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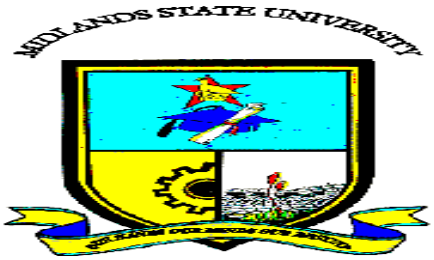

FACULTY OF COMMERCE

DEPARTMENT OF BANKING AND FINANCE

B.Com Banking and Finance

An investigation on the determinants of bank failures in Zimbabwe: 2009-2012

BY

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This dissertation is submitted in partial fulfillment of the requirements of the Bachelor of Commerce Banking and Finance Honors Degree in the Department of Banking and Finance at MSU.

Gweru: Zimbabwe, October 2013

DECLARATION OF PLAGARISM

I, Katuka Blessing, do hereby declare that this research represents my own work and has never been previously submitted for a degree at this or any other university.

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Student's Signature Date

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Supervisor's Signature Date

APPROVAL FORM

The undersigned certify that they have supervised the student BLESSING KATUKA dissertation entitled **an investigation on the determinants of bank failures in Zimbabwe: 2009-2012**, submitted in partial fulfilment of the requirements of the Bachelor of Commerce in Banking and Finance Honors Degree at Midlands State University.

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DEGREE TITLE: Bachelor of commerce Banking and Finance Honors Degree.

YEAR: 2013

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DEDICATION

I dedicate this study to my father Mr Kennedy Katuka who always gave me a word of encouragement that the easiest way to achieve something worthwhile is through maximum effort and commitment and that nothing is impossible if done in time.

ACKNOWLEDGEMENTS

Firstly and foremost, I would like thank God the Almighty for giving me the power, determination and intelligence for making all things possible. Without God's guidance, this research couldn't have been successful at all.

I would like to thank my supervisor Mr Dzingirai for his support and guidance during the period of study. I also want to thank the Katuka family for scarifies, patience and everlasting support they gave me. My gratefulness also goes to all Midlands State University Banking and Finance staff, in particular Dr Chikoko and Mr Mabonga, for awarding me such an opportunity to work on this research topic.

May God Bless you all

ABSTRACT

Upsurge in bank failure cases under a more stable currency environment raised the need to deeply investigate sources of bank failures in Zimbabwe. This is considered an imperative move considering the impact that bank failures pose to stakeholders outside the banking sector such as investors and depositors, the Zimbabwean banking sector itself as well as the entire economy. This study investigated the determinants of bank failures in Zimbabwe under the multiple currency environment. The study employed pooled logit estimator using general to specific logit estimation procedure on fourteen banks by making use of the financial panel data for the period 2009-2012. Empirical findings indicated that the macroeconomic environment, in particular GDP growth rate, has much influence on bank failure than any of bank fundamentals. Among bank fundamentals, liquidity, profitability and capitalisation proved to be prominent bank related determinants of bank failures in their respective order. Findings also suggest that loan-to-deposits ratio (LTD), deposits-to-assets ratio (DTA), gross revenue ratio (GRR), return on assets(ROA), efficiency ratio(EFR), SIZE and GDP growth rate (GDP) variables are negatively correlated to the possibility of banks failing while loan-to-assets (LTA) have positive influence on bank failures. Based on these findings the researcher recommends that RBZ must accentuate liquidity and capital requirements since both liquidity and capital ratios were significant and had higher marginal effects. Undoubtedly, the researcher recommends banks to curtail their operating expenses and also improve managerial efficiency so as promote and maintain bank safety and soundness and this will result in remarkable improvements in both profitability and efficiency ratios.

Table of contents

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ABBREVIATIONS AND ACRONYMS

DPB	Deposit Protection Board
DTA	Deposits-to-Assets Ratio
EFR	Efficiency Ratio
ELCH	Excessive Liquidity Creation Hypothesis
GDP	Gross Domestic Product
GRR	Gross Revenue Ratio
LSH	Liquidity Shortage Hypothesis

LTA	Loan-to-Assets Ratio
LTD	Loan-to-Deposits Ratio
MCR	Multi-currency Regime
NPL	Non Performing Loans Ratio
RBZ	Reserve Bank of Zimbabwe
ROA	Return on Assets
T1CR	Tier 1 Capital Ratio
TBTF	Too Big To Fail
WFH	Weak Fundamentals Hypothesis

CHAPTER 1: INTRODUCTION

1.1 Introduction

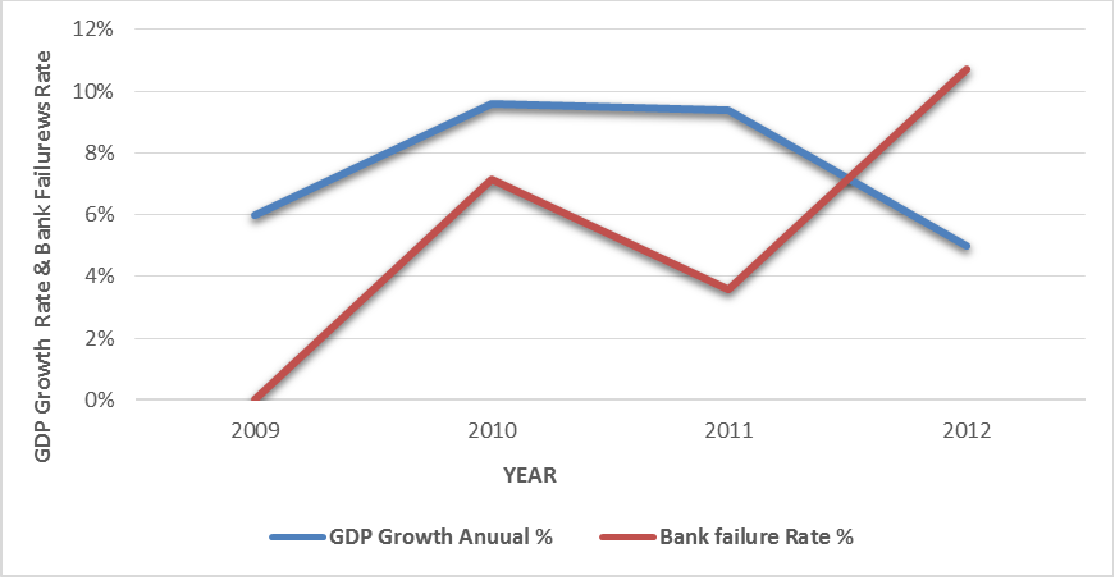
Banks balance sheets mainly constitute of liabilities that are usually short-term deposits and assets that take the form of both short and long-term loans to corporates, SMEs and individual consumers. When the value of bank assets falls short of the value of liabilities, banks are insolvent (Demirguc-Kunt and Detragiache, 1998). Bank insolvency thus can be explained as bank distress or bank failure and stakeholders such as investors, bank managers, depositors and regulators share keen interest in knowing what causes banks to fail and also desire the ability to predict which banks will get into difficulty so as to protect themselves from negative repercussions emanating from bank failures.

Bank failures normally brings dire consequences to stakeholders outside the failed banks themselves and are usually catastrophic because of domino fashioned fears that they may spread all over the banking and financial system as well as the entire economy. Considering that the banking sector is the hub for most financial activities in the financial system, failure of an individual banking institution introduces the possibility of systemic risk and this is perceived to spread wider. When a banking institution is placed under curatorship or liquidated, shareholders, clients and creditors may lose their funds which lead to bank runs and hence long-term panics in the economy. This was evidenced by RBZ (2013) when it announced that all funds invested with Interfin Bank Limited will remain frozen during the curatorship period. This engrains panics to stakeholders that were transacting with Interfin and other banking institutions leading to wane in public confidence. Bank collapses can impede employment, earnings, financial development, payment systems and economic growth through financial system instability.

1.2 Background to the Study

Bank failures remain a problematic phenomenon in the world. Major countries such as USA, Canada and Russia, to name a few, records bank failures almost every year. Africa as a continent is also documenting bank collapses on a yearly basis. Based on World Bank and RBZ figures, Zimbabwe as a country recorded increases in bank failures with corresponding deteriorating GDP growth rates since 2011 to 2012as shown in Figure 1.1.

Figure 1.1: Bank failure rate and GDP growth rate under Multicurrency regime



Source: World Bank (2009-2012)

Figure 1.1 clearly presents the relationship between GDP growth rate and bank failure rate in Zimbabwe. There was a simultaneous increase followed by a decrease in both bank failure rates and GDP growth rate during 2009-2010 and 2010-2011 respectively. From 2011-2012 there was an exponential rise in bank failures with a corresponding meltdown in GDP growth rate. However bank failure rate decreased during 2010-2011 and drastically rose during 2011-2012 while GDP growth rate gradually declined during 2010-2011 and steeply decreased during 2011-2012. Bank failures rate and GDP growth rate are exhibiting conflicting behaviours in different periods raising the question "does economic performance influence bank failure". There is no clarity from the presentation on the relationship that exists between economic performance and bank failures.

At the rear ofa series of bank failures that were experienced in Zimbabwe, the Reserve Bank of Zimbabwe (RBZ) had come up with a series of monetary policy reforms which were regarded as a panacea that pre-empts dire results emanating from failing banks. Most of these programs were

designed to capture both macroeconomic factors and some bank-specific variables that are presumed to fuel bank failure in Zimbabwe. Bank distress cases have ever since been in existence as we look back to Zimbabwean banking sector history fast-forwarding to the current multicurrency period. The common historic case was the collapse of Universal Merchant Bank Zimbabwe Ltd when the banking institution was acquired by CFX in 2002.

An exponential upsurge in bank collapses was documented in 2004when twelve (12) banks tumbled due to increased risk-taking which led to overexpansion without proper risk management systems, extreme asset and liability mismatches and abuse of corporate structures of firms (RBZ, 2005). Financial institutions that failed in 2004 were Barbican Bank Limited, Trust Bank Corporation, Royal Bank Zimbabwe Limited, Time Bank of Zimbabwe, CFX Bank Limited Rapid Discount House and Intermarket Banking Corporation. Corrective action by RBZ was taken, which resulted in the merging of Barbican, Royal and Trust Bank to form ZABG in 2005 which was latterly disintegrated in 2010. After some years of operations, some of the failed banks were reissued their operating licences to operate independently in September 2010 and these include Barbican, Trust and Royal bank.

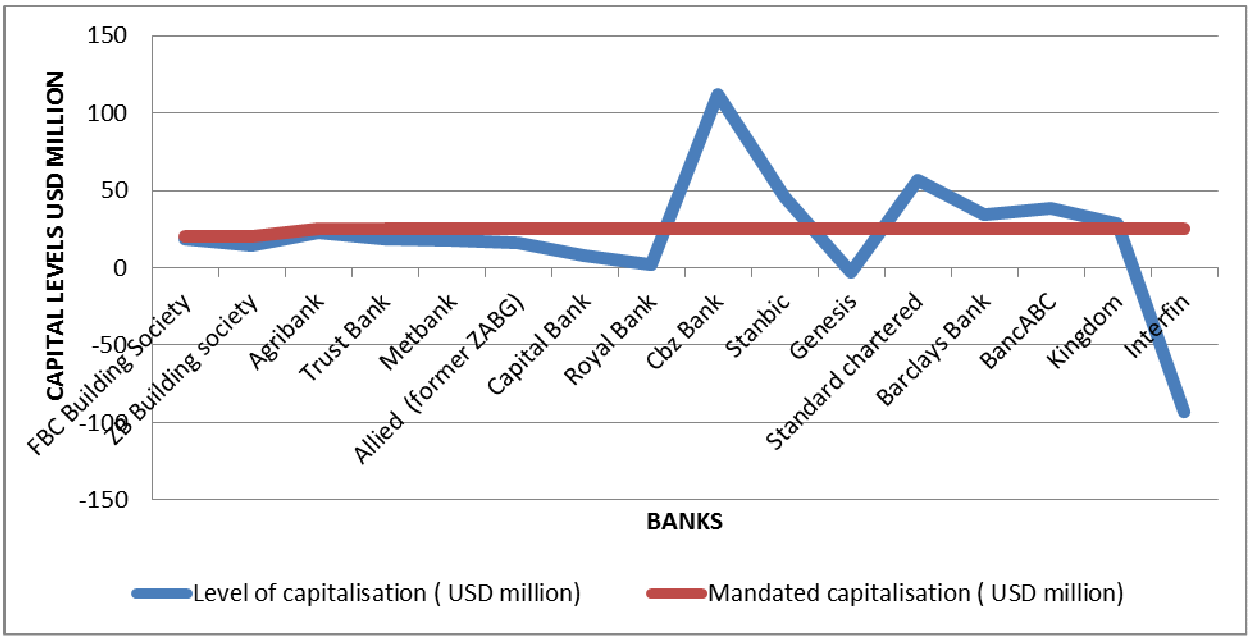
The 2007-08 financial crisis further accentuated bank failures and Beverly Building Society is one of the banks that disappeared during 2008 when it was acquired by CBZ. CFX which previously failed in 2004 collapsed for the second time when it was acquired by Interfin in 2010.Premier Banking Corporation was also acquired by Ecobank in the same year. Renaissance Merchant bank *(now Capital Bank Corporation Ltd*) partially failed in June 2011 and the bank managed to return back into the field after a period of curatorship by RBZ in March 2012.The institution failed due to gross irregularities which took the form of breakdown in corporate governance practices, abuse of group structure, technical insolvency and misuse of borrowed and depositors funds (RBZ, 2011)

According to IMF (2012) three small banks experienced severe distress, with one coming under curatorship and two giving up their licences. Bank that surrendered their operating licences were Royal and Genesis and this was in accordance with section 14(4) of the Banking Act [Chapter 24:20].Interfin was placed under recuperative curatorship by the central bank of Zimbabwe which was further

extended to 31th of December 2014. Barbican bank tumbled for the second time when failed to resume banking business since the period of relicensing and had its operating license revoked by RBZ in March 2013.

According to RBZ (2012) the major cause of recent bank failures were largely stemming from gross undercapitalization, higher non-performing loans and critical liquidity challenges that banks are facing. Banks such as Genesis and Royal bank were relenting unacceptable losses, such that Royal bank had posted a loss of US$598 million as at 30 June 2012. In terms of capitalization, Royal and Genesis had US$1.850 million and -US$3.20 million respectively, which were far below the mandated capital levels of US$25million. Another bank of issue is AFRASIA Kingdom bank which recorded debacle depletion in its capital base from US$31 million in December 2012 to $USD2, 4 million in June 2013. Figure 1.2 shows the levels of capitalisation between selected compliant and non-compliant banks.

Figure 1.2: Capitalisation levels as at 31 December 2012



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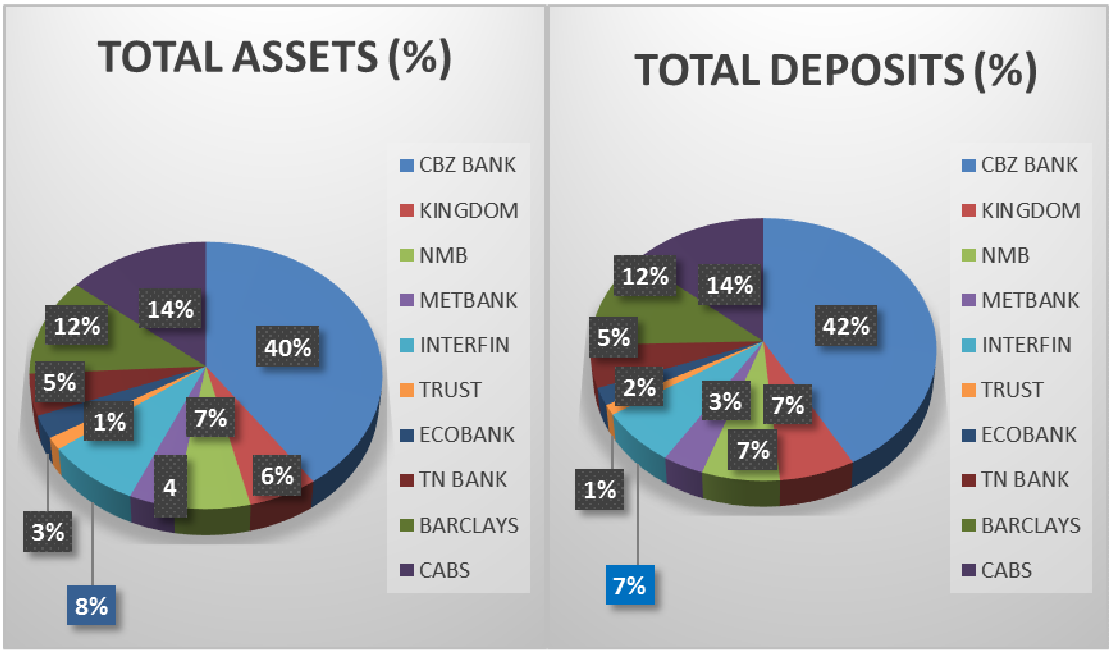
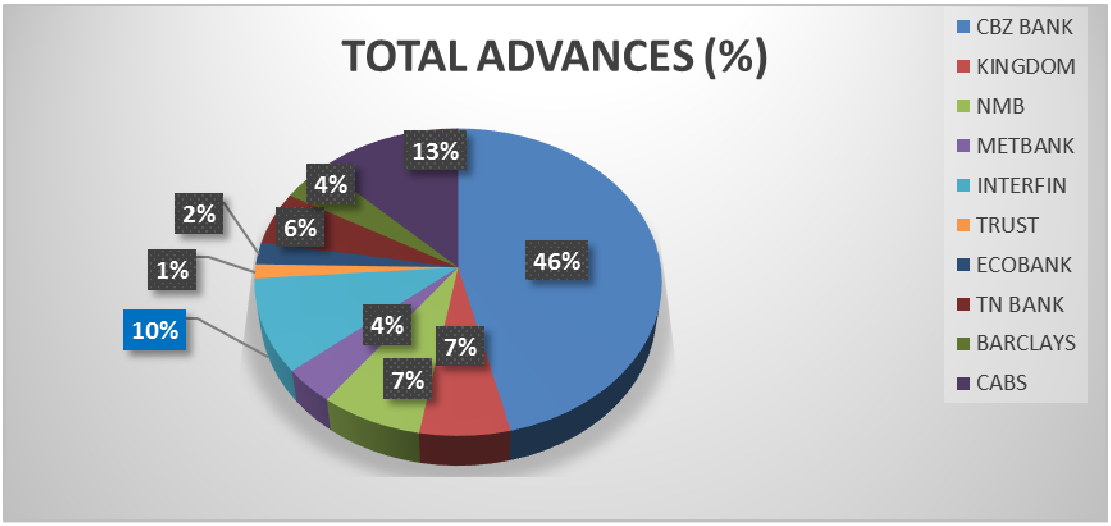
Source: RBZ (2013)

There is much oscillation in bank capitalisation relative to mandated levels as shown in figures 1.2. Only CBZ, Stanbic, Standard chartered, BancABC and Barclays are operating on safer capital levels. This situation is a clear signal that the Zimbabwean banking sector is surely under viability threat due to undercapitalisation of banks. According to RBZ (2013) seven out of twenty-two banks are undercapitalised and this is worrisome considering the fragility nature of the banking sector. Gross undercapitalisation of banks will remain a big challenge due to liquidity glitch that is crippling the entire economy. Banks have limited access to off-shore credit lines thus raising the question "how can banks be adequately capitalised or even have excess reserves in such a vacuumed economy characterised by low public confidence, lack of country's own currency and a closed lender of last resort window?"

Failure of some banks impacts the economy and some past bank failures witnessed a great loss to both the banking sector as well as the Zimbabwean economy. Li (2013) supported this view when indicated that an increase in bank failures can affect the overall economic health and the stability of a nation. This is clearer if we make the following comparisons based on specific variables on failed and surviving banks. Figure 1.3 shows each institution's market share in respective fields.

Figure 1.3: Market dominance between failed and surviving banks





Source: Audited financial statements (2012)

Apparently it can be seen that Interfin bank had a greater standing in the market in terms of market share of assets, deposits as well as advances. In terms of market share of total advances, the bank is ranked the third with 10% share in the sample. The institution was also ranked the forth in market share of assets and deposits with 8% and 7% share respectively. In terms of deposits market share, Interfin outperformed Barclays bank which operates internationally and this registered it a systemic importance bank based on the above analysis. The bank dominated the market than some of the surviving banks such as Kingdom, NMB, Metbank, Trust and TN bank. This being so, tumbling of such better standing banking institutions as Interfin is catastrophic to the economy and may abate the whole banking system.

However, in the wake of a series of bank failures, RBZ designed the Troubled Bank Resolution Framework (TBRF) in 2005 whose major objectives were to: strengthen the banking system and promote sound banking practices, develop permanent solutions for troubled banking institutions, promote economic development and growth and restore stability of the financial sector; and preserve indigenization of the financial sector. The formation of ZABG in September 2005 was in accordance with the aforesaid framework which was established under the Troubled Financial Institutions Resolution Act. It can be discerned from the given objectives that TBRF was proactive in scope.

RBZ had also recently implemented the Basel II accord that is aimed at aligning Zimbabwean banks to international banking standards. In its endeavour to ensure effective implementation of the Basel accord by subordinate banks, RBZ issued a Technical Guidance on Basel II Implementation framework that govern and outlines the implementation procedure of the accord. To complement the Basel II accord on an ongoing process, RBZ had also introduced a The Enhanced Troubled and Insolvent Bank Resolution Policy (TIBR) Framework in 2013. The policy provides a framework, underpinned by fair, consistent, transparent, cost effective and timely problem resolution principles to be followed by any troubled banking institution (RBZ, 2013). All these tools were developed to occlude bank failures but the problem seems to reign in the presence of the aforesaid policies.

1.3 Problem Statement

Zimbabwean financial system had experienced periods of financial distress characterised by a plethora of bank failures, as well as by severe deterioration of the whole financial system's health. In response to bank collapses that the Zimbabwean economy experienced, so many monetary policy revisions have been done by RBZ to reduce these bank failure cases. However, if Basel accords and resolution policies such as TBRF and TIBP were panacea to bank collapses, "why are bank failures still prevailing in the presence of these revisions?" Why bank failures still prevalent under the MCR which was considered to be the adoption of a more stable currency? How adequate are capital mandates and GDP growth rates in explaining bank failures in light of their behaviours as indicated in figures 1.1 and 1.2?"

1.4 Research Objectives

This study seeks to achieve the following objectives:

- To determine whether bank-specific variables are the major determinants of bank failures.
- To highlight any link, if any, between macroeconomic variables and bank failure.
- To develop and estimate a model of bank failures in Zimbabwe.
- To reveal possible ways to deal with failed banks

1.5 Research Hypothesis

The study will test the following hypothesis:

$H_{0:}$ Bank-specific and macroeconomic variables are not the major determinants of bank failure in Zimbabwe.

$H_{1:}$ Bank-specific and macroeconomic variables are the major causes of bank failures in Zimbabwe.

1.6 Scope of the Study

The study will look at bank failures experienced in Zimbabwe after the adoption of the multicurrency system, that is, from 2009-2012. The research will be concentrated between 2009 and 2012 because this is the period where recent bank failures took place after dollarization and the only period with sufficient data necessary for final analysis. Banks under consideration include three failed and eleven surviving banks registered as either commercial banks or merchant banks only.

1.7 Significance of the Study

In Zimbabwe banks are usually identified as failing when they already collapsed and much of RBZ on-site examination covers qualitative causes of bank failures as enshrined in the Basel accord, with little emphases on the quantitative effects or magnitude of individual causes. Since the commencement of MCR, all banks were subjected to RBZ's rating based on CAMELS framework but all the same bank failures are still alarming. This then raises questions on the adequacy of RBZ's rating system which can be used to identify and monitor weaker banks. Also Mabvure *et al.* (2012) analysed the sources of non-performing loans but did not dug into their influence on banks' survival equation thus the researcher wishes to cover this gap by identifying the influence of non-performing loan on the possibility of bank failure.

This study will create a better understanding on sources of bank failure along with quantitative effect of each variable and will derive a model based on identified sources. Basing on research findings, regulators and the government shall develop resolution policies based on effects of each cause not on subjective qualitative information associated with each cause. Managers and the other members of staff in the banking sector may be able to interpret, assess and manage their operating activities using the

expected bank failure model. The research, if useful, will be used as reference material for the university library and other related researches. The research may also be used to identify modules that may be added to the current ones as they may be of value in nurturing a total graduate ready to compete in the industry.

1.8 Assumptions of the study

The study will be conducted under a general guideline of the following assumptions:

- Data to be used in this study will be free from errors.
- Selected surviving banks fully represent non-failed banks' population.
- Financial statements are free from window dressing.
- The study will be objective in data analysis and presentation.

1.9 Limitations of the Study

The researcher faced a number of problems during the course of the study and they include:

- The main limitation to this study was time constraint to conduct a more detailed market research.
- The researcher had challenges in obtaining the required financial data from responsible regulatory authorities.
- The researcher had limited resources to conduct a full research on each and every variable that was involved in the Models used to simplify the study.
- The researcher had limited knowledge to very useful Stata data analysis package that are used to estimate data and so time was lost trying to grasp concepts.

1.10 Definition of key terms

Bank failure is when a weaker banking institution is placed under recuperative curatorship,

liquidated, merged or acquired by a healthier bank or when its operating license is revoked by RBZ.

1.11 Organization of the study

Chapter One looked at the background to the study, the problem statement, research objectives, research hypothesis, scope of the study, significance of the study, assumptions and limitations of the study. Chapter Two covered theoretical and empirical works related to bank failures and bank failure models used by various researchers. Chapter Three looks at the research methodology and Chapter Four works on research results and interpretations. Lastly the researcher will make some conclusions and recommendations in Chapter Five.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The literature review section will look at the theories and empirical studies on determinants of bank failures using various models.

2.1.1 Theoretical Literature Review

There is a limited number of theories on the factors that influences bank failures. The most widely discussed theories are the moral hazard and adverse selection theories which are usually discussed from the insurance perspective. Mishkin and Eakins (2009) are of the idea that adverse selection occurs when one party in a transaction has up to date information than the other party and that it exist before transaction occurs where potential borrowers that are most likely to produce adverse outcome are the ones that seek loans and get selected. Mishkin and Eakins (2009) also explained that moral hazard occurs when one party has an incentive to behave differently once an agreement is made between parties and that it exists after transaction occurs where the hazard that borrower has incentive to engage in undesirable (immoral) activities makes it more likely that borrowers won't pay loan back.

Based on the above theories, it is clear that both moral hazard and adverse selection are a result of information asymmetry. This was supported by Laiboni (2012) when cited that asymmetric information creates a problem in the banking sector both before the transaction is closed (adverse selection) and after the transaction has been closed (moral hazard). The author further explained that based on adverse selection theory, lender faces some challenges when attempting to differentiate between good borrowers with good credit risks and bad borrowers with bad credit risks profiles thus they will demand premium to compensate for the risk being assumed. Inability to pinpoint bad from good borrowers makes it more probable for bad credit risks (bad borrowers) to acquire loans than good credit risk (good borrowers). High interest charges will discourage good credit risk from borrowing because of devaluation of good borrowing reputation (credit history) while bad borrowers will be willing to borrower because they will be aware that they should get funds at higher rates due to their credit risk profiles. After loan disbursement, bad credit risk may venture into immoral projects (moral hazard).

Selection and disbursement of loans to bad credit risks exposes the bank to high defaults since loans would have been given to bad borrowers who have incentives to engage into immoral projects. As a result, lenders end up with loan portfolio comprising almost entirely of bad credit risk (Laiboni, 2012). Loan portfolio constituting high credit risk imply higher levels of non-performing loans, and high levels of non-performing loans infer deterioration in bank assets and hence failure. Issue of the impact of non-performing loans on banks have been discussed by Balasubramanyan (2010), Babanskiy (2012) and Shaffer (2012) and this will be discussed in the empirical review section.

Bank failures are sometimes explained by interconnection between “too big to fail” and moral hazard theories. Too big to fail (TBTF) theory holds the notion that large banks exhibit higher systemic importance in the economy. This being so, authorities endeavour to prevent tumbling of such an institution because its downfall poses disruptions and instabilities to the financial system as well as the entire economy. However preventing TBTF banks from failing is assumed to maintain financial system stability in the short-run (Labonte, 2013). The author explained that rescuing banks is anticipated to result in unstable financial system in the long run because of moral hazard that weakens market discipline.

Labonte (2013) defined moral hazard in the context of TBTF as a theory that if TBTF firms expect that failure will be prevented, they have an incentive to take greater risk than they otherwise would because they are shielded from negative consequences of those risks. However moral hazard problem does not always emanate from the thinking that banks will be rescued if they fail. This was evidenced by episodes of bank failures in Zimbabwe in 2004. None of the failed bank was considered systemically important and their engagement into risky activities was not based on the fact that they will be rescued because the lender of last resort window was closed and government had no funds to bailout banks. Also moral hazard may result from information asymmetry not merely from the availability of bailout programmes. This then abate Labonte hypothesis as the author assumed that moral hazard in bailout context lead to banks to venture into risky activities which lead to failure because they hold a belief that they will be rescued by the government.

Stern and Feldman (2004) further dug into moral hazard and TBTF problems when highlighted that moral hazard problem provides an incentive for firms to grow in order to be perceived as TBTF. In this regard, banks hold the belief that if they permit themselves to grow bigger, they will be considered "too big" thus authorities will not allow them "to fail". However systemic importance of an institution lies not only on its size as traditionally assumed, thus some authors eliminated the use of bank size as a measurement for systemic importance by suggesting new terms. Bernanke (2009) advocated for "too interconnected to fail" and Rajan (2009) is of the idea of "too systemic to fail". New terms were developed due to differences in views of measuring the systemic importance of a bank and that it is not size alone that cause contagion but rather the fact that most activities in certain key market segments flows through those firms (Labonte, 2013). This author was validating such theories as "too interconnected to fail" and "too systemic to fail". The assertion lies along the fact that financial institutions must be considered systemic important based on their linkage to other institutions' activities not on their size alone. Based on contemporary banking theory, banks are assumed to offer transfer and payment systems and failure of an institution, whether large or small in size, which links the majority of market players in the economy may lead to series of failures in other institutions. This means placing value on bank connectedness to other market players rather than basing on its size because there are also banks that are big in size but with little links with other institutions.

According to Labonte (2013) TBTF problem can be addressed by, inter alia, bailout efforts, designing preventative policies and reactive policies and mandating higher capital requirements. Each of these efforts has its own downside implications. For example higher capital requirements can induce higher risk as cited by Gennotte and Pyle (1991). Besanko and Kanatas (1993) supported this when reviewed that high capital requirements lead to greater outside equity which could increase moral hazard because managers (insiders) have a reduced stake in the bank. Bailout effort may or may not include removal of the management as highlighted by Labonte (2013). The author explained that even if management believes that losses will lead to their removal, they prefer risk taking (with higher expected profits) because they are personally not liable of the firm's losses and this lead to principal-agent problem. Thus bailout efforts may further complicate moral hazard and principal agent issues that may lead to ultimate failure of an institution.

In contrast to Labonte view, Honohan and Klingebiel (2000) documents relaxation in prudential requirements such as capitalisation levels and loan loss provisions in order to allow troubled bank to afloat. The researcher further postulate that regulatory forbearance can prevent disruptions to the banking system caused by closures of failed banks. However weaker banks must not operate and these researchers' theory was formulated ignoring the importance and fragility of the banking sector. If all banks are permitted to operate undercapitalised and with less or no loan loss provision, "how would these banks survive contingency events and where do the cushion comes from?" It is both impractical and unprofessional to allow banks operate undercapitalised and with insufficient loan loss provisions. The remedy to this is that bank capitalisation and loan loss reserves must not be subjected to "one-size-fits-all approach" but rather bank-specific considering such factor as risk inherent with a particular banking institution. Regulatory forbearance is just equivalent to ignoring a dying patient and this is detrimental to other banks. Regulatory forbearance is harmful because it promote systemic risk and the only way to block the wide spread is through early intervention by responsible authorities

Modern theory of financial intermediation suggest that banks exist to assume two major functions namely liquidity creation and risk transformation. Liquidity creation theory holds that banks can create liquidity on-the balance sheet by financing relatively illiquid assets with relatively liquid liabilities. Kashyap, Rajan and Stein (2002) suggests that banks can also create liquidity off-the balance sheet by loan commitments and akin claims to liquid funds. Risk transformation theory postulates that banks can transform risk through the issuance of riskless deposits to finance risky loans (Ramakrishnan and Thakor, 1984).

The liquidity creation and risk transformation theories coincide, that is to say, there is financing of assets with liabilities in both scenarios. The two theories explain bank failure when merged with the insolvency theory. Samad (2012) explained the insolvency theory as a theory which holds that banks fail when bank assets value falls short of its value of liabilities. Since assets (loans) that need to be financed are risky under the risk transformation theory, they are subject to default risk which ultimately accentuates non-performing loan levels. Samad (2012) supported this by adding on that assets value deteriorate as a result of credit risk emanating from non-performing loans. When the value of these

assets falls below bank liabilities, a bank will be said to have failed and this would have been initiated by risk transformation incentives. This was also reinforced by Allen and Gale (2004) when indicated that financial intermediaries 'role as risk transformers and liquidity creators exposes them to risk of failure. The authors further explained that when banks create liquidity, the likelihood of distress increases and severity of losses is execrated as assets are liquidated to meet liquidity demands.

Based on the liquidity creation theory, banks may also raise the likelihood of failure by creating excess liquidity as reviewed by excess liquidity creation hypothesis (ELCH) developed by Fungacova, Ariss and Weill (2013). According to ELCH a rise in bank's core liquidity creation activity increases its probability of failure. The hypothesis assumed that bank failure results from banks excessively engaging in its role as liquidity creators based on financial intermediation theory.

Fungacova, Ariss and Weill (2013) highlighted that there are two hypotheses that dominate the literature of bank failures namely, the weak fundamentals hypothesis (WFH) and the liquidity shortages hypothesis (LSH). The WFH and LSH were the foundation for the development of the ELCH. WFH covers poor bank fundamentals that warn of an impending bank failure. The hypothesis identifies banks with weak fundamentals and views fragility from assets risk perspective. WFH is usually proxied by CAMELS elements that act as early warning systems with decaying capital ratios, reduced liquidity, deterioration loan quality, and depleted earnings indicating a rising chance of bank failure (Fungacova, Ariss and Weill, 2013).

LSH focuses on bank's inability to meet liquidity commitments. It assumes that bank fragility arise from irrational behaviour of uninformed depositors who are incapable of differentiating between liquidity and solvency shocks (Fungacova, Ariss and Weill, 2013). The theory assumes risk of failure as emanating from liability side of the statement of financial position. LSH assumes banks to be solvent but because they finance illiquid assets with liquid liability (liquidity creation theory), they are exposed to external shocks that may lead to liquidity shortages. Probability of failure, thus rises with banks inability to timely and fully accommodate deposits redemption. However these authors failed to identify the equilibrium point were ELCH and LSH interacts because ELCH assumes failure from excess liquidity creation standing point and LSH assumes failure from liquidity shortage perspective thus there is need to determine the equilibrium liquidity creation point to hedge impending failure.

Fungacova, Ariss and Weill (2013) developed ELCH to explain bank failures resting on the interaction between assets (WFH) and liabilities (LSH) risks. These authors opine that regulators can hedge systemic distress under ELCH through early identification of excessive liquidity creators and enhanced monitoring of their activities. WFH can be used to hedge against bank failures by developing prudential macroeconomic policies that promote bank stability and limit moral hazard incentives. The authors further indicated that LSH addresses confidence-building assistance mechanism to reduce the depositors' incentives for bank runs (deposit insurance, central lender of last resort actions and government bail outs).Calomiris (2007) also identified central bank lending during crises, deposit insurance, and government-sponsored bank bailouts as public policies toward banks and these policies include assistance mechanisms intended to protect banks from unwarranted withdrawals of deposits. Calomiris identified prudential regulatory policies intended to promote banking system stability, and to prevent banks from taking advantage of government protection by increasing their riskiness through moral-hazard problem of protection. Prudential regulation that Calomiris had identified is similar to ways of hedging against WFH that Fungacova, Ariss and Weill (2013) had advocated.

However some of the suggested hedging mechanism that Fungacova, Ariss and Weill (2013) proposed on WFH, LSH and ELCH bears financial feedbacks in return and lead to conflicting objectives. For example (LSH) deposit insurances, lender of last resort actions and government bailouts efforts creates incentives for moral hazard which WFH attempts to minimize. The major weakness of WFH, LSH, and ELCH is that they hold a notion that failure is a function of liquidity levels and bank fundamentals ignoring such potential pressures from the macroeconomic environment and political interferences.

There are a number of macroeconomic and financial linkage theories but the researcher wishes to explain bank failures from creditors' perspective. Generally banks receive funds from bank creditors such as depositor which are then loaned out to borrowers. Bhattacharya and Thakor (1993) indicated that this deposit financing makes banks vulnerable to bank run. According to this author bank runs relates to an individual bank and panic is a simultaneous run on many banks. From this explanation, when individual banks fail to accommodate deposit redemption, they face bank runs which then affect the entire sector leading to panics and finally failure. In broader sense, when depositors (at macro level)

suddenly withdraw their funds from an individual institution, they subject that bank to failure and due linkages that an individual institution has with other banks, this will induce subsequent failures (systemic failures).

2.2 Empirical Literature Review

This section will focus on studies that were carried out to empirically test the theories that the researcher had sighted in the theoretical review section. Tannuri, Maria, Sales and Adriana (2005) applied duration model with exponential hazard and exponential piecewise-constant hazard function to study determinants of bank failures in Brazil from 1994-1998. The research included such variables as real assets, return on assets, coverage ratio, non-performing loans and adjusted operational margin. Findings showed that bank-level indicators used as covariates in conditional models showed to be significantly related to failure probability and none of liquidity indicators were relevant.

Bouvatier, Brei and Yang (2013) also examined the determinants of bank failures in the US during the financial crisis of 2008. Their analysis employed limited dependent variable regression techniques such as pooled logit estimator. Research variables were largely based on the CAMELS framework. Findings indicated that banks that failed were characterised by higher loan growth rates, lower levels of capital, higher non-performing loans and higher exposure to mortgage market. Also logit results showed that banks were more likely to fail when they were owned by lower capitalised bank holdings that relied more on funding from money markets and other non-bank subsidiaries. Regression results also supported the study hypothesis that bank specific together with macroeconomic indicators play an important role in determining failures.

2.2.1 Bank size

The most common determinant of bank failure that has been identified in almost every research is the size of the bank itself. Borovikova (2000), Nikolsko-Rzhevskyy (2003), Bagatiuk and Dzhamalova (2009), Cole and White (2011) and Li (2013) opines that size of the bank is a significant determinant of its

failure. These entire authors incorporated this variable in their model but were not in consensus as to whether bank size influences failure positively or negatively. Taran (2012) and Li (2013) remained sceptical of the correlation that exists between bank size and the probability of failure. However all these researchers agreed in their research papers that bank size is proxied by the natural logarithm of bank gross assets.

Bagatiuk and Dzhamalova (2009) employed both linear probability and binary response models such as probit model to investigate financial ratios that better explains bank failures in Russia and Ukraine. The researchers used these models to analyse data on banks from 2002-2008. Their research findings revealed that bank size influence bank failure negatively thus they concluded a negative correlation between bank size and failure. The research results also were also consistent with empirical results of Gonzalez and Kiefer (2006). Gonzalez and Kiefer (2006) concluded that size has negative impact on bank failure, ceteris paribus, and that increase in this variable decreases the risk of bank failure.

The negative sign implies a negative association between bank size and the probability of bank failure. Cole and White (2011) and Li (2013) in their studies carried in USA remained sceptical of the expected sign between bank size and the probability of bank failure. According to Shim (2013), large banks tend to be more diversified when managing capital assets and have easier access to capital markets than smaller banks, implying that small banks are more prone to bank failure than large banks. However Li (2013) cited that large banks might be prone to risky lending activities which may lead to huge losses and failure.

Nikolsko-Rzhevskyy (2003) examined causes of bank failures in Ukraine during 1998-2003 using micro-level data by employing Giant logit model and parametric survival estimator. Empirical results showed that bank size influences failure. Both models supported the findings that the bigger the bank, the less likely it will go into bankruptcy.

2.2.2 Moral hazard *(salary expenses)*

Some bank failures are also influenced by moral hazard but there is limited literature to econometrically support and incorporate moral hazard variables. Borovikova (2000) is one of the researchers who captured moral hazard problems by including the issue of salary expenses in the bank failure model. The author postulate that salary expenses influence bank failure and that this variable was a good detector

of moral hazard problem. According to Borovikova, salary expenses are assumed to be negatively correlated to the probability of bank failure.

Borovikova (2000) empirically tested the proposition that the probability and timing of bank failure depends on bank-specific factors, general macroeconomic conditions and political factors using a split-population survival time model to Belarusian banks. The model covered bank failures from 1992-1999. Research result revealed that salary expenses negatively influence bank failures.

2.2.3 Assets quality *(Non-performing loans)*

Copious studies document asset-related problem to be chief causes of bank failure. Oshinsky and Olin (2005), Shaffer (2012) and Babanskiy (2012) were of the opinion that bank failure was more sensitive to non-performing loans. Oshinsky and Olin (2005) showed that banks that have riskier assets tend to have a high probability of failure. They recognised that fee income from riskier assets result in a higher non-interest which bears a positive correlation with failure. Campbell (2007) further explained that non-performing loans, that are considered to be asset quality indicators, have been the most common factor in all recent researches.

Balasubramanyan (2010) further alluded that non-performing loans lead to huge write downs which erodes the capital base of the bank. This was evidenced by Afrasia Kingdom Bank Zimbabwe that recorded US$21million of non-performing loans in May 2013 and this misappropriated the survival equation of the institution. High levels of non-performing loans posted by Kingdom led to debacle depletion of its capital base from US$31 million as at December 2012 to US$2.4 million as at June 2013.

Shaffer (2012) used the logit estimator in the US and found that bank failures were largely related to non-performing loans (NPL) in 2008 and in 1980s. RBZ (2012) also identified the impact of non-performing loans on loan books. The 2012 on-site examination determined 99.22% non-performing loans on the total loan book of $1.52million as at 31 May 2012 for Royal Bank Zimbabwe. This non-performing loans level is far much above the prudential benchmark of 5% stipulated in Basel II. Apparently it can be seen that this was the master cause of Royal bank's collapse since loans constitute

a larger proportion of bank's assets. All research results showed positive sign associated with this variable, implying that the higher the non-performing loans level the greater the probability of failure.

Mabvure *et al*. (2012) further dug into the sources of non-performing loans in Zimbabwe. The researchers used a case study research design based on CBZ Bank Ltd backed by some questionnaires. Research found out that the major causes of non-performing in Zimbabwe were natural disasters, government policies and integrity of the borrower. These authors also revealed that failure of banks such as Renaissance Merchant Bank, Interfin Bank and Royal Bank was also due to higher non-performing loans. Non-performing loans could rise further with the ongoing deceleration in economic activity (IMF, 2012). If this is merged with other theories of bank failure, then banks are more likely to continue failing in Zimbabwe.

Samad (2012) empirically tested the significant determinants, among credit risk variables, of US bank failures in USA in 2009. The study employed the Probit Model and found that among credit risk variables, the credit loss to net charge off, loan loss allowances to non-current loans and non-current loans were significant for predicting bank failures. The model had 80.17 predictive power.

2.2.4 Excessive lending

Bank lending activity must be performed with much savvy in relation customers that an institution is dealing with, maximum volume of loan portfolio that the bank wishes to maintain and finally regulatory benchmarks. DeYoung (2003) stipulates that excessive lending, volatile assets growth and equity ratios substantially contribute to bank failure. The author found that increases in non-interest income are closely linked to volatile earnings. DeYoung and Rice (2004) further explained that banks that are managed better are less likely to focus on large scale of traditional fee-based activities.

This was further supported by Kim and Miner (2007) when they argued that banks that aggressively engage in area outside their expertise are more likely to face higher risk and eventually fail. The downfall of Interfin Merchant bank was related to excessive lending since the bank had loan to deposit ratio of

114.2%. This implied that the institution used more of its depositor's funds to finance loan requests and considering that the institution was a Merchant bank, it had exceeded its maximum limits by greater margins.

2.2.5 GDP growth rate

Banks do not operate in an isolated tower but rather in an economy where they transact with less ability to influence the outside environment. Calomiris and Joseph (2003) and Wai (2009) found that the major determinant of bank failure is the state of the economy. Wai (2009) revealed that banks are more susceptible to bank failure during economic slump, which aggravate mistakes made during periods of buoyant growth. Calomiris and Joseph (2003) declared that banks fail when the economy is contracting. Their justification lies on the fact that asset prices fall and loan defaults increases in response to the contracting economy which will ultimate spur bank insolvency. Their study also revealed significant correlations between the characteristics of banks, the environment in which they operate and their chance of surviving the contracting economy.

Some researchers such as Cebula, Koch and Fenili (2011), Mayes and Stremmel (2012) identified real gross domestic product (GDP) growth rate as a cause of bank failure. Researchers such as Lanine and Vennet (2006) neglected macroeconomic variables basing on the fact that all banks will be facing similar conditions. However there is need to incorporate this variable since similar macroeconomic variables such as GDP growth rate can influence banks differently. The bedrock assumption is that banks are affected differently by similar macroeconomic variables. This is the reason why some banks survived the Zimbabwean hyperinflationary environment of 2007-08. If inflation had exerted similar pressures on all banking institutions, then all banks could have collapsed.

Mayes and Stremmel (2012) used the logit technique and discrete time analysis in USA to determine the influence of GDP growth rate in predicting bank failures. The research used US bank data from 1992-2012 and research results revealed negative influence of GDP growth rate on bank failures. Cebula, Koch and Fenili (2011) empirical results also conformed to the research hypothesis that real GDP growth is

negatively correlated with the possibility of bank failures. Negative correlation implied that when economic conditions are good, real GDP will be high and banks are less likely to fail.

However, there is no clear-cut on whether bank failures influences economic growth or that it is economic growth that influences bank failures. Kupiec and Ramirez (2008) investigated the effect of bank failures on economic growth in the US using VAR and a difference-in-difference methodology. Their results indicated that bank failures reduce subsequent economic growth.

2.2.6 Political interference

Borovikova (2000) included government intervention and political risk as determinants of bank failure in the case of Belarus. Borovikova found that government intervention is negatively correlated to bank failure. RBZ (2006) also document that political interference with banks in the areas of lending and recovery played a significant role in bank solvency in 2004.

In contrast to RBZ (2006) findings, Borovikova (2000) used a split-population survival time model to Belarusian banks for the period from 1992-1999. Research findings showed that political variables had no significant influence on the probability of failure. The major reason why RBZ (2006) made a conclusion that varies from that of Borovikova (2000) is the difference in levels of political interference on banks by different government in their respective economies. In reiteration, political pressures that Zimbabwean banks face are different from those that were faced by Belarusian banks.

2.2.7 Loan type and concentration

Cole and White (2011) analysed why banks failed in 2009 in US using multivariate logistic regression technique. Using bank specific data, results revealed that real estate loans play an important role in determining which banks survive and which banks fail. Study findings also indicated that banks with higher loan allocations to construction-and-development, commercial mortgage and multi-family

mortgage were likely to fail. However investment in mortgage-backed securities was found to have little or no impact on likelihood of failure.

2.2.8 Capitalization

Various studies captured capitalisation from different standpoints but the majority relied on the CAMELS framework. Adeyemi (2011) established the main determinants responsible for bank failures in Nigeria from 1994-2003. The author used a survey research design through the use of questionnaires. The study observed that inadequate capital among other causes was accountable for bank failures in Nigeria.

Gonzalez and Kiefer (2006) employed a duration model to identify main bank specific determinants of bank failures in Colombia. To capture capitalisation, their study used the ratio of total equity to total assets ratio. The study suggested that capitalisation is negatively correlated to probability of bank failure, implying that capitalisation results in a reduction of banks' probability of failure. Research finding showed that capitalisation ratio was the most significant indicator explaining bank failures.

Estrella, Park and Peristiani (2000) used a logit model to compare the effectiveness of different types of capital ratios in predicting bank failure in US using 1988-1992 data. The researcher used leverage, gross revenue and risk-weighted ratios. These authors totally neglected the ratio of total equity to assets that has been used by Gonzalez and Kiefer (2006). The fact was that unlike assets, gross revenue includes components associated with off-balance-sheet activities. Moreover, gross revenue contains a crude risk adjustment in that riskier projects are likely to be undertaken only if they provide larger revenues, at least ex ante. Thus, gross revenue may reflect the riskiness of bank assets better than total assets.Li (2013) suggested a negative correlation between this variable and bank failure, which implies that banks with higher gross revenue ratio will be less likely to fail

Estrella Park and Peristiani (2000) also criticised the gross revenue ratio suggesting it captures factors other than risk. For example, banks engaging heavily in fee-generating activities, which may carry only a limited amount of risk, will report large revenue. Gross revenue may also be more sensitive to business cycles than total assets.Findings revealed that simple ratio, specifically the leverage ratio and the ratio of capital to gross revenue, predict bank failure as well as the more complex risk-weighted ratio.

However Mayes and Stremmel (2012) research findings were consistent with Estrella Park and Peristiani (2000) in terms of leverage ratios but not in the case of risk-weighted capital. Using the logit technique and discrete survival time analysis in US, they found that non-risk weighted capital and leverage ratio explained bank failures best.

Lanine and Vennet (2006) analysed the determinants of bank failure in Russia from 1998-2004 using the logit and trait recognition methods. The empirical results indicated that banks need sufficient capital to hedge against liquidity risk, default risk and capital risk that banks can face.

2.2.9 Managerial quality

Bank failures also emanate from managerial inefficiency. Chinn and Kletzer (2000), Deckle and Kletzer (2001) are of the opinion that the main source of failure rest on bank vulnerabilities to bad management practices reflected in deterioration of their portfolio and capital structure. DeYoung (2003), Wheelock and Wilson (2006) also identified managerial inefficiency as the primary cause for bank failures. DeYoung (2003) further document that operational cost inefficiency increase the likelihood of failure.

RBZ (2006) argued that mismanagement mainly excessive risk-taking is the major determinant of most bank failures in Zimbabwe. RBZ (2006) categorized mismanagement into four folds that are technical mismanagement, cosmetic management, desperate management and fraud. According to RBZ (2006), technical mismanagement involves inadequate policies and procedures, cosmetic encompasses concealing past and current losses to buy time and remain in control while looking and waiting for solution. Clearly cosmetic mismanagement shows central bank's ineffectiveness in terms of on-site examination.

Managerial quality assessment was captured from different angles by many researchers. Ploeg (2010) used the probit, logit, hazard and neural networks model on US banks from 1987-2008. The researcher employed the ratio of total operating expenses to total operating income as a measure of management performance. Researcher findings suggest that banks with high operating expenses relative to operating

income are expected to be less efficient and thus have higher probability of failure. Ercan and Evirgen (2009) advocate for the use of net income relative to the number of branches as the measure of managerial efficiency. Halling and Hayden (2006) states that the number of employees also could be indicators of management performance, indicating the bank's productivity. The baseline was that the more productive a bank is, the bank the lower is the likelihood of collapse. Nikolsko-Rzhevskyy (2003) indicated that managerial efficiency accounts for bank soundness using the duration model. The bedrock hypothesis was that the higher is managerial efficiency, the less likely that bank will go into bankruptcy.

Tatom and Houston (2011), Kao and Liu (2004) evaluated management efficiency using Data Envelopment Analysis (DEA). Tatom and Houston (2011) employed the logit and probit model to analyse US banks data for 1988-1994 and 2006-2010 and they explained that DEA is a method of examining production efficiency. Mayes and Stremmel (2012) used an efficiency ratio to assess the management quality. According to these researchers, the efficiency ratio reflects expenses as a percentage of revenue.

2.2.10 Earnings ability

Bongini *et al*. (2001), Lanine and Vennet (2005) advocate that the usual indicator for earnings is return on assets (ROA) which is the general measure of bank profitability. Lanine and Vennet (2005) used the logit and trait recognition methods in Russia from 1998-2004. Some researchers back this ratio with ROE. However according to Taran (2012) the effect of the earnings factor is quite ambiguous. From one side, earnings may reflect the efficiency and operational performance and thus have a negative effect on the probability of failure as suggested by Lanine and Vennet (2005). Taran (2012) further explained that from the other side, high profitability may reflect a high level of portfolio risk, and thus has the positive impact on the likelihood of crash as sighted by Jordan *et al*. (2010).

Shim (2013), Samad and Glenn (2012) also made use of ROA and documents that higher ROA means greater efficiency in converting assets into net income. Low ROA indicating less efficiency and that the

organization is more likely to experience financial difficulty. These researchers expect this variable to have negative impact on the failure of banks.

Popruga (2001) utilised the probit cross-section model to identify factors that reduces or raise the probability of becoming bankruptcy in Ukraine. The study employed data for the period of 1995-1996 and findings revealed that, among other indicators, ROA is not key determinant of the soundness of Ukrainian medium-sized bank.

2.2.11 Liquidity

Some researches considered bank liquidity as a potential source of failure. Arena (2008) stipulates that liquidity shocks provoke bank failures due to their inability to honour their short term obligations. Chang and Velasco (1999) supported this view by adding on that if bank potential short-term debt exceeds its liquidation value, the bank run equilibrium exist. It is this equilibrium that will lead to ultimate failure of the bank. In a more general, these authors were sighting on the importance of matching bank assets and liabilities basing on the grounds that failure of any banking institution to cover its short position can also cause failures.

Different ratios were used by many researchers with some augmenting each other to produce plausible results. Arena (2008) captured liquidity as a ratio of liquid assets to total liabilities. Arena shows that liquidity ratio have an inverse relationship with the probability of bank crash in East Asia and Latin America during the 1990's. Ercan and Evirgen (2009) investigated the factors that were important in the failure of Turkish banks in 2000-2001 and included liquidity ratios in their analysis banks using a principal component analysis methodology. Finding showed that liquid assets-to-liabilities ratio appears to be significant while the liquid assets-to-total assets ratio does not.

Another widely discussed variable in bank failure context is relation of retail deposits to total loans, as well share of retail deposits in bank liabilities. According to King (2006), higher share of such deposits increases bank vulnerability to the unexpected bank run. Andersen (2008) is of the view that reliance on

interbank deposits may indicate intentions to conceal the liquidity problems. The reason is that interbank financing is usually relatively expensive and short-term but easy to obtain.

Bobykin (2010) used logit and hazard models of prediction banking failures using efficiency measures and tested it empirically using the data on Ukrainian banks during 2006-2010. Empirical findings found an inverse relation between the probability of banking failure in Ukraine and a liquidity indicator, proxied by the cash to assets ratio. More specifically, empirical results showed that the most significant liquidity ratio was cash to assets ratio.

2.3 Summary

This chapter looked at various theories that have been discussed by various researcher and models that were used in testing the determinants of bank failures in different countries. It further looked at ways of resolving bank failures in an economy specifically based on regulatory policies. From literature review section, the researcher identified that Fungacova, Ariss and Weill (2013) failed to establish the equilibrium point model that can hedge banks as liquidity creators from falling into shortages in an attempt to avoid excess liquidity creation. There is also no clear cut from this chapter as to whether GDP growth rate causes bank failures or it is the one that results from bank failures. Overly, of all the causes that were cited in literature review section, there is no clarity or consensus on the key cause of bank failures in all researches. The next chapter is chapter three which looked at research methodology and some justification on vector explanatory variables to be incorporated into the model.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter will present the research methodology that the researcher had used in this study to fulfill research objectives. The chapter will also discuss diagnostic test that the researcher will perform and variables to be incorporated in this study. Lastly it will present data analysis plan.

3.2 Model Specification

Most of the studies relied on constructing financial ratios that proxied the CAMELS elements and used these ratios in discriminant and multivariate discriminant analyses, proportional hazard and logit, or multivariate probit econometric models (Kunt, 1989). This research will employ a pooled logit model using a general to specific estimation procedure on panel data for fourteen banks and will incorporate a variety of ratios whose greater part of their proportion will also be related to CAMELS components. The model is akin to that employed by Bouvatier *et al.* (2013) on USA banks.

The logit model has a binary outcome and these binary choice models are used when the dependent variable is binary and not completely observed. The dependant variable *failure* (failed or non-failed) is binary such that it equal to one if the bank is a failed one and zero if otherwise. The prediction model is as follows:

$$F(x) = exp(Z_i) / (1 + exp(Z_i))$$

Where:

$F(x)$ follows a logistic (cumulative) distribution.

$F(x)$ is a function such that $F: x \rightarrow [0; 1]$ and x equals to one if the bank under consideration is a failed one and zero if otherwise.

$$Zi = \beta_1 + \beta_2 X_i + \varepsilon$$

β_1= a constant term

β_2=the vector of coefficients of explanatory variables

X_i= the vector of explanatory variables

ε= error term

Employment of logit model is based on the fact that data analysis lies on binary dichotomous responses were the research will be dealing with both failed and non-failed banks. Inclusion of these two sets of banks of different status requires specification of the dependent variable which is *failure* in the model and this is mostly achieved by employing logit models. Since the dependent variable is binary, it would be inappropriate to use Ordinary- Least-Squares (OLS) also known as a linear probability model (LPM) models because it will produce biased and inconsistent results. The conceptual problem with linear regression with a dichotomous dependent variable stems from the fact that probabilities have maximum and minimum values of 1 and 0 which is a discrete and not a continuous change. Also logit model is not subject to stringent assumptions that are inherent to other models such as MDA, UDA analysis and a catastrophe model of bank failure.

Most empirical studies on banking failures consider banks to have failed if it either received external support or was directly closed. In this study, a financial institution will be considered to have failed if it fits into any of the following categories as sighted by Bongini, Claessens and Ferri (2001):

(i) The financial institution's operations were temporarily suspended ("frozen") by the government;
(ii) The government closed the financial institution;
(iii) The financial institution was absorbed or acquired by another financial institution

3.3 Justification of explanatory variables in vector Z_i

Independent variables will be drawn from financial statements, RBZ and DPB reports on both failed and some surviving banks. Refer to appendix 1 for a summary on explanatory variables.

3.3.1 Real GDP growth rate (GDP)

Bank-specific variables alone may be insufficient to explain determinants of bank failure as economic cycles may have impact on bank operations. To capture the macroeconomic effect on bank failure, the researcher will include real gross domestic product variable in the model.GDP is usually used to proxy economic growth and will be recorded at market price and the researcher expects negative relationship between GDP growth rate and bank failure. The sign implies that when GDP growth rate is increasing, there are less chances for banks to fail. GDP is the only macroeconomic variable to be considered in the research because the next best indicator which is inflation is no longer a problem in Zimbabwe. Exchange rate fluctuations cannot be incorporated because Zimbabwe does not own any currency currently.

3.3.2 Size (SIZE)

The variable is calculated as the natural logarithm of total assets. It can be argued that strength and solvent banks have the higher size of assets. The reasoning behind this is based on the fact that large banks hold more assets and are better able to diversify and to reduce their risks, thus small banks are more vulnerable to failure compared to large banks. The variable is expected to have a negative impact on bank failure.

3.3.3 Asset quality (NPL)

This is among CAMEL components and its negligence may imply inadequate research. Almost all researches identified that asset quality is determined by the levels of non-performing loans. Thus in this study, non-performing loans abbreviated by *(NPL)* will be used as a measure of assets quality in both failed and surviving banks. The ratio is calculated by dividing non-performing loans by total loans. The researcher expects this variable positively correlate to bank failure. The general hypothesis is that failed banks loan books records higher levels of non-performing loans than surviving banks. Non-performing loans levels for Royal bank were far much higher than for CBZ.

3.3.4 Capital Ratios

Bank capital is meant to cushion impending failure thus there exist a significant difference in capitalisation between failed and non-failed banks. All capital adequacy indicators are assumed a negative relationship to bank failure. In this study, capital adequacy is incorporated in two ways, the tier-one capital ratio and gross revenue ratio.

3.3.4.1 Gross revenue ratio (GRR)

The ratio is calculated by dividing tier one capital to total interest and non-interest income.

Gross revenue ratio includes off-balance sheet activities (Estrella, Park and Peristiani (2000)). This implies that gross revenue ratio reflects the riskiness of bank assets better than total assets.The research expect this ratio to have a negative correlation with bank failure, which suggests that banks with higher gross revenue ratio will be less likely to fail.

3.3.4.2 Tier 1 Capital Ratio (T1CR)

T1CR is the ratio of tier 1 capital to total risk-weighted assets. Tier 1 capital is a bank's core capital and indicates bank's financial strength. Bank that have lower tier 1 capital ratio tends to be weaker than those with higher ratios. Samad (2011) proved that there are significant difference between failed banks and survived banks with respect to tier 1 capital ratio. The researcher expect this variable to have a negative impact on possibility of failure of banks implying that banks with the higher tier 1 capital ratio are less likely to fail.

3.3.5 Liquidity Ratios

Liquidity risks are at the core of the traditional banking business, as banks receive deposits that can be withdrawn on demand and grant private and corporate loans with higher maturities. Liquidity is measured mainly to determine bank's resilience to liquidity risk, thus to hedge against liquidity risk

banks must place focus on current sources of liquidity and future cash flows. To capture liquidity more comprehensively, the following ratios will be incorporates.

3.3.5.1 Loan-to-total assets ratio (LTA)

LTA is the ratio of loans to total assets. The liquidity ratio captures the portion of bank's assets that are at risk or indicates what percentage of assets of the bank is burdened with loans. Higher ratios indicate weak liquidity and Wheelock and Wilson (2000) found that failure was more likely for banks with larger ratios. Shaffer (2012) and Li (2013) found a positive correlation between this ratio and bank failure thus the researcher expects positive sign from the regression results implying that the more loans a bank holds, the higher possibility of failure.

3.3.5.2 Loans-to-deposit ratio (LTD)

LTD is the ratio of total loans to total deposits. The ratio measures banks' ability to effectively accommodate deposits redemption by customers. Babanskiy (2010) indicated that too high ratios mean that banks might not have enough liquidity in case of contingency events. The ratio shows how much the bank depends on borrowed funds. The researcher expect this variable to positively correlate to bank failure indicating that banks with high ratios are more likely to fail due to failure settle their liabilities timeously and effectively.

3.3.5.3 Deposits-to-total assets ratio (DTA)

Is the ratio of total deposits to total assets and the ratio indicates level of investor trust in the bank. DTA ratio also represents a stable source of funding while the bank remains reliable. Higher level of deposits provides more wide opportunities for banks to operate at the financial market and meet the problems of liquidity. According to past researches, the ratio should negatively correlate to failure, thus the researcher also expects a negative sign from regression results.

3.3.6 Earnings Ability (ROA)

Earning ability of a bank is proxied by return on assets (ROA). It is calculated by dividing net income by total assets. This ratio reflects the efficiency of banks' management on using their assets to generate profit. Higher ROA means greater efficiency in converting assets into net income. Low ROA indicates less efficiency and that the organization is more likely to experience financial difficulty. This variable is expected to have negative impact on the failure of banks.

3.3.7 Management Quality (EFR)

The ability and skill of the bank management play a crucial role in the performance and success of the institution. The higher the management competence, the lower is the vulnerability of the bank and the likelihood of making wrong decisions. To capture management quality, the researcher will use efficiency ratio to assess the management quality. This efficiency ratio reflects expenses as a percentage of revenue. The research will assume a positive relationship; the higher the ratio, the more likely is a failure.

3.4 Diagnostic Test

The researcher carried out multicollinearity test on explanatory variables. This was done by constructing the correlation matrix that helps to identify variables with high correlation coefficients. Variables that exhibited highest correlation coefficients were not eliminated in data analysis.

3.5 Data Type

The research will use cross-sectional and time series data that is panel data in that both cross-sectional (different banks) and time-series (different points in time for each bank) ratios will be used. In addition to improve accuracy, this approach also enables the researcher to incorporate both bank specific and macroeconomic variables into the model.

3.6 Data characteristics, sources and time frame

This researcher employed secondary data that was sourced from financial statements, from RBZ and Deposit Protection Board (DPB). DBP was required to provide data mainly for failed banks since their website are not operational. Secondary data is best regarded as objective than subjective data from qualitative research. However secondary data may be wrong since institutions tend to window-dress their financial statements which then make the research unrealistic and also data can be unreliable if prepared by an incompetent individual. The researcher overcomes this by using only published information from recognized sources such as audited financial statements, RBZ and DPB statistics.The time frame of data to be used in the study was from 2009 to 2012. This period was chosen for the reason that this is the only good quality data that could be obtained from available sources.

3.7 Estimation Procedure

By using Stata, an econometric software, estimates have been made and interpreted based on logistic regression coefficients, odds-ratios and marginal effects. Also descriptive statistics such as mean, media, standard deviations and variances for failed and surviving banks were generated using the software to assist in interpreting research findings. Interpretations were based on bivariate and multivariate logit regression analysis. Both bivariate and multivariate logit regression results were interpreted in coefficient terms and odds ratios.

3.8 Data Analysis and Presentation Plan

Information found included numerical data that was presented in tables and equations to justify what the literature review postulated. The study used important statistical data to generate relationships between variables in finding the major determinants of banking failures.

3.9 Summary

This chapter covered model specification, explanatory variables to be incorporated into the model, diagnostic test to be carried out to test multicollinearity, data type and sources as well as estimation procedure and data analysis and presentation plan. The following chapter will analyze and present logit regression results in line with the research objective.

CHAPTER 4: RESULTS PRESENTATION AND INTERPRETATIONS

4.1 Introduction

The main purpose of this research was to investigate the determinants of bank failures in Zimbabwe under the multicurrency regime. Research findings were based on financial ratios that were generated from financial statements and those ratios obtained from DPB. The chapter discusses, analyse and interpret the findings for the research with the aid of statistical measures and analytical techniques. Main area of discussion includes interpretation of descriptive statistics (mean, median, variance and standard errors), construction of the correlation matrix and interpretation of logit regression results.

4.2 Descriptive statistics

Descriptive statistics are summarised such that Table 4.1 analyses banks according to their statuses as assumed in the model and Table 4.2 and 4.3 discusses mean values and variances associated with each bank separately.

Table 4.1: Descriptive Statistics by Group

Variables	Failed				Non-failed			
	Mean	***Mdn***	***S.E***	***Var***	***Mean***	***Mdn***	***S.E***	***Var***
	0.762	0.791	0.12	0.014	0.482	0.473	0.188	0.035
	1.068	0.95	0.479	0.230	0.676	0.708	0.297	0.088
	0.433	0.439	0.096	0.009	0.686	0.717	0.161	0.026
	0.463	0.469	0.069	0.005	1.168	1.255	0.301	0.090
	-0.108	0.045	0.326	0.106	0.212	0.201	0.055	0.003
	-0.188	-0.019	0.274	0.075	0.025	0.022	0.027	0.001
	3.012	1.694	2.865	8.210	0.922	0.807	0.366	0.134
	0.433	0.302	0.352	0.124	0.050	0.038	0.0620	0.004
	17.427	18.206	1.725	2.975	19.063	19.190	0.866	0.75

Table 4.1 results were constructed from Stata 11 output in appendix B. By comparing banks within the sample, the researcher observed that failed banks had significantly higher LTA mean and median values than surviving banks. Although failed banks had higher LTA mean and median, their variance and

standard deviation were significantly lower than that of non-failed banks. Lower variances for failed banks infer that there is greater dispersion in LTA ratio in non-failed banks sample which may indicate higher levels of risk of failure in surviving banks. High variance associated with surviving banks group was largely attributed by individual banks such as Kingdom, Agribank, Tetrad, Stanbic, Metbank and FBC that had high individual variances as depicted by Table 4.3.Standard deviation also reviewed that non failed banks sample is subject to greater risk of failure. The major reason why failed banks' variance is lower than that of surviving ones is that the average values of each of the failed banks were in a close range as the maximum mean value is 0.8329 for Genesis and the lowest is 0.6364 for Interfin as shown in Table 4.2 while surviving banks have outliers. Surviving banks had highest mean value of 0.65935 for Kingdom and lowest of 0.18975 for Barclays implying greater variability.

Failed banks had also high LTD mean and median values as compared to non-failed banks. From Table 4.1, it can be discerned that failed banks had high variance in respect of LTD ratio than surviving banks, indicating that they were surely subject to greater risk of failure. In efficiency terms, failed banks had both high EFR mean and variance values than those of surviving banks. Also standard deviation for failed banks is higher relative to non-failed banks indicating greater exposure to failing risk. High mean and variance values were largely attributed by high descriptive statistics values attached to individual banks as depicted in Table 4.2 and 4.3.

Mean, median, standard deviation and variances of NPL for failed banks were high relative to those of surviving banks. High mean, median, standard deviation, and variance figures indicated that failed banks were greatly exposed high risk of failure than non-failed banks. From Table 4.1, it is apparent that non-failed banks had NPL mean value of approximately 5% which is in line with international banking standards. However, some individual surviving banks such as Kingdom, Metbank and ZB have higher NPL mean as shown in Table 4.2 and this might increase their good chance of failing. Higher mean and variances for failed banks are largely emanating from higher values associated with each of the failed banks in Tables 4.2 and 4.3 with respect to mean and variance statistics.

In capitalisation terms, failed banks sample had lower GRR and T1CR mean and median values relative to surviving banks inferring that failed banks had less capital to cushion potential risks that were inherent to their operation. Although failed banks had lower mean and median GRR ratio, their variance was lower than that of surviving banks meaning that surviving banks still have a lot of homework to work on in order to reduce their risk of failure as a result of weak capitalisation. More specifically, banks such as Kingdom and Metbank largely contributed to high variances recorded in non-failed banks group raising the need to monitor capitalisation of the two institutions tightly. Failed banks showed lower mean, median and high variance and standard deviation in ROA indicating high levels of failing risk than surviving banking institutions. Although some surviving banks had lower mean ROA, none of them had negative ratio from Table 4.2 and from the same Table, it is clear that almost all failed banks had negative ROA ratios implying inability to generate economic profits for themselves.

Table 4.2 presents results that were generated from appendix C. An in-depth analysis in Table 4.2 indicated that banks such failed banks as Genesis, Interfin and Renaissance had higher loan to assets ratios which could have resulted from aggressive lending approaches which finally stimulated high non-performing loan levels.

Table 4.2: Mean values by Bank

	LTA	LTD	DTA	GRR	T1CR	ROA	EFR	NPL	SIZE
	.553975	1.132	.40015	1.4528	.19125	.073	1.2991	.046475	18.041
	.639275	.741125	.849975	1.3207	.20165	.0159	.75198	.03525	19.5235
	.18995	.250425	.757625	1.193075	.25515	.00195	.99465	.0018	19.25097
	.645925	.8037	.761325	1.07325	.281725	.041375	.61693	.0227	20.41915
	.471825	.6352	.6479	1.390125	.220875	.0154	.79478	.0399	19.02233
	.8329	.680575	.410825	.519775	-.35412	-.54225	6.4524	.658075	15.14753
	.6364	1.0485	.5139	.458075	.038875	-.00795	1.3405	.137075	18.7779
	.65935	.9414	.645925	.583325	.163075	.02245	1.0286	.178875	18.719

	.4304	.6934	.601125	1.117825	.2586	.029075	.81858	.0384	18.18545
	.816975	1.4764	.3754	.410275	-.0082	-.01468	1.2438	.50244	18.35672
	.356825	.421475	.852075	1.163925	.1497	.020675	.7458	.0485	19.62055
	.290225	.438475	.69845	1.184	.198825	.0288	.66827	.0286	19.68538
	.5974	.84555	.671975	.981825	.23845	.00305	1.5730	.02095	18.1882
	.46665	.53015	.658525	1.386325	.177875	.0275	.85035	.093375	19.04305

Some surviving such as CBZ, BancABC, Agribank and Kingdom bank are also characterised by high loan to assets ratios which are likely to increase their likelihood of default and fragility. Foreign owned banks such as Barclays, Stanchart and Stanbic have lower LTA and NPL ratios. Lower NPL ratio might be due to their reluctance to lend than any of the local banks as indicated by corresponding lower LTA ratios.

Renaissance reported the highest LTD mean followed by Interfin and Agribank. LTD mean values of foreign banks were the lowest in the sample with Barclays having approximately 25%. Surviving banks such as Agribank and Kingdom must curtail their LTD ratios to reduce their risk of failing. Most of the failed banks had DTA mean value of less than 50% indicating low liquidity power and lack of customer confidence. DTA mean value for Agribank is too low and is falling within the range of failed banks. However such big banks as BancABC and Stanbic reported higher DTA mean values which were above 80% indicating strong bank liquidity and high levels of consumer trust and confidence towards these banking institutions.

Failed banks were also characterised by low capitalisation mean values (GRR and T1CR). Genesis and Renaissance had negative T1CR and GRR mean values. Interfin had positive T1CR but was still heavily undercapitalised considering GRR and T1CR associated with the banking institution. However most of the surviving banks had high GRR mean value except Kingdom bank that is falling within the same range with failed banks. Descriptive statistics from Table 4.2 indicated that failed banks had low and negative ROA mean values. All surviving banks reported positive ROA means although the values are very low.

Research finding showed that Genesis, Renaissance and Interfin banks had highest EFR and NPL mean values indicating poor managerial and assets quality. Kingdom bank had high NPL mean that was falling within the range of the failed banks. Tetrad and Agribank competed with failed banks in terms of inefficiency; their EFR mean values were within the range with that was reported by failed banks.

Table 4.3 shows variances for individual banks incorporated in the sample. In terms of LTA variance, FBC showed to be at greater risk due to high variance showing greater dispersion in LTA ratio across the research period. Although failed banks and some surviving banks as CBZ and BancABC had high mean values, these bank set exhibited lower levels of risk than some surviving banks such as Agribank, Tetrad, Stanbic, Metbank, Kingdom and FBC which had relatively high variance compared Renaissance, Interfin and Genesis.

Table 4.3: Variance values by Bank

LTA	LTD	DTA	GRR	T1CR	ROA	EFR	NPL	SIZE
.040957	.1096144	.0106635	.0021857	.0017283	.0012448	.0551249	.0002654	.3223933
.0080155	.0086985	.0002338	.0020604	.0000416	.0000967	.0097825	.0017099	.1273128
.0025278	.0034808	.0012533	.1243468	.0019984	.0000434	.0059674	1.47e-06	.0480187
.0100489	.0114288	.0213667	.0541271	.005159	.0013408	.0010973	.0007695	.1724951
.0469772	.0767471	.0387663	.0154614	.0003597	.0001303	.0003533	.0001744	.070753
.0026745	.0091862	.0038876	.0036955	.1982243	.0193548	4.934651	.0955578	.0328709
.0118948	.1229034	.0022064	.0022311	.0172588	.0000381	.2357814	.0071545	.2917557
.0203804	.0372819	.0325875	.1004995	.0005745	.0007525	.0910871	.0190254	.0785754
.016225	.00834	.0205904	.1507329	.0041378	.0004414	.0026281	.0001205	.5930112
.006504	.286714	.0141846	.003598	.0517379	.0049671	1.257711	.1607691	.071113
.0131324	.0128152	.0028542	.0181626	.0001323	0000869	.0002724	.0000123	.0271165
.009326	.0229868	.0170209	.0396463	.0010252	.0004623	.0073813	.0001547	.0353077
.0174581	.0189978	.007396	.0002674	.0022337	.0001203	.6299081	.0000273	1.473028
.0000386	.0857645	.0082578	.0002779	.0016428	.0004158	.0109358	.0016835	.483748

Renaissance and Interfin had the highest LTD variance than any of the banks that were incorporated in the sample. Based on these results, these two failed banks proved that they were really fragile and according to the findings, they were exposed to greater risk of failing. Among surviving banks, Agribank showed greater risk as indicated by high LTD variance in surviving banks sample. This is really worrisome considering that the same banking institution (Agribank) had high LTA mean value in Table 4.2. Table 4.3 reveals that FBC and Kingdom were characterised by high levels of risk than any of the failed banks as shown by high DTA variances.

Kingdom and Metbank showed high levels of risk when considering GRR variance and banks such as Genesis and Renaissance proved that they were surely exposed to high levels of risks due to undercapitalisation. Banks such as Kingdom had low capitalisation mean values and high variance showing that the institution still has a lot of revisions to make in order to hedge against impending failure. Genesis and Renaissance indicated high variances in ROA which implies that the two banking institutions were subject to greater risk as a result of failing to effectively generate economic profits for themselves. However most of the surviving banks proved to be less risky although the ROA mean values are very low.

Genesis, Interfin, Renaissance and Tetrad banks are the most inefficiently managed banks and indicated higher levels of risk due to high EFR variances attached to these banks as shown in Table 4.3. From the same table, it is apparent that Genesis, Interfin and Renaissance had high variances in NPL ratios showing greater exposure to the risk of failure. From these findings, the researcher recommends an improvement in managerial efficiency in Tetrad bank.

Based on descriptive statistics in Tables 4.1, 4.2 and 4.3, it can be deduced that banks such as Kingdom and Agribank are at greater risk of failing since most of their mean, median, standard deviations and variance were in the same range with failed banks in most ratios thus much has to be done to align these two banks to other strong banks in surviving banks' sample.

4.2 Diagnostic test results

Diagnostic test was carried out prior to results estimations and interpretations.

4.2.1Multicollinearity test results

Table 4.4: Correlation matrix of vector explanatory variables

	LTA	LTD	DTA	GRR	T1CR	ROA	EFR	NPL	SIZE	GDP
LTA	1.0000									
LTD	0.6586	1.0000								
DTA	-0.342	-0.542	1.0000							
GRR	-0.528	-0.388	0.2813	1.0000						
T1CR	-0.470	-0.237	0.3913	0.5203	1.0000					
ROA	-0.392	0.0307	0.2988	0.4138	0.7545	1.0000				
EFR	0.4396	0.0619	-0.37	-0.396	-0.841	-0.883	1.0000			
NPL	0.5962	0.2437	-0.377	-0.567	-0.803	-0.700	0.7359	1.0000		
SIZE	-0.355	-0.106	0.559	0.3440	0.6032	0.7474	-0.794	-0.601	1.0000	
GDP	-0.099	-0.085	0.2375	0.1407	0.2252	0.2698	-0.335	-0.195	0.2713	1.0000

The researcher carried out a multicollinearity test by constructing a correlation matrix as indicated in Table 4.4. Before the researcher commences explanation of empirical findings, it is vital to indicate that the study should consider the presence of multicollinearity as most of the variables are showing high correlation coefficients in the matrix. However Babanskiy (2012) indicated that multicollinearity pose no threat to research findings since it does not reduce the predictive power or reliability of the model. This being so none of the variables was dropped, thus the researcher employed a do-nothing approach to multicollinearity as asserted by Babanskiy (2012).

4.3 Estimation of regression results

Table 4.5 shows logit regression results, statistical significance of variables incorporated in the models and marginal effects generated from bivariate and multivariate pooled logit regression results in appendix E and F. Empirical analysis used financial ratios that were calculated based on information

presented in annually audited financial statements and ratios obtained from DPB. The researcher analyzed ten variables in both bivariate and multivariate models. These ratios were calculated on a total sample of fourteen Zimbabwean banks by employing pooled logit estimator using general to specific logit estimation procedure on panel data from 2009-2012. Interpretation and discussion of research results was based on bivariate and multivariate analysis which was made in odds ratios, marginal effects and coefficients context.

Table 4.5: Pooled and specific to general logit regression results

Variables	Bivariate coefficients	Odds ratios	Marginal effects	Multivariate coefficients
	12.89353***	397730.2	.7611487	454.327***
	2.988742***	19.86069	.4317654	-103.284***
	-10.75743***	.0000213	-.9950278	-68.46534***
	-10.25009***	.0000354	-.1273134	-103.4679***
	-77.63694 ***	1.92e-34	-11.65697	25.32403***
	-56.08996***	4.37e-25	-14.0132	-265.0339***
	1.43253**	4.189284	.2438601	-8.387014***
	15.15673***	3823694	2.587835	-49.40341****
	-1.066726***	.3441332	-.1492843	-25.32048***
	-42.91765**	2.30e-19	-6.358587	-3961.7***

****** Statistically significant at 1% level***

***** Statistically significant at 5% level***

**** Statistically significant at 10% level***

LR ratio = 0.0000

4.4 Interpretation of regression results

All variables coincide with the theoretical expectations in terms of direction of influence in bivariate analysis. However some variables such as LTD, T1CR, EFR and NPL contradicted the theoretical expectations in multivariate model and the model was significant at 1%.

Multivariate logit results showed that liquidity is a bank-specific variable that is more likely to drive bank failures in Zimbabwe because of high coefficients, marginal effects and odds ratios attached to liquidity proxies in the study. In Table 4.5 liquidity is proxied by LTA, LTD and DTA. Multivariate analysis indicates a positive correlation between LTA ratio and the possibility of failure and findings coincide with theoretical expectations. LTA ratio is positive and significant at 1% level in both bivariate and multivariate analysis. This was in line with the findings of Babanskiy (2012). Large coefficient suggests that one unit change in LTA has greater influence on bank failure compared to the effects of other bank-specific variables. Based on research findings, a unit increase in LTA ratio is likely to increase the possibility of bank fragility by 0.7611487%.

The significance and positivity of the LTA ratio indicates that banks with higher loans are 397730.2 more likely to fail than those with lower LTA ratios. This was well cited by Wheelock (2000) when revealed that loans are normally the least liquid and most risk assets, meaning that when banks expands their lending activity without a corresponding increase in their capital base, they will be exposing themselves to greater risk of failure since loans are only liquidated when matured. In brief, if banks hoard more loans as a proportion of their assets, they will be increasing the portion of assets that are at risk. Most of recently failed banks such as Genesis and Interfin were characterized by a growing trend of higher loan to assets ratio, thus had a larger proportion of burdened assets. This was supported by higher LTA ratios in Table 4.1, 4.2 and 4.3 (mean, median and variance statistics).

More interestingly, consumer trust and confidence proved to be a relevant determinant of bank failure in Zimbabwe. Among liquidity ratios, DTA proved to be a significant cause of bank failures in Zimbabwe.DTA ratio also represents a stable source of funding and higher level of deposits provides wider opportunities for banks to participate in financial markets and meet liquidity problems. The ratio was negative and significant at 1% level. According the findings a unit change in DTA will reduce

the possibility of failure by 0.9950278%. Odds-ratio indicated that banks with higher DTA ratios are 0.0000213 times less likely to fail as compared to those with lower DTA ratios. This is to say that banks with low DTA have 0.999787 probability of failure compared to those with high DTA.

LTD variable is negative instead of being positive and is significant at 1% in the multivariate model. Negative sign might be due to increased demand for loans by economic agents with corresponding transitory nature of deposit as a result of low levels of customer confidence as shown by the significance of the DTA variable in the model. Negative sign was in line with the findings of Bagatiuk and Dzhamalova (2009) although these researchers didn't say anything on the meaning of the negative sign. The researcher interpreted LTD findings from loans demand and deposits supply sides. Marginal effects results showed that a unit change in LTD ratio will cause the possibility of bank failure to change by 0.4317654. Odds-ratios suggest that banking institutions with higher LTD ratios are 19.86069 times more likely to fail as compared to those banks characterised by lower LTD ratios.

Profitability (earnings ability) also proved to affect the possibility of banks failure in the multivariate model as expected. ROA variable was significant at 1% level and negatively correlate to the possibility of bank failure and this is in line with Li (2013) findings. According to empirical results, a unit increase in ROA will cause the probability of bank failure to decrease by 14.0132%. The ratio was ranked the second bank specific determinant in the model implying that bank profitability plays a linchpin role in hedging against impending failure if banks are capable of generating more profits. ROA is an indication that more profitable banks are less likely to fail and according multivariate model a unit increase in this ratio will decrease the possibility of failure by 265.0339.Descriptive statistic revealed that failed banks had lower ROA ratio meaning that it is a relevant determinant of bank failure in Zimbabwe. Failed banks such as Genesis, Interfin and Renaissance had negative ROA ratios in Table 4.2 in other terms failed banks were less efficient in converting bank assets into income.

Multivariate model suggest that capitalization is also a potential cause of bank failures. Capitalization was proxied by T1CR and GRR in the model. GRR ratio is negative and significant at 1% as expected and this conformed to Li (2013) and Estrella (2000). Inverse relationship implies that as banks increase one

unit of gross revenue, their possibility of failure will decrease by 0.1273134%. In general, GRR significance infers that bank capitalization is more likely to influence bank failure as odds-ratio suggest that banks with lower GRR ratios are 0.9999646 times more likely to fail than those with higher GRR ratios. Also descriptive statistics revealed that failed banks had lower GRR ratios as compared to surviving banks registering the notion that capitalization is a relevant determinant of bank failure. Based on Figure 2 in Chapter One most banks are oscillating below the mandated levels and this poses much threat to Zimbabwean banking sector viability.

Banks size is significant at 1% and is negatively correlated to possibility of failure as expected. Findings are in line with Nikolsko-Rzhevskyy (2003). Result revealed that as banks increase in size, probability of failure is reduced by 0.1492843. Odds-ratio indicated that big banks are 0.3441332 more likely to fail than small banks, thus small banks are much more vulnerable to risk of failure. Descriptive statistics indicated that most of the failed banks were of small size.

Managerial efficiency proxy (EFR) is negative and significant at 1% in the multivariate model. The empirical findings are not in line with theoretical expectations since the ratio was expected to be positive. However this is in line with the finding of Torna (2010) and the researcher indicated that in the presence of profitability measure, ROA, a negative coefficient for efficiency (EFR) might means that banks perceive that higher costs lead to a better outcome, indicating that perhaps, banks benefit from large expenditures on high quality workers.

The researcher observed that the NPL ratio is positive in bivariate analysis and negative in multivariate analysis but significant at 1% in both models. Bivariate results imply positive association between non-performing loans and the possibility of failure and this conforms to the findings of Shaffer (2012) and none of the researchers expected a negative sign from regression results. Negative might emanate from reluctance to lend by major banks such as Barclays, Stanbic and Stanchart as indicated by lower NPL and LTA ratios in Table 4.1 and 4.2.

Surprisingly, macroeconomic environment proved to influence bank failures than bank fundamentals in the multivariate model. Macroeconomic influence was proxied by GDP in the model and this variable was negative and significant at 1% in the model as expected. Considering the large coefficient attached to the variables, macroeconomic environment pose much influence to bank failure than any other variables, ceteris paribus. Research findings showed that an increase in GDP growth rate is likely to decrease the possibility of bank failure by 6.358587, bringing the notion that banks are less likely to fail during periods of high growth in GDP.

4.6 Bank failure prediction model

The model incorporated all significant variables and is as follows:

$$Z_i = 454.33LTA - 103.28LTD - 68.47DTA - 103.47GRR + 25.32T1CR - 265.03ROA - 8.39EFR - 49.4NPL - 25.32SIZE - 3961.7GDP$$

Given that we have two banks that have the following ratios:

Table 4.6: Hypothetical example

RATIOS	RISKY-BANK A	HEALTHY-BANK B
LTA	78%	58%
LTD	167%	42%
DTA	18%	34%
GRR	13%	23%
T1CR	9%	51%
ROA	-2.1%	41%
EFR	6.4	2.1
NPL	85%	5%

Assuming that Bank A (*risky*) and Bank B (*healthy*) have same total assets value of $63884285 and that GDP growth rate is expected to decline by 10%, according to this research's prediction model, the probability of Bank A failing is 99.99% and the likelihood of Bank B failing is 4.07%. Based on the results from the above examples, banks must keep the LTA and LTD ratios as low as possible to indicate high liquidity power and reduce the proportion of assets burdened with loans. DTA ratio must be high to indicate high levels of liquidity and customer confidence. From the given example, Bank A had substantially high LTA and LTD ratios. Also banks must endeavour to lower their NPL and EFR ratios to improve their assets and managerial quality respectively. Indeed, NPL ratio must equal or fall below the international benchmark which is 5% of the total loan book. From model's results, banks must raise DTA, GRR, T1CR and ROA. Raising these ratios imply strengthening bank liquidity, customer confidence, capitalisation and profitability.

4.7 Summary

This chapter worked on the analysis and interpretation of research findings along with diagnostic test for multicollinearity. Findings reviewed that bank-specific and macroeconomic variables can both influence the probability of banks failing. The study showed that banks associated with poor liquidity, capital and profitability ratios have high chance of failing as proved by past bank failures of such banking institutions as Interfin, Genesis and Royal bank. Some surviving banks such as Kingdom and Metbank proved to be highly subjected to failing risk due to mean and variance statistics attached to their capitalisation, liquidity and profitability ratios. The next chapter will articulate policy recommendations based on research findings and also suggestions for future research.

CHAPTER 5: CONCLUSIONS AND POLICY RECOMMENDATIONS

5.1 Introduction

This chapter summarizes all findings of the research, draws conclusions and gives policy recommendations and scope for further studies. Recommendations given here are specifically aimed hedging against bank failure based on identified causes in the country.

5.2 Summary

The study investigated the determinants of bank failures in Zimbabwe in the multicurrency era. Empirical findings supported the study hypothesis that bank-specific and macroeconomic variables are the causes of bank failures in Zimbabwe. Research revealed that macroeconomic environment poses much threat to bank stability than any of bank fundamentals. In Chapter Four research finding revealed that changes in GDP growth rate influences the possibility of bank failure by greater magnitude than any of bank-specific factors.

5.3 Conclusions

Based on analyse done in chapter four, the following conclusions were made on causes of bank failures in Zimbabwe. The study concludes that:

- Consumer trust and confidence are significant determinant of bank failure in Zimbabwe. This was statistically proved by the significance of the DTA ratio and this is true considering the transitory nature of deposits that is characterising the Zimbabwean banking sector.
- Macroeconomic environment affects banks' survival equation along with bank specific variables.
- Most banks in Zimbabwe are earnings driven as supported by high LTA ratios which results from aggressive lending so as to boost short-term profits.
- The majority of Zimbabwean banks are operating undercapitalised and are also characterised by poor liquidity positions.

- Based on magnitudes of each of the proxies of causes of bank failures, liquidity, profitability and capital indicators are reliable predictors of bank failures in Zimbabwe. Liquidity was identified as the most prominent bank related cause of failure. This was shown by higher coefficient associated with LTA and DTA ratios. Higher coefficient implied that banks with low DTA and high LTA have weak liquidity power. Also banks with low liquidity thresholds are more likely to fail than those with higher margins. Profitability and capitalisation were also identified as relevant determinants of bank failures. These were indicated by high coefficient associated with ROA and GRR ratios. Banks with low capital have higher chance of failure in the multicurrency era relative to those with high capital holdings. Among bank fundamentals, size of the banks also plays a key role in determining an impending failure. According to empirical findings, small banks are more likely to fail than bigger banks. Banks expenditure and revenue generation impacts on the rating of managerial efficiency.
- Large banks are more likely to fail regardless of their size due higher levels of loans as a proportion of bank assets. Banks such as CBZ, BancABC and Kingdom have higher LTA ratios which also characterised some failed banks as Genesis and Interfin. Off-balance sheet activities determine the riskiness of bank assets.

5.4 Policy Recommendations and Implications

From the conclusions drawn from the study, the recommendations arrived at try to come up with solutions to bank failure are:

- Policy implications of this research would be that, although bankers argue for lower capital and liquidity requirements, RBZ must keep on mandating higher requirements to help sustain banking sector resilience and stability. High capital and liquidity mandates could also help identify problem banks early thus help prevent future bank failures that may pose threat to economic and banking sector's health. Liquidity and capital regulations must be kept high as the research statistically proved that most of the failed banks had weak liquidity power and were less capital to cushion potential risks.

- To stimulate lending, banks must increase their capital holdings to support expansion in their lending business. This should be done by setting aside loan loss provisions and reserves which must be in proportion to loans disbursed. Provisions and reserves must be set by considering individual bank's characteristics such as risk associated with disbursed loans. This tends to be more holistic than making provisions based on orders from RBZ because loan portfolios for different banks are characterised by different risks and returns. From the study, the researcher identified that most of the failed banks had high loan-to-assets ratios and lower capital ratios and high non-performing loans.
- RBZ must periodically review bank liquidity to avoid excess liquidity creation as well as liquidity shortages. This was suggested to cover the gap that the researcher had identified from ELCH and LSH discussed in literature review section.
- Banks must ensure higher capital and liquidity holdings to boost customers' trust and confidence. To improve bank liquidity and capitalization in the Zimbabwean vacuumed economy, banks must venture into mergers or partnerships with foreign banks since accessing funds offshore is also a challenge due to inability to meet the stringent requirements needed to be met when applying for financial assistance. Higher capital and liquidity positions are regarded as a safety net by bank customers and other investors, thus consumer trust and confidents tend to boost when these stakeholders hold a perception that banks are capitalised and liquid. The notion behind this assertion is that capitalised and liquid banks have depositors funds secured and that they can also meet customers liquidity requirements timeously, thus increasing bank's integrity in the market and hence customer confidence. According to the study, failed banks had lower capital and liquidity ratios and were also characterized by low levels of consumer trust and confidence.

- Bank expenditures must be lower at all cost to improve profitability. Banks can achieve this by only spending on profitable activities such as marketing and other relevant revenue generation related processes. Also lowering directors' benefits to reasonable levels will help banks to improve their comprehensive income and hence profitability. According to research findings, failed banks were not efficiently generating profits and this might be due to failure to curtail cost of operations thus surviving banks must ensure lower levels of expenses whenever conducting banking business. Lower levels of expenditures will also improve bank profitability as well as managerial efficiency.
- Local banks must match loan advancements to bank capital to reduce the amount of assets that is burdened with loans. This will hedge against liquidity risk since loans are only liquidated when matured and that customers may default principal and interest payments.
- Banks must not maintain higher LTA ratios since this increases their risk of failing despite of their size. This must be taken serious since most of the banks such as Agribank, Metbank, Kingdom and FBC shown to be very risky in terms of their exposure to failing risk as a result of higher variance in LTA ratios.
- Off-balance sheet items must be incorporated when setting capital level both at bank level and on a regulatory scene by RBZ. Off-balance sheet activities also determine the riskiness of banks assets hence any expansion must be compensated by increasing capital holdings. Failed banks some surviving indicated lower GRR ratios and higher variance showing great exposure to failing risk as a result of unhedged off-balance sheet activities. Banks that must pay attention to improving their GRR include ZB and Kingdom bank.
- Regulatory mandates such as those related to capital and liquidity requirements must be imposed based on each bank's characteristics rather than the one-size fits-all approach. For example, minimum capital requirements must be bank driven rather than sector related. This was derived from the notion that most banks in this study had different capital and liquidity ratios.

- RBZ's rating systems and policy designing must be based on the magnitude effect of each of the causes of bank failures such that much focus is directed on relevant causes based on their rankings were liquidity, profitability and capitalizations are major areas of concern in this rank order.

5.5 Suggestions for Future Studies

Future researchers must consider such issues as political interference, loan loss provisions and ownership and capital structures of banks. These factors need to be considered because the researchers believes that bank failure are only occurring to locally owned banks, thus there is need to identify forces that are making foreign bank resilient to failures in the MCR. The researcher also wishes forthcoming researchers to consider if there are changes in determinants of bank failure in Zimbabwe when the country transform to another currency.

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Internet resources:

http://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG- World Bank Gdp data

APPENDICES

Appendix A: Explanatory variables in Vector Zi

GDP growth rate (GDP)	GDP	-
Non-performing loan ratio (NPL)	Non-performing loans / total loans	+
Gross revenue ratio (GRR)	Tier 1 capital / (total interest and non-interest income)	-
Tier 1 capital ratio (T1CR)	Tier 1 capital / total risk – weighted assets	-
Loans to assets ratio (LTA)	Loans / total assets	+
Loans to deposit ratio (LTD)	Loans / total deposits	+
Deposits to total assets (DTA)	Deposit / total assets	-
ROA	Net income / total assets	-
Efficiency ratio (EFR)	Total operating expenses / Net operating income	+
Size of bank (SIZE)	Ln (total assets)	-

Appendix B: Descriptive statistics

Appendix 1: Median statistics by Group

. tabstatlta ltd dtagrr t1cr roaefrnpl size, statistics(median) by(failure) columns(variables)

Summary statistics: p50

by categories of: failure (FAILURE)

failure	lta	ltd	dtagrr	t1cr	roaefrnpl	size
Non-failed	.473	.708	.71685	1.2549	.2008	.0219	.80655	.0381	19.1904
Failed	.79055	.9497	.43915	.46865	.0453	-.0189	1.69395	.30215	18.20555
Total	.5423	.7524	.6548	1.02915	.1915	.01275	.85565	.0479	18.97755

Appendix 2: Mean statistics by Group

. tabstatlta ltd dtagrr t1cr roaefrnpl size, statistics(mean) by(failure) columns(variables)

Summary statistics: mean

by categories of: failure (FAILURE)

failure	lta	ltd	dtagrr	t1cr	roaefrnpl	size
Non-failed	.4819818	.6757182	.6859136	1.167925	.2124705	.0253795	.9220091	.0504386	19.06355
Failed	.7620917	1.068492	.433375	.4627083	-.1078167	-.1882917	3.012225	.4325308	17.42738
Total	.5420054	.7598839	.6317982	1.016807	.1438375	-.0204071	1.369913	.1323155	18.71294

Appendix 3: Variance statistics by Group

. tabstatlta ltd dtagrr t1cr roaefrnpl size, statistics(var) by(failure) columns(variables)

Summary statistics: variance

by categories of: failure (FAILURE)

failure	lta	ltd	dtagrr	t1cr	roaefrnpl	size
Non-failed	.0354525	.0884037	.0259622	.0903407	.0029857	.0007137	.1342324	.0038405	.749571
Failed	.0144107	.2295894	.0092956	.0047894	.1063729	.07499	8.210274	.1238774	2.975319
Total	.0440501	.14148	.0330898	.1568445	.0411947	.0233826	2.495972	.0528057	1.640012

Appendix 4: Standard deviation statistics by Group

. tabstatlta ltd dtagrr t1cr roaefrnpl size, statistics(sd) by(failure) columns(variables)

Summary statistics: sd

by categories of: failure (FAILURE)

failure	lta	ltd	dtagrr	t1cr	roaefrnpl	size
Non-failed	.1882882	.2973276	.1611279	.3005672	.0546419	.0267154	.3663774	.0619718	.8657777
Failed	.1200445	.4791549	.0964135	.0692054	.3261486	.2738429	2.865358	.3519623	1.724911

Total | .2098811 .3761382 .1819061 .396036 .2029647 .1529138 1.579865 .2297949 1.28063

Appendix C: Descriptive Statistics by Bank

Appendix 1: Mean statistics by Bank

. tabstatlta ltd dtagrr t1cr roaefrnpl size, statistics(mean) by(id1) columns(variables)

Summary statistics: mean

by categories of: id1 (ID)

id1	lta	ltd	dtagrr	t1cr	roaefrnpl	size
Agribank	.553975	1.132	.40015	1.4528	.19125	.073	1.2991	.046475	18.04145
BancABC	.639275	.741125	.849975	1.3207	.20165	.0159	.751975	.03525	19.5235
Barclays	.18995	.250425	.757625	1.193075	.25515	.00195	.99465	.0018	19.25097
CBZ	.645925	.8037	.761325	1.07325	.281725	.041375	.616925	.0227	20.41915
FBC	.471825	.6352	.6479	1.390125	.220875	.0154	.794775	.0399	19.02233
Genesis	.8329	.680575	.410825	.519775	-.354125	-.54225	6.45243	.658075	15.14753
Interfin	.6364	1.0485	.5139	.458075	.038875	-.00795	1.3405	.137075	18.7779
Kingdom	.65935	.9414	.645925	.583325	.163075	.02245	1.028625	.178875	18.719

Metbank| .4304 .6934 .601125 1.117825 .2586 .029075 .818575 .0384 18.18545

Renaissance | .816975 1.4764 .3754 .410275 -.0082 -.014675 1.24375 .5024425 18.35672

Stanbic | .356825 .421475 .852075 1.163925 .1497 .020675 .745825 .0485 19.62055

Stanchart | .290225 .438475 .69845 1.184 .198825 .0288 .668275 .0286 19.68538

Tetrad | .5974 .84555 .671975 .981825 .23845 .00305 1.573025 .02095 18.1882

ZB Bank | .46665 .53015 .658525 1.386325 .177875 .0275 .85035 .093375 19.04305

----------+----------

Total | .5420054 .7598839 .6317982 1.016807 .1438375 -.0204071 1.369913 .1323155 18.71294

Appendix 2: Variance statistics by Bank

. tabstatlta ltd dtagrr t1cr roaefrnpl size, statistics(var) by(id1) columns(variables)

Summary statistics: variance

by categories of: id1 (ID)

id1	lta	ltd	dtagrr	t1cr	roaefrnpl	size
Agribank	.040957	.1096144	.0106635	.0021857	.0017283	.0012448	.0551249	.0002654	.3223933
BancABC	.0080155	.0086985	.0002338	.0020604	.0000416	.0000967	.0097825	.0017099	.1273128
Barclays	.0025278	.0034808	.0012533	.1243468	.0019984	.0000434	.0059674	1.47e-06	.0480187
CBZ	.0100489	.0114288	.0213667	.0541271	.005159	.0013408	.0010973	.0007695	.1724951
FBC	.0469772	.0767471	.0387663	.0154614	.0003597	.0001303	.0003533	.0001744	.070753
Genesis	.0026745	.0091862	.0038876	.0036955	.1982243	.0193548	4.934651	.0955578	.0328709
Interfin	.0118948	.1229034	.0022064	.0022311	.0172588	.0000381	.2357814	.0071545	.2917557
Kingdom	.0203804	.0372819	.0325875	.1004995	.0005745	.0007525	.0910871	.0190254	.0785754

Metbank| .016225 .00834 .0205904 .1507329 .0041378 .0004414 .0026281 .0001205 .5930112

Renaissance | .006504 .286714 .0141846 .003598 .0517379 .0049671 1.257711 .1607691 .071113

Stanbic| .0131324 .0128152 .0028542 .0181626 .0001323 .0000869 .0002724 .0000123 .0271165

Stanchart| .009326 .0229868 .0170209 .0396463 .0010252 .0004623 .0073813 .0001547 .0353077

Tetrad | .0174581 .0189978 .007396 .0002674 .0022337 .0001203 .6299081 .0000273 1.473028

ZB Bank |.0000386 .0857645 .0082578 .0002779 .0016428 .0004158 .0109358 .0016835 .483748

Total | .0440501 .14148 .0330898 .1568445 .0411947 .0233826 2.495972 .0528057 1.640012

Appendix D: Correlation Matrix

. correlatelta ltd dtagrr t1cr roaefrnpl size gdp

(obs=56)

| lta ltd dtagrr t1cr roaefrnpl size gdp

---

lta | 1.0000

ltd | 0.6586 1.0000

dta | -0.3422 -0.5415 1.0000

grr | -0.5280 -0.3881 0.2813 1.0000

t1cr | -0.4701 -0.2369 0.3913 0.5203 1.0000

roa | -0.3923 0.0307 0.2988 0.4138 0.7545 1.0000

efr | 0.4396 0.0619 -0.3699 -0.3962 -0.8406 -0.8826 1.0000

npl | 0.5962 0.2437 -0.3774 -0.5666 -0.8026 -0.7001 0.7359 1.0000

size | -0.3548 -0.1063 0.5588 0.3440 0.6032 0.7474 -0.7944 -0.6006 1.0000

gdp | -0.0993 -0.0848 0.2375 0.1407 0.2252 0.2698 -0.3351 -0.1952 0.2713 1.0000

Appendix E: Pooled logit regression results

. blogit failure id1 lta ltd dtagrr t1cr roaefrnpl size gdp size2

Logistic regression for grouped data Number of obs = 420

LR chi2(10) = 37.66

Prob> chi2 = 0.0000

Log likelihood = -35.660328 Pseudo R2 = 0.3456

_outcome | Coef. Std. Err. zP>|z| [95% Conf. Interval]

---

lta | 454.327 10.32454 44.00 0.000 434.0913 474.5627

ltd | -103.284 2.32519 -44.42 0.000 -107.8413 -98.72674

dta | -68.46534 5.497255 -12.45 0.000 -79.23976 -57.69092

grr | -103.4679 13.39887 -7.72 0.000 -129.7292 -77.20662

t1cr | 25.32403 3.825904 6.62 0.000 17.8254 32.82267

roa | -265.0339 4.684142 -56.58 0.000 -274.2146 -255.8531

efr | -8.387014 .6180668 -13.57 0.000 -9.598402 -7.175625

npl | -49.40341 2.653392 -18.62 0.000 -54.60396 -44.20285

size | 921.6669 1.574655 585.31 0.000 918.5807 924.7532

gdp | -3961.7 78.94485 -50.18 0.000 -4116.43 -3806.971

size2 | -25.32048 .0658954 -384.25 0.000 -25.44964 -25.19133

_cons | -8262.098 . . . .

Appendix F: Bivariate logit regressions, marginal effects and Odds ratios

. logit failure lta

Logistic regression Number of obs = 56

LR chi2(1) = 23.58

Prob> chi2 = 0.0000

Log likelihood = -17.30507 Pseudo R2 = 0.4053

---

failure | Coef. Std. Err. z P>|z| [95% Conf. Interval]

---

lta | 12.89353 4.00846 3.22 0.001 5.037092 20.74997

_cons | -9.687864 2.863566 -3.38 0.001 -15.30035 -4.075377

. logistic failure lta

Logistic regression Number of obs = 56

LR chi2(1) = 23.58

Prob> chi2 = 0.0000

Log likelihood = -17.30507 Pseudo R2 = 0.4053

---

failure | Odds Ratio Std. Err. z P>|z| [95% Conf. Interval]

---+---

lta | 397730.2 1594286 3.22 0.001 154.0215 1.03e+09

. mfx

Marginal effects after logistic

y =Pr(failure) (predict)

= .06300273

---

variable | dy/dx Std. Err. z P>|z| [95% C.I.] X

---+---

lta | .7611487 .34782 2.19 0.029 .079431 1.44287 .542005

. logit failure ltd

Logistic regression Number of obs = 56

LR chi2(1) = 10.19

Prob> chi2 = 0.0014

Log likelihood = -24.003054 Pseudo R2 = 0.1751

```
------------------------------------------------------------------------------
failure |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ltd |   2.988742   1.096151     2.73   0.006     .8403262    5.137158
      _cons |  -3.820747   1.038165    -3.68   0.000    -5.855514   -1.785981
------------------------------------------------------------------------------
```

```
. logistic failure ltd
Logistic regression                               Number of obs   =         56
                                                  LR chi2(1)      =      10.19
                                                  Prob> chi2      =     0.0014
Log likelihood = -24.003054                       Pseudo R2       =     0.1751
------------------------------------------------------------------------------
failure | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------+---------------------------------------------------------------------
ltd |   19.86069   21.77031     2.73   0.006     2.317123    170.2313
------------------------------------------------------------------------------
```

```
. mfx

Marginal effects after logistic
y  =Pr(failure) (predict)
=  .17513682
```

```
------------------------------------------------------------------------------
variable |      dy/dx    Std. Err.     z    P>|z|  [    95% C.I.   ]     X
---------+--------------------------------------------------------------------
ltd |   .4317654     .15712    2.75   0.006   .123808  .739723   .759884
------------------------------------------------------------------------------
```

```
. logit failure dta

Logistic regression                                     Number of obs   =        56
                                                        LR chi2(1)      =     20.88
                                                        Prob> chi2      =    0.0000
Log likelihood = -18.656707                             Pseudo R2       =    0.3588

------------------------------------------------------------------------------
failure |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
dta |  -10.75743   3.178562    -3.38   0.001    -16.9873   -4.527567
      _cons |   4.633641   1.634242     2.84   0.005     1.430586    7.836697
------------------------------------------------------------------------------
```

```
. logistic failure dta

Logistic regression                             Number of obs   =        56
                                                LR chi2(1)      =     20.88
                                                Prob> chi2      =    0.0000
```

Log likelihood = -18.656707 Pseudo R2 = 0.3588

---

failure | Odds Ratio Std. Err. z P>|z| [95% Conf. Interval]

---+---

dta | .0000213 .0000677 -3.38 0.001 4.19e-08 .0108069

. mfx

Marginal effects after logistic

y =Pr(failure) (predict)

= .10313323

---

variable | dy/dx Std. Err. z P>|z| [95% C.I.] X

---+---

dta | -.9950278 .32882 -3.03 0.002 -1.63951 -.350543 .631798

. logit failure grr

Logistic regression Number of obs = 56

LR chi2(1) = 39.55

Prob> chi2 = 0.0000

Log likelihood = -9.3219085 Pseudo R2 = 0.6796

```
------------------------------------------------------------------------------
failure|      Coef.   Std. Err.     z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
grr |  -10.25009   3.509431    -2.92   0.003    -17.12845   -3.371732
      _cons |   6.059292    2.00999     3.01   0.003     2.119785    9.998799
------------------------------------------------------------------------------
```

```
. logistic failure grr

Logistic regression                             Number of obs   =         56
                                                LR chi2(1)      =      39.55
                                                Prob> chi2      =     0.0000
Log likelihood = -9.3219085                     Pseudo R2       =     0.6796

------------------------------------------------------------------------------
failure | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------+---------------------------------------------------------------------
grr |   .0000354   .0001241    -2.92   0.003     3.64e-08    .0343301
------------------------------------------------------------------------------
```

```
. mfx

Marginal effects after logistic
y  =Pr(failure) (predict)
```

= .01257894

---

variable | dy/dx Std. Err. zP>|z| [95% C.I.] X

---+---

grr | -.1273134 .17697 -0.72 0.472 -.474166 .219539 1.01681

. logit failure t1cr

Logistic regression Number of obs = 56

LR chi2(1) = 45.73

Prob> chi2 = 0.0000

Log likelihood = -6.2334129 Pseudo R2 = 0.7858

---

failure| Coef. Std. Err. z P>|z| [95% Conf. Interval]

---+---

t1cr | -77.63694 31.46632 -2.47 0.014 -139.3098 -15.9641

_cons | 9.677659 4.413108 2.19 0.028 1.028126 18.32719

. logistic failure t1cr

Logistic regression Number of obs = 56

LR chi2(1) = 45.73

Prob> chi2 = 0.0000

Log likelihood = -6.2334129 Pseudo R2 = 0.7858

---

failure | Odds Ratio Std. Err. zP>|z| [95% Conf. Interval]

---+---

t1cr | 1.92e-34 6.03e-33 -2.47 0.014 3.15e-61 1.17e-07

. mfx

Marginal effects after logistic

y =Pr(failure) (predict)

= .18400509

---

variable | dy/dx Std. Err. z P>|z| [95% C.I.] X

---+---

t1cr | -11.65697 6.48641 -1.80 0.072 -24.3701 1.05616 .143837

. logit failure roa

Logistic regression Number of obs = 56

LR chi2(1) = 23.52

Prob> chi2 = 0.0000

Log likelihood = -17.335095 Pseudo R2 = 0.4042

---

failure | Coef. Std. Err. zP>|z| [95% Conf. Interval]

---+---

roa | -56.08996 26.43828 -2.12 0.034 -107.908 -4.271887

_cons | -1.196112 .4505479 -2.65 0.008 -2.07917 -.3130543

. logistic failure roa

Logistic regression Number of obs = 56

LR chi2(1) = 23.52

Prob> chi2 = 0.0000

Log likelihood = -17.335095 Pseudo R2 = 0.4042

---

failure | Odds Ratio Std. Err. z P>|z| [95% Conf. Interval]

---+---

roa | 4.37e-25 1.16e-23 -2.12 0.034 1.37e-47 .0139554

. mfx

Marginal effects after logistic

y =Pr(failure) (predict)

= .48713379

---

variable | dy/dx Std. Err. z P>|z| [95% C.I.] X

---+---

roa | -14.0132 6.84447 -2.05 0.041 -27.4281 -.598289 -.020407

. logit failure efr

Logistic regression Number of obs = 56

LR chi2(1) = 16.93

Prob> chi2 = 0.0000

Log likelihood = -20.633803 Pseudo R2 = 0.2908

---

failure | Coef. Std. Err. z P>|z| [95% Conf. Interval]

---+---

efr | 1.43253 .6112234 2.34 0.019 .234554 2.630506

_cons | -3.242355 .8284168 -3.91 0.000 -4.866022 -1.618688

. logistic failure efr

Logistic regression Number of obs = 56

LR chi2(1) = 16.93

Prob> chi2 = 0.0000

Log likelihood = -20.633803 Pseudo R2 = 0.2908

---

failure | Odds Ratio Std. Err. z P>|z| [95% Conf. Interval]

---

efr | 4.189284 2.560589 2.34 0.019 1.264345 13.88079

. mfx

Marginal effects after logistic

y =Pr(failure) (predict)

= .21756479

---

variable | dy/dx Std. Err. z P>|z| [95% C.I.] X

---

efr | .2438601 .1319 1.85 0.064 -.014666 .502386 1.36991

. logit failure npl

Logistic regression Number of obs = 56

LR chi2(1) = 28.32

Prob> chi2 = 0.0000

Log likelihood = -14.938717 Pseudo R2 = 0.4866

---

failure | Coef. Std. Err. z P>|z| [95% Conf. Interval]

---+---

npl | 15.15673 4.994199 3.03 0.002 5.368278 24.94518

_cons | -3.280101 .7371249 -4.45 0.000 -4.724839 -1.835363

. logistic failure npl

Logistic regression Number of obs = 56

LR chi2(1) = 28.32

Prob> chi2 = 0.0000

Log likelihood = -14.938717 Pseudo R2 = 0.4866

---

failure | Odds Ratio Std. Err. z P>|z| [95% Conf. Interval]

---+---

npl | 3823694 1.91e+07 3.03 0.002 214.4932 6.82e+10

. mfx

Marginal effects after logistic

y =Pr(failure) (predict)

= .21846562

---

variable | dy/dx Std. Err. z P>|z| [95% C.I.] X

---+---

npl | 2.587835 1.23768 2.09 0.037 .162027 5.01364 .132316

. logit failure size

Logistic regression Number of obs = 56

LR chi2(1) = 14.64

Prob> chi2 = 0.0001

Log likelihood = -21.774965 Pseudo R2 = 0.2516

---

failure | Coef. Std. Err. z P>|z| [95% Conf. Interval]

---+---

size | -1.066726 .357322 -2.99 0.003 -1.767065 -.3663882

_cons | 18.36355 6.578689 2.79 0.005 5.469561 31.25755

. logistic failure size

Logistic regression Number of obs = 56

LR chi2(1) = 14.64

Prob> chi2 = 0.0001

Log likelihood = -21.774965 Pseudo R2 = 0.2516

---

failure | Odds Ratio Std. Err. z P>|z| [95% Conf. Interval]

---+---

size | .3441332 .1229664 -2.99 0.003 .1708337 .6932336

. mfx

Marginal effects after logistic

y =Pr(failure) (predict)

= .16825644

---

variable | dy/dx Std. Err. z P>|z| [95% C.I.] X

---+---

size | -.1492843 .05416 -2.76 0.006 -.255436 -.043133 18.7129

. logi failure gdp

Logistic regression Number of obs = 56

LR chi2(1) = 6.30

```
                                                        Prob> chi2     =     0.0121
Log likelihood = -25.945622                             Pseudo R2      =     0.1083

------------------------------------------------------------------------------
failure |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gdp |  -42.91765   18.81364    -2.28   0.023    -79.79171   -6.043595
      _cons |   1.234823   1.089876     1.13   0.257    -.9012943     3.37094
------------------------------------------------------------------------------

. logistic failure gdp

Logistic regression                                     Number of obs   =        56
                                                        LR chi2(1)      =      6.30
                                                        Prob> chi2      =    0.0121
Log likelihood = -25.945622                             Pseudo R2       =    0.1083

------------------------------------------------------------------------------
failure | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
gdp |   2.30e-19   4.32e-18    -2.28   0.023     2.22e-35     .002373
------------------------------------------------------------------------------

. mfx

Marginal effects after logistic
```

y =Pr(failure) (predict)

= .18087285

---

variable | dy/dx Std. Err. z P>|z| [95% C.I.] X

---+---

gdp | -6.358587 2.52429 -2.52 0.012 -11.3061 -1.41107 .063966

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