PREDICTING BANK FAILURE IN KENYA

Samson Ndirangu Ndunyu

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DECLARATION

This is my own original work and has never been presented for any degree in any other university for award of degree.

……. ……..……..

Signature Date

Samson Ndirangu Ndunyu

X50/82704/2015

This research project has been submitted for examination with my approval as university supervisor.

……..…… …….

Signature Date

Dr. Owen Nyang'oro

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ABSTRACT

Predicting default or probability of failure is a concept that has brought out a lot of interest since 1960's, the banking sector has not been left out as models have been developed to predict bank failure. In this study, we estimate the probability of bank failure in a Kenyan context based on data between 2013 & 2017, inclusive.

We build a model using binary panel data regression to predict probability of bank failing twelve months in advance for Kenyan banks based on eleven micro factors. Empirical results show that early warning signal developed produces a robust result. In addition, we have established shareholders' funds, non-performing loans, insider loans ratio, return on equity, prudential liquidity ratio, average deposit market share, largest shareholder shareholding, years bank in existence, and weighted average cost of funds are the factors that contribute to bank failure in Kenya.

ABBREVIATIONS AND ACRONYMS

CBK-Central Bank of Kenya

CMA- Capital Markets Authority

GDP-Gross Domestic Product

IMF- International Monetary Fund

IRA- Insurance Regulatory Authority

RBA-Retirement Benefits Authority

SACCO-Savings and Credit Cooperative Organization

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CHAPTER ONE
INTRODUCTION

1.1 The study background

Banks have a key role to play in a country's economic development. They accumulate people's savings and make them accessible for investment, by giving loans and buying investment securities, they generate fresh demand deposits. By accepting and discounting bills of return, banks promote trade both within and outside the nation. Since banks are vulnerable to financial problems, the achievement of these benefits has been compromised (Kalpana & Rao, 2017).

Farlex (2012) defined bank failure as a situation where a bank cannot repay its debt either because there is a high default of the bank's loans or the bank has very few accounts providing it with cash flow. This study defines bank failure as recapitalisation of a financial institution by a strategic investor, acquisition by another financial institution or when the financial institution is closed by the regulatory authority (Gonzalez- Hermosillo, 1996).

Crises in the banking sector have a long history. In the 1930s, during the great depression banks failed in the United States and in other countries. Many nations have had bank failures of differing degrees of severity in latest years. In the eighties and nineties, banking crisis was experienced in many African countries which led to restructuring and recapitalizing of their banking systems, most of the banks lent to parastatal companies and as crop loans (IMF, 1998).

Kiyai (2003) noted that bank failure in Kenya became ostensible the late 1980s and manifested in the uncontrolled and disintegrated financial system. The government embarked on reforms in the early 1990s to encourage an effective and market-centred financial system. Reformation program concentrated on policy, legal and institutional framework. The drastic policy change

that the Kenyan economy underwent was geared towards a free economy under the banner of trade liberalization after which the industry underwent immense changes. Micro-finance houses and cooperative societies competition, resulted to them opening front-office operations which provided services which were much like those of banks and Non-Bank Financial Institutions converting to commercial banks (Koros, 2001).

Kathanje (2000) noted that in the period after comprehensive liberalization, there were massive failures in the banking sector. These failures cost the economy about Kshs.19.6 billion regarding restructuring grants and loans, depositors repayment and instant losses as some deposited funds were not insured by Deposit Protection Fund. This was 10% of Kenya's GDP. There were also high non-cash costs from lack of employment and unstable financial system. As a result, deposit protection fund was set up in 1985 to instil some confidence in the sector. It further prompted the CBK to take corrective measures some of which were to strengthen its supervisory role through the implementation of the worldwide Basel accord principles (CBK, Banking Supervision, 1998 Annual report).

As at June 30, 2017, KDIC has paid Kes. 1,170.80 million of total protected deposits for all institutions it has placed under liquidation. This averaged 72% of the total deposits insured from when KDIC commenced the liquidation of banks and other financial institutions (KDIC, 2017 Annual report).

The breakdown of each institution's payment of protected deposits is as shown below

Table 1. 1: Summary of payments of protected deposits as at 30th June 2017 (Kes. Million)

	Name of financial Institution	Date of liquidation	Deposits as at Liquidation	Protected Deposits	Protected Deposits paid as at 30th June 2016	Protected Deposits paid as at 30th June 2017	% of Protected Deposits paid as at 30th June 2017
1	Inter-Africa Credit Finance Ltd.	31st Jan 1993	138	4	2	2	50
2	International Finance Ltd.	16th Apr 1993	168	2	1	1	50
3	Central Finance Ltd.	19th May 1993	106	15	12	12	80
4	Postbank Credit Ltd.	20th May 1993	3834	30	30	30	100
5	Trade Finance Ltd.	18th Aug 1993	203	10	6	6	60
6	Trade Bank Ltd.	18th Aug 1993	4767	280	248	248	88.57
7	Pan-African Bank Ltd.	18th Aug 1993	615	107	90	90	84.11
8	Nairobi Finance Ltd.	20th Aug 1993	188	5	4	4	80
9	Diners Finance Co. Ltd.	20th Aug 1993	667	142	95	95	66.9
10	Middle Africa Finance Ltd.	20th Aug 1993	242	17	13	13	76.47
11	Allied Credit Ltd.	20th Aug 1993	81	14	8	8	57.14
12	Pan-African Credit & Finance Ltd.	18h Aug 1994	139	8	6	6	75
13	Thabiti Finance Co. Ltd.	19th Dec 1994	850	54	33	33	61.11
14	Meridien BIAO Bank Ltd.	15th Apr 1996	781	45	38	38	84.44
15	Heritage Bank Ltd.	13th Sep 1996	370	10	7	7	70
16	Kenya Finance Bank Ltd.	20th Oct 1996	1782	381	323	323	84.78
17	Ari Bank Corporation Ltd.	5th Dec 1997	287	11	6	6	54.55
18	Prudential Bank Ltd.	5th May 2000	600	16	12	12	75
19	Reliance Bank Ltd.	12th Sep 2000	969	88	50	50	56.82
20	Fortune Finance Co. Ltd.	14th Sep 2000	320	33	23	23	69.7
21	Trust Bank Ltd.	15th Aug 2001	159	111	20	20	18.02
22	Euro Bank Ltd.	21st Feb 2003	2040	19	8	8	42.11
23	Prudential Building Society	18th Jan 2005	2025	8	3	3	37.5
24	Daima Bank Ltd.	13th June 2005	669	93	76	76	81.72
25	Dubai Bank Ltd.	24th Aug 2015	1355	123	48	57	46.18
	TOTALS		**23,354.00**	**1,626.00**	**1,162.00**	**1,170.80**	**72**

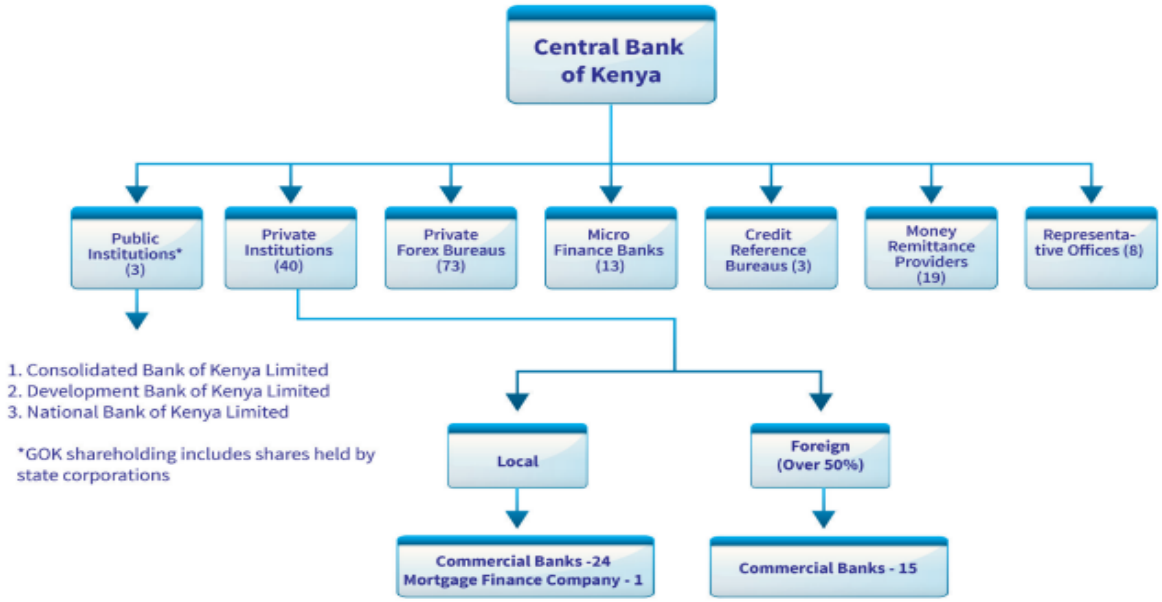
Source: KDIC, 2017 Annual report

1.2 Overview of the Banking Sector in Kenya

As of 31 December 2017, banks in Kenya comprised of the central bank of Kenya as regulator, 43 bank agencies of which 42 are commercial banks and 1 mortgage finance corporation, 9 foreign bank representative offices, 13 microfinance banks, 3 credit reference bureaus, 19 providers of money remittance providers and 73 forexes. Among the 43 banks, 40 are privately owned, while 3 institutions had majority ownership of the Kenya government. Of the 40 private companies, 25 were owned locally (the controlling shareholders are domiciled in Kenya) while

15 were owned by foreigners (many with minority shareholdings). There were 24 commercial banks and 1 mortgage financial institution in the 25 locally owned organizations. Of the fourteen foreign-owned organizations, all commercial banks, eleven were foreign banks' local subsidiaries while three were foreign bank branches. The private sector owns all licensed credit offices, microfinance banks, money remittance providers and forex offices. (CBK, 2017).

Figure 1: Banking Sector structure-December 2017



Source: CBK

1.3 Problem statement

Mamo (2011) found out that bank failures cost the economy and the fiscal costs may vary from 3% of GDP to as high a 50% as experienced in countries like the United States of America, Indonesia and Chile (IMF, 2003). In Kenya, bank failures, some of which could have been avoided cost the economy about 10% of GDP in the form of grants and loans for rebuilding the economy, reimbursing depositors and instant losses of funds of depositors which were not under the protection of the deposit protection fund.

The vulnerabilities of the financial sector continue to exist originating from low capitalisation and liquidity and high non-performing loans with differentiation across banks (IMF, 2014). The central bank of Kenya has taken measures to improve the regulatory and legal framework. From the 2016 bank supervisory annual report the quality of the supervisory structure of the central bank has continued to improve key among them; requiring banks to reveal information of their major shareholders on their websites, as bank shareholders are at the core of banks' corporate governance, external auditors are required to guarantee that insider lending in banks comply with the banking act 2016, and carefully tracking the banking sector, especially on liquidity and credit risk. Additionally, the CBK has been using stress test to assess the health of the banks in Kenya which assess bank performance during a hypothetical economic and financial crisis.

Early identification of failure in banks is an issue for regulators of banks around the world as it's likely to be the perfect to minimize and deter market risk by taking proactive remedial action before the issue spreads. Bank failure prediction has revived interest in implementing an appropriate early warning system in banking supervision and regulation with the latest episodes of banking crises. Despite tight laws enforced by regulators globally, bank failure continues to happen. The aim of this study is to develop and implement a system for early warning capable of estimating the likelihood of failure for Kenyan banks 12 months in advance.

1.4 Research Questions

This study attempts to answer the following questions:

1. Which factors contribute to banking failure in Kenya?
2. How do we predict bank failure in Kenya?

1.5 Study Objectives

The focus of the study is predicting the failure of individual commercial banks as a number of bankruptcies of financial institutions are closely linked to the banking sector difficulties. The objectives are as follows:

a) Identifying the micro variables that contribute to banking failure in Kenya.

b) Develop a model for predicting banking failure in Kenya.

c) Suggest policy recommendation.

1.6 Study Significance

Today banking crises in Kenya shows a strong persistence, knowing that banks are the core of economic activity and its financing. Any fail of the banking system changes the behaviour of economic agents; depositors and investors become distrustful of credit institutions that lead to severe economic disturbances. This study seeks to come up with a predictive model of Kenyan bank failure to avert eventual financial crises. The study results will give policymakers a better understanding of the current banking environment from the early prediction of bank failure. Finally, the study will contribute to the knowledge existing knowledge on the prediction of bank failure by providing proactive measures that can stop any emerging bank failures.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

The first part focuses on theories on bank failure determinants. The second part is empirical literature and methodologies used to determine bank failure.

2.2 Theoretical Literature

2.2.1 Diamond-Dybvig Model

Banks issue loans with a long maturity (low liquidity) at high prices. They also take deposits where depositors can withdraw at any moment (high liquidity). This results in a liquidity mismatch where liabilities of the bank are more liquid than bank assets, leading in banking issues when too many depositors simultaneously attempt to cancel their deposits, known as a bank run. Most banks have developed policies to end the runs while deposit insurance have been instituted by governments to avoid bank runs. Diamond et al. (1983) came up with an explanatory model on why banks are subject to runs and are willing to issue less liquid assets than the deposits. Investors have an unpredictable need for cash due to unforeseen expenditures. So, they have liquidity demands and will opt to invest through a bank, instead of directly holding assets. The investors will prefer to liquidate their assets at multiple dates instead of a particular date. Creating more liquid deposits than bank-owned assets may be viewed as an insurance contract in which depositors share the risk of early liquidation of an asset. This model describes a major role of banks and demonstrates that if too many depositors withdraw, providing these demand deposits will subject banks to bank runs. When many banks suffer runs at the same time (bank

panic) this leads to a bank failure as this shrinks its liquid assets since depositors withdraw them from the bank.

2.2.2 Asymmetric information

Akerlof (1970), argues that in most markets the buyer uses market information to measure the value of the goods and on the other hand the seller has more information of the good he/she is selling. This information asymmetry offers the seller with a motivation to sell products that are less than the market's average value.

Nyoni (2018), argues that asymmetric information for banks as when one party to the dealings either has larger information to the loan agreement that the opposite party. Information asymmetry generates issues within the banks before transactions are finalised (adverse selection) and when the transactions are finalised (moral hazard). Adverse selection in banks come about when poor credit risks (companies with elevated intrinsic risks and poor investment options) make it more likely to accumulate loans than good credit risks (companies with greater investment options and lower intrinsic risks). Moral hazard occurs after the borrower has received money, it comes from the reality that the borrower may have incentives to break the credit covenants by investing in unacceptable ‘immoral projects’ since, in as much as they have a high chance of making a profit to the borrower, they also have a high chance of failure that will result in the borrower being unacceptable. In conclusion, Nyoni (2018) links asymmetric information for banks to bank failure as banks that lend money to people or companies that are willing to default deliberately will experience heavy losses and eventually close.

2.3 Empirical Literature

Beaver (1967), predicted bankruptcy using financial ratio analysis and defined a firm to have failed if it has overdrawn bank accounts, is bankrupt, has defaulted its bonds or missed paying preferred dividends. Beaver (1967), identifies three financial ratios that can predict financial failure: net income to total debt, cash flow to total assets and cash flow to total debt. Companies were classified as possible non-failures or potential failures based on cut-off points for each ratio which he derives from the original sample. Beaver (1967), concludes that bankruptcy can be predicted by a single financial ratio. Altman (1968), did not agree with Beaver (1967) in basing prediction of bankruptcy using a one ratio as it was too easy to nail the complexity in the bank failure. Altman (1968), noted that companies with certain financial structure –more debt than equity - have a greater probability to fail in comparison to companies with the opposite characteristics.

Altman (1968) used multiple discriminant analysis (MDA) to build a predictive model based on the financial ratios. Z-index is calculated with financial ratios to predict bankruptcies. The Z-index by Altman was highly contested. Academics seem to disagree on the main ratios to be used in the assessment of the Z-index. Boritz (1991), identifies 65 distinct ratios to be used as variables for predicting bank failure. In addition, Hamer (1983) claims that the chosen ratios for the Z-index assessment have no significant impact on the Z-index capacity to estimate failure. Karels and Prakash (1987) propose quite the contrary, they propose picking closely the ratios to be included in the Z-index to enhance predictability.

Martin (1977), used a logit model to sample and analyse 5,700 banks, 58 of which failed over the period 1970–1976 where one of the explanatory variables was gross capital. The study found that

the variable was significant and had an adverse impact on the bank failure probability. Return on assets was found to be adverse on the likelihood of banks failing, while the gross amortization ratio compared with net bank income had a favourable outcome.

Hanweck (1977), sampled 209 banks, of which 29 were failing using a probit model. Ratio of total assets to share capital was used to approximate the bank creditworthiness. This variable can be compared the Cooke ratio (Cooke ratio is used to determine the level of banks capital adequacy), the only distinction is that its calculated using the total balance sheet. It therefore generates proportion of loans to capital. The two factors increase the likelihood of bank failure.

Pantalone and Platt (1987), conducted a study between 1983-1984 by sampling 339 banks, of which 113 were failing. They asserted that capital ratios ought to have a significant adverse relation to risk bank failure risk. In addition, they found that return on assets has an inverse relationship to the bank failure probability.

Estrella et al. (2000), underline importance of capital ratios as a useful tool for evaluating banks stability. Minimum capital ratio has been a requirement for banks in the U.S from 1981 and since 1988 from the Basel Accord capital ratio requirements became mandatory to banks worldwide. They argued that capital ratios should have a substantial negative relationship to the risk bank failure risk. Estrella et al. (2000), developed a model from their sample of 11,473 banks to predict bank failure in which 42 banks failed by including variables that only measure the amount of equity. The variables include ratio of loans to equity, net income to equity and total assets to and found out that only equity to gross income ratio contributed to the stability of banks.

Minsky (1957), found that excess credit contributes to a financial crisis. Minsky (1957), explains that when there is stability and economic growth banks tend to give more and more loans without

conducting enough checks to the debtor's ability to honour their obligations. The overall loan might exceed GDP growth. Increase in size of the loan is suspicious when it exceeds the growth of the GDP. The growth in credit results in excess risk-taking from banks.

Taran (2012), also found that capital and liquidity were the main predictors for both banking crises. Taran (2012), used a logit model to obtain results which show that banks with low liquidity and low capital had a higher risk of failure. The other important factors in predicting banking failure are dependent on a market and economic circumstances. Taran (2012), concludes that to identify a reliable bank one has to look at the percentage of retail deposits in the liabilities. A bank is more vulnerable to the financial crisis when it has high retail deposits.

It is hard to capture management performance with data from the balance sheet. Barr and Siems (1996) focused on management quality as one of the variables that explains bank failure. Barr and Siems (1996), used the portfolio quality as a proxy variable for management. They sampled 739 banks, of which 294 were failing. On one hand, they discovered bad debts in the assets at a high level contributed to bank indebtedness. It was also found that management quality strengthens bank stability. The likelihood of a banking failure was found to be countercyclical to economic circumstances.

Survival analysis has also been used to predict bank failures. González et al. (1996), employed survival analysis in their study on bankruptcy to determine the likelihood of failure. Likelihood of failure was estimated using panel data on a logit model. Survival models address the conditional probability problem that is probability that an occurrence will end in the subsequent period if it hasn’t ended. They concluded that you can determine the timing and likelihood of an imminent bank failure.

Demirguc-Kunt et al. (1998), sampled developed and developing countries between 1980 and 1994 and used a logit multivariate model to study the factors that cause systematic banking crises. Demirguc-Kunt and Detragiache (1998), found that crises tend to erupt when economic growth is low and inflation is high, that is, when the macroeconomic environment is weak. High-interest rates is also associated with the problems in the banking sector and exposed the balance of payments crises has played a role. Countries with weak law enforcement and an explicit deposit insurance scheme were at risk.

2.4 Literature Overview

Most empirical studies evaluated the researchers have used financial ratio analysis to determine the likelihood of bank failure. Beaver (1967), used a single financial ratio to determine the likelihood of bank failure which was later improved by Altman (1968) and Boritz (1991) by including more financial ratios to determine the likelihood of bank failure. Hanweck (1977), Demirguc-Kunt et al. (1998) and Taran (2012) used probit and logit models to predict banking failure as it's more robust, may handle non-linear effects and is more accurate in predicting bank failure. This study will follow a similar logit framework as used by Demirguc-Kunt and Detragiache (1998) to predict bank failure in Kenya.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter outlines methodology used in this study. Succeeding the introduction is the theoretical model, followed by the empirical model. The remaining sections are the variable measurement and definition and finalize by giving the data, data types and sources

3.2 Theoretical model

Banks exist in a competitive market. To model bank failure, this study adopts Zaruk and Madura (1992), model and modifies it further. Bank is characterized by the following: On the assets side, we have; treasury bills (B), loans (L) and reserve (R), while on the liability end, we have shareholders deposits (D) and equity (K). From this, we can conclude that the banking sector reserve is a share of the deposits, denoted as α. The central bank requires that the banking sector should be capital adequate that is the capital be greater or equal to a part of weighted-risk assets (ϑ). This can be represented by equation 1 and 2 for reserve and capital adequacy respectively:

$$R = \alpha D \quad \ldots\ldots\ldots 1$$

And,

$$\vartheta(\sigma_l L + \sigma_b B) \leq K \quad \ldots\ldots\ldots 2$$

σ_l represent the risk-weight of loans while σ_b represent treasury bills risk-weight respectively. Since the treasury bills are free of risk, then, $\sigma_b = 0$. This gives the following capital requirement inequality:

$$\vartheta(\sigma_l L) \leq K \quad \ldots\ldots\ldots 3$$

The balance sheet identity is given as follows:

$$L + B + R = K + D \ldots\ldots\ldots\ldots 4$$

Substituting equation 1 and 2 in equation 4 and further re-arranging it gives the following:

$$B = D(1-\alpha) - L(1-\vartheta\sigma_l) \ldots\ldots\ldots\ldots 5$$

A banks objective is to maximize profit. To achieve this, a bank will choose the optimal deposits amounts and loans amounts. Thus, the profit function is given as:

$$\pi = r_l(1-\bar{p})L + r_b B - r_d D - \gamma_l L - \gamma_d D - \bar{p}L \ldots\ldots\ldots\ldots 6$$

Where; r_l- loans interest rates; r_b- treasury bills interest; r_d -deposit interest; $\bar{p}$ -expected default rate; γ_l the marginal costs of loans and γ_d is the marginal cost of deposits.

Substituting equation 5 to the profit function (equation 6), it becomes:

$$\pi = r_l(1-\bar{p})L + r_b(1-\alpha)D - r_b(1-\vartheta\sigma_l)L - r_d D - \gamma_l L - \gamma_d D - \bar{p}L \ldots\ldots\ldots\ldots 7$$

Banks want to maximize profit. Banks choose the optimal amounts of deposits and loans to achieve this. Thus, the first order condition is:

$$\frac{\partial\pi}{\partial L} = r_l(1-\bar{p}) - r_b(1-\vartheta\sigma_l) - \gamma_l - \bar{p} = 0$$

$$r_l = \frac{1}{1-\bar{p}}[r_b(1-\vartheta\sigma_l) + \gamma_l + \bar{p}] \ldots\ldots\ldots\ldots 8$$

$$\frac{\partial\pi}{\partial D} = r_b(1-\alpha) - r_d - \gamma_d = 0$$

$$r_d = r_b(1-\alpha) - \gamma_d \ldots\ldots\ldots\ldots 9$$

We replace the rate of interest on loans and deposits with the respective value (equation 8 and 9) hence the following profit function (equation 6):

$$\pi = \frac{1}{1-\bar{p}}[r_b(1-\vartheta\sigma_l)+\gamma_l+\bar{p}](1-\bar{p})L + r_bD(1-\alpha) - r_bL(1-\vartheta\sigma_l) - r_bD(1-\alpha) + \gamma_dD - \gamma_lL - \gamma_dD - \bar{p}L$$
…………………………………………………………………………………10

$$\pi = \frac{1}{1-\bar{p}}[r_bL - r_b\vartheta\sigma_lL + \gamma_lL + \bar{p}L - r_bpL + r_b\vartheta\sigma_lpL - \gamma_lpL - \bar{p}pL - r_b(1-\vartheta\sigma_l)(1-\bar{p})L - \gamma_l(1-\bar{p})L - p(1-\bar{p}L]$$
…………………………………………………………………….…………11

When we simplify equation 11 further, we get the below equation:

$$\pi = \frac{\bar{p}-p}{1-\bar{p}}\, L\,[1+(1-\vartheta\sigma_l)r_b+\gamma_l] \quad \text{…12}$$

The banks relative efficiency is the difference between expected default rate of a bank and individual bank default rate ($\bar{p} - p$). Central bank can tighten the monetary policies through subjecting an increase in interest rate hence various cases may occur as outlined below. We first get the first order condition (FOC) of the profit function in relation to the treasury bills interest rate hence the following:

$$\frac{\partial\pi}{\partial r_b} = \frac{\bar{p} - p}{1-\bar{p}}\, L\,(1-\vartheta\sigma_l) \quad \text{…13}$$

Given the above FOC, if the banks relative efficiency is negative, $\bar{p} - p < 0$, a tight monetary policy increases losses to the bank. A change in the monetary policy has no effect if the banks relative efficiency is null, i.e., $\bar{p} - p = 0$. If the banks relative efficiency is positive, i.e., $\bar{p} - p > 0$, a tight monetary policy will increase its profits.

It can be considered that interest rate increase in the on-treasury bills increases the likelihood of a bank failure. A bank will be considered as failed when it's insolvent, that is when the amount of

equity and profit of the shareholders is negative. Hence the likelihood of a bank failure denoted as ρ is given as follows:

$$\rho = \sum(K + \pi < 0) = P(\pi < -K) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots 14$$

Substituting the equations, we have the following resulting probability of bank failure:

$$\rho = \sum(\bar{p} - p < -\frac{K}{L}\frac{1-\bar{p}}{1+(1-\vartheta\sigma_l)r_b + \gamma_l}) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots 15$$

The partial derivatives of Equation 15 above with respect to interest rate shows an increase treasury bills rate leads to an increase in the likelihood of bank failure. The same applies to the partial derivative with respect to loans, where the probability of failure increases as you increase loans.

3.3 Empirical model

Researchers have used various approaches to model banking failure which include the logit model, probit model, Bayesian method and the ANN model. Most studies on bank failure prediction used probit/logit framework (Demirguc-Kunt and Detragiache, 1998; Beck, Demirguc-Kunt, & Levine, 1998), we will therefore follow the same approach. The Logit model gives accurate estimates as it may handle nonlinear effects, the dependent variable does not need to be distributed normally and doesn't assume the relationship between dependant & independent variables is linear variables this makes it a user-friendly tool for analysing bankruptcies.

Banking data is not normally distributed hence the logit model has an advantage over the probit model as it does not assume multivariate normality between the independent variables. In addition, we use logistic regression since the response variable (bank failure) is binary; either a bank failure or not.

$$Y_i = \begin{cases} 1, if\ the\ outcome\ shows\ \ bank\ failure \\ 0, if\ othewise \end{cases}$$

The functional form being:

$$Y_{it} = f(x_{1it}, x_{2it}, \dots x_{11it}) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \, 16$$

The logistic form being:

$$Y_{it} = e^{\beta_0 + \beta_1 x_{1it} \dots + \beta_k x_{kit} + \mu} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \, .17$$

$$log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_{i1t} \dots + \beta_k x_{kit} + \mu \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \, .18$$

Where:

β_0 to β_k = coefficients of the variables

x_{1it} to x_{kit} = determinants of bank failure for bank i at time t

μ = error term

Alternatively, in terms of probability:

$$p(Y_{it} = 1) = \frac{e^{\beta_0 + \beta_1 x_{1it} \dots + \beta_{11} x_{11t} + \mu}}{1 + e^{\beta_0 + \beta_1 x_{1t} \dots + \beta_{11} x_{11t} + \mu}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \, 19$$

Where:

$p(Y_{it} = 1) = probability\ of\ a\ bank\ i\ failing\ at\ time\ t$

3.4 Variable definition and measurement

Log of Shareholders Funds (LSF)

A banks capital base is very key for protecting its depositors and this maintain the general confidence in its operations which is key for the stability and development in the long term. Goodhart (1998), found out as capital of a bank decreases, bank failure risk increases. This was measured using the shareholder's fund in the balance sheet. An inverse relationship between capitalization and bank failure is expected.

Non-Performing Loans Ratio (NPL)

Bank institutions which are failing in most cases have high non-performing loans (Dermirgue-Kunt 1989). Non-performing ratio which was be calculated as follows;

$$\frac{\text{Total Substandard,Doubtful \& Loss Loans}}{\text{Total Exposures}}$$

Positive correlation was expected with the probability of failure.

Insider Loans Ratio (ILR)

Insider loans arises when related parties are advanced unjustified loans from commercial banks. When a bank has poor has poor structures in corporate governance thus being weekly monitored it creates a room where funds are diverted from their intended purpose and this weakens the banks' capital position. Insider loans ratio was calculated as;

$$\frac{\text{Insider \& Related Exposures}}{\text{Total Exposures}}$$

A priori positive correlation between the probability of bank failing and insider loans was expected.

Average Experience of Executive Directors (Av_Exp)

Dziobek and Pazarbasioglu (1997), found a weak management and bank (among other factors) can cause bank failures. It is difficult to objectively measure management quality using financial statement data. In this study we will measure management quality using average working experience for the executive directors to evaluate the likelihood of a bank failing. It's because the executive committee which comprises of the executive directors are responsible for the bank decision making. The average experience of executive directors was calculated as;

$$\frac{\text{total banking experience of executive directors}}{\text{no.of executive directors}}$$

A priori negative relationship was expected.

Return on Equity (ROE)

Companies use their profit to implement their growth and investment strategies. Wheelock and Wilson (2000), found an inverse relationship between profitability and probability of bank failure. Thus, banks profitability should be taken as the key liquidity and solidity factor of a bank. For a bank to service its debt in the long term, it must create enough operational margin. Return on equity measures the return on funds of the shareholder, it therefore quantifies the bank's effectiveness in creating earnings from each shareholder fund unit. Return on equity was measured as follows;

$$\frac{\text{net profit after tax}}{\text{shareholder`s fund}}$$

A high ratio means high profitability and the likelihood of failure was therefore anticipated to be negative.

Prudential Liquidity Ratio (Prud_Liq_Ratio)

Diamond and Dybvig (1983), found out significant liquidity issues can lead to bank failure of the solvent bank. Banks must retain a level of liquidity that is sufficient for present and future commitments. This means that a bank should be capable of handling unforeseen market circumstances and shifts in sources of financing that directly influence asset liquidity. In short, the liquidity risk is based on present and future liquidity and methods of maintaining liquidity. The liquidity ratio measures the capacity of a bank to resist a possible bank run. Bank liquidity position is an important variable for the study as currently the market is characterized by a

limited alternative source of funding and high turnover of deposits (IMF, 2012). The prudential liquidity ratio was measured as;

$$\frac{\text{Liquid Assets}}{\text{Short Term Liabilities}}$$

The higher the prudential liquidity ratio is, the higher the banks liquidity. A priori negative relationship was expected this ratio and the probability of failure.

Average Deposit Market Share (Bank_Size)

DeNicolò (2000), found a favourable and substantial connection between banks likelihood of failure and bank size in Japan, the U.S. and several European nations. Mishkin (1999), noted that big banks have less probability of failure as they are taken to be very significant to fail. Average deposit market share was measured as;

$$\frac{\text{size of bank deposits}}{\text{market deposits}}$$

Largest Shareholder Shareholding (Larg_Share)

In most banks that have failed in Africa, there was interference by the owners where most shares were owned by one person or family in the operational decisions (Brownbridge, 1998). A more independent management and diverse ownership structure was expected to put more constraints on insider lending as managers wouldn't want to risk their reputations and careers. Largest Shareholder Shareholding was calculated as;

$$\frac{\text{largest shareholding}}{\text{total shares}}$$

Years Bank in Existence (Bank_Age)

Young (1999), found that the age of a bank affects the risk of failure. Newly founded banks have the highest probability of failing than banks which are older (Bickerdyke et al., 2000). In the

Kenyan context the connection between the likelihood of failure and the bank age was established as the failed banks were relatively new. The study calculated this as the publication date less the bank incorporation date in Kenya. A negative relationship was expected.

Founder-Director Role (Act_Found)

Jensen and Meckling (1976), discovered that banks with big dominant shareholders–have simple control on management –mostly take many aggressive risks than banks with few dispersed shareholdings dominated by managers, as big dominant shareholders have greater motivation to take aggressive risks compared to non-shareholders. The study includes this variable to get the connection between conflict of interest and failure in banks. If the founding director role is active in the bank, then it was given a value of 1 and 0 if otherwise. A negative relationship was expected.

Weighted Average Cost of Funds (WACOF)

Ellis and Flannery (1992), found out high deposit levels act as a signal for bank failure. A rise in the rate of interest could make borrowers to select greater yields investments if fortunate with reduced likelihood of achievement (Stiglitz and Weiss, 1981), so deposit prices increase can lead to bank policy that is riskier. A rise in bank loan prices may have comparable incentive impacts on borrowers from the bank. The weighted average cost of funds was calculated as

$$\frac{\text{total interest expense}}{\text{average deposit size}}$$

A direct relationship between the likelihood of failure and the cost of funds was expected.

Table 3. 1: Notation of variables, variables & measurement

Notation of Variable	Variable	Measurement	Predicted sign
LSF	Log. of Shareholders' Funds	Shareholders' Funds on Balance Sheet	-
NPL	Non-Performing Loan Ratio	$\frac{\text{Total Substandard, Doubtful \& Loss Loans}}{\text{Total Exposures}}$	+
ILR	Insider Loans Ratio	$\frac{\text{Insider \& Related Exposures}}{\text{Total Exposures}}$	+
Av_Exp	Average Experience of Executive Directors	$\frac{\text{Total banking experience of executive directors}}{\text{no. of executive directors}}$	-
ROE	Return on Equity	$\frac{\text{Net profit after tax}}{\text{Shareholder`s fund}}$	-
Prud_Liq_ Ratio	Prudential Liquidity Ratio	$\frac{\text{Liquid Assets}}{\text{Short Term Liabilities}}$	-
Bank_Size	Average Deposit Market Share	$\frac{\text{Size of bank deposits}}{\text{Market deposits}}$	-
Larg_Share	Largest Shareholder Shareholding	$\frac{\text{Largest shareholding}}{\text{Total shares}}$	+
Bank_Age.	Years of Bank in Existence	Date of Publication less Date the bank was incorporated in Kenya	-
Act_Found	If founder is still Active in the management of the bank	If founder is still active in the bank =1 and 0 otherwise	+/-
WACOF	Weighted Average Cost of Funds	$\frac{\text{Total interest expense}}{\text{Average deposit size}}$	+

3.5 Diagnostic tests

Multicollinearity

Multicollinearity was tested to check the relationship between the various pairs of independent variables.

Specification and normality test

Linktest was ran to check if independent variables are incorrectly specified. In addition, normality test was done to check if the variables are distributed normally or not.

3.6 Type and source of data

This study included commercial banks with publicly available financials between 2013 to 2017. The study will use panel data to get the various independent variables. The data will be obtained from the database of the central bank of Kenya from the different banks released audited financial statements and annual banking sector report.

CHAPTER FOUR
REUSLTS AND DISCUSSION

4.1 Introduction

In this chapter, descriptive statistics of the variables identified in the previous chapter and the panel logistic regression results of the are presented.

4.2 Descriptive statistics

Table 4.1 present the summary of descriptive statistics that is means, standard deviation, minimum and maximum of each variable. Means represent the average values of each variable while standard deviation shows how each variable is far from the mean (measure of dispersion).

We can make various inferences from table 4.1: the average non-performing loans ratio for the 34 banks between 2013 and 2017 is 0.11 which is low with the same standard deviation meaning that there is a small deviation of the banks non-performing loans ratio from the mean. Insider loans ratio for the banks is quite low with a mean of 0.06 meaning most banks have low insider loans, there are some banks with zero insider loans and the highest ratio of insider loans is 0.30. The average experience of executive directors for the 34 banks is 19.33 years with the bank with the least experience of the executive directors being 12 years while the bank with most experience of executive directors being 35 years.

Most banks have a good return on equity ratio averaging is 1.08 meaning most banks are profitable but there are some banks that make losses as their minimum return on equity ratio of -0.78. The prudential liquidity ratio which shows how liquid banks are is quite low with a mean of 0.23 and with a standard deviation of 0.15 meaning the prudential liquidity ratio of most banks is does not fall that much from the mean.

The mean for the average deposit market share is 0.03 which is quite low meaning that the market share is evenly distributed across the banks. The bank with the largest deposit market share has 15% market share. Most banks have the largest shareholder with 53.65% shares while there is a bank with its largest shareholder with 1.77% shares while another bank which is wholly owned by one person (100% shared).

The average existence of most of the banks is 31.73 years where the youngest bank is 2 years old and the oldest bank 123 years old. We also see that most banks don't have their founder still active in management as the average is 0.28 however, there are some banks where the founder is still active in management.

The deposit level of the banks which is indicated by weighted average cost of funds is quite low with an average of 0.07 for most banks, in addition there is a bank with a high weighted average cost of funds of 70% indicating a high customer deposit level. In regard to the log of shareholders fund, the mean the 34 banks is 21.54 meaning most of the banks are well capitalised.

Table 4. 1: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Non-performing loans ratio	158	0.11	0.11	0.00	0.53
Insider loans ratio	158	0.06	0.04	0.00	0.30
Average experience of executive directors	158	19.33	3.80	12.00	35.00
Return on equity	158	1.08	1.64	-0.78	6.45
Prudential Liquidity ratio	158	0.23	0.15	0.03	0.75
Average deposit market share	158	0.03	0.03	0.00	0.15
Largest shareholder shareholding	158	53.65	38.90	1.77	100.00
Years bank in existence	158	31.73	29.01	2.00	123.00
If founder is still active in management of the bank	158	0.28	0.45	0.00	1.00
Weighted average cost of funds	158	0.07	0.06	0.00	0.70
Log of Shareholders' funds	158	21.54	1.06	19.52	24.12

The correlation coefficient shows how two variables are related. Negative coefficients show inverse relationship while positive coefficients show a direct relationship. Results from table 4.2 show the correlation coefficients range from |0.02| to |0.73|. Most of coefficients are significantly low, however years of bank existence (Bank_Age) and return on equity (ROE) have a high correlation of 0.73. The variable non-performing loans is inversely related to average experience of executive directors (-0.17), return on equity (-0.28), prudential liquidity ratio (-0.19), the years of existence of a bank (-0.12) and variable if founding director is still active in management of the bank(-0.07). On the other hand, there is a direct relationship between return on equity and the largest shareholder shareholding (0.16).

Table 4. 2: Multicollinearity test

	NPL	ILR	Av_Exp	ROE	Prud_Liq_Ratio	Bank_Size	Larg_Share	Bank_Age	Act_Found	WACOF	LSF
NPL	1.0000										
ILR	0.0946	1.0000									
Av_Exp	-0.1723	0.0911	1.0000								
ROE	-0.2799	-0.2454	0.0516	1.0000							
Prud_Liq_Ratio	-0.1944	-0.1381	0.0452	0.1978	1.0000						
Bank_Size	-0.2371	-0.2555	-0.0338	0.6958	0.2069	1.0000					
Larg_Share	0.1583	-0.1118	-0.1316	0.1615	0.2102	-0.0536	1.0000				
Bank_Age	-0.1195	-0.1142	-0.0125	0.7320	0.3388	0.6732	0.1610	1.0000			
Act_Found	-0.0678	-0.0332	0.0494	-0.2251	-0.1261	-0.1162	-0.4570	-0.2724	1.0000		
WACOF	0.1293	0.0900	-0.0911	-0.2093	0.0184	-0.2741	-0.0251	-0.1696	0.1445	1.0000	
LSF	0.0248	-0.2114	-0.2350	-0.0392	0.2051	0.4774	0.2083	0.0889	0.0083	-0.1623	1.0000

4.3 Model Estimation and Interpretation

We ran the binary panel logistic regression model with confidence interval of 95% and the below results in table 4.3 were tabulated. Average experience of executive directors and If founder is still active in management of the bank variables were omitted because of collinearity and left with nine variables in the regression. The coefficients indicate the relationship between the various variables and the probability of bank failing. A negative coefficient indicates inverse relationship with probability of bank failing while a positive relationship indicates a direct relationship with probability of bank failure. The p values indicate whether the coefficient determined is significant or not in determining probability of bank failure. We observe that most of the coefficients are significant in determining bank failure as their p values are less than 0.05 except for variable largest shareholder shareholding whose p value is 0.06.

The coefficient for weighted average cost of funds is 19.35 and is significant in determining probability of bank failure as its p value (0.01) is less than 0.05. This means that a unit increase in the weighted cost of funds, we expect a 19.35 increase in the log-odds of probability of bank failure ceteris paribus. Log of shareholders fund has a negative (-15.28) significant coefficient (p value = 0.02) meaning a unit increase in the log of shareholders' funds is expected to result to a 15.28 decrease in the log-odds of probability of bank failure ceteris paribus.

A number of variables have a negative coefficients and are significant (p value < 0.05) in explaining the probability of bank failure, this include: years of bank in existence is negative (-0.38) interpreted as a unit increase in the number of years of bank in existence results to a 0.38 decrease in the log-odds of the probability of bank failure ceteris paribus. Average deposit market share coefficient is -613.62 meaning a unit increase in average deposit market share of a bank results to 613.62 decrease in the log-odds of the probability of bank failure ceteris paribus.

Prudential liquidity ratio has a -9.15 coefficient and significant meaning a unit increase in the banks prudential liquidity ration results to a 9.15 decrease in the log-odds of the probability of bank failure ceteris paribus. In addition, return on equity has a -7.49 significant coefficient meaning a unit increase in the banks return on equity results to 7.49 decrease in the log-odds of the probability of bank failure ceteris paribus.

Insider loans ratio has positive (65.98) significant (p value = 0.04) coefficient which means a unit increase in the banks insider loans ratio results to a 65.98 increase in the log-odds of the probability of bank failure ceteris paribus. Similarly, non-performing loans has a positive (12.15) significant (p value = 0.03) coefficient which means a unit increase in the banks non-performing loans ratio results to a 12.15 increase in the log-odds of the probability of bank failure ceteris paribus. Largest shareholder shareholding is not significant in explaining the probability of bank failure as its p value is > than 0.05 hence cannot be used to determine probability of bank failure.

Table 4. 3: Panel logistic regression results

Bank status	Coef.	Std. Err.	z	P>|z |	[95% Conf. Interval]	
Weighted average cost of funds	19.35	173.18	0.11	0.01	-358.77	320.08
Log of Shareholders' funds	-15.28	6.52	-2.34	0.02	2.49	28.06
Years bank in existence	-0.38	0.38	-1.00	0.03	-1.12	0.36
Largest shareholder shareholding	1.37	0.72	1.91	0.06	-2.78	0.04
Average deposit market share	-613.62	267.75	-2.29	0.02	-1138.41	-88.84
Prudential Liquidity ratio	-9.15	34.76	-0.26	0.03	-58.98	77.28
Return on equity	-7.49	6.76	-1.11	0.03	-5.76	20.74
Insider loans ratio	65.98	83.76	0.79	0.04	-98.20	230.15
Non-performing loans	12.15	54.87	0.22	0.03	-119.69	95.39
cons	-314.87	144.55	-2.18	0.03	-598.18	-31.56

Notes: (Number of observations 158, number of groups 34, Prob > chi2 = 0.0259). The figures were rounded off to two decimal places

4.4 Specification and normality tests

Linktest was ran to check if independent variables are incorrectly specified. The outcome from table 4.4 shows that the variables are correctly specified and predict the bank failure hat and hatsq are significant as $p<0.05$

Table 4. 4: Specification test

	Coeff.	Std Err.	z	P>|z|.	[95% Conff. Interval]	
_hat	2.110	0.3217	6.550	0.001	0.868	3.680
_hatsq	0.121	0.050	2.42	0.004	0.065	0.377
_cons	0.000	0.582	0.000	1.000	-1.925	1.924

Normality test was performed as shown in table 4.5. The probability of skewness for most of the variables is less than 0.005 which implies that skewness is not asymptotically normally distributed as p-value of skewness < 0.05. Its only largest shareholder shareholding that is normally distributed as the p-value pf skewness > 0.05. Kurtosis on the other hand is not asymptotically distributed as the p-value of kurtosis is < 0.05 for all variables. This means that the variables are not normally distributed. Logit model was thus used as it handles nonlinear effects on variables.

Table 4. 5: Normality test

Variable	Obs	Pr (Skewness)	Pr (Kurtosis)	adj chi2(2)	Prob >chi2
Non-performing loans	158	0.000	0.000	55.840	0.000
Insider loans ratio	158	0.000	0.000	0.000	0.000
Average experience of executive directors	158	0.001	0.013	15.060	0.001
Return on equity	158	0.000	0.002	39.610	0.000
Prudential Liquidity ratio	158	0.000	0.000	40.550	0.000
Average deposit market share	158	0.000	0.003	34.560	0.000
Largest shareholder shareholding	158	0.400	0.000	0.000	0.000
Years bank in existence	158	0.000	0.000	45.640	0.000
If founder is still active in management of the bank	158	0.000	0.000	38.000	0.000
Weighted average cost of funds	158	0.000	0.000	0.000	0.000
Log of Shareholders' funds	158	0.021	0.781	5.330	0.069

4.5 Model validation

We validated this model to check its strength in prediction by simulating to the 2017 financials for non-failed banks and a year before failure for failed banks. The simulation results are shown in table 4.6.

The result obtained in table 4.6 are like the actual situation facing banks in Kenya. Simulating the 2014 financials using the model Chase and Imperial Banks had a high probability of failure at 56.14% for Imperial Bank and 40.24% for Chase bank. Both Chase and Imperial Bank failed in 2015. On the other hand, simulating 2017 financials using the model its shows that National bank is among the banks with the highest probability of failure at 22.40%. Currently, National Bank has been taken over by KCB thus considered as failed as per the study definition where bank failure is defined as recapitalization of a financial institution by a strategic investor, acquisition by another financial institution or when the financial institution is closed by the regulatory authority.

Most of the banks that have a high probability of failure have high non-performing loans, high insider loans ratio, high weighted average cost of funds, low return on equity and they are small banks. International banks like Stanbic, Barclays, Standard Chartered and Citibank have remained stable and their probability of failure is very low. The results are in line with Gumbo et al. (2016) who found out that insider loans and non-performing loans are the key drivers to probability of bank failing in Zimbabwe.

Table 4. 6: Simulation results on probability of failure

Bank Name	Probability of failure	
	2017	2014
Imperial Bank		56.14%
Chase Bank		40.24%
Prime Bank	35.12%	12.26%
Spire Bank	33.43%	2.22%
National Bank	22.40%	5.12%
Credit Bank	19.02%	4.20%
ABC	17.21%	2.31%
First Community	14.95%	1.03%
Transnational Bank	6.66%	2.32%
Paramount bank	6.17%	1.02%
Consolidated Bank	5.62%	16.41%
GT Bank	3.16%	7.12%
Ecobank	2.86%	0.26%
Jamii Bora	2.22%	0.40%
BOA	2.20%	0.41%
UBA bank	2.07%	0.03%
Gulf African Bank	1.88%	3.80%
Family Bank	1.61%	2.36%
Bank of Baroda	1.26%	0.49%
Barclays	1.23%	1.54%
CBA	1.21%	2.26%
KCB	0.90%	0.30%
Cooperative Bank	0.85%	0.20%
NIC Bank	0.79%	0.03%
DTB	0.69%	0.28%
Citibank	0.47%	0.06%
Standard chartered	0.40%	0.15%
I&M	0.39%	0.40%
Guardian Bank	0.31%	0.42%
Development Bank	0.12%	Not in existence
Sidian Bank	0.10%	7.60%
Equity Bank	0.08%	0.10%
Stanbic Bank	0.05%	0.08%
DIB Bank	0.02%	Not in existence

Table 4.7 tests whether the model designed to predict bank failure can misclassify non-failed bank as failed or a failed bank as non-failed. The model correctly predicted 88.23% of failures and misclassified 11.77 % as failed. Of the 11.77 % National Bank was classified to fail in 2018 while in fact it is under stress.

Table 4. 7: Prediction classification

	Failed	Non-Failed
Predicted Failure	Correctly Predicted 88.23.%	Type II Error 0.00%
Predicted Non-Failure	Type I Error 11.77%	Correct Prediction 100.00%

CHAPTER FIVE
SUMMARY, CONCLUSIONS AND POLICY RECOMMENDATIONS

5.1 Introduction

This chapter summarises the results, draws conclusion and suggest policy recommendations.

5.2 Summary

This study investigated the micro factors that contribute to bank failure in Kenya and develop a model that predict bank failure in Kenya. The study used data from 2013 to 2017 audited financial statements from the various banks database, CBK and KDIC annual reports. A logit model was estimated with probability of failure as the dependent variable. The independent variables were: Shareholders funds, non-performing loans, insider loans ratio, average experience of executive directors, return on equity, prudential liquidity ratio, average deposit market share, largest shareholder shareholding, years bank in existence, if founder is still active in management of the bank and weighted average cost of funds.

5.3 Conclusion

The regression results show that: non-performing loans, insider loans, the bank size, the extent a bank is capitalised the years a bank has existed, the liquidity of a bank and a banks return on equity are the key drivers that determine probability of bank failing in Kenya.

Banks should be more capitalised, more liquid in terms being able to cater for the present and future commitments. This means that a bank should be capable of handling unforeseen market circumstances and shifts in sources of financing that directly influence asset liquidity. In addition, banks should also minimise the insider loans ratios and reduce the non-performing loans in order to reduce the probability of failure.

5.4 Policy Implications

Predicting bank failure in Kenya not only reduces and deters systemic risk caused when banks fail but also acts as an appropriate early warning system for the CBK. This model can be used as an early warning mechanism to predict banks that may be experiencing challenges. This will greatly reduce the expense of bank surveillance by reducing the on-site inspections and provide valuable information to the various decision makers and other interested parties. Early warning signal will also help individual banks put in place proactive measures that can prevent any forthcoming distress.

5.5 Areas of further research

This study examined the micro factors that cause banking failure in Kenya and used them to predict banking failure in Kenya. However, we did not consider any macro factors that cause banking failure in Kenya. Similar studies can be done using macro factors to predict bank failure in Kenya. Further studies can also be taken to determine both micro and macro factors that cause bank failure and use them to predict bank failure in Kenya.

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