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IS THE FINANCIAL HEALTH OF URBAN CO-OPERATIVE BANKS SOUND? A STUDY BASED ON ALTMAN Z-SCORES

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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.). Urban Co-operative Banks 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, Urban Co-operative Banks face many challenges which affect their financial health. These challenges include difficulties in 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 Urban Co-operative Banks.

Kerala is one of the states in India, the economy of which is characterised by a strong co-operative sector. This sector has brought significant socio-economic change, especially in the rural sector of the state, since its formation. 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, Urban Co-operative Banks in Kerala focus on priority sector lending. At present, there are 59 Urban Co-operative Banks in Kerala that are directly regulated and supervised by the Reserve Bank of India. Administrative control of the Urban Co-operative Banks 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 co-operative banking sector in Kerala has been questioned by major co-operative bank scams, especially in the form of misappropriation of huge amounts of money, fraudulent loan approvals, etc. These scams have affected the

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lives of large number of people who have invested their lifetime 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 Primary Agricultural Credit Societies, as Urban Co-operative Banks form a major part of the co-operative banking sector, they are also susceptible to financial instability. Thus, it becomes necessary to evaluate the financial health of Urban Co-operative Banks 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 sectoras well as the promotion of 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), which assesses banks based on six critical parameters-Capital adequacy, Asset quality, Management quality, Earnings, Liquidity, and Sensitivity to market risks. In addition to that, there are other techniques like Multi Criteria Decision Making Methods (Trung et al., 2024) which aid in ranking alternatives by considering multiple factors simultaneously, Data Envelopment Analysis(Raju, 2018) which evaluates efficiency by comparing input-output ratios across entities, Stochastic Frontier Analysis(Raju, 2018) which uses econometric modelling to measure operational efficiency, accounting for random errors and inefficiencies, Machine learning techniques (Cindik & Armutlulu, 2021; Desheng Wu et al., 2022; Viswanathan et al., 2020)which analyse large datasets to identify patterns and predict outcomes, providing dynamic and accurate assessments, etc.

When evaluating the financial health of banks, traditional methods like financial ratios and regulatory compliance were initially employed, but these methods have proven to be unreliable(Altman & Hotchkiss, 1993). 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 model was applied by Singh & Mishra, (2016), Cindik & Armutlulu, (2021), Desheng Wu et al., (2022), etc. However, it has not been widely used for predicting the financial distress of Urban Co-operative Banks.This research paper tries to fill this gap by analysing the financial health of Urban Co-operative Banks using Altman Z scores and re-estimated Z scores, and evaluating the predictive accuracy of these models in predicting the financial distress of Urban Co-operative Banks.Thus, the study tries to provide a tool for bank management to detect forewarning signals of financial distress and take corrective actions if necessary.

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REVIEW OF LITERATURE

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

Financial Health

(Raju, 2018)studied the efficiency of off-balance sheet activities and core banking processes of Urban Co-operative Banks in India for a period 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 Urban Co-operative Banks 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.

(Viswanathan et al., 2020) focused on classifying the 44 Indian banks on the basis of financial health. The study was undertaken from the perspective of investors 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 banks 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. Using the Multi-Criteria Decision Making 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.

Altman Z score model

(Altman, 2018) noted that his model is arguably the most renowned and, the most 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 namely, application by analysts outside the company and application by board members and managers of the distressed company.

(Singh & Mishra, 2016) introduced a model for forecasting bankruptcy of the companies

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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. The key findings indicate that the total predictive accuracy of all these models will be enhanced if the coefficients are re-estimated.

(Boda & Uradnicek, 2016)challenged Altman's Z score model's extensive application. They aimed at assessing the effectiveness of the model 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, to attain more accuracy in prediction, re-estimating the model's coefficients is preferable.

(Cindik & 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 Altman model. 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 neural network with 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 review of the literature clearly states that financial health of institutions has been the subject matter of research for many authors and many of them have used 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 tries to add new contributions to this area of research.

METHODOLOGY

The study examined the financial health of 16 Urban Co-operative Banks 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 & Hotchkiss (1993) which is designed for the service industries and based on the multiple discriminant function:

$$Z'' = 6.56(X1) + 3.26(X2) + 6.72(X3) + 1.05(X4)$$

Where,

Z'' = Altman-Z-Score

X1 = Working Capital/Total Asset (indicatethe firm'sliquidity)

X2 = Retained Earnings/Total Asset (show thefirm's cumulative profitability)

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X3 = Earnings before Interest and Taxes/Total Asset (reflect productivity of the firm's assets)

X4 = Book Value of Equity/Total Debt (measurefirm'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 further re-estimated using Binomial Logistic Regression and Multilayer Perceptron Neural Networks. Given the small dataset, ten-fold cross-validation was used to mitigate overfitting, ensuring all observations were included in both training and testing.The model performance metrics of both models were compared to determine which method more effectively predicts financial distress in Urban Co-operative Banks.

RESULTS AND DISCUSSION

Altman Z Score

Altman Z scores of 16 Urban Co-operative Banks under study are shown in Table 1 for 10 years from 2012-13 to 2021-22 and Table 2 shows the frequency of performance of the banks 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 the year 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 the year 2021-22, four banks are in the distress zone.

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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)

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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

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 prediction of financial distress for the selected Urban Co-operative Banks in Kerala and is more appropriate for the observed data.The dataset had 122 instances of UCBs in the grey zone and 38 in the distress zone, resulting in an imbalance. To address this, a cost-sensitive classifier with logistic regression as the base was employed to re-estimate the model, adjusting misclassification costs to better account for the minority class and improve predictive performance.

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Table 3. Coefficients for re-estimated Altman model using BLR

Predictor	Coefficients	Odd Ratios
WC/TA	0.701	2.015
RE/TA	0.298	1.347
EBIT/TA	1.235	3.439
BV/TD	-0.163	0.849
Intercept	1.529	-

Source: Authors' calculations

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

Table 4. Confusion matrix of the re-estimated Altman model (BLR)

Actual / Predicted	Predicted 0	Predicted 1	Total	Percentage Correct
Actual 0	119	3	122	97.54%
Actual 1	3	35	38	92.10%
Total	122	38	160	**96.25%**

Source: Authors' calculations

As per Table 4, it is clear that the model correctly predicted 119 cases out of 122 for non-distress cases, resulting in 97.54per cent accuracy. The model correctly identified 35 out of 38 distress cases as distressed and the predictive accuracy was 92.10per cent. Only two cases were misclassified by the model, resulting in an overall predictive accuracy of 96.25 percent. This suggests that the re-estimated Altman model is highly effective in distinguishing between distressed and non-distress firms using binary logistic regression.

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. By applying MLPNN to the financial data, the study aimed to check whether the accuracy of

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the Altman model will increase. For this purpose, a cost-sensitive classifier using multilayer perceptron as the base classifier is used to re-estimate the model.

Table 5. Parameter estimates of the re-estimated Altman model (MLPNN)

Predictor		Predicted				
		Hidden Layer 1			Output Layer	
		H(1:1)	H(1:2)	H(1:3)	[B=0]	[B=1]
Input Layer	(Bias)	-6.732	-2.498	-3.342		
	WC/TA	-0.486	6.729	5.286		
	RE/TA	8.892	5.613	7.392		
	EBIT/TA	-1.892	8.615	-3.631		
	BV/TD	6.758	6.605	6.950		
Hidden Layer 1	(Bias)				-7.340	7.341
	H(1:1)				5.838	-5.845
	H(1:2)				5.586	-5.588
	H(1:3)				4.907	-4.904

Source: Authors' calculations

WC/TA and EBIT/TA have mixed weights across the hidden neurons, reflecting their complex, nonlinear influence on predictions. Conversely, RE/TA and BV/TD consistently exhibit positive weights across all hidden neurons, indicating a positive impact on the network's outputs. At the output node, B=0 receives primarily positive contributions, while B=1 receives negative contributions, ensuring effective class separation.

Table 6. Confusion matrix of the re-estimated Altman model (MLPNN)

Actual / Predicted	Predicted 0	Predicted 1	Total	Percentage Correct
Actual 0	117	5	122	95.90%
Actual 1	0	38	38	100.00%
Total	122	38	160	**96.88%**

Source: Authors' calculations

It is evident from Table 6 that the model accurately predicted 117 out of 122 non-distress cases, achieving 95.90 per cent accuracy. It also correctly identified all 38 distress cases, with a perfect predictive accuracy of 100 per cent. With only five misclassified instances, the overall accuracy of the model stands at 96.88 per cent. This indicates that the re-estimated Altman model using MLPNN is highly effective in differentiating between distressed and non-distressed firms.

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Table 7. Comparison of re-estimated models

Model performance Statistics	Altman Model (BLR)	Altman Model (MLPNN)
RMSE	0.1784	0.1585
Precision	0.963	0.972
Recall	0.963	0.969
F-Measure	0.963	0.969
ROC Area	0.991	0.997
Predictive Accuracy	96.25%	96.88%

Source: Authors' calculations

The comparison highlights that both re-estimated models perform well, but the Neural Network model slightly outperforms the Logistic Regression model across all metrics. Neural Network model achieves lower RMSE (Root Mean Squared Error), indicating better prediction accuracy, and higher precision, recall, and F-measure, reflecting its superior ability to classify cases correctly. Additionally, the Neural Network model shows a higher Area under the Receiver Operating Characteristic Curve (ROC area), indicating better discriminatory power, and a slightly higher overall predictive accuracy, making it the more effective model for distinguishing distressed and non-distressed firms.

CONCLUSION

This research attempts to study the financial health of Urban Co-operative Banks in Kerala amidst the recent instances of bank scams in the co-operative sector. The study underscores the absence of Urban Co-operative Banks in the safe zone over the analysed period, a concerning trend that emphasizes the financial vulnerability of these institutions. While many banks persist in the Grey Zone, several show frequent distress, necessitating proactive measures for financial health improvement.The study combined the modified Altman Z-Score model with Binomial Logistic Regression and Multilayer Perceptron Neural Networks to measure the financial health of Urban Co-operative Banks. The analysis demonstrates that both the Binary Logistic Regression and Multilayer Perceptron Neural Network models are effective tools for predicting financial distress among Urban Co-operative Banks. However, the Neural Network model proves to be marginally superior in terms of overall performance. By leveraging advanced predictive models such as Neural Networks, stakeholders can better identify early warning signs of financial distress and implement targeted strategies to mitigate risks, ensuring the stability and sustainability of Urban Co-operative Banks.

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