Article: DOI: 10.70906/20241804126137

Assessing the Financial Health of Urban Co-operative Banks using Altman Z-Scores

Radhika V R*

Resmi R**

Abstract

A
b
s
t
r
a
c
t

The long-term sustainability of banks is determined by measuring their financial health. This study was initiated due to the recent bank scams in the co-operative banking sector in Kerala, which raised a need to prove the financial stability of Urban Co-operative Banks (UCBs), which are an integral part of the Indian banking sector. The financial soundness of sixteen UCBs in Kerala is assessed in this study over ten years from 2012-13 to 2021-22 using Altman Z scores, re-estimated Altman Z scores using Binary Logistic Regression (BLR) and Multilayer Perceptron Neural Network (MLPNN). BLR was used to classify banks into grey and distress zones, and MLPNN was used to identify non-linear relationships in the data. The study's findings show that the re-estimated Altman Z score model using BLR exhibited high predictive accuracy in predicting distressed and non-distressed UCBs; therefore, it may be considered a reliable tool for predicting financial distress in UCBs. The MLPNN model needs further improvement in the inclusion of new variables, which will be included within the future scope of the research. The bank management and other stakeholders will be able to monitor the financial stability of UCBs with the help of the study findings.

Keywords: *Financial Health, Urban Co-operative Banks, Altman Z scores*

How to cite: Radhika, V. R., & Resmi, R. (2024). Assessing the financial health of urban co-operative banks using Altman Z-scores. *Journal of Management and Entrepreneurship*, 18 (4), 126-137

DOI: 10.70906/20241804126137

* Research Scholar, PG and Research Department of Commerce, Maharaja's College, Ernakulam, Kerala, India-682024, Email: radhikakottath@gmail.com, Mob.No. 9961092754

** Assistant Professor, Sree Sankara Vidyapeetom College, Valayanchirangara, Perumbavoor, Kerala, India- 683556, Email: resmir@ssvcollege.ac.in, Mob.No. 9496513431

1. Introduction

Urban Co-operative Banks serve the financial needs of urban and semi-urban populations and are a crucial component of the Indian banking industry. Their performance significantly influences economic resilience and stability (Sinha, n.d.). UCBs have a unique organisational structure, which makes them highly effective in promoting financial inclusion among the urban poor (Raju, 2018). Therefore, this sector will require focused attention in the coming years (The Institute of Chartered Accountants of India, 2013). Despite their importance in the banking industry in India, UCBs face many challenges which affect their financial health. These challenges include raising capital, inadequate corporate governance, improper professional management, inadequate IT infrastructure, intense competition from other banks and financial institutions, etc. (Reserve Bank of India - 2021, n.d.). These challenges increase the chances of financial distress and limit the growth potential of UCBs.

Kerala is one of the states in India, and a strong co-operative sector characterises its economy. Since its formation, this sector has brought significant socio-economic change, especially in the state's rural sector. According to the (Kerala Co-operative Policy), the co-operative movement has permeated every sector in the state, and almost all people in Kerala are the beneficiaries of this movement. Along with the two-tier structure consisting of Kerala State Co-operative Bank and Primary Agricultural Credit Societies (PACSs), Urban Co-operative Banks in Kerala focus on priority sector lending. 59 UCBs in Kerala are directly regulated and supervised by the Reserve Bank of India. Administrative control of the UCBs vests with the Registrar of Co-operative Societies, Kerala and the Banking Regulation Act of 1949 applies to all these banks.

In recent years, the credibility of the cooperative banking sector in Kerala has been questioned by major cooperative bank scams, especially in the form of misappropriation of huge amounts of money, fraudulent loan approvals, etc. (Balan, 2022). These scams have affected the lives of many people who have invested their savings in these banks. These have also resulted in the suspicion of financial instability in the co-operative sector. Although these scams happened mainly in some PACSs, as UCBs form a major part of the cooperative banking sector, they are also susceptible to financial instability. Thus, it is necessary to evaluate the financial health of UCBs in Kerala for the sake of bank management, investors, and other stakeholders.

Evaluating the financial health of banks facilitates measuring the financial stability and sustainability of the banking sector and promoting economic growth (Trung et al., 2024). It also helps the banks to improve their performance. Usually, the CAMELS framework has been used to study the financial health of Indian banks (RBI, 2012). In addition to that, there are other techniques like Multi Criteria Decision Making (MCDM) Methods (Trung et al., 2024), Data Envelopment Analysis (Gaurav & Krishnan, 2017; Raju, 2018), Stochastic Frontier Analysis (Gaurav & Krishnan, 2017; Raju, 2018), Machine learning techniques (Cındık & Armutlulu, 2021; Desheng Wu et al., 2022; Viswanathan et al., 2020) etc.

When evaluating the financial health of banks, traditional methods like financial ratios and regulatory compliance were initially employed, but these methods have proven unreliable. To get a clear picture of the financial stability of banks, we need to employ models that can correctly predict the risk of financial risk or bankruptcy. In this regard, one model that has been widely used is the Altman Z score model. This tool will help identify forewarning signals of financial distress in UCBs and provide proactive measures to ensure financial stability. However, it has not been widely used to predict the financial distress of UCBs. This research paper tries to fill this gap by studying the financial health of UCBs using Altman Z scores. The study also tries to provide a tool for bank management to detect forewarning signals of financial distress and take corrective actions if necessary.

2. Review of literature

This literature review is organised into two main sections: Financial Health and the Altman Z-Score Model. The first section reviews existing research on financial health assessment, and the second section discusses the studies based on the Altman Z-Score model.

2.1. Financial Health

Roman and Sargu (2013) analysed Romanian Commercial banks' financial soundness using Camels criteria. The research identified the strengths and vulnerabilities of Romanian banks and how they can improve their financial position by concentrating on these areas.

Raju (2018) studied the efficiency of off-balance sheet activities and core banking processes of UCBs in India from 2013-14 to 2015-16. They employed Stochastic Frontier Analysis and Data Envelopment Analysis. The study found that compared to off-balance sheet activities, core banking activities of UCBs exhibit higher mean efficiency.

Salina et al. (2020) investigated the financial soundness of banks in Kazakhstan. Principal component analysis was used to identify the indicators of financial soundness, and cluster analysis was used to group the banks into sound, unsound, and risky banks. Their findings highlighted the decline in the financial soundness of the banking industry in Kazakhstan. They found that the decline in financial distress has affected the structure of the Kazakh banking sector.

Viswanathan et al. (2020) focused on classifying the 44 Indian banks based on financial health. The study was undertaken from investors' perspectives using machine learning tools such as linear discriminant analysis, random forest method, and classification and regression tree method. The study developed a model for classifying the banks into high, moderate, and low risk.

Heniwati et al. (2021) compared the financial health of Islamic and conventional banks in Indonesia. Unbalanced panel data was used in the study from 2011 to 2018. Two dependent variables, i.e., Z score for Return on Average Assets and Liquid Assets to Deposit Ratio, were used for regression analysis. The results reveal that Islamic banks are not as healthy as conventional banks, and they face a higher risk of bankruptcy in the long term. Islamic and conventional banks contribute differently to the national financial stability system.

Karim et al. (2021) examined how COVID-19 affected the financial stability and liquidity of listed banks in Bangladesh. Liquidity ratios are computed to assess the liquidity position of banks. A revised Z-score model for service industries is applied to evaluate financial health. The study's findings reveal a decline in the banks' financial stability and liquidity position after COVID-19 began.

Using the Multi-Criteria Decision Making (MCDM) techniques and the CAMELS rating system, (Trung et al., 2024) evaluated the financial health of Vietnamese banks. The study distinguished banks with robust and poor financial health and found that the ranking produced by all three methods was similar.

2.2. Altman Z score model

Altman (2018) noted that his model is arguably the most renowned and widely used method for forewarning financial distress in firms by academicians and practitioners worldwide. The paper discussed the number of applications of the model, which took two forms: application by analysts outside the company and application by board members and managers of the distressed company.

Singh and Mishra (2016) introduced a model for forecasting bankruptcies of companies engaged in manufacturing business in India, taking 208 firms as the sample. The study re-estimated the Altman Z-Score, Ohlson Y-Score, and Zmijewski X-Score. Probit and Multiple Discriminant Analysis (MDA) were used to estimate Altman Z-Score and Zmijewski X-Score models. At the same time, the Logit technique was applied to the Ohlson Y-Score and other models. The key findings indicate that the total predictive accuracy of all these models will be enhanced if the coefficients are re-estimated.

Boda and Uradnicek (2016) challenged Altman's Z score model's extensive application. They aimed to assess the model's effectiveness within the Slovak economic context. The findings suggest that Altman's bankruptcy formula can be effectively applied to Slovak economic conditions, and the model will help predict financial difficulties. They recommend that for financially distressed firms, re-estimating the model's coefficients is preferable to attain more accuracy in prediction.

The financial health of some co-operatives in a province in the Philippines was measured by (Melvin S. Sarsale, 2020) using the Altman model. The study followed the document analysis method using data from annual reports for five years. The study found that large co-operatives fell into the grey zone compared to small and medium co-operatives. The study also observed that financial health size and age of co-operatives exhibit a negative relationship. Further, the Altman model is a good tool for valuing the financial health of co-operatives.

Cındık and Armutlulu (2021) aimed to forecast the financial distress of Turkish companies by applying the Altman Z score model, modified Altman model, Random Forest Deep Learning Model, and Quadratic Discriminant Analysis using variables of the Altman model. Data for the study consisted of both public and private companies. The random forest model has demonstrated 95% performance and outperformed the other three models.

Desheng Wu et al. (2022) introduced a forecasting model for the stock market that combines MLPNN with the Altman Z score model, taking data gathered from companies in China. The findings reveal that, compared to the Altman Z-score and simple neural network methods, the average precision rate of the composite neural network model is high.

The literature review clearly states that the financial health of institutions has been the subject matter of research for many authors, and many of them have used the Altman model for studying this. However, there are limited studies found in the co-operative sector. Moreover, studies based on re-estimation of the model are limited. Thus, this study adds new contributions to this area of research.

3. Objectives of the Study

- To analyse the financial health of UCBs using Altman Z scores and re-estimated Z scores
- To evaluate the predictive accuracy of the models in predicting the financial distress of UCBs

4. Methodology

The study examined the financial health of 16 UCBs in Kerala by utilising the Altman Z scores calculated from their annual reports for ten years, from 2012-13 to 2021-22. Z scores are calculated based on the modified model suggested by Altman and Hotchkiss (1993), which is designed for the service industries and based on the multiple discriminant function::

$$Z'' = 6.56(X_1) + 3.26(X_2) + 6.72(X_3) + 1.05(X_4)$$

Where,

Z'' = Altman-Z-Score

X_1 = Working Capital/Total Asset (indicate the firm's liquidity)

X_2 = Retained Earnings/Total Asset (show the firm's cumulative profitability)

X_3 = Earnings before Interest and Taxes/Total Asset (reflect productivity of the firm's assets)

X_4 = Book Value of Equity/Total Debt (measure firm's financial leverage)

The criteria for the classification of firms into various zones according to Altman & Hotchkiss (1993) are: If the bank's Z score is less than 1.10, it will be classified in the distress zone; if it is between 1.10 and 2.60, it will be classified in the grey zone; and if it is greater than 2.60, it will be classified in the safe zone.

Altman Z scores are re-estimated using binomial logistic regression and multilayer perceptron neural networks. Binary logistic regression was used to identify the relationship between the modified Altman model variables and the probability of financial distress. The MLPNN was employed to model the non-linear relationships between the modified Altman model variables and the probability of distress. The predictive accuracy of both models was compared to determine which method more effectively predicts financial distress in UCBs.

5. Results and Discussion

5.1. Altman Z Score

Altman Z scores of 16 UCBs under study are shown in Table 1 for 10 years from 2012-13 to 2021-22, and Table 2 shows the banks' performance frequency during these years. No banks were in the safe zone, which indicates a concerning trend. Most banks, including Kottayam UCB, Meenachil UCB, Muvattupuzha UCB, and Perinthalmanna UCB, spent the entire period in the Grey Zone with no signs of distress. On the other hand, some banks, such as

Adhyapaka UCB, Changanassery UCB, Kaduthuruthy UCB, Pala UCB, and People's UCB, showed a greater frequency of distress and were in the Distress Zone for several years. In 2012-13, only one bank was in the distress zone, but the number of banks in the distress zone increased in the subsequent years. In 2021-22, four banks are in the distress zone.

Table 1. Altman Z scores of selected UCBs from 2012-13 to 2021-22

Bank	2012-13	2013-14	2014-15	2015-16	2016-17	2017-18	2018-19	2019-20	2020-21	2021-22
Adhyapaka UCB	1.35 G	1.25 G	1.05 D	1.02 D	1.07 D	1.05 D	1.09 D	1.04 D	1.08 D	1.08 D
Aluva UCB	1.35 G	1.24 G	1.28 G	1.25 G	1.23 G	1.24 G	1.27 G	1.29 G	1.32 G	1.09 D
Changanassery UCB	1.26 G	1.25 G	1.08 D	1.23 G	1.05 D	1.01 D	1.17 G	1.09 D	1.24 G	1.16 G
Kaduthuruthy UCB	1.34 G	1.02 D	1.16 G	1.26 G	1.25 G	1.13 G	1.02 D	1.07 D	1.04 D	1.16 G
Kottayam UCB	1.38 G	1.31 G	1.34 G	1.31 G	1.29 G	1.28 G	1.25 G	1.27 G	1.25 G	1.30 G
Manjeri UCB	1.38 G	1.34 G	1.35 G	1.31 G	1.25 G	1.27 G	1.09 D	1.08 D	0.90 D	1.32 G
Mattancherry UCB	1.33 G	1.29 G	1.30 G	1.32 G	1.32 G	1.34 G	1.30 G	1.31 G	1.09 D	1.02 D
Meenachil UCB	1.29 G	1.25 G	1.31 G	1.28 G	1.26 G	1.26 G	1.24 G	1.26 G	1.24 G	1.26 G
Muvattupuzha UCB	1.34 G	1.31 G	1.33 G	1.29 G	1.34 G	1.32 G	1.33 G	1.32 G	1.32 G	1.36 G
Nilambur UCB	1.36 G	1.26 G	1.26 G	1.27 G	1.26 G	1.27 G	1.25 G	1.03 D	1.23 G	1.29 G
Pala UCB	1.06 D	1.27 G	1.23 G	1.30 G	1.01 D	1.24 G	1.09 D	1.04 D	1.29 G	1.32 G
Peoples' UCB	1.23 G	1.06 D	1.09 D	1.06 D	1.25 G	1.23 G	1.07 D	1.29 G	1.34 G	1.28 G
Perinthalmanna UCB	1.37 G	1.23 G	1.30 G	1.25 G	1.36 G	1.39 G	1.33 G	1.29 G	1.33 G	1.28 G
Ponnani UCB	1.25 G	1.32 G	1.32 G	1.30 G	1.33 G	1.26 G	1.08 D	1.26 G	1.36 G	1.30 G
Tirur UCB	1.35 G	1.23 G	1.14 G	1.09 D	1.07 D	1.06 D	1.16 G	1.23 G	1.28 G	1.32 G
Vaikom UCB	1.23 G	1.32 G	1.30 G	1.20 G	1.17 G	1.15 G	1.08 D	1.25 G	1.01 D	1.03 D

Source: Authors' calculations based on annual reports of the individual banks (G –Grey zone, D – Distress zone)

Table 2. Frequency of performance of the selected UCBs

Bank	No.of years in		
	Safe Zone	Grey Zone	Distress Zone
Adhyapaka UCB	0	2	8
Aluva UCB	0	9	1
Changanassery UCB	0	6	4
Kaduthuruthy UCB	0	6	4
Kottayam UCB	0	10	0
Manjeri UCB	0	7	3
Mattancherry UCB	0	8	2
Meenachil UCB	0	10	0
Muvattupuzha UCB	0	10	0
Nilambur UCB	0	9	1
Pala UCB	0	6	4
Peoples' UCB	0	6	4
Perinthalmanna UCB	0	10	0
Ponnani UCB	0	9	1
Tirur UCB	0	7	3
Vaikom UCB	0	7	3

Source: Authors' calculations

5.2. Re-estimation of Altman Model using Binary Logistic regression

Although the original Altman Model classified banks into three distinct zones—Safe, Grey, and Distress—in this study, the banks were found to fall exclusively into two categories: the Grey and Distress Zones. Consequently, the model is re-estimated using Binary Logistic Regression (BLR), focusing on the binary classification of banks into the Grey Zone and the Distress Zone. This method seeks to give a more accurate financial distress prediction for the selected UCBs in Kerala and is more appropriate for the observed data.

Table 3. Coefficients for re-estimated Altman model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.0003	0.123	3.274	0.001*
WC/TA	6.5560	0.113	3.333	0.001*
RE/TA	8.1107	2.846	3.175	0.002*
EBIT/TA	1.0437	1.838	0.933	0.351
BV/TD	0.0072	0.083	3.095	0.002*

Source: Authors' calculations

The Altman Z score model was re-estimated with Binary Logistic Regression. The findings of Table 3 showed that the variables WC/TA (Working Capital to Total Assets), RE/TA (Retained Earnings to Total Assets), and BV/TD (Book Value of Equity to Total Debt) have positive coefficients, so, they are statistically significant predictors of the dependent variable. It implies that the dependent variable will also increase when these ratios increase. However, the p-value of EBIT/TA (Earnings before Interest and Taxes to Total Assets) indicates that this variable is not statistically significant, i.e., its impact on the dependent variable is irrelevant in this model.

Table 4. Model fit summary of re-estimated Altman model

LogLikeli-hood	Deviance	AIC	BIC	Cox and Snell's R-Square	Nagelkerke's R-Square
-12.358	24.716	32.716	44.483	0.618	0.928

Source: Authors' calculations

The model fit statistics of the re-estimated Altman model in Table 4 show that the model describes a substantial portion of the variation in the dependent variable. The R square values suggest a good model fit.

Table 5. Predictive Accuracy of the re-estimated model

From/To		Predicted			Percentage correct
		0	1	Total	
Actual	0	121	1	122	99.2
	1	1	37	38	97.4
	Total	122	38	160	98.8

Source: Authors' calculations

Table 5 shows that the model correctly predicted 121 cases out of 122 for non-distress cases, resulting in 99.2 per cent accuracy. The model correctly identified 37 out of 38 distress cases as distressed, and the predictive accuracy was 97.4 per cent. Only two cases were misclassified by the model shown in the grey shade in Table 6, resulting in an overall predictive accuracy of 98.8 per cent. This suggests that the re-estimated Altman model is highly effective in distinguishing between distressed and non-distress firms using binary logistic regression.

Table 6. Classification by the model

Bank	2012-13		2013-14		2014-15		2015-16		2016-17		2017-18		2018-19		2019-20		2020-21		2021-22	
	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted
Adhyapaka UCB	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Aluva UCB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
Changanassery UCB	0	0	0	0	1	1	0	0	1	1	1	1	0	0	1	0	0	0	0	0
Kaduthuruthy UCB	0	0	1	1	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0
Kottayam UCB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Manjeri UCB	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0
Mattancherry UCB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
Meenachil UCB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Muvattupuzha UCB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Nilambur UCB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
Pala UCB	1	1	0	0	0	0	0	0	1	1	0	0	1	1	1	1	0	0	0	0
Peoples' UCB	0	0	1	1	1	1	1	1	0	0	0	0	1	1	0	0	0	0	0	0
Perinthalmanna UCB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Ponnani UCB	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0
Tirur UCB	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0
Vaikom UCB	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	1	1	1

Source: Authors' calculations *(0 – non-distressed, 1 – distressed)*

5.3. Re-estimation of Altman Model using Multilayer Perceptron Neural Network

Re-estimating the Altman Model using Multilayer Perceptron Neural Networks (MLPNN) provides a contemporary method for forecasting financial distress. MLPNNs are artificial neural networks capable of capturing non-linear relationships and are highly accurate (Cheng et al., 2018; Zhang et al., 2018). By applying MLPNN to the financial data, the study aimed to check whether the accuracy of the Altman model will increase. For this purpose, 70 per cent of the dataset is allocated to training data and 30 per cent for testing data. The neural network after training appears as in Figure 1.

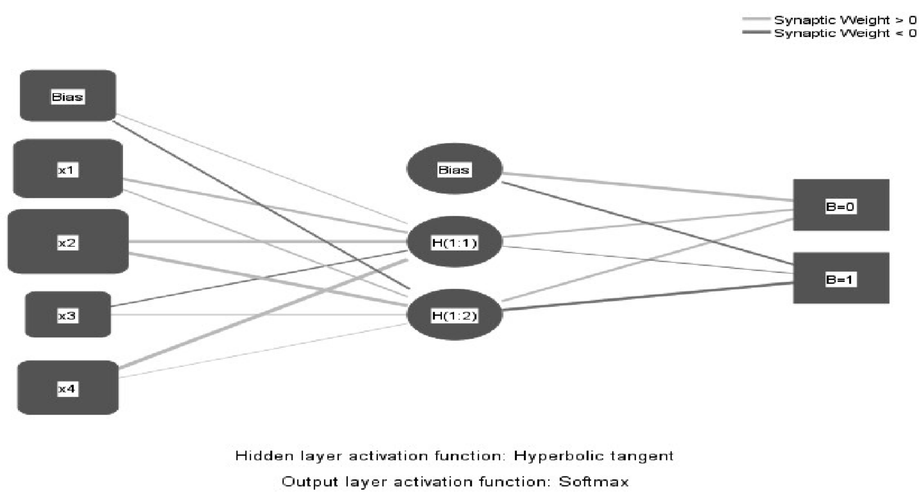

Figure 1. Neural Network

Table 7. Predictive Accuracy of the re-estimated model

Sample	Observed	Predicted		
		0	1	Percent Correct
Training	0	75	4	94.9%
	1	17	13	43.3%
	Overall Percent	84.4%	15.6%	80.7%
Testing	0	40	3	93.0%
	1	6	2	25.0%
	Overall Percent	90.2%	9.8%	82.4%

Source: Authors' calculations

Table 7 provides a brief account of the predictive accuracy of the re-estimated model in both the training and testing datasets; by correctly classifying 75 cases in the training set and 40 cases in the testing set, the re-estimated model using the MLPNN shows high accuracy in predicting non-distressed UCBs with accuracies of 94.9% and 93.0%, respectively. However, the model misclassified 17 cases in the training set and 6 cases in the testing set with lower accuracies of 43.3% and 25.0%, respectively. Thus, the model failed to predict distressed UCBs correctly. Classification as predicted by the model is given in Table 8. The overall predictive accuracy is reasonably high; for the training set, it was 80.7%, and for the testing set, it was 82.4%. The ROC curve, as exhibited in Figure 2, also indicates the same. This suggests that while the model works well for identifying undistressed banks, it might require more improvement or new features to predict distressed UCBs accurately.

Table 8. Classification by the model

Bank	2012-13		2013-14		2014-15		2015-16		2016-17		2017-18		2018-19		2019-20		2020-21		2021-22	
	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted	Actual	Predicted
Adhyapaka UCB	0	0	0	0	1	0	1	0	1	0	1	0	1	1	1	0	1	0	1	0
Aluva UCB	0	0	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0
Changanassery UCB	0	0	0	0	1	0	0	0	1	1	1	0	0	0	1	1	0	0	0	0
Kaduthuruthy UCB	0	0	1	1	0	0	0	1	0	1	0	0	1	1	1	1	1	0	0	1
Kottayam UCB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
Manjeri UCB	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0
Mattancherry UCB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0
Meenachil UCB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Muvattupuzha UCB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Nilambur UCB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0
Pala UCB	1	1	0	0	0	0	0	0	1	0	0	0	1	1	1	1	0	0	0	0
Peoples' UCB	0	0	1	1	1	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0
Perinthalmanna UCB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ponnani UCB	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
Tirur UCB	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0	0	0
Vaikom UCB	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	1	0

Source: Authors' calculations *(0 – non-distressed, 1 – distressed)*

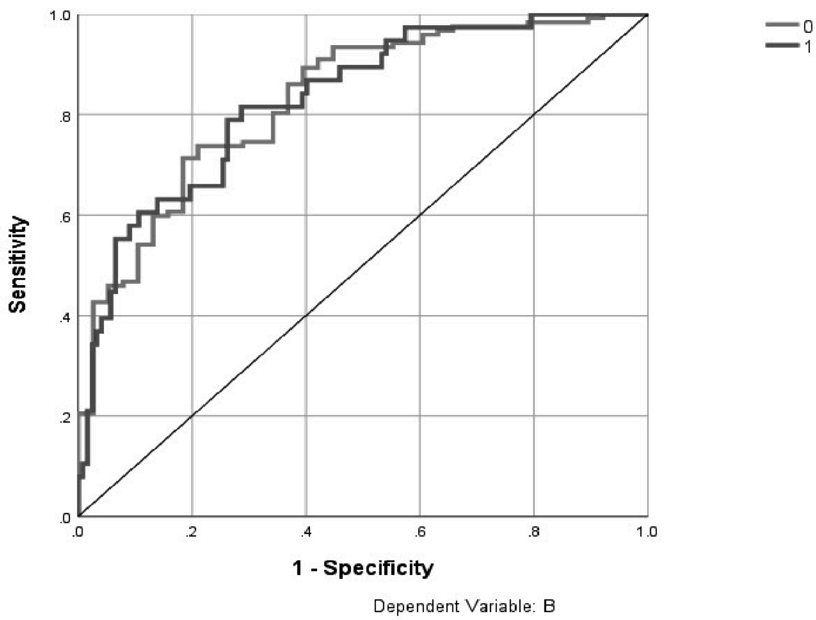

Figure 2. ROC Curve of the model

Table 9. Independent Variable Importance

Variable	Importance	Normalized Importance
WC/TA	.287	76.2%
RE/TA	.377	100.0%
EBIT/TA	.111	29.5%
BV/TD	.224	59.5%

Source: Authors' calculations

Table 9 shows that the most important independent variable in the re-estimated model is RE/TA. WC/TA also plays a substantial role, followed by BV/TD, which is moderately important. EBIT/TA has the least influence on the model's predictions. These findings suggest that focusing on variables RE/TA and WC/TA will help to improve model performance or interpret financial distress predictions.

6. Conclusion

This research attempts to study the financial health of UCBs in Kerala amidst the recent bank scams in the co-operative sector. The study identified that some of the UCBs have been in the distress zone in the last few years, which requires particular attention from the management of the respective banks. The study combined the modified Altman Z-Score model with Binomial Logistic Regression and Multilayer Perceptron Neural Networks to measure the financial health of UCBs. The re-estimated Altman model using Binomial Logistic Regression shows high predictive accuracy by incorporating significant variables, including WC/TA, RE/TA, and BV/TD. These findings suggest that increases in these ratios are closely linked to better financial position, with an overall accuracy of 98.8%.

Although the application of MLPNN shows reasonable accuracy overall, especially in predicting non-distressed UCBs, it is not sufficient to accurately predict distressed banks. The study suggests that the Altman model re-estimated with the Binary Logistic Regression is a valuable tool for predicting financial distress among UCBs in Kerala. The re-estimated MLPNN model needs further improvement in the form of new variables, which will be included in the research's future scope. This will help to understand the financial standing of the co-operative banking sector.

References

Agricultural co-operative staff training institute. (n.d.). *Kerala Co-operative Policy.*, retrieved from https://www.acstikerala.com/documents/Cooperative%20Policy%20%20Kerala.pdf

Altman, E. I. (2018). Applications of distress prediction models: What have we learned after 50 years from the z-score models? *International Journal of Financial Studies*, *6*(3). https://doi.org/10.3390/ijfs6030070

Altman, E. I., & Hotchkiss, E. (1993). Corporate Financial Distress and Bankruptcy: Predict and Avoid Bankruptcy, Analyze and Invest in Distressed Debt, Third Edition. In *Corporate Financial Distress and Bankruptcy: Predict and Avoid Bankruptcy, Analyze and Invest in Distressed Debt, Third Edition*. https://doi.org/10.1002/9781118267806

Balan, S. S. (2022). *How a multi-crore cooperative bank scam in Kerala has shattered lives of depositors*. https://www.thenewsminute.com/kerala/how-multi-crore-cooperative-bank-scam-kerala-has-shattered-lives-depositors-166666

Boda, M., & Uradnicek, V. (2016). The portability of altman's Z-score model to predicting corporate financial distress of Slovak companies. *Technological and Economic Development of Economy*, *22*(4), 532–553. https://doi.org/10.3846/20294913.2016.1197165

Cheng, C. H., Chan, C. P., & Yang, J. H. (2018). A Seasonal Time-Series Model Based on Gene Expression Programming for Predicting Financial Distress. *Computational Intelligence and Neuroscience*, *2018*(1), 1–14. https://doi.org/10.1155/2018/1067350

Cındık, Z., & Armutlulu, I. H. (2021). A revision of Altman Z-Score model and a comparative analysis of Turkish companies' financial distress prediction. *National Accounting Review*, *3*(2), 237–255. https://doi.org/10.3934/NAR.2021012

Desheng Wu, Ma, X., & Olson, D. L. (2022). Financial distress prediction using integrated Z-score and multilayer perceptron neural networks. *Decision Support Systems*, *159*(113814). https://doi.org/10.1016/j.dss.2022.113814

Gaurav, S., & Krishnan, J. (2017). How Efficient Are India's Cooperative Banks? *Economic and Political Weekly*, *52*(12), 115–124.

Heniwati, E., Yantiana, N., & Desyana, G. (2021). Financial health of Syariah and non-Syariah banks: a comparative analysis. *Journal of Islamic Accounting and Business Research*, *12*(4), 473–487. https://doi.org/10.1108/JIABR-07-2020-0216

Karim, M. R., Shetu, S. A., & Razia, S. (2021). COVID-19, liquidity and financial health: empirical evidence from South Asian economy. *Asian Journal of Economics and Banking*, *5*(3), 307–323. https://doi.org/10.1108/ajeb-03-2021-0033

Melvin S. Sarsale. (2020). Measuring Financial Health of Selected Cooperatives in an ASEAN Province Using Altman Model. *Journal of Educational and Human Resource Development (JEHRD)*, *8*(December 2020), 80–93. https://doi.org/10.61569/67cath78

Raju, S. (2018). Assessing the Efficiency of Urban Co-Operative Banks in India. *The Central European Review of Economics and Management*, *2*(1), 11. https://doi.org/10.29015/cerem.550

RBI. (2012). Report of the high level steering committee for review of supervisory processes for commercial banks. In *2012* (Issue June).

Reserve Bank of India - 2021. (n.d.). *Report of the Expert Committee on Urban Co-operative Banks*.

Roman, A., & Şargu, A. C. (2013). Analysing the Financial Soundness of the Commercial Banks in Romania: An Approach based on the Camels Framework. *Procedia Economics and Finance*, *6*(13), 703–712. https://doi.org/10.1016/s2212-5671(13)00192-5

Salina, A. P., Zhang, X., & Hassan, O. A. G. (2020). An assessment of the financial soundness of the Kazakh banks. *Asian Journal of Accounting Research*, *6*(1), 23–37. https://doi.org/10.1108/AJAR-03-2019-0022

Singh, B. P., & Mishra, A. K. (2016). Re-estimation and comparisons of alternative accounting based bankruptcy prediction models for Indian companies. *Financial Innovation*, *2*(1). https://doi.org/10.1186/s40854-016-0026-9

Sinha, A. (n.d.). Financial Inclusion and Urban Cooperative Banks. In *Edited transcript* (Issue January 6). https://www.bis.org/review/r120112b.pdf

The Institute of Chartered Accountants of India, N. D. (2013). *An Information Booklet on Urban Coopera tive Banks , their Problems , Expect ations and Remedies*.

Trung, D. D., Dudić, B., Dung, H. T., & Truong, N. X. (2024). Innovation in Financial Health Assessment: Applying MCDM Techniques to Banks in Vietnam. *Economics*, *12*(2), 21–33. https://doi.org/10.2478/eoik-2024-0011

Viswanathan, P. K., Srinivasan, S., & Hariharan, N. (2020). Predicting Financial Health of Banks for Investor Guidance Using Machine Learning Algorithms. *Journal of Emerging Market Finance*, *19*(2), 226–261. https://doi.org/10.1177/0972652720913478

Zhang, T., Zhang, W., Xu, W., & Hao, H. (2018). Knowledge-Based Systems Multiple instance learning for credit risk assessment with transaction data. *Knowledge-Based Systems*, *January*, 0–1. https://doi.org/10.1016/j.knosys.2018.07.030