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Bank Distress Prediction Model for Botswana

Hassan Kablay[1*] and Victor Gumbo[1]

[1] *Department of Mathematics, University of Botswana, Botswana.*

Authors' contributions

This work was carried out in collaboration between both authors. Author HK designed the study, performed the statistical analysis and wrote the first draft of the manuscript. Author VG managed the analysis of the study and proofreading of the manuscript. Both authors read and approved the final manuscript.

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Abstract

"Financial distress" has many different meanings but generally it is said to be a state of unhealthy condition. Botswana's banking system comprises of commercial, development and savings banks. None of these types of banks has actually failed but rather some of them have experienced some form of distress. The Bank of Botswana uses the CAMELS ratings to measure distress. The CAMELS ratings is based on a score between 1 and 5, with 1 being the best score and indicates strong performance, while 5 is the poorest rating and it indicates a high probability of bank failure and the need for immediate action to rectify the situation. For this study, we consider 1-3 to be good scores (non-distressed) and a bank to be distressed if it has a score of 4-5. Utilising secondary data sources for the period 2015 to 2019, inclusive, the study evaluated the drivers of bank distress in Botswana. The data was sourced from the audited financial statements and annual reports of the 11 banks involved in the study. Panel data logistic regression was used for analysis. The results of the study showed that Non-Performing Loans (NPL) ratio and Return on Equity (ROE) were the best predictors of bank distress.

Keywords: CAMELS; bank distress; panel data; logistic regression.

**Corresponding author: E-mail: hassankablay@gmail.com;*

1 Introduction

Motivated by the lack of research on bank distress in Botswana, this study seeks to analyse the drivers of bank distress in Botswana and to build a bank distress prediction model for Botswana.

A bank is said to be distressed when it cannot be able to meet its objectives or its obligations to its customers, shareholders and the community where it was established. The Bank of Botswana (BOB) monitors solvency, liquidity, insider loans, provisioning, risk management strategies, adequacy of management and governance structures for the sound operation of the banks (BOB Banking Supervision Annual Report [1]).

The CAMELS rating system, amongst other various performance methods, has become an important tool in measuring the overall performance of banks in the light of global financial crises and bank failures. Using logistic regression, a study by Khokher and Alhabshi [2] aimed at establishing key capital adequacy measures and other parameters that effectively predict distress in Islamic banks was carried out and the findings suggested that most of the standard CAMELS indicators were relevant for studying distress in such banks.

In Botswana, a study by Sathyamoorthi et al. [3] was carried out in which the financial performance of three listed commercial banks was evaluated using the CAMEL model, and it was found out that these listed banks were highly leveraged and that their liquidity position was sound. Sathyamoorthi et al. [3] also found out that the Earnings Per Share (EPS) had a significant positive correlation with liquidity ratio of total customer deposits to total assets, while leverage ratio was significantly negatively correlated to the ratio of equity capital to assets. However, other CAMEL ratios were not significantly correlated to EPS. The findings revealed that the three listed banks performed well during the study period (Sathyamoorthi et al. [3]).

Suss and Treitel [4] state that in predicting bank distress events, classical statistical models such as logistic regression and Cox proportional hazard models have been used before, although hazard models predict the timing of failure rather than the probability. Asykin et al. [5] analysed the financial performance, capital ratio, profitability ratio, liquidity ratio and financial distress ratio influencing Islamic financial bank distress in Indonesia using descriptive analysis and logistic regression. Some of their findings were that CAR, ROA and ROE have a negative and significant effect on financial distress.

For the Zimbabwean banking system, Gumbo and Zoromedza [6] developed a model based on 12 micro factors to predict the probability of failure for Zimbabwean banks and their analysis proved that the model produced a robust result with a high prediction accuracy of 92.31% compared to 60% of the Altman Z-Score model. Bankruptcy prediction research continues to evolve with many different predictive models developed using various tools, but many of the tools are used with the wrong data conditions or for the wrong reasons (Alaka et al. [7]). Valaskova et al. [8] noted that regression analysis is often used for bankruptcy prediction.

By using Logistic Regression, all indicators are given the opportunity to predict financial distress (Jabeur [9]). We propose to use panel data logistic regression for this study and compare the results with CAMELS outputs.

2 Bank Distress Impact

Financial institutions play a central role in national and international financial stability. Bank bailout costs associated with resuscitating a failing bank are enormous. The domino effect of a distressed bank on financial stability can cause the collapse of the entire financial system and the economy. The importance of banks in financial stability clearly motivates the need to develop early warning models for predicting banking crises and individual bank failures. These special features require early warning models based on publicly available bank-specific and country-level indicators for predicting vulnerable banks that could potentially experience distress given suitable triggers. In Kenya, 2 local Banks and 110 NBFIs were closed or taken over by the regulatory authorities between 1984 and 1989 with another 5 local banks and 10 NBFIs being taken over in 1993/1994 (Brownbridge [10]). In addition to the closure of banks in Kenya, Brownbridge [10] states that the Bank of Zambia (BOZ) closed 3 local banks in 1995 and some of the cited reasons for the bank failures /distress of these banks were non-performing loans. In Nigeria, Adeyefa et al. [11] studied the effects of bank distress on the economy and the study revealed that the ratio of non-performing loans to total loans had a significant negative effect on economic growth.

Chile experienced a banking crises in 1981-1983 that affected about 60% of total loan portfolios and the root cause of this was macroeconomic problems (Claessens [12]). Furthermore, Claessens [12] states that in 1984 some banks were liquidated, others rehabilitated, and this reduced the number of banks by one-third and finance companies by two-thirds. The economic crises in Turkey, especially in November 2000 and February 2001, caused an increase in the number of bank failures and brought about the need for an early-warning system to detect bank failures (Toktas-Palut [13]). Toktas-Palut [13] carried out a study that aimed at developing an early-warning system to predict bank failures in Turkey up to three years in advance, using logistic regression and neural networks to develop the models. It was found out that neural network models had better predictive abilities than logistic regression models and that capital adequacy, asset quality, liquidity position, profitabililty, and income expenditure structure of a bank are the indicators of its likelihood of failure at a posterior time (Toktas-Palut [13]).

In most recent research, Barua [14] states that the COVID-19 pandemic generates multifaceted crises for banks mostly through the increase in default rates. The Bangladesh banking sector already has a high level of non-performing loans and the pandemic is likely to worsen the situation Barua [14].

3 CAMELS Rating System

CAMELS rating system is an internationally recognized supervisory tool which was developed in the US to measure bank's or other financial institution's level of risk with the help of its financial statements (Prachi [15]). Prachi [15] further states that the concept was initially implemented as a Uniform Financial Institutions Rating System (UFIRS) in the year 1979 in the US as a CAMEL rating. It was modified to include the sixth component 'sensitivity' to it, in the year 1995, by the Federal Reserve and the Office of the Comptroller of the Currency (OCC). The six components unanimously form the word CAMELS (Prachi [15]).

A CAMELS rating is assigned to individual banks by a Bank Examiner and it is based on: capital adequacy, asset quality, management, earnings, liquidity, and sensitivity to market risk. When a bank's CAMELS rating is very low, the regulator may enforce regulations by taking such formal actions as cease and desist in order change the bank's behaviour or even close the bank (Mishkin [16]).

- **Capital Adequacy (C):** Assesses an institution's compliance with regulations on the minimum capital reserve amount. Regulators establish the rating by assessing the financial institution's capital position currently and over several years.
- **Asset Quality (A):** This category assesses the quality of a bank's assets. Asset quality is important as the value of the assets can decrease rapidly if they are high risk.
- **Management Capability (M):** Measures the ability of an institution's management team to identify and then react to financial stress. The category depends on a bank's business strategy, financial performance and internal controls.

- **Earnings (E):** These help to evaluate an institution's long term viability. A bank needs an appropriate return to be able to grow its operations and maintain its competitiveness.
- **Liquidity (L):** For banks, liquidity is essentially important, as the lack of liquid capital can lead to a bank run. This category of CAMELS examines interest rate risk and liquidity risk. Liquidity risk is defined as the risk of not being able to meet present or future cash flow needs without affecting day-to-day operations.
- **Sensitivity (S):** Measures an institution's sensitivity to market risks. Sensitivity reflects the degree to which earnings are affected by interest rates, exchange rates, and commodity prices.

In this study, historical financial distress was calculated using the CAMELS Rating. The rating of individual banks is done along the 5 key parameters being; Capital Adequacy, Asset Quality, Management Quality, Earnings, Liquidity and Sensitivity. The banks are rated on a scale of 1 to 5, with 1-3 being the best (healthy) banks and 4-5 being the distressed (unhealthy) banks.

The best (healthy) bank is the bank with the strongest performance and risk management practices relative to the institutions size, while the distressed (unhealthy) bank is the bank with the least performance and risk management practices relative to the institutions size.

Table 1 and Table 2 below show the ratios used for computing each of the CAMELS parameters and the description of the composite range, respectively.

Table 1. CAMELS parameters and ratios for bank performance analysis

CAMELS Parameters	**Ratios / Formula**
Capital Adequacy Ratio	(Tier 1 Capital + Tier 2 Capital) / Risk Weighted Assets
Asset Quality Ratio	Non-Performing Loans / Total Loans
Management Efficiency	Cost / Income
Earnings Ability (ROA) Earnings Ability (ROE)	Net Income / Total Assets Net Income / Total Equity
Liquidity (TL/TD) Liquidity (CA/TA)	Total Loans / Total Deposits Circulating Assets / Total Assets
Sensitivity Ratio	Financial Securities / Total Assets

Source: Babar [17].

Table 2. Composite range of CAMELS rating

Rating	**Composite Range**	**Description**	**Meaning**
1	1.00-1.49	Strong	Basically sound in every aspect Findings are of minor nature and can be handled routinely Resistant to external economic and financial disturbances No cause for supervisory concern
2	1.50-2.49	Satisfactory	Fundamentally sound Findings are of minor nature and can be handled routinely Stable and can withstand business fluctuations well Supervisory concerns are limited to the extent that findings are corrected
3	2.50-3.49	Fair	Financial, operational or compliance weaknesses ranging from moderately severe to unsatisfactory Vulnerable to the onset of adverse business conditions Easily deteriorate if actions are not effective in correcting weaknesses Supervisory concern and more than normal supervision to address inefficiencies
4	3.50-4.49	Marginal	Immoderate volume of serious financial weakness Unsafe and unsafe conditions may exist which are not being satisfactory addressed Without corrections, these conditions could develop further and impair future viability High potential for failure Close supervision surveillance and a definite plan for correcting deficiencies
5	4.50-5.00	Unsatisfactory	High immediate or near term probability failure Severity of weaknesses is so critical that urgent aid from stockholders or other financial sources is necessary Without immediate corrective actions, will likely require liquidations, merger or acquisition.

Source: Bari [18].

4 The Modelling Approach

For this study, the CAMELS rating will be used to measure historical bank distress and results will be analyzed using panel data logistic regression. The dependent variable was defined as the measured "bank distress/non-distress" and the Botswana banks were classified into two groups: distress (unhealthy, non-prosperous) and non-distress (healthy, prosperous), using the calculated financial ratios in the CAMELS rating.

The data for 11 banks was collected from the annual reports and financial statements from the respective banks' websites. The observation period was from 2015 to 2019. The CAMELS rating for each of the banks was computed and classified into the below categories:

- A CAMELS rating of 1-3 was classified as "Non-Distress"
- A CAMELS rating of 4-5 was classified as "Distress"

Using the ratios computed in Table 1 and the composite ranges provided in Table 2, the CAMELS rating results in Table 3 below were obtained.

Table 3. Banks CAMELS Rating

	CAMELS Rating					
Bank Name	**2015**	**2016**	**2017**	**2018**	**2019**	**Average Rating**
ABSA (formerly Barclays)	3	3	3	3	3	3
Stanbic Bank Botswana	3	3	3	3	3	3
Botswana Savings Bank	3	3	3	3	3	3
First National Bank Botswana	3	3	3	3	3	3
Banc ABC	3	3	3	3	3	3
State Bank of India	3	3	3	3	3	3
First Capital Bank	3	3	3	3	3	3
Bank Gaborone	4	3	3	3	3	3
Standard Chartered Bank Botswana	3	3	4	3	3	3
Bank of Baroda	3	3	3	3	3	3
Botswana Building Society	3	3	4	4	4	4

Source: Computed ratings.

4.1 Data analysis

The main financial ratios for banks were selected by observing those most widely used in recent research, such as by Sree [19] and Gebreslassie [20]. Table 4 summarises the independent variables used in the modelling process, and their a priori conditions.

With the independent variables explanation in Table 4, the logit regression (where Z is the natural logarithm of the odds) then takes the form:

$$Z = \beta_0 + \sum_i \beta_i * X_i + \mu \tag{4.1}$$

where;

- i ranges from 1 to 14,
- β_0 is the constant term to be determined,
- β_i are the coefficients to be determined,
- X_i is the i^{th} driver of bank distress,
- μ is a random error.

Table 4. Independent Variables Used and Explanations

Variable	Explanation	Calculation	A priori Signs
NPL_Ratio	Non Performing Loans Ratio	Non Performing Loans / Gross Advances	+
ROE	Return On Equity	Net Income / Average Equity	-
A_E	Assets to Equity Ratio	Assets / Equity	-
C_I	Cost to Income Ratio	Cost / Income	+
II_IE	Interest Income to Interest Expense Ratio	Interest Income / Interest Expense	-
LA_TD	Liquid Assets to Deposit Ratio	Liquid Assets / Deposits	-
NET_II_TI	Net Interest Income to Total Income	Net Interest Income / Total Income	-
NII_TI	Non-Interest Income to Total Income	Non-Interest Income to Total Income	-
NIM	Net Interest Margin	Non-Interest Income / Average Assets	-
I_A	Total Income to Average Assets Ratio	Total Income / Average Assets	-
CA_TA	Circulating Assets to Total Assets Ratio	Circulating Assets / Total Assets	-
TL_TA	Total Liabilities to Total Assets Ratio	Total Liabilities / Total Assets	+
CAR	Capital Adequay Ratio	(Tier 1 Capital + Tier 2 Capital) / Risk Weighted Assets	-
ROA	Return On Assets	Net Income / Average Assets	-

Financial ratios based on the income statement and balance sheet were used to understand the connection between bank stability or instability. In this study, banks were assumed to face similar macroeconomic conditions.

The possible influence of each independent variable is as follows:

- **X_1=NPL_Ratio** (Non Performing Loans Ratio): Substantial numbers of banks have failed mainly due to non-performing loans. Poor loan quality is amongst the root causes in the informational problems that afflict financial markets (Brownbridge [10]). Huge non-performing loans portfolio erodes the ability of banks to make profits (Ugani [21]). In a study by Gebrelassie [20], it was found out that the NPL ratio has statistically negative influence on the financial health of the banks. Moreover, the European Semester Thematic Factsheet [22] states that the NPL ratio shows by how much the quality of loans granted by banks has deteriorated, and the higher the ratio, the worse the quality of the assets and as a result the higher the expected losses.
- **X_2=ROE** (Return on Equity): ROE is an indicator of banks' overall profitability. A high profitability suggests that banks are in a favourable position to increase their capital buffer in the immediate future, namely through retained earnings (European Semester Thematic Factsheet [22]). Asykin et al. [5] states that ROE has a negative and significant effect on financial distress.
- **X_3=A_E** (Financial Leverage): Asset / Equity indicates the relationship of the total assets of the bank to the portion owned by shareholders and it is an indicator of the leverage (debt) used to finance the bank.
- **X_4=C_I** (Cost-to-Income): Total cost / total income measures the income generated per unit cost. That is, how expensive it is for the bank to produce a unit of output. The lower the C_I ratio, the better the performance of the bank (Kumbirai and Webb [23]). On average distressed banks have a higher level of cost-to-income ratio (Poghosyan and Cihak [24]).
- **X_5=LA_TD** (Liquid Assets / Total Assets): Banks need to maintain a level of liquidity sufficient to meet current and future financial obligations (Babanskiy [25]). Therefore, the higher the LA_TD ratio, the lower the probability of distress.
- **X_6=II_IE** (Interest Income / Interest Expenses): The higher the interest income/interest expenses, the lower the probability of distress.

- **X_7=NET_II_TI** (Net interest income to total income): Net interest income to total revenue ratio has statistically significant positive influence on the financial health of banks (Gebrelassie [20]).
- **X_8=NII_TI** (Non-Interest Income/ Total Income): Revenue income generated from the non-core activities by banks and financial institutions plays a vital role in its overall profitability. The higher the NII_TI ratio the lower the probability of distress.
- **X_9=NIM** (Net Interest Margin): A positive NIM indicates that an entity operates profitably, while a negative figure implies investment inefficiency. Credit risk tends to be positively associated with net interest margin.
- **X_10=I_A** (Total Income/Total Assets): A bank with a higher level of liquid assets is normally expected to earn less interest income and therefore a lower asset yield (Total income / Total Assets) (Sree [19]). Therefore, the higher the total income/total asset ratio, the higher the interest income earned, hence the higher the performance of the bank.
- **X_11=CA_TA** (Circulating Assets/ Total Assets): All the assets and resources that can be easily converted to cash in a short period, also represents a bank's liquid assets.
- **X_12=TL_TA** (Total Liabilities/ Total Assets): TL_TA ratio shows the percentage of assets that are being funded by debt. The higher the ratio is, the more financial risk there is in the bank.
- **X_13=CAR** (Capital Adequacy Ratio): Banks with high debt and low level of capital relative to its assets are more prone to failure in the event of a financial crisis (Badalashvili [26]). CAR has a negative and significant effect on financial distress (Asykin et al. [5]).
- **X_14=ROA** (Return on Assets): It is used to measure the ability of a company to generate revenue from asset management. The higher the ROA, the lower the possibility of bank distress, therefore, the ROA has a negative effect on bank distress (Kowanda et al. [27]). (Asykin et al. [5]) also found out that ROA has a negative and significant effect on financial distress.

5 Data Analysis and Presentation

In order to detect multicollinearity among the independent variables, cross correlations were performed and the outcome is in Table 5. Total liabilities to total assets (TL_TA) is highly correlated with the financial leverage ratio (A_E), liquid assets to total deposit (LA_TD) ratio is highly correlated with circulating assets to total assets (CA_TA) ratio and ROE is highly correlated to ROA . The correlation shall be dealt with in the modelling process.

Table 5. Multicollinearity Results

	A_E	*C_I*	*CA_TA*	*CAR*	*I_A*	*II_IE*	*LA_TD*	*NET_II_TI*	*NII_TI*	*NIM*	*NPL_RATIO*	*ROA*	*ROE*	*TL_TA*
A_E	1													
C_I	-0.0431	1												
CA_TA	0.0870	-0.1785	1											
CAR	-0.6437	0.5150	-0.1851	1										
I_A	-0.1674	-0.2613	-0.1106	-0.2753	1									
II_IE	-0.1763	-0.1858	-0.1240	-0.0222	0.6982	1								
LA_TD	-0.2068	-0.1498	0.8239	0.1669	-0.1996	-0.1957	1							
NET_II_TI	-0.1187	0.1055	0.3332	0.2268	-0.4005	-0.3185	0.4333	1						
NII_TI	0.1187	-0.1055	-0.3332	-0.2268	0.4005	0.3185	-0.4333	-1.0000	1					
NIM	-0.2470	-0.1978	0.0626	-0.1442	0.7936	0.5209	0.0243	0.2251	-0.2251	1				
NPL_RATIO	-0.0422	-0.4256	0.1460	-0.1021	-0.1478	0.1001	0.3167	0.0094	-0.0094	-0.2028	1			
ROA	-0.0639	-0.7652	0.1804	-0.2789	0.4301	0.4275	0.1785	-0.1351	0.1351	0.3520	0.2700	1		
ROE	0.0101	-0.5776	0.1962	-0.3704	0.5549	0.5061	0.0571	-0.2588	0.2588	0.3936	0.0650	0.8429	1	
TL_TA	0.8884	-0.2182	0.1601	-0.8425	0.0021	-0.0227	-0.2189	-0.2250	0.2250	-0.1460	0.0473	0.0865	0.2561	1

Taking the confidence level as 95% and then running the logistic regression analysis, the following results were obtained:

Table 6. Panel Data Logistic Regression Results

Driver	Coefficients	Standard Error	Wald	df	Significance	Exp(B)	95% C.I.for EXP(B)	
							Lower 95%	Upper 95%
NPL_RATIO	63.8018	29.0671	4.8180	1	0.0282	5.1143E+27	9.2645E+02	2.8233E+52
ROE	-19.8731	9.1147	4.7539	1	0.0292	2.3400E-09	4.0811E-17	1.3417E-01
CONSTANT	-4.9524	2.0136	6.0491	1	0.0139	7.0665E-03		

Given the above results, the resultant multiple logistic regression model was deduced to be:

$$Z = -4.9524 + 63.8018 * NPL\_RATIO - 19.8731 * ROE \tag{5.1}$$

The above model shows that the major drivers of Probability of Distress (PD) in Botswana are NPL Ratio and ROE. NPL ratio has a coefficient of 63.8018 that is significant and positively correlated to PD, hence it increases the probability of distress of a bank. This implies that a 1-unit increase in the NPL ratio results in a 63.8018 increase in Z and therefore an increase in the probability of distress assuming all other variables are held constant. The positive coefficient of the NPL ratio is in agreement with the a priori condition in Table 4 and the European Semester Thematic Factsheet [22] that the higher the NPL ratio, the worse the quality of the assets, and consequently the higher the expected loss. Further, the results indicate that in line with economic theory, the PD is negatively correlated to ROE. Thus, empirical evidence suggests that ROE reduces probability of bank distress since a 1-unit increase in ROE results in a -19.8731 decrease in Z and therefore a decrease in the probability of distress when all other variables are held constant. The negative coefficient of the ROE is in agreement with the a priori condition in Table 4 and also in agreement with Asykin et al. [5] that ROE has a negative and significant effect on financial distress. The intercept is -4.9524 and implies that in the absence of all the other drivers, all banks in the banking system of Botswana are in a non-distress state since the PD is 0.70%. This is in agreement with the initial statement that none of the banks in Botswana have actually failed.

The Probability of Distress (PD) is given by:

$$PD(Z) = \frac{1}{1 + \exp(-Z)} \tag{5.2}$$

where Z is given by:

$$Z = -4.9524 + 63.8018 * NPL\_RATIO - 19.8731 * ROE \tag{5.3}$$

6 Model Validation

6.1 Kolmogrov-Smirnov test

The two-sample Kolmogrov-Smirnov test was used to test whether the two underlying one-dimensional probability distributions differ. The Kolmogrov-Smirnov statistic is defined below:

$$D_{N_1,N_2} = \sup_x |F_{1,N_1}(x) - F_{2,N_2}(x)|, \tag{6.1}$$

where F_{1,N_1} and F_{2,N_2} are the empirical distribution functions of the development and validation sample, respectively, where N_1 and N_2 are the size of the respective samples (total number of banks in each sample).

The null hypothesis is rejected at level α if:

$$D_{N_1,N_2} > C(\alpha)\sqrt{\frac{N_1+N_2}{N_1 * N_2}} \tag{6.2}$$

The value $C(\alpha)$ is given in Table 7 for each level of α.

Table 7. Critical Values Table

α	0.10	0.05	0.025	0.01	0.005	0.001
$C(\alpha)$	1.22	1.36	1.48	1.63	1.73	1.95

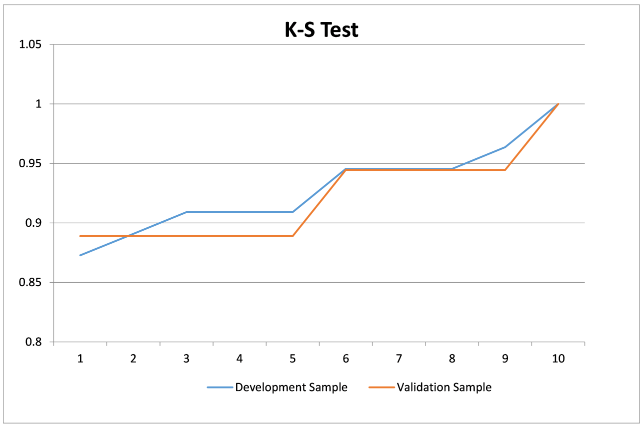

Fig. 1. K-S Test

Table 8. Kolmogrov-Smirnov Statistic

D_{N_1,N_2}	0.0202
N_1	55
N_2	18
C(α)	1.36
D(α)	0.3693

In this study, the model was developed using 100% of the sample, that is, $N_1 = 55$. For the validation, a randomly selected sample of one-third of the total sample was used, that is, $N_2 = 18$ as seen on Table 8. This validation sample comprised of 16 non-distressed observations and 2 distressed observations.

Since α=0.05 and $0.0202 = D_{N_1,N_2} < D(\alpha) = 0.3693$ (as seen in Table 8), we fail to reject the null hypothesis. Therefore, this implies that the two samples come from the same distribution.

6.2 ROC analysis

The ROC curve was used for the assessment of the predictive strength of the logit model.

Under ROC analysis, the hit rate HR is given by:

$$HR = \frac{H}{N_D} \tag{6.3}$$

where;

- H is the number of distressed banks predicted correctly,
- N_D is the total number of distressed banks in the sample.

On the other hand, the false alarm rate FAR is given by:

$$FAR = \frac{F}{N_{ND}} \tag{6.4}$$

where;

- F is the number of false alarms, that is, number of non-distressed banks that were classified as defaulters,
- N_{ND} is the total number of non-distressed banks in the sample.

The accuracy of the model given by the area under the ROC curve (AUROC) denoted by A is:

$$A = \int_0^1 HR(FAR)\, d(FAR) \tag{6.5}$$

$A = 98.4\%$ as can be seen in Fig. 2 below. The closer AUROC is to 1, the better the model. This is a very good model.

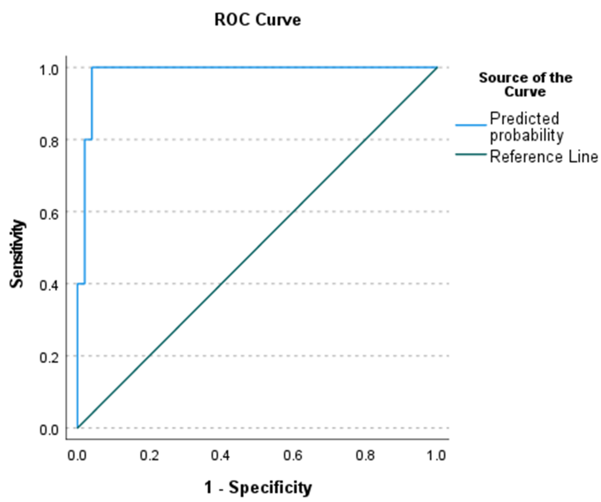

Fig. 2. ROC Curve

Area Under the ROC Curve=98.4%.

6.3 Back testing

The model was back-tested using data set compiled from 2015-2019 and the results in Table 9 were obtained. When using a cut-off value of 50.00%, two banks were incorrectly classified; Botswana

Building Society in 2017 had a CAMELS rating of 4 meaning it was distressed, however, our model predicted it with a probability of distress of 12.81% (non-distress). In 2018, Bank of Baroda, had a CAMELS rating of 3 (non-distress), however, our model predicted a probability of distress of 88.24% (distress). The model was able to predict both distress and non-distress of all other banks accurately, except for Botswana Building Society which was on average rated as a distressed bank but our model rated it on average as a non-distressed bank. The actual result for all the banks are in line with the actual situation in Botswana at the present moment, that is, Botswana comprises of a non-distressed banking sector.

Table 9. Back Testing

	CAMELS RATING						MODEL RATING						RISK LEVEL
Bank Name	**2015**	**2016**	**2017**	**2018**	**2019**	**Average Rating**	**2015**	**2016**	**2017**	**2018**	**2019**	**Average Rating**	
ABSA (formerly Barclays)	3	3	3	3	3	3	0.38%	0.18%	0.12%	0.23%	0.12%	0.20%	Insignificant
Stanbic Bank Botswana	3	3	3	3	3	3	0.84%	0.22%	0.07%	0.06%	1.19%	0.48%	Insignificant
Botswana Savings Bank	3	3	3	3	3	3	0.31%	0.38%	0.27%	1.47%	0.16%	0.52%	Insignificant
First National Bank Botswana	3	3	3	3	3	3	0.07%	0.37%	2.01%	0.77%	0.57%	0.76%	Insignificant
Banc ABC	3	3	3	3	3	3	0.19%	0.19%	0.44%	1.92%	1.82%	0.91%	Insignificant
State Bank of India	3	3	3	3	3	3	2.61%	6.52%	0.81%	1.13%	0.31%	2.27%	Insignificant
First Capital Bank	3	3	3	3	3	3	1.84%	7.40%	0.42%	0.19%	0.10%	1.99%	Insignificant
Bank Gaborone	4	3	3	3	3	3	55.02%	6.62%	2.29%	2.51%	3.50%	13.99%	Modest
Standard Chartered Bank Botswana	3	3	4	3	3	3	1.09%	0.76%	97.70%	2.04%	1.09%	20.54%	Average
Bank of Baroda	3	3	3	3	3	3	2.93%	4.11%	3.13%	88.24%	21.34%	23.95%	Average
Botswana Building Society	3	3	4	4	4	4	3.01%	6.27%	12.81%	58.58%	91.27%	34.39%	Average

6.3.1 Prediction classification

The results in Table 10 show that 1 out of 55 observations was predicted as distressed, however, in actual fact it was not distressed, as a result 80% of the distresses were accurately predicted. On the other hand, there was 1 out of 55 observations that was predicted as non-distressed, however, the observation was a distress in actual fact, as a result 98% of the observations predicted as non-distress were observed to be non-distressed. In overall, the accuracy of the regression model amounted to 96.4%.

Table 10. Prediction Classification

	Actual Distress	Actual Non-Distress	Percentage Correct
Predicted Distress	4	1	80%
Predicted Non-Distress	1	49	98%
Overall Percentage			**96.4%**

7 Conclusion

The study examined the drivers of bank distress in Botswana for the period covering 5 years and found out that the NPL ratio and ROE are the main drivers of bank distress with the NPL ratio being the most influential driver. When the NPL ratio increases, the economy suffers as a result of bank distress and when the ROE increases, the economy improves. Our model was proven to have a predictive strength of 98.4 % as shown by the AUROC, and the results of the model prove that indeed Botswana has a non-distressed banking sector. The model has a high classification capacity of 96.4%.

The model may be used by the Central Bank as an analytical early warning decision support tool to detect banks that may be experiencing challenges. Additionally, the model can be used as an alternative to the CAMELS, or as an extra tool to measure bank distress. On the other hand, the model may be used by banks, investment companies as well as individual investors seeking Botswana-based banks to invest in.

A limitation to the research was the unavailability of the 2020 financial data for a majority of the banks, hence the data range was limited to 2015 to 2019. For further research, 2020 should be included due to a very big change in the banking sector as a result of the COVID-19 pandemic. The next part of this research will be the assessment of bank performance measures in Botswana.

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Competing Interests

All authors have declared that no competing interests exist.

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