant classification based on total observation

Classification Results[a]					
		Group	**Predicted group membership**		**Total**
			Failed	**Non-failed**	
Original	Count	Failed	16	8	24
		Non-failed	1	23	24
	%	Failed	66.7	33.3	100.0
		Non-failed	4.2	95.8	100.0

a. 81.3% of the original grouped cases correctly classified.

The table presents actual and predicted outcomes prior to failure based on total observation. The row denotes the actual status, the column denotes the prediction made of the banking/financial institutions, and each cell contains the number of the banking / financial institutions fulfilling each condition.

There are total 48 observations including 24 observations each from failed and non- failed companies. 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 significant test for differentiation of failed and non-failed BFIs. The ratios include the list are frequently used by previous researchers and 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 require 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.

Table 6. Accuracy of logistic regression classification

Observed			Predicted		
			Group		
			Failed	Non-failed	Percentage correct
Step 1	Group	Failed	20	4	83.3
		Non-failed	1	23	95.8
	Overall Percentage				89.6

a. The cut value is. 500

The table presents actual outcome and predicted outcome prior to failure based on total observations. The row represents the actual status, the column represents the prediction made of the BFIs, and each cell contains the number of the BFIs fulfilling each condition.

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.

Conclusions

Failure identification and early warnings of future financial crisis are 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. The selected seven CAMEL financial ratios of the failed and non-failed BFIs demonstrated that there are differences in the mean ratios since three year prior to failures. The ratios of non-failed BFIs are quite stable throughout the three years before failures compared to failed BFIs. The problem should be identified based on the analysis of CAMEL variables i.e. capital adequacy, assets quality, management capability, and earning and liquidity ratios prior to failure. The precautions can be taken against future bank failures by analyzing these ratios and improving the weakness of the company as shown by above analysis. It can be used as a tool in predicting future problems in BFIs by the supervising body of Nepal. It helps to improve the quality of a BFI's assets to prevent bank failure. 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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