AN INVESTIGATION OF THE CREDIT SCORING METHODS USED BY ZIMBABWEAN FINANCIAL INSTITUTIONS

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DECLARATION

I,…Desmond Mutava……………………………………………………….., do hereby affirm that this thesis is centered on my own research, apart from the references, acknowledgments and comments in this thesis and this thesis has not been submitted at any educational level to any other academic institution.

Signed by…………………….........at this date…27……..Month of ……February…….Year……......2015.

(Student)

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ABSTRACT

There has been a surge in the level of non-performing loans in the Zimbabwean economy as a result of the information asymmetry problem that leads to the adverse selection and moral hazard problems in the credit markets. The study sought to look into the types of credit scoring techniques used by Zimbabwean financial institutions.

To obtain the empirical data, questionnaires were administered to loan officers, operations managers and general managers of 19 banking institutions. The study adopted a survey approach in the sense that all banking institutions were covered. Structured interview questions were used to collect data from the respondents. A qualitative research approach was used for the purposes of this research, and the data collected was analysed through the use of content analytical summary tables, statistics and frequencies.

The study found that all financial institutions use statistical scoring techniques as compared to ancient and subjective judgmental scoring techniques. As a result, the scoring techniques used by Zimbabwean financial institutions are good and are in line with international best practice. However, the problem lies in the variables that are inputted into these "good" scoring models. The levels of borrower information sharing are very low in the Zimbabwean economy. The study results also agree with a similar survey that was performed by the World Bank in 2013, which gave Zimbabwe a rating of one out of a maximum possible six, on the level of information sharing between financial institutions. The study also found that due to the low levels of information sharing, the loan approval process was generally very slow in Zimbabwe as compared to other countries such as South Africa where some financial institutions approve a loan application within a matter of a few minutes. In light of these findings this study recommends that, policy makers accelerate the setting up of a Credit Referencing Bureau.

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LIST OF ABBREVIATIONS

AfDB	African Development Bank
ANN	Artificial Neural Network
CRA	Credit Rating Agency
CRB	Credit Referencing Bureau
GAs	Genetic Algorithms
GDP	Gross Domestic Product
GNU	Government of National Unity
HMT	Her Majesty's Treasury
NPL	Non Performing Loan
OECD	Organisation for Economic Cooperation and Development
RBZ	Reserve Bank of Zimbabwe
RP	Recursive partitioning
SMEs	Small and Medium Size Enterprises

CHAPTER 1: INTRODUCTION AND BACKGROUND TO THE STUDY

1 Introduction

In developing countries, lending is a challenging proposition because information about the ability and willingness of borrowers to repay may not be readily available, and also because in most developing nations, the legal/judicial systems may be weak. Most of the borrowers may not have borrowed before and cannot have any form of collateral to pledge as security (Navajas, Conning, and Gonzalez-Vega, 2003; Udry, 1990).

One of the main activities of a financial institution is to offer credit, and the main inherent risk associated with lending is default risk, that is, the uncertainty associated with the borrower's ability and willingness to pay back these loans as well as the interest portion charged on the loans.

Financial institutions often find themselves in a dilemma of giving out credit to their clients and increasing revenue and profits but at the same time, risk losing out due to counter party/default risk.

Because of the information asymmetry and moral hazard problem, most banks in Zimbabwe have resorted to giving out loans to existing clients with existing or past credit history. CABS for example, recently introduced a new product, Equity Release finance, whereby paid up clients can re-borrow at most half of the value of paid up properties. NMB Bank has of late been giving out loans to clients with existing loan facilities as these have a proven credit record. This practice of giving out loans to clients with existing loan facilities has got a tendency of disadvantaging new credit worthy prospective lenders who truly deserve credit (Bank of England, 2014).

The importance of credit scoring and credit referencing cannot be underestimated as it is the objective of every financial institution to lend profitably. Lending profitably entails getting the maximum possible returns and at the same time minimizing any counter party/ default risk. The ideal scenario for any financial institution would be to issue the maximum quantity of loans with a very high recovery rate, so as to maximize profits.

This study seeks to investigate credit control techniques employed by Zimbabwean companies focusing on companies in the financial services sector, specifically banking institutions.

1.1 Background of the banking industry

1.1.1 Financial services sector operating environment analysis

According to the Reserve Bank of Zimbabwe (RBZ), the Zimbabwean economy has nineteen(19) operating banking institutions, made up of fourteen (14) commercial banks, three building societies, one savings bank, one merchant bank and 147 microfinance institutions (RBZ, 2015).There seems to be no institution that deals with credit rating of prospective borrowers on behalf of banking institutions. As a result, the credit vetting function is an in-house function for most if not all of the financial institutions (including micro finance institutions).

1.1.2 Political environment

Political factors that affect an industry are the government stability, government policy consistency, foreign trade regulations, foreign policy and social welfare policies (Johnson and Scholes, 2004). Relations between the government of Zimbabwe and Western countries have not been normal. Traditionally, these countries provided the most needed budgetary support to the government of Zimbabwe.

Government policy, mainly the Indigenisation and Economic Empowerment Act has not been in favour of foreign owned banks. Under this Act, local blacks should own a minimum of 51 percent in companies valued over $500,000. The effect of this Act has been to restrict the injection of any fresh capital from the parents of foreign owned institutions. The other notable effect of the Indigenisation Act on the operations of foreign owned banking institutions has also seen most of them changing their strategies from growth to survival strategies as most of them are maintaining a wait and see attitude.

The high rate of employment and low industry capacity utilisation have promoted the rapid growth of the informal sector and this has had the effect of increasing the demand for microfinance products which are more flexible and tailor made for the unbanked segment of the population (Kinkhamer, 2009).

1.1.3 Economic environment

According to Johnson and Scholes (2004), economic factors that can affect a business include interest rates, money supply, inflation, business cycles and disposable incomes. The Zimbabwean economy stabilized and showed signs of recovery after the formation of the Government of National Unity (GNU). Positive Gross Domestic Product (GDP) rates were recorded in 2009:6.3%, 2010: 9.6%, 2011:9.4%, 2012:4.4% and 2013:3.8% (AfDB, 2014).

According to the RBZ (2014), in real terms, economic activity fell from 10.6% in 2012 to about 4.5% in 2013. A further slowdown in GDP growth was anticipated for the 2014 fiscal year and was revised to 3.1% (RBZ, 2014). On the other hand, inflation remained in the negative territory during the period February to June 2014. The inflation rate in Zimbabwe was recorded at -0, 80 percent for the month of December 2014. This deflationary trend is as a result of low aggregate demand as well as a price correcting phase as Zimbabwean goods and services were generally higher than those obtaining in neighboring states.

As of December 2012, interest rates that were quoted by banks were on the high side. This was mainly due to liquidity shortages as a result of limited access to credit lines as well as the adverse balance of payments position of the country. The lending rates also reflected the high premiums charged by most banks and were not reflective of their cost structures (RBZ, 2013).

1.1.4Technological environment

The fast changing technological landscape has changed the ways of doing business in the financial services sector. There has been a marked increase in the use of internet services, satellite communications and mobile phones and these have reduced the cost of doing business at an added convenience. In Zimbabwe, the introduction of mobile banking has negatively impacted on the revenue and profitability of the traditional brick and mortar financial institutions. The effect of mobile banking has been to reduce the volume of transactions/business for the financial institutions in Zimbabwe as mobile banking services are more convenient and flexible as compared to services offered by financial institutions. For example, mobile banking services are conveniently located such that the customer does not have to travel long distances to transact.

1.1.5 Legal environment

The financial services sector is a highly regulated industry and is regulated by the following Acts of parliament and legal statutes:

- Companies Act Chapter 24:03
- Banking Act Chapter 24:20
- Prescribed Rates of Interest Act Chapter 8:10
- Statutory Instrument 126 of 1993
- Microfinance Act Chapter 24:09
- Money lending and Rates of Interest Act Chapter 14:4
- Indigenisation and Economic Empowerment Act Chapter 14:33
- Statutory Instrument 126 of 1993
- Statutory Instrument 33 of 1999 and
- Statutory Instrument 62 of 1996

The minimum capital requirement for banks, as per the Monetary Policy Statement of January 2014 was reviewed and the deadline for compliance with capital requirements was extended to 31 December 2014. Table 1.0 overleaf shows the current requirements with respect to the capitalization of financial institutions;

Table 1: Banking Institutions Capital Requirements

Segments	Types of information	Capital requirements Current	2020	Activities
Tier I	Large indigenous commercial banks and all foreign banks	$25M	$100M	Core banking activities plus additional services such as mortgage, lending, leasing and hire purchase
Tier II	Commercial banks, Merchant banks, Building societies, Development banks, Finance and Discount houses	$25M	$25M	Core banking activities only
Tier III	Deposit taking micro finance banks	$5M	$7,5M	Deposit taking microfinance activities

Source: RBZ - Mid-Term Monetary Policy Statement (June 2014)

1.1.6 Financial performance

1.1.6.1 Capitalisation

According to the RBZ (2014), out of a total of 19 operating banks (excluding POSB), 14 were in compliance with the prescribed minimum capital requirements. In total, core capital for the banking sector amounted to $753, 09 million as at 30 June 2014 as compared to $790.35 million as at 31 December 2013. The decrease in the aggregate core capital is largely attributable to loan loss provisions and subdued income performance by some banks.

Banks have submitted recapitalization plans which are premised on capital injection by shareholders, organic growth, rights issues and mergers and acquisitions. The banks' efforts to increase their capitalization have been greatly constrained by a number of challenges including subdued foreign direct investment and macroeconomic environment, among others.

1.1.6.2 Profitability

According to the Reserve Bank of Zimbabwe (RBZ), January 2015 monetary policy statement, most banks generally recorded a profit as at 31 December2014, with a total profit of $52, 8 million for year ended 31 December 2014, as compared to $49,4 million for the corresponding prior period ended 31 December 2014. The losses that were recorded by the other few banks were as a result of high levels of non-performing loans, a deliberate strategy by some banks to clean up their loan books through provisioning and due to a lack of critical mass in terms of revenue to cover operating costs (RBZ, 2015).

1.1.6.3 Deposits, Loans and Advances

Total deposits held by financial institutions (excluding interbank deposits), increased by 13, 6% from $3, 9 billion as at 31 January 2014 to $4, 4 billion as at 31 December 2014. Loans and advances increased by 4% to $5, 1 billion from $4, 9 billion, during the same period (RBZ, 2015).

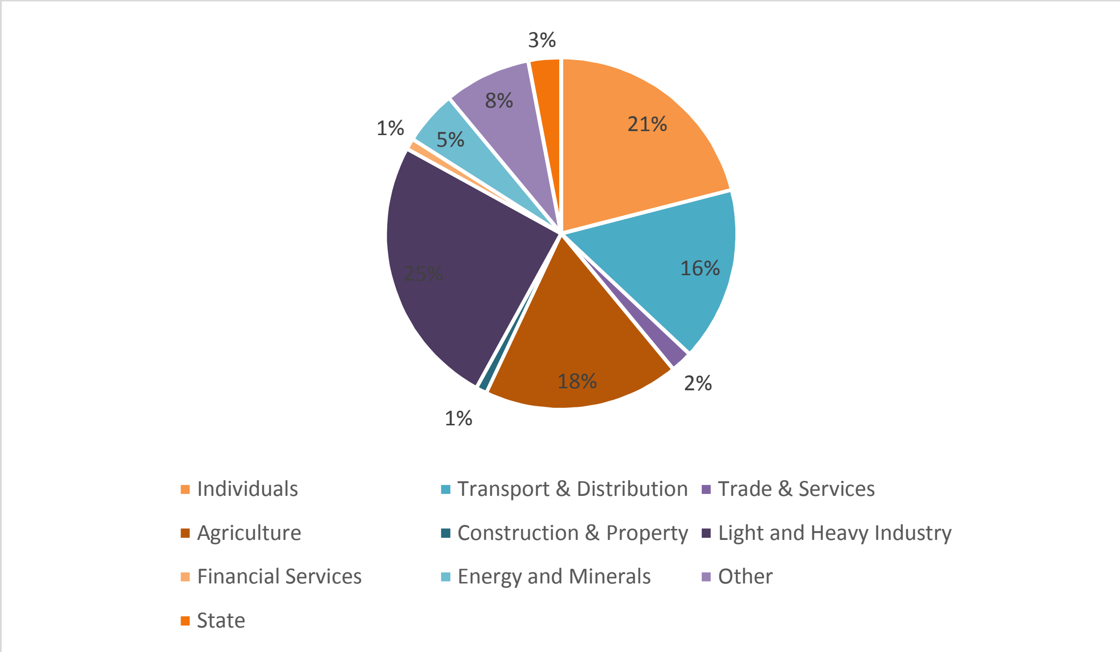

Figure 1: Sectorial distribution of loans (RBZ, 2015)

1.2 Statement of the problem

The issue of non-performing loans and bad debts is an area of interest for banking institutions and other credit issuing institutions. In the past two years, many banking institutionshave written off significant amounts off their loan books due to non-performing loans and bad debts (The Daily News, 2014). This is mainly attributable among other factors to the credit vetting performed before credit is issued to corporates and individuals, whereby there is an information asymmetry problem, that is, the lender has got less information on the prospective borrower than the borrower. This results in the adverse selection problem, and in most cases, credit is issued to undeserving corporates and individuals.

Many corporates and individuals in Zimbabwe are in the habit of having loans/credit facilities with multiple financial institutions but they do not disclose that to the concerned institution. This can be largely blamed on the credit scoring and vetting exercises performed before credit is issued. Some unscrupulous borrowers even go to the extent of borrowing from one institution and default on the terms of the credit issued then they move on to the next lender and borrow without disclosing their credit history (The Daily News, 2014). As a result, lenders have got very little information about prospective borrowers. Maintaining multiple borrowing relationships creates informational problems for lenders where each prospective lender may not have clear information about how much credit the prospective borrower has already obtained or will be able to obtain from other lenders. A borrower's default risk, from the point of view of a given lender, depends on the overall indebtedness of the borrower when his obligation towards that lender will mature.

However, if this information is unavailable to the lender, the borrower will have the incentive to over-borrow. When a multi banked customer applies for a loan from the bank, each additional dollar he borrows reduces their probability of repayment of both the capital and interest to all the financial institutions that they owe. As a result, the borrower's expected repayment per dollar of debt is a decreasing function of his total debt and as such has the incentive to over borrow (Gehrig and Stenbacka, 2007). In anticipation of moral hazard, both lenders would ordinarily ration the quantum of credit and or require a higher interest rate, or even decline credit.

Most financial institutions and credit retailers that are battling defaulting clients have no intelligence on them. Most of which are multi banked clients who are serial defaulters with non-performing loans with several banking and retailing institutions (The Daily News, 2014)

Therefore this research investigates whether this problem on non-performing loans is as a result of the problem with credit scoring techniques used by financial institutions or not and make the necessary policy recommendations about credit scoring techniques.

1.3 Research objectives

The specific objectives of this study were:

1. To assess the different types of credit scoring methods used by financial institutions in Zimbabwe.
2. To establish whether or not financial institutions share information pertaining to their clients/customers.

3. To determinethe factors that are considered when vetting a prospective loan/credit applicant.
4. To establish the average time taken in the vetting of prospective credit applicants by financial institutions in Zimbabwe.
5. To assess the similarities and differences between credit scoring methods used for corporates and individuals.

1.4Research questions

Research Specific Questions

1. What credit scoring methods are used by Zimbabwean financial institutions?
2. Do financial institutions share information pertaining to creditworthiness of their clients/customers?
3. What factors are considered by financial institutions before they make the lending decision?
4. What is the average turn-around time for a loan/creditapplication by Zimbabwean financial institutions?
5. Are there any similarities in the credit scoring methods and techniques used for corporates and individuals?

1.5 The study's proposition

This study maintains the proposition that the credit scoring methods in use by Zimbabwean financial institutions are not effective, and that there is inadequate borrower information sharing between lenders which has resulted in borrowers obtaining credit from multiple financial institutions without being detected by the lending institutions that they would then go on to borrow from.

1.6Justification of the study

This study was justified with the following beneficiaries in mind: the researcher, Zimbabwean financial institutions, other users of credit scoring information like credit departmental stores, insurance companies and mobile phone network operators and the academic world.

To the researcher

This study was of importance to the researcher as it was done as an academic requirement towards completion and attainment of the Masters of Business Administration Degree. The research was carried out after completion of a rigorous two year academic portion of the degree programmeand this is a final hurdle towards the attainment of the Masters of Business Administration qualification. The research tested the researcher's ability to apply learnt concepts from the MBA curriculum in a practical setting. This research was important to the researcher as it gave him a chance to apply learnt principles to tackle organizational practical situations.

To Zimbabwean financial institutions

Thisstudy criticallyassessed the robustness of the credit scoring methods currently in use by Zimbabwean financial institutions and was to highlight strengths and weaknesses of the credit rating methods currently employed by these institutions. Appropriate recommendations based on the results of this study shall be availed to financial institutions and credit retailers.

The study could also be of importance to prospective investors who want to invest in the banking and credit retail organisations, as well as any other business that issues credit terms to their customers such as mobile phone operators.

To the world at large

The research will contribute to the national body of knowledge by providing new findings to the study area. This research will be of value to the other researchers to follow, as it can be used either as a basis for further study or reference material for related research.

1.7 Scope of the study

The study sought to investigate and critically evaluate the credit scoring methods used by Zimbabwean financial institutions. The research was based on a survey of financial institutions in Zimbabwe.

1.8 Structure of the research

The research comprises five chapters, which are structured as follows:

Chapter 1 gives a background to the study and also highlights the research problem. It lays the foundation of the study through setting up of the objectives of the study, research questions and study preposition. The researcher also outlined justification and the scope of the research in this chapter.

Chapter Two gives an extensive account of relevant literature on the subject of credit rating. The researcher discusses various types of credit rating being applied by various financial institutions and credit retailers. Chapter two discusses some relevant literature pertaining to credit rating. In this chapter, the researcher looks at some of the theoretical underpinnings of credit rating.

Chapter 3outlines and justifies the research methodology, which includes selection of research philosophy, approaches and strategies. It also covers the data collection methods used in the study.

Chapter four provides the presentation and analysis of the study’s findings.

Chapter five gives conclusions of the research in relation to the objectives of the study as laid down in Chapter One. The researcher proposes recommendations in this chapter and also highlights areas for further research.

1.9 Chapter summary

In this chapter, an overview has been given of both the study and the banking industry at which the study was carried out. The study is an evaluation of the credit scoring methods used by Zimbabwean banking institutions. Research objectives mainly relate to an assessment of credit scoring methods used by financial institutions in Zimbabwe. The research is justified from the point of view of the researcher as the final step towards attaining a qualification of Masters of Business Administration Degree. It is also of importance to financial institutions (including micro financial institutions), credit retail organisations, landlords/estate agents, insurance companies and mobile phone network operators, among others. The research also provides a platform for further research in the subject area. A road map that was followed when carrying out the research isoutlined from Chapter1toChapter5.

CHAPTER 2: LITERATURE REVIEW

2 Introduction

The reviewing of literature is important for the purposes of this research because; it gives a thorough and up to date understanding of the area of study, it helps in identifying the methodology that was used in prior studies that were performed on the research topic, research findings from this study are compared against existing literature on similar studies that were performed in the past. The ultimate objective is for the researcher to become very much knowledgeable on the topic of study as this helps in carrying out a research that has got the potential to advance knowledge on the topic.

This chapter covers the following key areas:definitions of credit scoring methods as well as a description of the various methods used by different financial institutions, information sharing between lenders, the benefits associated with sharing borrower information, conceptual framework, any notable gaps in the literature and chapter summary.

2.1Credit scoring

According toSadatrasoul, et al (2013), credit scoring can be defined as the formal statistical methods used in the classification of credit applicants into a set of risk classes i.e. either good or bad risk classes. Credit scoring refers to methods used to classify a credit applicant into classes based on their likelihood of repaying. The probability of default by a credit applicant must be estimated based on information available at the time of the application (Avrey, Calem and Canner, 2004). Accurate screening is of benefit to both the lender (entails increased profit or loss reduction) and to the prospective borrower (avoids over borrowing).

Traditional methods of credit vetting use human judgment based on previous decisions or some set parameters to determine the risk of default. Before formal credit scoring techniques became popular, the decision to grant credit was subjectively made based on human judgment (Chandler and Coffman, 1979). Nowadays, scoring methods are very popular with many lenders because of their ability to handle many transactions and they enable more accurate classifications than subjective judgmental assessments performed by human experts (Rosenberg and Gleit, 1994).

Empirical credit evaluation processes do not have serious deficiencies as compared to judgmental evaluation methods (Chandler and Coffman, 1979). Moore and Reichert (1983), were not convinced by the predictive ability of credit scoring techniques but concluded that, statistical credit scoring methods may not have high predictive power but are highly objective, consistent and efficient.

Sadatrasoul et.al, (2013); Berger and Frame (2011), have identified three types of credit scoring based on the type of credit applicant:

- Enterprise credit scoring – This approach uses audited financial statements, other internal and external, private and publicly available information to extract a score for the credit applicant which would be a business enterprise/corporate;
- SME credit scoring – For Small and Medium Enterprises (SMEs) and especially small companies, financial statements may not always be readily available and where they are available, they may not be reliable. There is no separation of ownership and control with such kind of business establishments. It is in most cases up to the owner to withdraw or retain cash. Small firms are easily affected by the good/bad financial status of their owners. To that end, monitoring the counterparts of the SME is a very good and common method used for scoring them; and
- Individual credit scoring – This approach is used for scoring individuals and it scores people based on variables like the applicant's monthly/annual income, source of income, age, home status, marital status and other variables.

Sadatrasoul et.al(2013),goes a step further by identifying three kinds of scoring techniques based on the purpose of scoring;

- Application scoring – Refers to assessment of creditworthiness of a prospective borrower. It quantifies the default, associated with credit requests, by questions in the application form, e.g., current income, number of dependents, period at current address. A score is then generated, usually in the form of a number and this score serves as a proxy of the creditworthiness of the credit applicant;

- Behavioural scoring – It uses the same principles as application scoring, the difference is that it is meant for the lenders existing clients. Behavioural scoring models use historical data of the customer, e.g., account balance, age of account, nature of transactions, delinquencies and account activity among others to predict the probability of defaulting;
- Collection scoring – This method categorises customers with different levels of insolvency into classes, separating those which require more decisive action from those who do not need urgent attention. These customers are classified according to delinquency (early, middle and late repayment). This allows better management of delinquent borrowers, from the first signs of stress (30-60days late), to subsequent stages and non-recoverability; and
- Fraud detection – These rank credit applicants based on the likelihood that their applications may be fraudulent.

Credit scoring models and techniques can be classified into three main categories, namely, application, behavioural and collection models, based in the stage of the consumer credit cycle in which they are applied (Miller, 2003). These methods are mainly differentiated by the set of variables available to estimate the prospective borrower’s creditworthiness, i.e. the earlier the credit cycle stage, the lower the level of client information possessed by the bank. In essence, this entails that the prediction power of application credit scoring models is lower than that of collection and scoring behavioural models.

Credit scoring models may also be classified either as parametric or non-parametric techniques. Parametric scoring techniques include, probit and logit models, discriminant analysis models. Non parametric models include recursive partitioning trees, expert systems and neural networks among others (Thomas, 2000).

In constructing scoring models, a wide range of statistical techniques are made use of. The majority of these statistical models (some of these are nonlinear), are used in the building of effective and efficient credit scoring systems that can effectively be used for predictive purposes. The most commonly used techniques by lenders, credit analysts, software developers and researchers in the building of credit scoring models are; probit analysis, logistic regression, linear programming, logistic regression, k-nearest neighbor, generic algorithms, decision trees, neural networks, Cox's proportional hazard model, genetic programming (Ben-David and Frank, 2009).

2.1.1 Judgmental Scoring Model

Judgmental scoring models are based on traditional variables or standards of credit analysis (Chandler and Coffman, 1979). Factors such as client history, employment/trade references and financial statement ratios among others, to compute an overall credit score. The determination of the factors to use as well as the appropriate weight to attach to each variable in computing the score is based on the credit analyst's past experience with the individual or company, the industry they are in, their source of income, products or services that they sell. Judgmental models are also based on comparing industry financial profiles using peer groups or information from other similar companies in that industry, as well as scoring factors that reflect the individual characteristics (Steven, 2009).

This technique is very straight forward to implement because the rules and decision criteria are easily set and the grading scale is usually very simple. Therefore, it is much easier to understand and augment. Its major limitation is that it lacks objectivity and consistency (Crone and Finlay, 2012).

2.1.2 Statistical scoring techniques

2.1.2.1 Discriminant analysis

Discriminant analysis is made up of two techniques, namely; discriminant functions and discriminant analysis. The former aims at finding an optimal way of classifying various elements in a group whilst, the latter is used in the analysis of differences among a group of individuals (Hand and Henley, 1997).

When applied in credit scoring, individuals applying for credit are classified into two distinct categories based on their perceived ability to pay back the loan or not. This procedure involves assigning a probability to every credit applicant i.e. the probability of repaying or the probability of defaulting. The probabilities can then be transformed into a score that will be used in making a decision whether to accept or decline the credit application (Berger, Frame and Loannidou, 2011).

The method is premised on a number of assumptions. It assumes that a data base is usually and readily available, containing information about customers that would have applied for loans, and that their behavior is known throughout the credit repayment period (Nan-Chen, 2005). Characteristics of clients, private information, socio-economic status and past financial behavior are available, that can be used as the basis of future applications, are also assumed to be available.

Discriminant analysis is only useful when the groups under investigation are discrete and clearly identifiable (Taffler, 1982). However, Hand and Henley (1997), proved that this is not true. They argue that the discriminant analysis function that is obtained by segmenting a multivariate normal distribution into two categories is parallel to the optimal discriminant function.

Abdou, Pointon and Masry (2008), also concur with the notion that discriminant analysis is a useful technique in the construction of credit scoring models. However, several authors have criticized the using discriminant analysis as acredit scoring technique. Hena and Tiwari (2012), identified some problems in the use of discriminant analysis, such as, their use of linear functions as opposed to quadratic functions, their definition of groups, appropriation of prior probabilities and prediction of classification error, among others. He emphasized on the need to consider those factors or inherent limitations when using discriminant analysis techniques.

A good example of a discriminant model, is the Z score by Altman (1968), which uses accounting data to predict or to come up with a score that discriminates between healthy companies and those with a higher probability of bankruptcy;

$$Z\ score = 0.717.X1+0.847.X2+3.107.X3+0.420.X4+0.998.X5$$

According to Altman (1968), the variables that best discriminate between healthy and bankrupt are;

X1 = Working Capital/Total Assets

X2 = Retained Earnings/Total

X3 = EBIT/Total Assets

X4 = Market value of Shares/Total Assets

X5 = Sales/Total Assets

X5 = Sales / Total assets.

Altman's study concluded that the Z score was normally distributed for both sets of companies, i.e. healthy and bankrupt companies and that the respective means (score) for healthy companies was 4.14 and 0.15 for the bankrupt.

One of the main characteristics of statistical scoring techniques, of which discriminant analysis is no exception, is that absolute classification with regards to the group a particular company belongs, is not possible (Nani and Lumini, 2009).

2.1.2.2 Linear regression

This technique has been in use for a long period of time and has been used especially for the two class credit scoring problem (Wang, Guo and Wang, 2010). Linear regression methods are especially important for any data analysis that aims to describe the relationship between a response variable and one or more independent variable. Using linear regression to set up a score for each factor, the credit analyst can then use factors such as historical payments, guarantees and default rates on the customer (Hand and Henley, 1997).

Because regression using dummy variables for the class labels, it produces a linear combination of the predictive characters which is parallel to the discriminant technique, this method performs reasonably well (Lanchenbruch, 1975).Orgler (1970) used this technique to construct a model for commercial loans and he then used the technique to come up with a score card for evaluating loans that were already outstanding, rather than assessing and screening new loan applications. He concludes that behavioural characteristics are more predictive of future loan quality than the other characteristics. Therefore this technique is a behavioral scoring model.

A Poisson regression model could be used instead, to accommodate cases where the customer has been making partial repayments of varying degrees. As a result, the proportionate loan repayments can then be re-expressed as 'Poisson counts". Credit analysts can then use linear regression, taking into consideration factors such as, the applicant's default rates, historical payments and guarantees, among others, to set up a score for each factor, which they would then compare against the financial institutions cut off score. If the score falls within the passing range, credit will be granted (Chen and Li, 2010).

2.1.2.3 Logistic regression

This technique is often used by credit analysts for developing credit scoring models (Nan-Chen, 2005)**.** When using logistic regression models, the dependent variable, is generally a binary variable (nominal or ordinal) and for as long as they are dichotomized after transformation, the independent variables may be categorical.

The forward stepwise method is used to select the variables and this is the most commonly used method in the logistic regression models.

According toFenstertoc (2005), the use of logistic regression in the construction of credit scoring models has got the following advantages:

- The model so generated, takes account of the correlation between variables, and in the process, identifying relationships that would not have been visible and eliminating redundant variables;

- It considers variables individually and simultaneously; and
- The credit analyst may easily check for sources of error and optimize the model.

In the same text, the author also identifies some of the disadvantages of this technique:

- The preparation of the variables can take a long time;
- Some of the resulting models can be difficult to implement in practice; and
- In cases where there are many variables, the credit analyst needs to pre-select the more important variables, based upon a separate analysis.

Wiginton (1980), compares logistic regression with discriminant analysis and concludes that the use of the logistic regression approach gives superior classification results but also notes that neither of the two approaches were cost effective in credit scoring. In another study, Hand and Henley (1997), found that the logistic regression approach was no better than linear regression. This they attribute to the fact that a significant proportion of the credit applicants whom they studied had credit scores (scores associated with probability estimates of being good risks) between 0.2 and 0.8. In such a case, the logistic curve can be very much approximated by a straight line.

2.1.2.4Artificial Neural Networks

- These are computational techniques that produce a mathematical model based on the neural structure of intelligent organisms which acquire knowledge through experience. The development of the back propagation algorithm was the turning point that led to the popularity of neural networks. An artificial neural network (ANN) model has got certain characteristics that makes it capable of producing replies similar to those of the human brain. According to Chuang and Lin (2009), artificial neural networks are developed using mathematical models which make the following suppositions;
- Information is processed within the "neurons";
- Through connections, the neurons transmit stimuli;

- A connection is then associated to a weight, which in a standard neural network, upon receiving stimulus multiplies itself; and
- Each neuron would then contribute for the activation function (generally not linear) to determine the output stimulus (network response).

There are three main types of neural networks, namely, single feed forward networks, multiple layer feed forward networks and recurring networks (Yobas and Crook, 2000). Feed forward networks with a single layer are the less sophisticated type of network, where there is a single input layer and a single output layer as well. Examples of credit scoring networks that utilize this architecture are: the Perceptron, Hebb and ADALINE networks, among others. Multilayered feed forward networks have at least one intermediate layer. Examples of credit scoring systems that utilize the multilayer feed forward networks are MLP and Madaline, among others. In a recurrent network, there is at least one connection from the output layer that feeds back the network (Arijit, 2007).

The most important attribute of a neural network, according toHuang, Hung and Jiau (2006), is its capability to learn from the environment and in the process improves their performance.Arie (2008), points out the following advantages in the use of neural networks:

- They are highly versatile as they can be used to solve different types of problems such as prediction, identification of patterns or clustering;
- Their ability to identify non-linear relationships between variables; and
- They are widely used and can be found in various software.

Arie (2008), also notes the following advantages of using neural networks:

- There is no guarantee that the ANN will find the best possible or optimal solution i.e. it may converge to a local maximum or in other words, towards a lesser solution; and
- As no explicit rules are produced, results cannot be easily explained.

2.1.2.5Genetic Algorithms

According to Holland(1992), the general principles of genetic algorithms (GAs) are derived from the Darwinian principles of human evolution, natural selection and survival of the fittest. Using this technique, a set of all possible solutions to a particular problem is analogous to a population of individuals (loan applicants in the context of credit scoring). The desired objective would be combining together and mutation of different solutions so that better solutions evolve with time. Individual solutions found in the population are represented in the form of finite strings, consisting a finite alphabet on which the string and its component variables/characters are analogous to chromosomes and genes (Hussein, 2009). New populations are then created from an initial from an initial set of strings which are usually generated randomly, through the application of the genetic operators listed below;

- Selection – a number of strings are selected for breeding from the existing population, with a bias towards those strings that represent the best solutions that have been found to date. In the context of credit scoring, it implies that the credit applicants (strings) are selected for scoring/vetting with a bias towards that have got a good credit history with the financial institution;
- Crossover – Pairs of strings are then matched for breeding and "child" strings are produced by combining different characters from each of the string of parents; and
- Mutation – each character within a string has an equal chance of getting selected to undergo mutation, based on a random process. Upon getting selected, the value of the character within the string is reassigned randomly to one of the probable values defined by the encoding alphabet (Baesans and Gostel, 2003).

When a number of generations have occurred, or when the improvement from a particular generation from the next falls below the pre-defined threshold, the algorithm terminates. According to Coley (1999), GAs have been successfully applied to a variety of complex and diverse optimization problems.

The following positive points in the use of GAs have been noted:

- Compared to neural networks, results produced are explicable (Ben David and Frank, 2009);
- They are very easy to use (Hand and Henley, 1997); and
- They are capable of working with large data and variable sets (Fenstertoc, 2005).

The negatives of using GAs are as follows;

- They continue to be infrequently used for credit scoring problems;
- Require a lot of computational effort; and
- Only available in a few credit scoring software (Fenstertoc, 2005).

2.1.2.6Expert systems

Expert systems are a computer code replica of a credit analyst's data steps in evaluating a particular customer's account that would be very close to a manual credit application review (Hena and Tiwari, 2012). Expert systems therefore, provide speed and efficiency to the whole credit evaluation process, by minimizing human intervention on routine transactions. The other advantage of using expert systems is that they are able to explain their recommendations and decisions, i.e. are able to explain outcomes and this can provide reasons for denying credit to an applicant.

Credit scoring expert systems are made up of four knowledge sources, namely; decision, guarantees, finance and profile. The decision knowledge source, assesses the loan application on the basis of the applicant's profile, guarantees and financial situation (Yingxu, 2007). Decision could assume any one of three values: to accept, reject or to consult the decision with the superior. The main assumption made by the credit expert systems is that the financial institution does not grant credit to clients with a bad financial situation, bad guarantees or bad profile and sufficient financial situation (Chen and Li, 2010). In other cases for example, the financial situation is only sufficient but the applicant's profile is bad, the final decision has to be consulted with the superior. This is so because there is a high risk for the financial institution and the applicant may be asked to provide additional credit guarantees, which would decrease the level of risk. An example of how the expert system makes a credit scoring decision is as shown below;

Decision = “Accept” if

Guarantees = “Very Good”

Finance = “Sufficient”

Profile = “Very good”

The major limitation of the use of expert systems for the purposes of credit scoring is that, they are unable to bring greater effectiveness and accuracy to the credit scoring process (Hair et.al, 2005).

2.1.2.7Time varying model

This model takes account of the fact that default probability is not only influenced by the applicant’s predictor variables but, to some extent, by other exogenous macroeconomic factors (Yingxu, 2007). Exogenous variables such as unemployment rates and interest rates can act as additional important predictors to enhance the model fit and ultimately, to predict the probability of default. For example, in Zimbabwe, the liquidity crunch, high rate of company closures and job layoffs, high unemployment rates as well as high international migration should be factored in scoring models for them to be more effective in managing credit risk. A study by Wang (2012), found that a stable exchange rate coupled with a high consumer price index can lead to a relatively high default rate.

Survival analysis is one commonly used time varying technique. It is a relatively simple technique that does not in involve a highly parameterized model. When using survival analysis for credit scoring, the objective would be to model the distribution of time (T) to default (or to some other event that can be associated with default). The distribution can be a function of an applicant applicant’s predictor variables (Thomas, 2009). Survival analysis offers a number of advantages; Firstly, it has got an inherent mechanism that takes the most recent data into consideration. Secondly, it gives a consistent means of predicting the probability of default with several different time periods e.g. 6, month default rate, 12 month or 24 month default rate.

2.1.2.8Recursive Partitioning

Recursive partitioning (RP) is a non-parametric method that is used to analyse categorical and or dependent variables as a function of explanatory variables (Perlich, Provost and Simonoff, 2003). In a decision tree, a dichotomous tree is built through splitting the records at each node based on the function of a single node. To find the best possible split (solutions), the system considers all possible splits. The winning branch or sub tree is selected based on its total error rate or lowest misclassification cost (Wang, 2012).

RP tress or loosely translated as decision trees, can be used to offer simple insights, to clean variables, split data into segments and to find breaks in cut-offs of other variables (Wang, 2012). It is possible to produce large numbers of trees that look vastly different yet perform equivalently. Trees can be used to improve performance when used in the modelling of rare or unique events such as fraud or low default risk credit portfolios by using prior probabilities in the configuration of trees (Sohn and Kim, 2012).

The use of RP trees offers numerous benefits to credit scoring; very quick technique, simple logic can be turned into credit policies and rules, they are non-parametric and are able to deal with interactions. The disadvantage of RP trees is that, they are not stable, minor changes to data can result in large deviations in models and unless built using cross validation and pruning, they can over fit (Perlich, Provost and Simonoff, 2003).

According to Perlich et.al(2003), using random forests in place of trees or model based RPs, is strongly recommended. However, the author alludes to the fact that the decision tree remains a powerful tool in credit scoring.

However, regardless of all these problems associated with using indiscriminate analysis, it is still one of the commonly used credit scoring techniques(Abdou, 2008; Taffler, 1982).

2.1.3 The best scoring technique

There is generally no "best" scoring technique. In most cases the "best" approach will depend on the details of the problem, i.e. variables used, data structure, the ability and extent to which it is feasible to separate the classes by using those characteristics and objectives of the classification (overall misclassification rate, cost weighted misclassification rate, bad risk rate among those accepted, some measure of profitability, etc.). Hand and Henley (1997); Ben-David and Frame, (2011); Chen and Li, (2010), concur that the use of hybrid approaches or a combination of approaches is likely to produce the best results. Table 2.0 below, shows the results of a study that was performed by Hand and Henley (1997). They concluded that, the differences in the scoring systems, as measured by the bad risk rate, were of no practical value.

Table 2: A comparison of the effectiveness of different scoring techniques

Method	Bad risk rate (%)
K nearest neighbor (any D)	43.09
K nearest (D=0)	43.25
Logistic regression	43.30
Linear regression	43.36
Decision graph or tree	43.77

Source: Henley and Hand (1997)

2.2 Credit information sharing

According to Akerlof (1970), the cost of dishonesty, does not only lie in the amount that the purchaser is cheated but also includes the loss incurred from legitimate business driven out of the market. He also notes that in the developing countries there is a problem of dishonesty.

Credit markets in the developing countries strongly reflect the operation of the market for lemons principle. Credit information sharing is a mechanism through which several lenders pool and pull information about their borrowers, with the objective of addressing the information asymmetry problem i.e. where the borrower possesses more information on his creditworthiness than the borrower. Vercammen(1995), defines credit information as the systematic exchange of valuable of borrowers' credit information between lenders.

There are three levels of information sharing (Janvry, Mclntosh and Sadoulet, 2010). The lowest level, is that of zero information sharing. In such an environment, lenders have exclusive knowledge of their customers. This makes it difficult for borrowers to shop between lenders for the best terms, especially for those borrowers with no form of collateral to offer. A lender from whom the borrower has never taken a loan does not have a way to assess the risk associated with the borrower (Houston, Lin, Lin and Ma, 2010). Granting credit to a borrower without an accompanying reputation increases the level of risk since there is very little the lender can do to ascertain the quality of the loan (Berger and Loannidou, 2011).

The second level is a manual credit referencing which involves obtaining credit reference letters and making telephone inquiries about borrowers from other lenders. A credit reference letter is issued by a financial institution to inform the enquirer of the credit position of its customers who may need to obtain a loan or credit facility with another financial institution (Berger and Loannidou, 2011).

These two techniques above are not efficient and effective in a market that has got many lenders and borrowers.

The third level includes formal information sharing arrangements and systems.According to (Akerlof, 1970), to counteract the effects of quality uncertainty, many institutions have arisen. These institutions are mainly in the form of public and private credit referencing bureaus. They collect data on borrowers and make the information available to financial institutions and any other interested parties (Djankov, McLeish and Shleifer, 2007).

Information asymmetry can lead to credit market failure in the form of credit rationing. Credit information systems act as information brokers because they increase the transparency of credit markets. In most developed countries, information sharing between lenders remains very weak as credit information systems are still in their infancy. As part of their assessment of the risks associated with lending, lenders need to access credit information on borrowers (Attanasio and Pavoni, 2011).

2.2.1 Sharing versus withholding credit information

Lenders are usually in a dilemma between sharing information with competitors which may lead to loss of market power and not sharing information which can lead to adverse selection and in turn higher borrower default. However, the impact of competition comes second in the order of importance (Jappelli and Pagano, 2002).

The sharing of credit information among lenders can help reduce the problem of borrowers being better informed about their creditworthiness more than the lenders and aid the ongoing monitoring of the risk taking behavior of borrowers (Bank of England, 2014). This can help mitigate the problem of adverse selection, where lenders are unable to map borrowers' risk profiles.

According to Padilla and Pagano(2000), information sharing by financial institutions alleviates the information asymmetry problem in the following ways;

- Countering adverse selection. By reducing information asymmetry between lenders and borrowers, credit information sharing allows credit to be extended to safe borrowers who had previously been priced out of the market, resulting in higher aggregate lending;
- Countering moral hazard. By sharing credit data, financial institutions can increase borrowers' cost of defaulting and thus enhancing repayment of debt. Borrowers are motivated to exert more effort and well execute their projects when they know that their credit data is shared between lenders; and
- Countering monopoly of information. Another benefit of sharing credit information is that it reduces the information monopoly that a lender may have on its borrowers because financial institutions which have long standing relationships with their

borrowers have got credit history knowledge of those borrowers but the other lending institutions do not have such information (Jin and Leslie, 2003; Schenone, 2009). This provides an opportunity for the financial institution to charge higher interest rates as well as other rents from the borrowers, some of which would be high quality borrowers. Moreover, information sharing can overcome moral hazard.

Credit data can also be shared for monitoring purposes so as to assist lenders to curtail the effects of moral hazard, whereby the borrowers' risk taking behavior and profile may change after receiving a loan (Pagano and Jappelli, 1993). Sharing of credit data can lead to more informed credit decisions as well as enhanced competition in the credit market, in turn this should result in financial institutions charging low risk premium and thus lower lending rates and increased availability of credit. On the other hand, when credit data is not adequately shared among lenders, it can create a barrier to entry to new players, inhibit the effectiveness of existing competitors by limiting their ability to assess creditworthiness and restrict the level of competition between incumbents (Bank of England, 2014).

According to Bath, Lin, Lin and Song (2009), increased availability and sharing of credit data could give a better understanding of some key loan and borrower characteristics that assist lenders in decision making. This may help foster innovations which have emerged in the personal loans market, for example, loan price comparison on websites, in some credit markets. Such innovations have got the potential of driving greater competition between lenders and in the process improving the quality of offerings of competing financial institutions.

Lenders' attitude towards information sharing is most likely to be influenced by lenders' market share, lenders'target market shares and by the market structure (Bouckaert and Degryse, 2006). Ordinarily, lenders with relatively large share of the market and who are not seeking an increase in their market presence are less likely to see the potential benefits accruing to them because of information sharing and as a result may not be willing to participate in or in the worst case resist any such arrangement. In some cases, lenders do not make money from the inherent quality of their offering but they rather take advantage of information rents to make money (Dunn and Spatt, 1998).

In a market where borrowers know that their credit data is shared amongst financial institutions, the borrowers tend to be disciplined (Klein, Crawford and Alchian, 1978). However,Vercammen (1995), argues that sharing information may not be sustainable in the long run because, the more the lenders learn about their borrowers, the greater the possibility that the value of adverse information is reduced, suggesting that a certain level of adverse selection is needed in a credit market so as to give rise to borrower reputation incentives. This is so because, as credit history period lengthens, lenders become more informed about the behavior of borrowers with whom they dealing. He further explains that, reputation effects would be very high when lenders are very uncertain about the type of a prospective borrower since it is at this point that the lender is willing to change their beliefs the most when they are presented with new information. Thus, Vercammen (1995), argues that policies that limit the flow of information from borrowers to lenders may be to some extent desirable from a social efficiency perspective as such policies would sustain reputation effects

Information is vital for the purposes of supporting credit lending (Brown and Zehnder, 2010). Financial institutions such as banks specialize in the acquisition and dissemination of information. This information includes data on the pattern of repayment of loans and other transactions of their customers (Stigitz and Weiss, 1981). Thus, in the process, they perform the process of resource allocation in an economy.

2.2.2 Voluntary versus forced information sharing

Information sharing among lenders is more likely to happen when the credit market is large, the cost of sharing information is low, the borrowers are heterogeneous and where the mobility of borrowers is high (Jappelli and Pagano, 2002). The adverse selection problem could result in the pricing out of safe borrowers out of the market. Information sharing leads to an increase in the levels of lending. Financial institutions can deal with the information asymmetry problem by exchanging information about prospective borrowers (Kallberg and Udell, 2003).

Where a lender is confronted by a large number of customers on which it has no previous intelligence, for example, where there is high borrower mobility, this acts as an incentive for information sharing by lenders. The size of the credit market also acts as an incentive for sharing information i.e. the larger the market the greater the need for exchanging information on prospective lenders (Padilla and Pagano, 2000).

In some countries like the United Kingdom, there are some policies that were crafted to foster the availability and sharing of credit information. For example, an initiative by Her Majesty's Treasury (HMT) to mandate the sharing of Small and Medium Enterprises (SME) credit data between lenders (Bank of England, 2014). There are some lenders who may not be willing to share credit data with other players. Therefore some degree of policy interventions may therefore be needed.

In situations where sharing credit information does not arise naturally, it creates a role for the state to support and facilitate the development of a transparent credit reporting infrastructure (World Bank, 2013). This also enables regulators to access credit data. Regulatory access to credit data can bring number of benefits, especially with respect to the functions of central banks. For example, access to credit data enables the study and analysis of credit conditions and as a result supports monetary and other macroeconomic policy makers in making decisions. Assessments of credit risk at aggregate and institutional level can also be made using credit data and this supports assessments on stress testing, financial stability and the supervision and monitoring of financial institutions. Increased sharing and availability of credit information can be used by government and policy makers to produce statistics that can be used for policy making and public debate on credit issues (World Bank, 2013).

2.2.3 Types of information shared

The type of data reported is an important element in the design of a credit information system. The simplest, most inexpensive and common systems are "black lists", which contain information on defaulters only (Mclntosh et.al; Camion, 2001). These are very effective in dealing with the moral hazard problems in the credit market, due to their disciplinary effect via reputational mechanisms. An example of a credit database only collecting negative information is the Banque de France National Database on Household Credit. Borrowers will ordinarily have a greater incentive not to default if only negative information is exchanged (Padilla and Pagano, 2000).

Other systems also include reporting of loan amounts, to enable lenders to estimate the total indebtness of prospective borrowers. Such information helps to curtail the moral hazard problem if debt contracts are non-exclusive (Jaffe and Russell, 1976).

On the other hand, the most sophisticated systems are not only limited to adverse information but include other forms of positive data about the borrowers characteristics and behavior, for example, demographic information for individuals and financial/accounting for business enterprises (Padilla and Pagano, 2000).

A system that provides much comprehensive information about borrowers' characteristics may lead financial institutions to so identify high quality borrowers more easily, nevertheless, by the same token, such borrowers will be less concerned to be reported as defaulters, with the belief that their reputation will not be tarnished by such an event. As a result, they may put less effort in avoiding default (Miller, 2003).

Padilla and Pagano (2000), further state that credit information systems need to go beyond negative information and provide data pertaining to total indebtedness of each debtor, it must unambiguously identify their debtors and liabilities. For individuals, this can be relatively simple, however, it may be much more difficult for firms belonging to group of companies. A subsidiary company may have a very limited debt exposure, but the parent company or other sister companies may be heavily over-indebted. As a result, a distressed group will want to disguise its true leverage by obtaining new loans via its relatively healthy subsidiaries (Jentzsch, 2007).

2.2.4 Ethical and legal issues around sharing of customer information

Information sharing may expose financial institutions to increased competition by releasing important and private information about their clients. In competitive credit markets, financial institutions may not be willing to share client credit information with close competitors (Pagano and Jappelli, 2002).

According to the OECD (2014), the following legal and ethical issues need to be considered for any credit information sharing arrangement:

- Legislation should clearly specify the circumstances and purposes for which data may be collected and used. The OECD cites an example of the Hong Kong where the sharing of credit information is regulated by the Personal Data Privacy Ordinance (No. 81 of 1995). This ordinance clearly stipulates that private personal data may only be collected and shared if it is to be used for a lawful purpose;
- The data collected and shared should be at the required quality, timeliness and accuracy. A good example is the Personal Data Protection Act, Article 13:2 of Holland. It stipulates that the responsible party needs to take all the necessary steps that personal data collected, subsequently processed and shared, are correct;
- Appropriate levels of security should be considered and enforced to protect the data. To this end, there are some International security standards that may be considered, such as International Standards Organisation ISO 27000, which identifies appropriate processes, systems, checks and infrastructure required to protect data from various threats that include theft and destruction;
- It is unethical to deny individuals access to their information and should also have the right to dispute inaccurate or incomplete data and have any disputes appropriately investigated and any errors corrected. It is also proper and ethical to notify the credit applicant in cases where an adverse decision has been made about them based on their past credit records; and
- In many jurisdictions it is illegal to collect data based on race, gender. In the USA for example, congress in 1974 adopted the Equal Credit Opportunity Act which prohibits

classification and using information on potential borrowers based on gender, race or marital status.

2.3 Credit rating agencies and credit referencing bureaus

Credit rating agencies (CRAs) perform the credit assessment and evaluation for corporates and governments. The entity that needs credit rating pays the rating agency fees. The rating agency would then perform a credit rating exercise on the company as a whole or for one of its debt instruments or any other financial instrument (Miller, 2003). Examples of credit rating agencies include Moody and Standard & Poor (S&P). Credit ratings for borrowers and governments are based on extensive due diligence performed by rating agencies. Many borrowers will strive to have the best/highest possible rating as this has got a major bearing on interest rates charged by lenders. On the other hand, the rating agency needs to make a balanced and objective assessment and analysis of the borrowers' financial position and capacity to repay or service the debt.

CRAs in most cases assign letter grades to indicate ratings on companies or debt instruments. S&P, for example, has a rating scale that ranges from AAA (excellent), AA+ (good), all the way to D. Debt instruments with a rating that is below BBB- is considered as a junk bond (Miller, 2003).

A credit referencing bureau is an agency that gathers and maintains credit information on individual, and in most cases provides that information to lenders and any other interested parties, for a fee (Jentzsch, 2007). CRBs receive consumer credit information from financial institutions and other credit issuing institutions. Common examples of CRBs include Transunion, Experian and Equifax.

In essence, the major difference between a CRA and a CRB is that, the former provides credit rating services for governments and companies' equity and debt securities whilst the latter provides credit rating information for individuals (Miller, 2003).

2.4 Factors considered when determining the creditworthiness of an applicant

The factors that are taken into account by a lenders when determining the creditworthiness of an applicant can best be summarized by Figure 2 below;

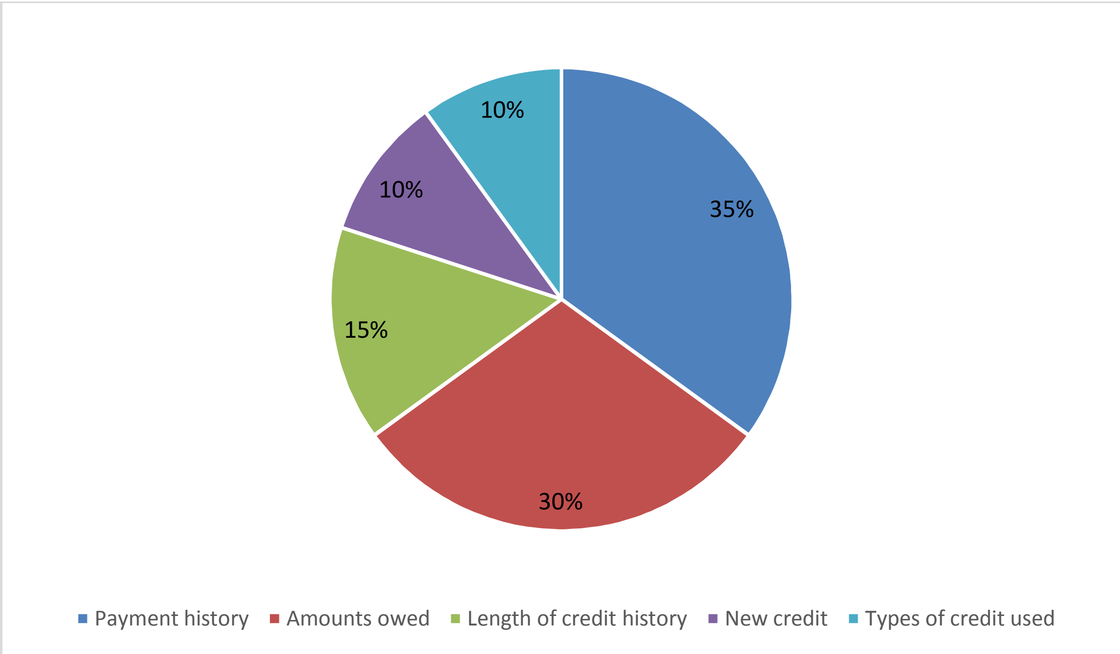

Figure 2: Factors that determine creditworthiness (FICO, 2015)

According to the Fredric Isaacs Corporation (2015), 35 percentage weight is attached to a borrowers' payment history, 30 percent to credit utilization, 15 to length of credit history, 10 percent weight each to new credit and credit mix. Fredrick Isaacs Corporation (FICO) is one of the world's leading independent credit scoring agencies:

- Payment history (35 percent of overall credit score) – According to FICO, repayment of past debt is the most important factor in producing a credit score because past long term behaviour is the basis of predicting long term future behaviour;
- Credit utilization (30 percent weight of total credit score) – This refers to the level of indebtedness of the applicant. An applicant who has already utilized credit and is already close to their credit limit is risky to lend as their ability to repay new credit is

limited by other obligations and such borrowers are likely to default. According to FICO, individuals with the best scores tend to have an average credit utilization ration of 7 percent, however, an average of 10 to 20% utilization is acceptable;

- Length of credit history (15 percent of overall credit score) – This refers to length of credit relationship between the financial institution and the credit applicant as well the frequency of transactions, in most cases depicted by the date of the last transaction in the account. A relatively longer relationships offers more information and provides a better picture of long past and future financial behaviour to the lender;
- New credit (10 percent of total score) – This means that borrowers should avoid opening and utilizing too many lines of credit concurrently, as such behaviour could imply they are in financial trouble; and
- Credit mix (10 percent of the total credit score) – This, according to FICO, because based on historical data, borrowers who have a good mix of instalment loans and revolving credit ordinarily represent less risk to lenders.

Table 2.1 overleaf shows some of the most critical factors considered by lenders when making the decision whether or not to extend credit to a credit applicant.

Table 2.1: Indicators of creditworthiness

Demographic indicators	**Financial indicators**	**Employment indicators**	**Behavioural indicators**
1. Age of borrower 2. Sex of borrower 3. Marital status of borrower 4. Number of dependants of borrower 5. Residential address	1. Total assets of borrower 2. Gross income of borrower 3. Gross income of the company/hou se hold 4. Monthly costs of household/ company	1. Type of employment/ company line of business 2. Length of employment/ period company in operation 3. Length of current employment 4. Number of jobs over the past xxx years	1. Average bank account balance 2. Loans outstanding 3. Loans defaulted or delinquent 4. Number of payments per annum 5. Collateral

Source: Miller, 2003

Sustersic, Mramor and Zupan (2009), concluded that a smaller number of variables could predict just the same as 21 variables that had high risk discrimination potential. He thus concluded that, if the lender fails to justify the use of different variables in their scoring model, chances would be high that scoring would not be used or wrongly used.

As part of their assessment of the risks associated with lending, lenders need to access credit information on borrowers.

2.5 Literature Gap

Several studies have concentrated on credit scoring techniques for banks at the expense of other institutions that offer loans and credit, such as credit retail departmental stores, mobile phone companies and insurance companies, among others. These studies have mostly been performed in the developed nations which have got different economic, legal, social and political environments as compared to developing countries such as Zimbabwe. No study has focused on the credit scoring techniques in Zimbabwe, and therefore, this study seeks to close this literature gap.

2.6 Chapter summary

This chapter has discussed the following key areas: different credit scoring techniques that are used by financial institutions, borrower information sharing by lenders, scoring methods used for corporates and individuals, and factors that are considered by lenders for the factors of credit scoring. Most authors conclude that there is no best scoring technique but they concur that a combination of techniques produces optimal results. Lenders are usually in a dilemma between sharing information with competitors which may lead to loss of market power and not sharing information which can lead to adverse selection and in turn higher borrower default. However, the impact of competition comes second in the order of importance. Scoring for individuals is basically similar with scoring for companies, the main difference lies in the variables used in the models, for example, financial statements data are used for corporates. Lastly the factors that are considered when determining whether or not a borrower is credit worthy, were highlighted, as summarized by FICO. However, the existing literature is not best fit to answer research objectives outlined in Chapter 1, therefore this research examines the Zimbabwean financial sector.

CHAPTER THREE: RESEARCH METHODOLOGY

3 Introduction

This chapter outlines the methodology adopted for the study. These mainly include the research design, sampling, data collection and analysis techniques, among others. According to Saunders, Lewis and Thornhill (2012), a good methodology can make the researcher's findings valid whilst a poor methodology might can make a good research invalid. The methodology was selected on the basis of resource availability, cost, effectiveness and time constraints.

In a nutshell, this chapter basically focuses on the research philosophy, design and strategy used in the research. The researcher discusses the research design, philosophy and strategy in detail in this chapter. The researcher also discusses the rationale of adopting a census survey approach using the phenomenological philosophy.

3.1 Research design

According to Yin (2006), the research design is a framework that links the empirical data to the study's questions, right up to the findings and its conclusions. It gives the researcher a roadmap in the data gathering, analysis, presentation and interpretation processes and in the process, allows the researcher to draw inferences and relationships between the dependent and independent variables under investigation (Yin, 2006). The choice of an appropriate research design takes consideration of the relevance of all the possible designs to the objectives of the study, as well as the setting and environment in which the study is conducted. The researcher used a census approach, whereby all the 19 operational banking institutions were used to get information.

3.1.1 Research philosophy

The research philosophy can adopt either one of the following approaches; phenomenological or positivism. These approaches are also known as the quantitative and qualitative research methods. However, it is important to note that the two approaches can be used in combination to carry out a research (Saunders et al, 2012).

The quantitative and qualitative approaches are premised on different assumptions about the nature of the world, and as a result, they require different procedures and instruments to obtain the required data (Robson, 1993). Both approaches were used in carrying out this research.

3.1.1.1 Quantitative approach

According to Denzin and Lincoln (2005),qualitative research is an approach which takes account of valuable descriptions of observed phenomena and explains the relationships between the descriptive surveys, longitudinal developments, ex-post and correctional factors. Quantitative research maintains a very high level of objectivity and is based on a set of rules that cannot be varied and it emphasises on a highly structured methodology and quantifiable observations that can lead to statistical analysis (Saunders et al, 2012). Quantitative research is premised on the thorough evaluation of evidence, theory development, and hypothesis testing and further refining these (White, 2000).

3.1.1.2 Qualitative approach

Qualitative philosophy is an unstructured research approach that is specifically designed to conduct research based on a carefully selected and relatively smaller sample with the objective of producing non numerical insights into attitudes, motivations and behaviour of the sample under study (Wilson, 2006). It is an approach that focuses on the definition of characters, meanings, traits, people interactions, events and settings (Wilson, 2006). An exponent of qualitative research methods explains that quality refers to the what, how and when of a thing, its essence and ambience. In other words, qualitative research refers to the concepts, definitions, characteristics, symbols, meanings, metaphors and description of things (Berg, 2007).

3.1.2 Research strategy

The research strategy maps an overall direction of the research as well as the process by which the research is carried out (Remenyi, Williams, Money and Swartz, 2003). Saunders et al (2009), define research strategy as the plan of action on how the researcher will go about answering the research questions. The appropriate research strategy has to be selected based on three factors, which are; the extent of control that the researcher possesses over actual behavioural events, type of research questions and the degree of focus on contemporary or historical events (Yin 2006).

Research strategies that can be used for business and management problems are, case study, survey, cross sectional studies, longitudinal studies, participative enquiry, experiment, action research, grounded theory, archival research and ethnography, among others. This study used the census strategy, as it was deemed to be the most appropriate strategy in light of the research objectives. According to O'Leary (2004), the use of a survey approach has the following advantages and disadvantages;

3.2Population and Sampling Techniques

3.2.1 Population

Population is defined as a set of units that the research is oriented on, for example events, objects, people, or transactions (Salant and Dillman, 1994). In this study, the population consisted of 19RBZ registered banks. Table 3.0 below shows the target population.

Table 3: Target population

Type of Institution	Number
Commercial banks	14
Building societies	3
Merchant Banks	1
Savings Banks	1
Total banking institutions	**19**
Microfinance Institutions	147

Source:RBZ Monetary Policy Statement 2015

The census survey approach was adopted, as 19 banks were used to obtain the required information.From 19 banks (six from each bank), 114were selected conveniently in Harare, to be in the sample for the research. For the purposes of this study, a sample of 114 was considered to be adequate and appropriate.

3.2.2 Population

Sampling is the process by which selections are made from the population of interest for the purposes of a study (O'Leary, 2004). There are several sampling techniques in literature and these are; simple random sampling, systematic sampling, stratified sampling, cluster sampling, judgmental sampling, convenience sampling. Purposive sampling was used to select the 114 banking staff from the 19 operational banks. Bank employees with knowledge on the credit scoring processes were chosen for the purposes of this study.

3.3 Sources of data

Primary and secondary data sources were used in this study. Primary data sources were used to obtain credit scoring techniques in use by Zimbabwean financial institutions. On the other hand, secondary sources were used when the researcher reviewed literature on the credit scoring techniques in use in other countries. These were then compared against the techniques in use by Zimbabwean financial institutions.

3.4 Data collection procedure

Data collection was done through the use of questionnaires as well as telephone interviews. The questionnaire was administered to loan officers, operations managers, credit managers and general managers of the selected banking institutions. The questionnaire enabled some interaction between the interviewer and the interviewee.

3.5 Data analysis

When all the data had been collected and all completed questionnaires had been returned, the questionnaires were coded and the data was entered into SPSS Version 16.0 as well as Microsoft Excel. The data was analysed in two stages; the first stage involved checking the data for accuracy, the second stage involved the use of descriptive statistics where the results obtained from the study was presented in the form of Excel graphs, tables, charts and graphical formats. In addition, factor analysis was used to explore and extract some of the vital factors that measured the variables under study.

3.6 Research limitations

- Data on banking systems is very sensitive, and as a result obtaining such data was a very difficult task. The researcher obtained the data on condition that the data was treated with utmost confidentiality and that that the data was supposed to be used for the purposes of the research only. A letter was obtained from the Graduate School of Management (GSM) to overcome this problem.

- The Zimbabwean macro-economic landscape is quite unique, and some of the literature that is available might not be applicable in the Zimbabwean context.
- Some respondents could not attend to the questionnaires either as a result of busy work schedules or attitude problems
- Some of the questions were too difficult for some of the respondents to understand, especially the question on the type of credit scoring technique. However, the researcher explained the questions to the respondents. Questionnaires were personally administered by the researcher, and any necessary clarifications were given where needed.

3.7 Research ethics and data credibility

Some key ethical considerations were taken into account in conducting the research. Participation to this research was voluntary and confidentiality was maintained on the data obtained from the participants. The responses were kept and treated with utmost confidentiality. The respondents were asked not to provide their names or identification, to avoid possible harassment and intimidation of the respondents.

Joppe (2000), defines credibility as the extent to which results are consistent over time as well as the extent to which they accurately represent the absolute population. A research instrument is valid if the results of any given study can be reproduced using a similar methodology.

To ensure that the results of the research were valid and reliable, the study used triangulation, as this approach strengthens any given study by combining different methods, as it involves the use of various methods or data, including the use of both qualitative and quantitative techniques. Further, in performing this research, the research objectives led the whole process, and the researcher dwelt on obtained answers to the research questions as outlined in Chapter 1, the research instrument was designed and pre-tested.

3.8 Chapter summary

In a nutshell, this chapter dealt with the research design, research strategy, research philosophy, and methods of collecting data, data sampling strategies and data analysis and the chapter conclusion. This chapter articulated the research design and methodology used in quest of answers to the research questions. This study used both qualitative and quantitative research strategies. Finally, research limitations and the ethical considerations were pointed out.

CHAPTER 4: RESULTS AND DISCUSSION

4 Introduction

This chapter presents the results obtained from the study as well as an analysis of these findings and any appropriate conclusions shall be drawn from these findings. The analysis of data is a vital step in any research. After collecting data using the appropriate tools, the next step is to analyse and interpret the data.

4.1 Response Rate

Table 4.1 Questionnaire response rate

Gender	Total Questionnaires	% Response Rate
Male	73	70
Female	31	30
Total	**104**	**100**

For this study, a sample of 114 participants was targeted from all the 19 operational banking institutions, and a questionnaire was administered successfully to the participants. Out of the 114 questionnaires that were distributed, 104 were successfully completed and returned. This represents a 70% response rate.

4.2 Demographic information

4.2.1 Age

Table 4.2: Age of respondents

Age group	Total Questionnaires	% Response Rate
20-35	23	22
36-45	51	49
46-55	24	23
>56	6	6
Total	**104**	**100**

The age of the respondents ranged from 20-60 years. The 36-45 age group had the highest number of respondents, constituting 49% of the responses, 23% for the 46-55 age group, 22% for the 20-35 age group and 6% for the more than 56 years age group. The age range is diverse, which implies that they are experienced staff.

4.3.3 Number of years served in current position

Table 4.3: Number of years served in current position

Number of years in service	Total Questionnaires	% Respondents
< one year	6	6
1-2 years	15	15
2-5 years	28	28
5-10 years	47	45
> 10 years	6	6
Total	**104**	**100**

51% of the respondents have worked in their current roles for a period of at least 5yrs. This reflects that more than half of the respondents are experienced banking staff members. This also points to the fact that there has been relatively low job mobility in this sector as a result of the macroeconomic conditions in Zimbabwe.

4.3. Section B: Credit scoring methods and approaches

Question 1: Do you perform credit scoring before issuing out a loan?

Table 4.4: Financial institutions that perform credit scoring

Perform credit scoring	Response	% Respondents
Yes	104	100
No	-	-
Total	**104**	**100**

Table 4.4 above shows that all the banks perform credit scoring before issuing out loans to borrowers. This is in conformity to risk management best practices and reduces the risk of bad loans to an acceptable level. Credit scoring ensures that there is consistency and accuracy in decision making and it also enables the financial institution to support decisions made by tracking data evaluated and the steps that were taken in making decisions (Miller, 2003).

Question 2: Do you use similar scoring techniques for corporates and individuals?

Table 4.5: Type of scoring technique

Scoring technique	Response	% Respondents
Judgmental	8	8
Statistical	96	92
Do not know	-	-
Total	**104**	**100**

Table 4.5 above shows that the majority of the banks use statistical scoring techniques, as 92% of the respondents indicated that they use statistical scoring techniques. Statistical scoring techniques are more efficient and effective than judgmental techniques as they are not based on subjective human judgment. Statistical scoring models take account of many factors and variables simultaneously (Sadatrasoul et.al, 2013). The key factors and variables used in the scoring model are generally obtained from credit files of the credit applicant.

Question 3: Do you use similar scoring techniques for corporates vs individuals?

Table 4.6: Scoring for corporates and individuals

Scoring technique	Response	% Respondents
Yes	12	12
No	92	88
N/A	-	-
Total	**104**	**100**

Table 4.6 above shows that the majority of financial institutions use a different scoring approach when performing credit scoring for corporates and individuals. This is consistent with the studies performed by Sadatrasoul et.al, (2013); Berger and Frame (2011), which identified three types of credit scoring based on the type of credit applicant; enterprise credit scoring, SME credit scoring and individual scoring.

4.4SectionC: Borrower information sharing

Question 1: Do you share information with other financial institutions when they are approached by your clients for credit?

Table 4.7: Information sharing by lenders

Borrower information sharing	**Response**	**% Respondents**
Yes	15	14
No	89	86
Do not know	-	-
Total	**104**	**100**

Table 4.7 above shows that the majority of financial institutions do not share borrower information, as 86% of the respondents said that they do not exchange borrower information with other financial institutions. This is consistent with the results of a survey that was performed by the World Bank in 2013, which gave Zimbabwe a low rating, i.e. a score of one out of a maximum possible six, on the level of information sharing between financial institutions.

Question 2: If you share information with other institutions, please specify how the information is shared?

Table 4.8: Means of sharing borrower information

Borrower information sharing	Response	% Respondents
Over the phone	-	-
Letters/emails/faxes/bank statements	15	14
Other	-	-
N/A	89	86
Total	**104**	**100**

Table 4.8 above shows that of the 14% financial institutions that share borrower information, this is done by means of credit reference letters, historical bank statements and making telephone inquiries about borrowers from other lenders. This kind of approach, according to Berger and Loannidou (2011) is not effective.

Question 3: If you share information with other financial institutions, please specify the type of information shared?

Table 4.9: Type of information shared

Borrower information sharing	Response	% Respondents
Adverse	2	2
Positive	2	2
Both	11	11
N/A	89	85
Total	**104**	**100**

Table4.9 above shows that the majority of the lenders that share information, share both adverse and positive information about borrowers. Studies by Padilla and Pagano (2000), show that credit information systems need to go beyond negative information and provide

data pertaining to total indebtedness of each debtor, it must unambiguously identify their debtors and liabilities.

4.5 Section C: Time taken to approve a loan application

Question 1: On average, how long does it take for the bank to approve a loan application?

Table 4.10: Time taken to approve a loan application

Average time taken to approve loan applications	Response	% Respondents
Same day	-	-
< 1 week	23	22
1-2 weeks	72	69
> 2 weeks	9	9
Total	**104**	**100**

The results in table 4.10 above indicate that 78% of the banks take more than a week to process a loan application. This is not in line with international standards as it takes just a matter of hours or a day to get a loan approved in some other countries like South Africa. This is not in line with international standards as it takes just a matter of hours or a day to get a loan approved in some other countries like South Africa (Wonga, 2015).

Question 2: If more than more than one week, what causes the delays?

Table 4.11: Cause of delays

Cause of delays in credit vetting process	**Response**	**% Respondents**
Credit vetting procedures not yet completed	31	60
System bottlenecks	10	20
Availability of funds	10	20
Other	-	-
Total	**51**	**100**

Table 4.11 above shows that the major cause of delays in the loan approval process mainly lies in the lengthy credit vetting exercise performed by various financial institutions.

4.6 Chapter summary

This chapter presented and analysed the study findings as well as their implications and their connection with relevant literature. In the next chapter, the researcher covers the conclusions made through the study, recommendations as well as the limitations of the study and areas for future study.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5 Introduction

In this chapter, the researcher makes inferences based on the information acquired from the research findings from the previous chapter. Any recommendations for this research are discussed in this chapter. The areas proposed for further study by researcher are also highlighted.

5.1 Conclusions

5.1.1 Credit scoring techniques

The major finding of this study was that most financial institutions use statistical scoring techniques. This is in line with best practice, as the same systems are being used the world over.Based on this finding, the credit scoring techniques in use in Zimbabwe are adequate and appropriate.

5.1.2 Borrower information sharing

Borrower information sharing between lenders is very minimal. Information sharing between lenders is mainly in the form of background checks in the form of historical bank statements from other financial institutions, telephone and written inquiries. The lenders judgment is mainly based on the information provided by the credit applicant, where in most cases, every credit applicant would want to provide only information that portrays them as creditworthy, whilst at the same time they conceal any information that they feel might undermine their chances of obtaining credit. This means that the borrower has more information on their creditworthiness than the lender. The potential impact of this scenario is that credit is in most cases granted to people who are not creditworthy.

Therefore, the research concludes that the credit scoring techniques are good. However, it is the variables (information available on borrowers) that are inputted into these scoring models that lead to the adverse selection problem and as a result high levels of non-performing loans (NPLs).

5.1.3Comparison of scoring techniques for corporates vs for individuals

Another finding from the study is that, the scoring techniques used for both individuals and corporates are more or less similar. The main difference lies in the variables that are used in the different credit scoring models and that for most corporates, information is easily accessible. For example, on the type of income variable, for a company it would be revenue from the sale of goods/ services, whereas for an individual, it would be income from employment.

5.1.4 Time taken to process a loan application

The study noted that on average it takes about 14 days to process a loan application. In some countries like South Africa, it takes less than an hour on average for a loan application to be approved. This mismatch in processing times between the two countries is so because, in South Africa, there are some advanced information sharing techniques that enable the lender to make a very quick and well informed decision on whether or not to grant credit, whereas in Zimbabwe, due to lack of borrower information sharing mechanisms, there are so many other processes and procedures involved before a loan application can be approved.

5.2 Research hypothesis validation

The research proposition is restated as follows:

This study maintains that the credit scoring methods in use by Zimbabwean financial institutions are not effective, and that there is inadequate borrower information sharing between lenders which has resulted in borrowers obtaining credit from multiple financial institutions without being detected by the lending institutions that they would then go on to borrow from.

The proposition of the study has been partly fulfilled as the credit scoring techniques used by Zimbabwean financial institutions are strong and are similar to those in use in other best practice countries, as described by the literature. However, the assertion on poor information sharing between lenders was proved to be true, as evidenced by the information sharing practices and mechanisms in place. As a result, the credit scoring techniques are very good but the variables (information about borrowers) that are inputted into the models are not sufficient.

5.3 Recommendations

In light of the findings highlighted above, the researcher proposes the following recommendations:

5.3.1 Credit referencing bureau

Since there is limited scope for financial institutions in Zimbabwe to share borrower information, Zimbabwean financial institutions are exposed to high information asymmetry levels. To bridge this information asymmetry gap, he authorities (RBZ, parliament and or cabinet) should quickly move to facilitate the creation of a credit reference bureau (CRB). Policy makers should craft the necessary legislation that enables the creation and licensing of a CRB(s).

Banks should lobby regulatory authorities and policy makers to facilitate the creation and licensing of a CRB(s), whose function is to collect information on borrower behaviour and financial position, and then make that information available to banks and other interested legitimate parties. This has got the potential impact of reducing the levels of NPLs in the economy, because when borrowers know that information about their credit history is shared, they will have the additional incentive not to default. This can also have the impact of increasing bank lending, as studies by Jappelli and Pagano (2002), have shown that the level of bank lending is twofold in countries where borrower information is shared.

5.3.2 Internal blacklists

Banks can also maintain a list of blacklisted customers, comprising, clients that have a bad credit history, which can be accessed by other authorized financial institutions, so that they can quickly refer to when approached by a new credit applicant whom they do not have any knowledge on the credit history.

5.3.3Timely processing of loans

Banks should also reduce the average time taken to process loan applications because, in most cases, credit/loan applications are usually made to meet urgent and pressing needs, such as, covering funeral expenses, cost of medical procedures and hospitalisation, emergency travel expenses, among others. Zimbabwean banks need to align their practices, with regards to timely processing of credit applications, to international best practice. In some countries like South Africa, fast small personal loans and vehicle purchase loans are approved within a matter of minutes.

5.4 Study limitations and areas of further study

Time was the main constraint that was faced by the researcher in carrying out this study. Secondly, obtaining information from bank employees was a challenge, as bank information is treated with confidentiality.

The study population was small, in the sense that, it is not only banking institutions that perform credit scoring, use borrower credit information and give out loans, but other institutions such as microfinance institutions, credit departmental stores and mobile phone network operators.

Further studies can be carried out on other sectors of the economy, such as microfinance institutions and credit retail departmental stores that issue out loans and credit terms to their clients. Studies can also be carried out to investigate whether the limited availability of credit information has got an impact on the quantity of loans being given out by Zimbabwean financial institutions. The effectiveness of the different scoring techniques in use by Zimbabwean financial institutions is another area that can be explored.

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Appendix 1

RESEARCH QUESTIONNAIRE

Mynameis Desmond Mutava, a University of Zimbabwe, Graduate School of Management, MBA student.Iam undertaking a research on"An investigation of thecreditscoring techniques by Zimbabwean financial institutionsasmyfinalyeardissertation work. This questionnairewould beveryuseful in thestudyof the credit scoring techniques in use by various financial institutions in Zimbabwe. Pleasespare afewminutes andfill it up. The questionnaireconsists of 4 sections.All four sectionsneed to be filledexceptwhen specificallyredirected to otherquestion(s).Please makesureyoureadallquestions and answerthemappropriately. The researchercarryingout thisprojectguaranteesyouacomplete confidentialityin theuse of the datacollected in thesurvey.Dataand results based on the surveywill always be presented in tabularform andat alevel of aggregation thatwill safeguard the confidentialityof individual banks.

SECTION A: BACKGROUND OF RESPONDENT

1. Please kindly state your age group

☐20-35years ☐ 36-45years ☐ 46-55years ☐ above 56years

2. Gender ☐ Male ☐ Female

3. For how many years have you been working for this financial institution?

- ☐ less than one year
- ☐ More than 1 year but less than 2 years
- ☐ 2-5 years
- ☐ 5-10ys
- ☐ More than 10 years

SECTION B: CREDIT SCORING METHODS AND APPROACHES

1. Do you perform credit scoring before issuing out a loan?

- ☐ Yes
- ☐ No
- ☐ Do not know
- ☐ N/A

2. What type of scoring technique do you use?

- ☐ Judgmental
- ☐ Statistical
- ☐ Do not know
- ☐ N/A

3. Do you use similar scoring techniques for corporates and individuals?

- ☐ Yes
- ☐ No
- ☐ N/A

4. If your answer to question 3 above is "No", please specify how these two techniques differ?

SECTION C: BORROWER INFORMATION SHARING

1. Do you share information about your clients with other financial institutions when they are approached by your clients for credit?

- ☐ Yes
- ☐ No
- ☐ N/A

2. Do you contact other financial institutions for reference on any prospective borrowers/ loan applicants?

- ☐ Yes
- ☐ No
- ☐ N/A

3. If you share information with other institutions, please specify how you share the information?

- ☐ Over the phone
- ☐ Letters/emails/faxes
- ☐ Other (Please specify)

………………………………………………………………………………………………

4. If you share information with other financial institutions, please specify the type of information shared?

- ☐ Adverse information only
- ☐ Positive information only
- ☐ Both Positive and Adverse information
- ☐ N/A

SECTION D: TIME TAKEN TO APPROVE A LOAN APPLICATION.

1. On average, how long does it take for the bank to approve a loan application?

- ☐ Same day
- ☐ less than 1 week
- ☐ 1-2 weeks
- ☐ More than 2 weeks

2. If more than more than one week, what causes the delays?

- ☐ Credit vetting procedures not yet completed
- ☐ System bottlenecks
- ☐ Availability of funds
- ☐ Other (Please specify)

………………………………………………………………………………………………

Appendix 2

SELECTED BANKS

1. Agricultural Development Bank of Zimbabwe (Agribank)
2. AfrAsia Bank Zimbabwe Limited
3. Banc ABC (formerly ABC Bank)
4. Barclays Bank of Zimbabwe Limited
5. CBZ Bank Limited (formerly Commercial Bank of Zimbabwe Limited)
6. CBZ Building Society
7. Central Africa Building Society
8. Ecobank (formerly Premier Banking Cooperation)
9. FBC Bank Limited (formerly First Banking Cooperation
10. FBC Building Society
11. MBCA Bank Limited
12. Metbank (formerly Metropolitan Bank of Zimbabwe Limited)
13. NMB Bank Limited
14. People’s Own Savings Bank
15. Stanbic Bank Zimbabwe Limited
16. Standard Chartered Bank Zimbabwe Limited
17. Tetrad Investment Bank
18. ZB Bank Limited
19. ZB Building Society