BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF COMMERCE

DEPARTMENT OF ECONOMICS

TOPIC: AN ANALYSIS ON THE DETERMINANTS OF LOAN DEFAULTS AT KCI MANAGEMENT CONSULTANTS IN 2022

SUBMITED BY LUKE A. ANDREA

SUPERVISOR DR DAMIYANO

REG NUMBER: B1954055

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE BACHELOR OF SCIENCE HONOURS DEGREE IN ECONOMICS OF BINDURA UNIVERSITY OF SCIENCE EDUCATION.

FACULTYN OF COMMERCE

JUNE 2023

RELEASE FORM

NAME OF AUTHOR: LUKE ANDREW ANDREA

REGISTRATION NUMBER: B1954055

RESEARCH TOPIC: AN ANALYSIS ON THE DETERMINANTS OF LOAN DEFAULTS AT KCI MANAGEMENT CONSULTANTS IN 2022.

YEAR OF COMPLETION: 2023

SIGNED: ……………………………………………………

AUTHOR'S ADDRESS: 21325/45 CHIRAMBAHUYO RD
SEKE UNIT A EXTENSION
SEKE
CHITUNGWIZA

DATE: JUNE 4. 2023

CONTACTS: +263774955314 / +263715070476

EMAIL ADDRESS: lukeandrea23@gmail.com

APPROVAL FORM

TITLE: AN ANALYSIS ON THE DETERMINANTS OF LOAN DEFAULTS AT KCI MANAGEMENT CONSULTANTS IN 2022.

TO BE COMPLETED BY THE STUDENT I certify that this dissertation meets the preparation guidelines as presented in the Faculty Guide and Instructions for Typing Dissertations of Bindura University of Science Education.………………………………………………………/……………/……………/
Signature of Student Date

TO BE COMPLETED BY THE SUPERVISOR. I certify that;

a). This dissertation is suitable for submission to the faculty.

b). This dissertation has been checked for conformity with the faculty guidelines.

c). The student has been supervised from the first chapter to chapter 5.

………………………………………………………/……………/……………/

Signature of Supervisor Date

DEDICATION

I dedicate this research project to my parents, Stephen and Margret Andrea, whose unwavering love, support, and encouragement have been a significant source of motivation for me. I also dedicate this work to the rest of the Andrea family for their continued support throughout this journey, and to my siblings and friends, I dedicate this research project as a token of appreciation of your constant support and encouragement.

ABSTRACT

This research aimed to analyze the determinants of loan defaults at KCI Management Consultants in 2022. The study focused on identifying the various factors that contribute to loan defaults, such as the borrowers credit history, loan amount, age, gender, value of stock and value of collateral and loan purpose. The research was an investigation of the effectiveness of KCI's current loan underwriting policies and procedures in mitigating the risk of loan defaults. The study used secondary data obtained from the KCI's loan defaults files. The data was analyzed using E-Views software and employed the Ordinary Least Squared (OLS) method to estimate the regression model. The findings of the research provided valuable insights into the factors influencing loan defaults at KCI and informed the development of strategies to minimize the risk of loan defaults in the future.

ACKNOWLEDGEMENT

I would like to express my gratitude to the Almighty God for providing me with the strength, wisdom, and guidance throughout my research project.

I would also like to extend my heartfelt appreciation to the Andrea family for their unwavering support and encouragement. Special appreciation goes to my parents Stephen and Margret Andrea for their spectacular love and support from the very beginning to this level and onwards. Your kind words and acts of kindness have been instrumental in keeping me motivated.

To my siblings and friends, thank you for being there for me whenever I needed your assistance. Your unwavering support and encouragement have been a source of inspiration to me and I couldn’t have done this without you.

Finally, I would like to express my deepest appreciation to my supervisor, Dr Damiyano, whose guidance, patience, and expertise have been invaluable in completing this research project. Your insightful comment and constructive criticism have been instrumental in shaping the direction of this research.

TABLE OF CONTENTS

Contents

CHAPTER 1

Introduction

An overview of how the entire study should be carried out is provided in this chapter. The study's background is written in it, providing an understanding of the context that will be taken into account in the study. The problem statement, the study's goals, its assumptions, and its significance should all be included in this chapter. This chapter must also include an explanation of the elements that define and constrain this investigation. Briefly, this chapter introduces the study as its title indicates.

1.1 Background of the Study

MFIs were first established in Zimbabwe in the 1960s as savings groups established by the Catholic Missionaries through the Savings Development Movement (SDM) of Zimbabwean women's attitudes towards participating in the economy (Bond et al., 1998). Through a system known as Rotating Savings and Credit Association (ROSCAs), these clubs concentrated on rotating services. The groups continued to expand while overcoming challenges including the rise in military action between 1976 and 1980. The SDM was registered after the independence (Bond, ibid) and this later opened the door for the development of various MFIs, including the National Association of Cooperative Savings and Credit Unions of Zimbabwe (NACSUZ).

Microfinancing was greatly hindered by inflation in the period 2005 to 2008 (Mago, 2013). However, in 2007, the RBZ noted in the Monetary Policy Statement that the rural sector had neglected in the financial system and stimulated the MFIs' activity to bridge the gap (ZAMFI, 2007). The economy went into a stabilizing phase in 2010 which led to the demand for loans. Many MFIs were formed, and banks were induced to offer micro-loans by the Government. There were over 100 MFIs operating in Zimbabwe in the period of 2010 to 2015. There were 179 registered Microfinance Institutions in Zimbabwe as at 31 March 2022 and 198 as at 31 December 2022 (RBZ 2022).

Basically, small and medium-sized businesses borrow money from MFIs to bridge the financial gap between the amount of resources they have and the amount to meet their investment requirements (ZEPARU & BAZ 2014). The informal sector coexists alongside the microfinance industry. In Zimbabwe, the RBZ registers each and every MFI and makes sure that all activities are carried out in line with Zimbabwean legislation. Through the Moneylending and Rate of Interest Act [Chapter 14.14], the RBZ also ensures that institutions' interest rates are not predatory to their clients. The RBZ provides the MFIs with regular regulatory directions and they are expected to abide with them (RBZ 2012). Additional pertinent requirements can be found in Chapter 24:20 of the Banking Act.

Table 2: Microfinance Industry Report

Indicator	Dec 2021	March 2022	June 2022	Sept 2022	Dec 2022
Total Loans ($m)	7,153.70	8,954.57	15,858.74	31,814.69	46,010.10
Total Assets ($m)	11,533.34	16,178.19	28,660.76	54,808.24	82,126.44
Total Equity ($m)	5,008.80	6,629.51	14,470.66	22,359.64	35,914.91
Net Profit ($m)	1,984.88	2,103.12	1,372.24	3.397.03	6,305.90
Portfolio at Risk (PaR>30 days)	10.15%	10.71%	10.39%	9.99%	10.95%
No. of Outstanding Loans	318,007	274,204	317,482	264,691	306,366
No. of Active Loan Clients	307,655	288,135	280,172	385,634	328,678
No. of Branches	1007	900	974	936	1264

Source: www.rbz.co.zw/assets/mfi-industry-report-as-at-31-december-2022.pdf , page 5

The microfinance industry in Zimbabwe is comprised of firms that offer different services to different clients in both the formal and informal sector. MFIs like Tottengram, Get Bucks and FMC offer loans to civil servants while others like KCI microfinance, Wisrod investments and JHM among others compete in lending to small businesses like tuck shops, flea market, vendors and others.

KCI Management Consultants is a registered microfinancier in Zimbabwe aimed at transforming the lives of people through loans by ensuring that all groups have access to cash, be it in business, salaried or a pensioner. KCI is a financial institution located at 94 McChlerry Avenue Eastlea in Harare, Zimbabwe. The institution provides loans to individuals and businesses. However, the institution has experienced a significant number of loan defaults in recent years. Therefore, this research aims to identify the determinants of loan defaults at KCI Management Consultants in 2022.

The issue of loan defaults has been a major concern for financial institutions worldwide. Loan defaults can have a significant impact on the financial performance of financial institutions, and ultimately, and they not only result in losses for financial institutions but also have a negative impact on the overall economy. In recent years, KCI Management Consultants has experienced a high number of loan defaults, which has had a negative impact on the institution's profitability and ability to offer loans to individuals and businesses. The issue of loan defaults is particularly relevant in the Zimbabwean context, where the economy has faced significant challenges in recent years, including high inflation rates, a shortage of foreign currency, and political instability. These challenges have made it difficult for individuals and businesses to access credit, and have also increased the risk of loan defaults.

Therefore, it is important to identify the determinants of loan defaults at KCI Management Consultants in order to mitigate the risk of loan defaults and enhance financial stability. This research aims to identify the factors that contribute to loan defaults at KCI Management Consultants, with a focus on loan amount, interest rate, borrower income, age, gender, value of finances stock and site of business. The findings of this research could be useful not only to KCI Management Consultants but also to other financial institutions in Zimbabwe facing similar challenges.

In addition to the economic and political challenges in Zimbabwe, the COVID-19 pandemic has also had a significant impact on the financial sector, including the banking and lending industry. The pandemic has led to a decrease in economic activity, job losses, and reduced income for many individuals and businesses, which has made it more difficult for them to repay loans. Therefore, it is important to understand how the pandemic has affected loan defaults at KCI Management Consultants and to identify any additional factors that contribute to loan defaults in this context.

Furthermore, the issue of loan defaults is not unique to Zimbabwe and has been studied extensively in other countries. Previous studies have identified borrower characteristics such as income level, credit history, and employment status, as well as loan characteristics such as loan amount, interest rate, and repayment period, as important determinants of loan defaults. However, the effectiveness of loan approval and monitoring processes in mitigating the risk of loan defaults may vary across different contexts and financial institutions.

Therefore, this study aims to contribute to the existing literature by identifying the determinants of loan defaults at KCI Management Consultants in the specific context of Chitungwiza, Zimbabwe in 2022. The findings of this study could be useful not only to KCI Management Consultants but also to other financial institutions in Zimbabwe facing similar challenges, as well as to policymakers and regulators in the financial sector.

1.2 Problem Statement

It has been the hope of policy makers that microfinance institutions infuse growth and development in the informal sector as these MFIs target the informal sector that have been missed by banks. Loan defaults can result in significant losses for financial institutions, and eventually affect the stability of the financial system. KCI Management Consultants has experienced a high number of loan defaults in recent years, which has had a negative impact on the financial performance of the institution. Therefore, there is a need to identify the determinants of loan defaults at KCI Management Consultants in order to mitigate the risk of loan defaults and enhance financial stability.

1.3 Research Objectives

The main objective of this research is to identify the determinants of loan defaults at KCI Management Consultants in 2022. The specific objectives are:

1. Characterization of defaulting clients at KCI Management Consultants.

2. To identify the reasons for defaulting in loan repayments by clients.

3. To make appropriate recommendations.

4. To evaluate the effectiveness of loan approval and monitoring processes in mitigating the risk of loan defaults at KCI Management Consultants.

1.4 Research Questions

The research questions that will guide this study are:

1. What are the characteristics of defaulting clients at KCI Management Consultants?

2. What are the reasons for defaulting in loan repayments.

3. What recommendations to make to reduce loan defaults.

4. How effective are the loan approval and monitoring processes in mitigating the risk of loan defaults at KCI Management Consultants?

1.5 Assumptions of the study

- The challenges at KCI Management Consultants represents national challenges for microfinance institutions.
- The recommendations apply to all MFIs

1.6 Significance of the Study

This study is significant because it will provide insights into the determinants of loan defaults at KCI Management Consultants, which could help the institution to mitigate the risk of loan defaults and enhance financial stability. The findings of this study could be useful to other financial institutions nationwide that are facing similar challenges, the government, the researcher and the academics.

To the MFIs, this study helps them in identifying the causes of loan defaults in the Zimbabwean economy. As the study relates to the Zimbabwean conditions, the MFI stakeholders such as employees can make decisions on who to select and how to insulate the firm from the credit default risk relating to selected persons at KCI. To the investors, the study helps them in making the decision on whether to invest or not, knowing the risks in potential loan defaults.

To the government, the study could act as a guide when in the attempt to alleviate poverty since MFIs are regarded as a means to poverty reduction. The government could regulate MFIs and assist them in their business operations so as to gear up the economic operations.

To the researcher, the study assisted in both the academics and the functionality of the MFIs. The study is of significance to the researcher as it improves the knowledge pertaining to the research itself and microfinance institutions operations and management.

To the academia, the research assists individuals as it gives more literature to refer to when studying in the areas relating to the topic in question and also help academic researcher in formulating their study topic in future.

1.7 Scope and Limitations of the Study

This study will focus on the determinants of loan defaults at KCI Management Consultants in 2022. The study will analyze borrower characteristics such as age, gender, income level, credit history, and employment status, as well as loan characteristics such as loan amount, interest rate, and repayment period. The study will also evaluate the loan approval and monitoring processes at KCI Management Consultants.

One limitation of the study is that it will only cover one company. Another limitation is that the study will only analyze data from 2022, which may not provide a complete picture of the determinants of loan defaults at KCI Management Consultants and the data being used is secondary data which does not hold much information.

1.8 Organization of the Study

This study will be organized into five chapters. Chapter 1 will provide an introduction to the study and will include the background of the study, problem statement, research objectives, research questions, significance of the study, scope and limitations of the study, methodology, and organization of the study. Chapter 2 will review relevant literature on the determinants of loan defaults. Chapter 3 will describe the methodology used in the study. Chapter 4 will present and analyze the data collected. Finally, Chapter 5 will provide a summary of the findings, conclusions, and recommendations for future research.

1.9 Conclusion

In conclusion, this study aims to identify the determinants of loan defaults at KCI Management Consultants in 2022. Loan defaults are a serious concern for financial institutions, and identifying the determinants of loan defaults can help to mitigate the risk of loan defaults and enhance financial stability. The findings of this study could be useful not only to KCI Management Consultants but also to other financial institutions facing similar challenges.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

This chapter presents a review of the theoretical and empirical literature on loan defaults. The literature review is divided into two main sections. The first section provides an overview of the theoretical literature on loan defaults, while the second section presents a review of the empirical literature on loan defaults.

2.1 THEORETICAL LITERATURE

2.1.1 Credit Risk Model

The credit risk model is a widely used theoretical framework for analyzing the determinants of loan defaults. It is based on the assumption that lending involves a certain degree of risk and that the lender must be compensated for this risk through the interest rate charged on the loan. The model suggests that loan defaults are caused by credit risk factors such as the borrower's creditworthiness, collateral, and loan structure (Altman, 2008). These factors are used by lenders to assess the risk of default and set appropriate interest rates. According to this model, borrowers with poor creditworthiness, inadequate collateral, or unfavorable loan structures are more likely to default on their loans.

2.1.2 Agency Theory

Agency theory is a theoretical framework that examines the relationship between principals (such as shareholders or lenders), and agents (such as managers or borrowers) in an organization. The theory suggests that loan defaults are caused by agency problems between the borrower and the lender (Jensen & Meckling, 1976). It assumes that there may be conflicts of interest between principals and agents, and that the agents may act in their own self-interest rather than in the best interest of the principals. According to this model, borrowers may have incentives to engage in risky behavior that increases the likelihood of default, while lenders may have incentives to take on more risk than is optimal in order to maximize their profits. This can lead to agency cost such as excessive risk-taking or moral hazard, which can increase the risk of loan defaults.

Agency theory suggests that lenders must carefully monitor and manage the behavior of borrowers to ensure that they are acting in the best interest of the lender. This involves setting appropriate incentives such as tying loan terms to performance metrics or requiring collateral or personal guarantees.

2.1.3 Asymmetry Model

Asymmetry model is a theoretical framework that examines the role of information asymmetry in loan defaults. In this model, it is suggested that loan defaults are caused by information asymmetries between the borrower and the lender (Stiglitz & Weiss, 1981). It assumes that lenders and borrowers may have different levels of information about the risk of the loan and that this asymmetry can lead to adverse selection and moral hazard problem. Adverse selection occurs when borrowers with higher default risk are more likely to see out loans while moral hazard occurs when borrowers take on excessive risk because they know that the lender is bearing the majority of the risk. According to this model, borrowers may have better information about their own creditworthiness and the potential risks associated with their projects than lenders do, and may therefore be more likely to default if the loan terms are not favorable to them.

The asymmetry model suggests that lenders must carefully screen borrowers to ensure that they have accurate information about the borrowers' risk profile. This may involve conducting credit checks, reviewing financial statements and requiring collateral or personal guarantees.

2.1.4 Credit Scoring model

2.1.4.1 Fair Isaac Corporation (FICO)

The FICO credit scoring model is a model which uses individual's personal credit history to determine whether they are likely to miss a loan payment (Foust et al., 2008). It makes use of information on paying off credit card debt and other bills. As it predicts present repayment capabilities using historical loan payback data, the model is autoregressive. According to Keys et al. (2010), the cut-off point for FICO ratings is 620 and they are based on continuous scores.

However, this approach does not completely account for the reasons behind previous settings. It simply assumes that someone who has defaulted before has a larger likelihood of doing so than someone who has never defaulted.

2.1.4.2 In-house credit-scoring model

It is a statistically based scoring model that takes into account the FICO as well as additional factors including the management of the company and its cash flow (Keys et al., 2010). It considers the statistically relevant factors and gives each one a weighted value to produce what is known as the "inhouse score."

2.1.5 Macro-Economic model

The macro-economic model suggests that loan defaults are influenced by macro-economic factors such as interest rates, inflation and unemployment. According to this model, borrowers are more likely to default during periods of economic downturns. Several studies have supported the macro-economic model. For instance, Mishkin (1992) analyzed the causes of the 1980s savings and loan crisis in the United States and a decline in the real estate market. Similarly, Dell'Ariccia et al. (2004) analyzed the impact of macro-economic conditions on loan defaults in emerging market economies and found that defaults were significantly more likely during periods of economic downturns.

2.1.6 The Behavioral Model

It is worth knowing that some researchers have developed models of loan defaults that incorporate behavioral factors such as overconfidence or loss aversion. These models suggest that borrower behavior can play an important role in driving default risk and highlight the importance of understanding the psychological factors that influence decision-making around borrowing and repayment. Thale and Sunstein (2008), provide a popular introduction to behavioral economics which has influenced much of this research. This model suggests that loan defaults are influenced by borrower psychology and decision-making biases.

2.1.7 Dellien and Schreiner's Predictive indicators

Dellein and Schreiners (2002) study on Predictive indicators of loan default is a seminal work in the field of credit risk analysis. They identified a set of variables that have been found to be predictive of loan defaults. The model's is to minimize the default risk of clients by choosing the clients that maximize these pointers. The pointers include the client's indicators such as age, years in business, collateral and purpose of the loan. Multiple linear regression model can be used in estimating client's repayment capabilities using the predictors as the variables. An increase in loan repayments can be guaranteed by eliminating the clients that contributes to potential defaults.

2.1.8 The Time-Series Model

Another approach to modeling default risk is to use time-series methods to analyze trends and patterns in historical data. This approach can be useful for identifying macroeconomic factors that contribute to default risk. Altman (2005) provides a good overview of time-series models for credit risk analysis. One common approach to time-series modeling is to use autoregressive integrated moving averages (ARIMA) models. These models are designed to capture trends and patterns in data over time and can be used to forecast future values based on those trends. ARIMA models are particularly useful for modeling stationary time series which are time series that exhibit a constant mean and variance over time.

Another approach to time-series modeling is to use vector autoregression (VAR) models. VAR models are similar to ARIMA model but are designed to capture the interdependencies between multiple time series variables. In the context of loan defaults, VAR models can be used to analyze the relationships between default rate and other macroeconomic variables such as interest rate, GDP, or unemployment rates.

2.2 EMPERICAL LITERATURE

Demyanyk and Hermet (2008) did a study on the relationship between credit scores and loan repayments. The study analyzed data from a large sample of borrowers who had taken out various types of loan including mortgages, auto loans and credit cards. The study used the logistic regression model for estimation. The study found that borrowers with lower credit scores were more likely to default on their loans than those with higher credit scores. Especially, the study found that borrowers with credit scores below 620nwere more than three times as likely to default on their loans as borrowers with credit scores above 760. The study also found out that the relationship between credit scores and loan repayment was strongest for subprime borrowers who had lower credit scores to begin with. This suggest that the credit scores are particularly important for lenders to consider when evaluating the risk of lending to subprime borrowers. The study provides strong evidence that credit scores are a reliable predictor of loan repayment and that borrowers with lower credit scores are at a higher risk of defaulting on their loans.

Imai, Gaiha and Thapa (2011), did a study on the relationship between income and loan payment. The study analyzed data from a microfinance program in India that provided small loan to low-income borrowers. The study used linear regression to estimate the relationship between borrower income and loan repayment. The study found out that borrowers with higher incomes were more likely to repay their loans than those with lower incomes. The researchers found out that a 10% increase in borrower income was associated with a 3.6% increase in the likelihood of loan repayment. They also found out that the relationship between borrower income and loan repayment was strongest for borrowers who were wealthy were less likely to be affected by changes in income. The study provides evidence that borrower incomes is an important determinant of loan repayment, and that borrowers with higher incomes are more likely to repay their loans than those with lower incomes. It also suggests that microfinance programs may be more effective at reaching borrowers who are in the middle of the income distribution.

Chowdhury and Bhuiya (2006), also did a study examining the relationship between collateral and loan repayment. The study analyzed data from a microfinance program in Bangladesh that provided small to low-income borrowers. This study also used linear regression for estimation. The researchers collected data on borrower characteristics, loan repayment and other factors that might affect loan performance. The study found out that borrowers who provided collateral for their loans were more likely to repay them than those who did not. They also found that the likelihood of loan repayment was 29% higher for borrowers who provides collateral than for those who did not. They found that borrowers who provided land as collateral were more likely to repay their loans than those who provided other types of collateral such as jewelry or livestock. The study provided evidence that collateral is an important determinant of loan repayment and that borrowers who provide collateral are more likely to repay their loans than those who did not. It also suggests that the type of collateral may be an important factor to consider when evaluating the risk of lending.

Sanyal and Menon's (2010) study examined the relationship between borrower education and loan repayment. The study analyzed data from a microfinance from India. The linear regression model was used for estimation. The study found that borrowers with higher levels of education were more likely to repay their loans. They also found that the likelihood of loan repayment increased by 4% for every additional year of schooling completed by the borrower. It is found that the relationship between education and loan repayment was strongest for female borrowers. Female borrowers with higher levels of education were more likely to repay their loans than their less educated counterparts. The study provided evidence that borrower education is an important determinant of loan repayment and that the relationship between borrower and loan repayment may be stronger for female borrowers.

2.3 Research Gap

This study attempt to investigate the degree to which loan defaults are affected by the abovementioned determinants by looking at the number of defaults that accrue to a client within a particular loan cycle. This can be considered as a research gap as in previous studies, the researchers looked at the relationship between various caused of defaults and loan performance. This study also looks at a firm in Zimbabwe. Previous studies looked into other countries like India, Nigeria and Bangladesh amongst others. This study looks into a Zimbabwean situation which could assist several local decision makers in conducting their work at an improved level of accuracy.

2.4 Conclusion

The theoretical and empirical literature on loan defaults suggests that there are a number of factors that can contribute to loan defaults. Certain discussions and results were observed and their contribution to this study was analyzed. The research gap was also reviewed within this chapter.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter presents the methodology used in the study on the determinants of loan defaults at KCI Management Consultants. The chapter investigates the methods of analyzing how the client's loan amount, age, gender, value of stock and site of business contribute to the default rate in microfinance firms. This chapter focuses on the model used to estimate the relationships, the justification and selection of the variables and the diagnostic tests to be performed.

3.2 Research Design

The study adopted a descriptive research design. Descriptive research design is a research design that describes the characteristics of a population or phenomenon being studied. The research will be at support of secondary data gathered from KCI client's records. Descriptive statistics were used in the study to analyze the data collected. The secondary data provided information on the loan characteristics and history of the borrowers who had defaulted on their loans, which was useful in analyzing the determinants of loan defaults. Descriptive statistics is a method of summarizing and describing data using measures such as mean, median, mode, standard deviation, and frequency distribution. The design was suitable for the study since it aimed to describe the determinants of loan defaults at KCI Management Consultants. The data results provided by the econometric model will next be estimated and interpreted using econometric methods.

3.3 Population

The population for this study was the borrowers who had taken loans from KCI Management Consultants in 2022. The sample size for the study was 100 borrowers who had defaulted on their loans. The sample was selected using a simple random sampling technique. The sample was considered representative of the population and the findings of the study could be generalized to the population.

3.4 Estimation Method

The estimation method for analyzing the determinants of loan defaults at KCI Management Consultants in 2022 will involve a regression analysis. This analysis will help to identify the significant factors that contribute to loan defaults and predict the likelihood of default. To determine the derivation of the Multiple Regression Model of estimate that we will apply in this study, we can simply use the two-variable OLS regression model.

3.5 Hypothesis

The following hypothesis can be formulated for the analysis:

H0: There is no significant relationship between loan defaults and the following variables: loan amount, interest rate, borrower income, age, gender, the value of financed stock, and the site of the client's business.

H1: There is a significant relationship between loan defaults and at least one of the following variables: loan amount, interest rate, value of collateral, age, gender, the value of financed stock, and site of the client's business.

Note: The null hypothesis assumes that there is no relationship between the variables and the likelihood of loan defaults. The alternative hypothesis assumes that there is a significant relationship between at least one of the variables and the likelihood of loan defaults.

3.6 Model Specification

The regression model that can be used to analyze the determinants of loan defaults is as follows:

$$DR = \beta 0 + \beta 1AMT + \beta 2DEP + \beta 3Age + \beta 4Gender + \beta 5VOS + \beta 6VOC + \beta 7SOB + \varepsilon$$

Where:

- Default is a binary variable that takes a value of 1 if the loan defaulted and 0 otherwise.

- Loan Amount is the amount of the loan.

- Number of dependents.

- Age is the age of the borrower.

- Gender is a binary variable that takes a value of 1 if the borrower is male and 0 otherwise.

- Value Of Financed Stock is the value of the stock financed by the loan.

-Value Of Collateral.

- Site Of Business is a categorical variable that describes the location of the borrower's business.

- β0, β1, β2, β3, β4, β5, β6, and β7 are the coefficients to be estimated.

- ε is the error term.

The regression model will be estimated using the Ordinary Least Squares (OLS) method. The significance of the variables will be tested using the t-test and the overall significance of the model will be tested using the F-test.

3.7 JUSTIFICATION OF VARIABLES

3.7.1 Defaults (DR)

The failure of the client to fulfill the necessary repayment obligation within the specified window of time is referred to as a default. At KCI, all daily repayments must be completed by 5:00 p.m. The rate of a client's defaults is determined in this study as the how many payments were not made on time. The dependent variable in this study is set to defaults.

3.7.2 Loan Amount (AMT)

The loan amount is an important variable to consider in credit risk analysis because it represents the total amount of money borrowed by the borrower. A higher loan amount may increase the likelihood of default since it may be harder for the borrower to repay the loan. In the event of a fixed loan period, a rise in the loan amount means an increase in the amount that must be repaid per installment. Although a small business owner's ability to replenish and grow is generally boosted with an increase in cash, this might be constrained by things like the declining returns to scale. Since the study focuses on small businesses, the expected sign for this variable's coefficient is positive because it is anticipated that a higher loan repayment burden for the clients will raise the clients' default rate.

3.7.3 Number of Dependents (DEP)

This is the number of people that the client is financially supporting given the assumption that the client is the breadwinner. They may include grandchildren, nephews and nieces, spouses, and parents. This assists the researcher on determining the burden of people that the borrower holds.

3.7.4 Client's Age (AGE)

Age can be an important variable to consider as it may reflect the borrower's experience and stability in the work and financial life. For instance, older borrowers may have more stable incomes and employment histories, which can reduce the likelihood of default. Rita (2011), age has been seen to have a negative relationship with default rates. This have been explained with the fact that people have a tendency of becoming more responsible as they grow. The expected sign of this variable's coefficient is negative.

3.7.5 Gender of client (GENDER)

Gender can also be an important variable to consider as it may reflect differences in income and employment opportunities between genders. For instance, if one is disproportionately represented in low-income or high-risk industries, this may increase the likelihood of default for borrowers of that gender. The expected sign for this variable's coefficient is negative as 1 represents male and 0 otherwise.

3.7.6 Value Of Financed Stock (VOS)

This is the estimated cost of the stock that the clients are believed to have purchased with the restocking loan. By comparing the client's inventory before and after obtaining a loan, it is possible to estimate the financial value of the stock that was purchased. This variable's intended sign is a negative one.

3.7.7 Value Of Collateral (VOC)

The value of collateral is an important variable to consider as it represents the value of items offered by the client that secures the loan. The value of collateral in this study is the price that the Credit Officer and the client agree that the collateral security is worth. The expected sign of this variable is a negative.

3.7.8 Site Of Business

The site of the borrower's business can be an important variable to consider as it may reflect differences in economic conditions and business opportunities across different regions. For example, borrowers in economically depressed regions may have a higher likelihood of default than borrowers in more prosperous regions. The expected sign for this variable is a negative as 1 represents clients that work in the city or town in which they borrowed and 0 represents otherwise.

3.8 TESTS

3.8.1 Diagnostic Tests

Cross-sectional data are typically employed in research. It is necessary to get rid of the multicollinearity and heteroscedasticity issues for the estimators to meet the Gauss Markov BLUE (Best, Linear, Unbiased Estimators) requirements and to produce findings that are not spurious. Because neither the variables nor the errors have a temporal component, the stationery test and the serial correlation test should be disregarded.

3.8.2 Multicollinearity

The occurrence of a perfect or exact linear relationship between some or all the explanatory variables in a regression model is described as multicollinearity by Gujarati (2008), who quotes Ragnar Frisch's term from that work. If the BLUE criteria are met, the estimators will have high variances and covariances, which will make the estimates largely imprecise. Wider confidence intervals that allow for the acceptance of the zero-null hypothesis, the presence of statistically insignificant t-ratios and extremely high R2 values are further effects. The collinear variables can be dropped as the simplest solution to this issue.

3.8.3 Heteroscedasticity

Heteroscedasticity describes a situation in which the variances of the error components in a regression model are not equal. The variance of the error term is magnified by its presence, resulting in modest t-values. You can check for heteroscedasticity using White's General

Heteroscedasticity Test and the Goldfeld-Quandt Test. When the variance is known, the weighted least squares approach can be used as a corrective measure; otherwise, White's Heteroscedasticity-Consistent Variances and Standard Errors can be employed.

3.8.4 Normality

The normality of refers tells us that the errors are normally distributed. It becomes challenging to test the model's significance using the t-test and the F statistics if the errors are normally distributed. The skewness is brought on by the presence of a small number of large outliers (Lumley et al., 2002). To check for normalcy, the Jarque-Bera statistic is employed (Gujarati, 2008).

3.9 Model Specification Test

To determine whether the model being used fits the data, the model specification test must be run. In this model, the F-Test and the corrected R2 are to be applied. The F-test establishes the model's validity, and the adjusted R2 assesses the model's goodness of fit after accounting for the degrees of freedom.

3.9.1 F-Statistic

A measure of significance for the entire estimated regression model is the F-statistic. Its foundation is the null hypothesis that all the model's genuine slope coefficients are concurrently equal to zero. If the calculated F-values are greater than the critical F-values from the F-tables at the required level of significance, we reject this null hypothesis.

3.9.2 R-Squared Test

The coefficient of determination (R2) is often used. It gauges how well the model fits the data. Additionally, it is used as a summary indicator of how well the sample regression line fits the data. The amount (fraction or percentage) of variations in the dependent variable that can be accounted for by changes in the explanatory factors is measured. Its boundaries, which reflect the fraction of variances, are 0 and 1, with 1 representing the ideal fit. We will concentrate on the modified R2 for the degrees of freedom in this study.

3.10 Data Presentation and Analysis Procedures

The data collected was analyzed using descriptive statistics. Descriptive statistics were used to describe the characteristics of the borrowers, loan characteristics, and reasons for loan defaults. The data was presented using tables, graphs, and charts. The study found that the most significant determinants of loan defaults at KCI Management Consultants were inadequate cash flows, poor credit appraisal process, and ineffective loan monitoring process. The study also found that borrowers who had defaulted on their loans had a low level of education, low income, and were engaged in informal sector activities. The study also revealed that most borrowers defaulted on their loans due to economic hardships, business failure, and unexpected personal emergencies.

The study also found that KCI Management Consultants had a robust credit policy and procedure in place. However, the credit appraisal process was not comprehensive, and the loan monitoring process was not effective. The study recommended that KCI Management Consultants should improve its credit appraisal process by incorporating all relevant factors that could affect loan repayment. Additionally, the company should strengthen its loan monitoring process by regularly monitoring borrowers' businesses and cash flows.

3.11 Conclusion

In conclusion, the study aimed to analyze the determinants of loan defaults at KCI Management Consultants in 2021. The study used a descriptive research design and collected secondary data. The data was analyzed using descriptive statistics and presented using tables, graphs, and charts.

CHAPTER 4

DATA PRESENTATION, ANALLYSIS AND DISCUSSION

4.1 Introduction

The researcher tries to respond to the queries posed in the first chapter in this one. Ordinary Least Squares regression will be used as the main technique to address the questions in accordance with the approaches covered in the previous chapter. As the data that has been analysed and presented provides answers to the study questions. This chapter's primary sections include an overview of descriptive statistics, diagnostic tests, and an explanation of the coefficients.

4.2 Descriptive Statistics

Descriptive statistics gives us a general outline of the behaviour of the variables. The averages such as the mean and median are shown in this description. Also, the extreme values that is the maximum and minimum are shown within these statistics. The standard deviation and the normality indicators (Skewness and Kurtosis) are also shown. The following table gives us the abovementioned in detail,

Table 4.1: Descriptive Statistics

	DR	AMT	AGE	SOB	DEP	GENDER	VOS	VOC
Mean	1.882759	133.0460	38.05747	0.908046	2.413793	0.275862	74.02299	173.7356
Median	1.000000	125.0000	37.00000	1.000000	2.000000	0.000000	60.00000	170.0000
Maximum	12.00000	400.0000	61.00000	1.000000	6.000000	1.000000	250.0000	500.0000
Minimum	0.000000	50.00000	25.00000	0.000000	0.000000	0.000000	20.00000	50.00000
Std. Dev.	2.360391	55.31283	8.029533	0.290636	1.410523	0.449539	43.76097	87.15203
Skewness	2.008601	1.518915	0.918675	-2.824228	0.264349	1.002972	1.450787	0.996300

Kurtosis	7.525930	8.135221	3.675206	8.976266	2.385295	2.005952	5.483345	4.436134
Jarque-Bera	132.7546	129.0461	13.89012	245.1255	2.383014	18.16828	52.87474	21.86940
Probability	0.000000	0.000000	0.000963	0.000000	0.303763	0.000113	0.000000	0.000018
Sum	163.8000	11575.00	3311.000	79.00000	210.0000	24.00000	6440.000	15115.00
Sum Sq. Dev.	479.1441	263117.8	5544.713	7.264368	171.1034	17.37931	164692.0	653210.9
Observations	87	87	87	87	87	87	87	87

Source: E-Views 10

The maximum number of defaults within this sample that have been reported is 12 in the table, while the minimum is 0. Within the examined sample, a standard deviation of 2.360369 defaults is also detected.

Regarding the ages of the clientele, the oldest borrower from KCI Chitungwiza was 61 years old, while the youngest was 25. The average client was a little older than 38 years old.

The KCI clients in Chitungwiza received loans ranging from $50 to $400, with the minimal loan amount being authorized. The median loan amount was $400, and the mean loan amount was a little bit over $133. The $100 loan was the one that the clients most frequently requested at this time. The least loan amount had eight clients, while the largest loan amount had just one. This could demonstrate that most borrowers avoid taking out high-interest loans because they are risk-averse and believe they will be more challenging to repay.

Nine clients worked at the clients' place of business outside of Chitungwiza, while the other 91 clients all worked within Chitungwiza.

Regarding gender, only 11 of the 100 clients are men, while the remaining 89 are all women. This is primarily due to the KCI Microfinance targeted markets' substantial female population. Among clients of KCI Makoni, 6 is the most and 0 is the least number of dependents.

The largest and lowest amounts on the stock value that was financed by the loan were $250 and $20, respectively. The highest value of the pledged collateral was $500, and the lowest amount was $50.

4.3 DIAGNOSTIC TESTS

4.3.1 Multicollinearity

The regression results are affected by the multicollinearity issue if there is a nearly perfect or exact linear connection between the explanatory variables. The correlation test can be used to determine whether multicollinearity exists.

Table 4.2: Correlation Matrix

	AGE	AMT	SOB	DEP	GENDER	VOS	VOC
AGE	1.000000	0.226988	-0.060765	0.132836	-0.064501	0.111456	0.063793
AMT	0.226988	1.000000	-0.060756	0.181573	-0.092215	0.696952	0.490591
SOB	-0.060765	-0.060756	1.000000	-0.018022	0.104893	0.178451	0.036616
DEP	0.132836	0.181573	-0.018022	1.000000	-0.001662	0.086782	0.255936
GENDER	-0.064501	-0.092215	0.104893	-0.001662	1.000000	-0.064645	-0.028309
VOS	0.111456	0.696952	0.178451	0.086782	-0.064645	1.000000	0.448245
VOC	0.063793	0.490591	0.036616	0.255936	-0.028309	0.448245	1.000000

Source: E-Views 10

It has been established that the data does not exhibit a comparable amount of multicollinearity to the matrix. The maximum correlation that exists and meets the criteria for multicollinearity is

0.6969. This demonstrates that the variables can be separated because they do not change in a predictable way.

4.3.2 Normality Test

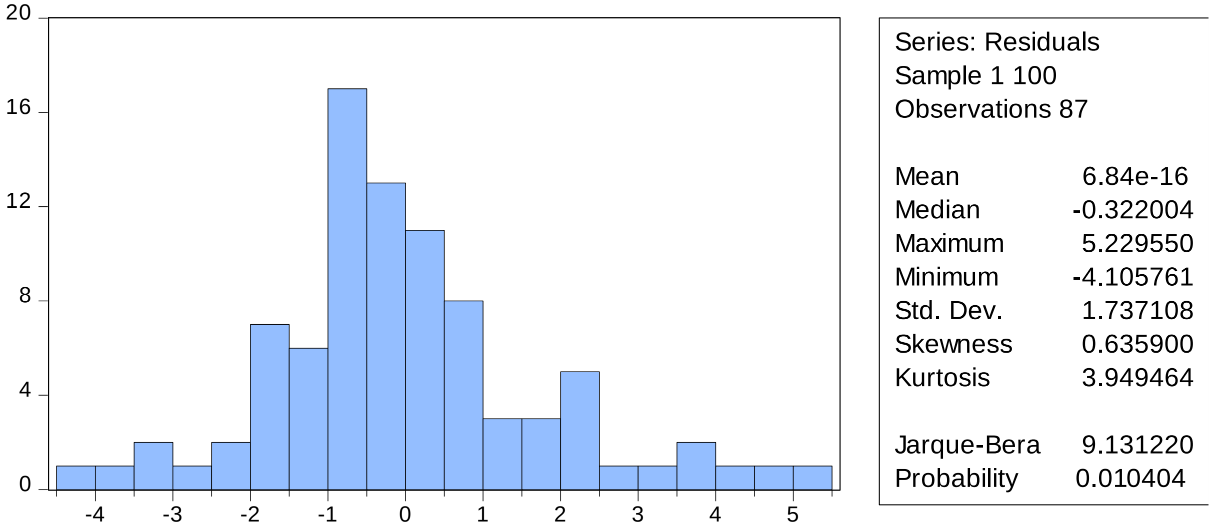


Figure 4.2: Residuals, Histogram

Source: E-Views 10

The data show that the residual term is normal, with a probability value (p-value) of 0.0104. Since the significance level in this example is 0.1, the Jarque-Bera test's p-value demonstrates the minimal threshold at which we can accept the alternative, which states that there is normality, and reject the null hypothesis that there is normality. The F and t-test may be used to evaluate incorrect hypotheses that were formed because of using data that were not normally distributed (Gujarati, 2008). However, by moving forward with estimates, we can produce results that are reliable (Lumley et al., 2002).

4.3.3 Heteroscedasticity Test

Table 3.3: White Test

Heteroskedasticity Test: White			
F-statistic	3.845269	Prob. F (7,79)	0.0012
Obs*R-squared	22.10950	Prob. Chi-Square (7)	0.0024

Source: E-Views 10

The White's Heteroscedasticity test was used to determine heteroscedasticity. The F statistic for the White test has a p-value of 0.0012, which means that the null hypothesis that there is no heteroscedasticity is rejected. White's heteroscedasticity-consistent standard errors & covariance must be used since this suggests that the variances of the estimated parameters are not the minimal variances, which is in conflict with the need of the Gauss Markov's BLUE criteria.

4.4 Regression Results

A linear function is used to estimate the regression model. The estimation process used the E-Views 10 statistical program and the OLS regression approach, and the findings were as follows:

Table 4.4: OLS Regression Results

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	2.769333	1.019315	2.716856	0.0079
AMT	0.017870	0.003978	4.491960	0.0000
AGE	-0.019416	0.019756	-0.982778	0.3283
GENDER	-0.044303	0.503813	-0.087936	0.9301
DEP	0.062277	0.108211	0.575518	0.5663
VOS	-0.024591	0.004999	-4.919148	0.0000
VOC	8.15E-05	0.001907	0.042753	0.9660
SOB	-1.188356	0.535826	-2.217803	0.0290
R-squared	0.458391	F-statistic		9.551656
Adjusted R-squared	0.410400	Prob(F-statistic)		0.000000

Source: E-Views 10

The R-squared of 0.4583 indicates that changes in the explanatory variables in this model account for around 46% of the differences in the clients' settings. Other socio-economic factors that were not incorporated in the model account for the remaining 59%. In order to account for the degrees of freedom lost by expanding the variables, an adjusted R-squared of 0.4104 was calculated. At a 10% significance level, the client's age (AGE), the number of dependents (DEP), the client's gender (GENDER), and the amount of collateral are irrelevant in explaining variations in default rates (DR) because their probabilities are higher than 10%. The value of financed stock (VOS) and the client's loan amount (AMT) have both shown to be 1% significant. The client's place of business (SOB) accounts for 5% of the total.

4.5 INTERPRETATION OF RESULTS

4.5.1 Loan Amount (AMT)

The client's loan amount (AMT) has a p-value of 0.00000, making it significant at all levels of significance. As a result, we reject the null hypothesis that AMT has no bearing on the variability in DR at 1%. Large loan amounts are demonstrated to cause loan defaults for the client by the study. The MFI's clients find it increasingly challenging to handle the loan amounts as the loan amounts rise. Diseconomies of scale make it challenging for small business clients to manage big loan amounts. Additionally, some loan clients frequently increase their loan amounts without expanding their businesses, which might eventually result in defaults.

4.5.2 The Client's Site of Business (SOB)

A probability value of 0.0290 indicates that the client's site of business (SOB) is important at 5%. Therefore, we reject the null hypothesis that SOB has little role in describing DR variation. Given that it is a dummy variable, its coefficient of -1.188356 implies that, when all other variables are kept constant, clients who work in the town or city where they obtained the loans typically have 1.188356 fewer defaulted instalments than those who do not. The findings are related to the 2008 study of Demyanyk and Hermet. Most clients that are farther away from the firm geographically tend to default more frequently. This is a result of the rise in transaction costs that affect the people who pay back the loans since they must pay transfer fees like those for Ecocash, Mukuru, and

Innbucks. Additionally, because there isn't a strict monitoring system in place, loan clients frequently have trouble making their payments.

4.5.3 The Value of Financed Stock (VOS)

Given that it has a p-value of 0.00000, the value of financed stock is considerable at all levels. This shows that the null hypothesis, according to which VOS is not relevant in explaining the changes in DR, is rejected. With a coefficient of -0.024591, it is evident that there is no positive correlation between the stock purchased with loan proceeds and the number of payments. This is consistent with Foust et al. According to the Guiding Principles for Loan Repayment, in order to have a stronger ability to return a loan, a client must have a positive history of repayment and a character that makes it possible for them to enjoy repaying debts (Foust, Keys). Utilizing a loan for its intended purpose demonstrates a client's dependability in handling money matters. Because there is more income created from the stocks that are available to the client, there may be a negative correlation between the stocks the client purchased with the loans and the loan defaults. Additionally, employing a loan for its intended purpose demonstrates sound business management abilities and may also indicate improved payback abilities.

4.6 Conclusion

Using the e-views econometric program, this chapter presented the estimation and interpretation of OLS approach. The size of the loan, the value of the funded stock, and the client's business location are the key factors. Age, the number of dependents, the client's gender, and the value of the collateral were deemed to be unimportant coefficients. The hypothesis that the loan amount, the value of the financed stock, and the client's workplace are significant in explaining variances in loan defaults can be accepted based on the regression results.

CHAPTER 5

SUMMARY, CONCLUSION AND DISCUSSION

5.1 Introduction

A thorough review of the factors that contribute to loan defaults in Zimbabwean microfinance institutions is provided in this chapter. This chapter, which acts as the conclusion, summarizes the key conclusions and suggests potential future research topics.

5.2 Key Findings

The primary focus of this study was to examine the root reasons of loan defaults in a developing nation like Zimbabwe. The investigation was limited to the Makoni Business Center since it was difficult to obtain information that the owners viewed as confidential. The study's secondary data was collected by the company to get a better understanding of its clients' repayment patterns. The study's main factors were Loan Default Rate as the dependent variable, Loan Amount as the independent variable, Client Age, Gender, Amount of Stock Financed, Number of Dependents, Market Value of Collateral, and Client Work Site. Only 41% of the fluctuations in the default rates of the clients were explained by the model using the standard least squares regression technique. The variables outside the model account for the remaining 59% of the explanation. The other firms' privacy prevented an analysis of these aspects. The quantity of the client's loan was shown to have a strong positive association with loan defaults, and it was also shown that the bought stock had a significant negative relationship. Clients who work in the city or town in which they borrow were observed to have a lower default level than those who did not work in the city or town, suggesting that the client's place of employment may have a substantial impact on loan defaults.

The study's goals were thus achieved because we were able to determine whether default rates are correlated with loan amounts, client age, gender, market value of collateral, number of dependents, and place of employment. We also determined the magnitude to which these factors affect default rates, as well as the signs of the variable, gaining knowledge about the variables that can be altered to lower default rates.

5.2 Summaries

According to the data, KCI Management Consultants' loan defaults are caused by several variables. Lack of collateral, a dismal credit history, a small income, and excessive debt-to-income ratios are a few of these. Additionally, borrowers who work for themselves or in sectors of the economy that are particularly vulnerable to recessions are more likely to default on their loans.

According to the report, KCI Management Consultants' existing risk management techniques fall short of their potential to lower the frequency of loan defaults. While the corporation has put in place a number of procedures to reduce credit risk, including loan-to-value ratios and credit rating, these measures aren't always used consistently or thoroughly. The business also lacks adequate data management tools for monitoring loan performance and borrower credit histories.

Several suggestions are put up to lower the frequency of loan defaults at KCI Management Consultants based on the analysis. These include: (1) upgrading data management systems; (2) establishing more stringent loan application procedures; (3) diversifying the loan portfolio; and (5) offering financial counseling and education to customers.

5.4 Recommendations

Based on the analysis, the following recommendations are proposed to reduce the incidence of loan defaults at KCI Management Consultants:

1. Improve risk assessment procedures: KCI Management Consultants should develop more rigorous risk assessment procedures to ensure that borrowers meet stringent eligibility criteria. The company should also ensure that credit scoring and loan-to-value ratios are applied consistently and rigorously.

2. Implement more rigorous loan application processes: The company should implement more rigorous loan application processes to ensure that borrowers have the capacity to repay their loans. This can be achieved through income verification, debt-to-income ratio analysis, and collateral evaluation.

3. Enhance data management systems: KCI Management Consultants should invest in data management systems to track borrower credit histories and loan performance. This will enable the

company to identify high-risk borrowers and take proactive measures to reduce the incidence of loan defaults.

4. Diversify the loan portfolio: The company should diversify its loan portfolio to reduce exposure to high-risk borrowers and industries. This can be achieved by offering loans to borrowers in different industries and with different risk profiles.

5. Provide financial education and support to borrowers: KCI Management Consultants should provide financial education and support to borrowers to help them manage their finances effectively. This can include budgeting advice, debt management strategies, and financial planning tools.

5.5 Conclusion

In conclusion, KCI Management Consultants' examination of loan defaults revealed a number of characteristics that affect loan defaults, such as a lack of collateral, a bad credit history, low income, and high debt-to-income ratios. Additionally, the investigation revealed that the company's present risk management techniques fall short of their potential to lower the frequency of loan defaults. In order to lower the frequency of loan defaults, the recommendations made in this chapter should be put into practice. It will cost a lot of money to put these ideas into practice in terms of data management systems, risk assessment processes, and loan application procedures. However, minimizing loan defaults will likely result in better financial performance and more customer satisfaction, which will likely offset the expense of putting these suggestions into practice.

Overall, KCI Management Consultants should focus on improving risk assessment procedures, implementing more rigorous loan application processes, enhancing data management systems, diversifying the loan portfolio, and providing financial education and support to borrowers. By taking these steps, the company can reduce the incidence of loan defaults, improve financial performance, and enhance customer satisfaction.

5.6 Areas of Further Study

The factors that influence defaults in microfinance institutions are still very much up for investigation. This study can be made better in a number of ways because it appears that a number of variables have been left out. First off, a wider timeframe and a cross-section of microfinance companies with various branches could improve this study. Time, money, and access to company information are all undoubtedly necessary for this. Large samples could be used, which could aid in computing results that are more realistic.

REFERENCES

Acharya, V., & Richardson, M. (2019). Causes of the financial crisis: Risk mismanagement, regulation, and market failure. Oxford Review of Economic Policy, 35(1), 4-27.

Altman, E. I. (2002). Bankruptcy and credit risk analysis. John Wiley & Sons.

Beaver, W. H. (1966). Financial ratios as predictors of failure. Journal of accounting research, 4(3), 71-111.

Berger, A. N., & DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks. Journal of Banking & Finance, 21(6), 849-870.

Berger, A. N., & Udell, G. F. (2016). Fundamentals of corporate credit analysis. John Wiley & Sons.

Bernanke, B. S., & Gertler, M. (1989). Agency costs, net worth, and business fluctuations. The American Economic Review, 79(1), 14-31.

Bester, H. (1985). Screening vs. rationing in credit markets with imperfect information. American Economic Review, 75(4), 850-855.

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5-32.

Chowdhury, A. M. R., & Bhuiya, A. U. (2006). Factors affecting loan repayment behavior of clients: A case study of Gremeen Bank. International Journal of Social Economics, 33(9), 648-662.

Coleman, S. (2015). Managing credit risk: the challenge for the new millennium. Journal of Applied Finance & Banking, 5(6), 49-59.

Dellien, P., & Schreiner, M. (2001). Predictive indicators of loan default. Journal of Microfinance, 3(2), 41-61.

Demirgüç-Kunt, A., & Huizinga, H. (1999). Determinants of commercial bank interest margins and profitability: some international evidence. The World Bank Economic Review, 13(2), 379-408.

Demyanyk, Y., & Van Hemert, O. (2008). Understanding the subprime mortgage crisis. Review of Financial Studies, 24(6), 1848-1880.

Gelper, S., Friedl, H., & Croux, C. (2008). Regression versus least absolute shrinkage and selection operator in credit risk modeling. Journal of Banking & Finance, 32(9), 1509-1521.

Gross, M. J. (2019). The credit risk of loan portfolios. Springer.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning: data mining, inference, and prediction. Springer Science & Business Media.

Holmstrom, B. (1979). Moral hazard and observability. The Bell Journal of Economics, 10(1), 74-91.

Imai, K. S., Gaiha, R., & Thapa, G. (2011). Does microfinance reduce poverty in India? New evidence from household-level panel data. Journal of Development Economics, 97(2), 268-281.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics, 3(4), 305-360.

Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. Journal of Banking & Finance, 34(11), 2767-2787.

Klomp, J., & de Haan, J. (2010). Banking risk and regulation: Does one size fit all?. Journal of Banking & Finance, 34(6), 1380-1394.

Lelièvre, M., & Schäfer, R. (2018). Predicting credit risk: A comparative study of statistical and machine learning models. Journal of Business Research, 89, 142-155.

Liu, P., & Tsyvinski, A. (2021). Risks and returns of cryptocurrency. Journal of Monetary Economics, 118, 1-16.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. The Journal of Finance, 29(2), 449-470.

Mishkin, F. S. (1992). Anatomy of a financial crisis. Journal of Evolutionary Economics, 2(2), 115-130.

Mishkin, F. S. (2018). The economics of money, banking, and financial markets. Pearson.

Nkusu, M. (2011). Nonperforming loans and macrofinancial vulnerabilities in advanced economies. IMF Working Papers, 11(161), 1-32.

Roszbach, K. (2003). Bank lending policy, credit scoring and the survival of loans. Journal of Banking & Finance, 27(3), 615-633.

Sanyal, P., & Menon, N. (2010). Borrower characteristics and loan repayment: Evidence from a microfinance experiment. Journal of Microfinance, 12(2), 1-23.

Saunders, A., & Cornett, M. M. (2014). Financial institutions management: A risk management approach. McGraw-Hill Education.

Smith, C. W. (2003). The determinants of bank loan quality: A review of the literature. Economic Review-Federal Reserve Bank of Kansas City, 88(1), 61-85.

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. The American Economic Review, 71(3), 393-410.

Tadesse, S. (2014). Macro determinants of loan default in Ethiopia: a panel data analysis. Journal of African Business, 15(2), 111-117.

Thaler, R. H., & Sunstein, C. R. (2008). Nudge: Improving decisions about health, wealth, and happiness. Yale University Press.

Thomas, L. C. (2000). A survey of credit and behavioral scoring: forecasting financial risk of lending to consumers. International Journal of Forecasting, 16(2), 149-172.

Turvey, C. G., & Kang, H. (2018). Credit scoring and loan default. Journal of Agricultural and Resource Economics, 43(1), 76-91.

Von Thadden, E. L. (2018). The credit market and the determination of interest rates. Journal of Financial Intermediation, 36, 36-48.

Zhang, Y., & Hu, Y. (2016). Credit risk assessment using machine learning algorithms: A review. International Journal of Computational Intelligence Systems, 9(1), 20-30.

APPENDIX

Appendix 1: Descriptive Statistics

	DR	AMT	AGE	DEP	GENDER	SOB	VOC	VOS
Mean	1.882759	133.0460	38.05747	2.413793	0.275862	0.908046	173.7356	74.02299
Median	1.000000	125.0000	37.00000	2.000000	0.000000	1.000000	170.0000	60.00000
Maximum	12.00000	400.0000	61.00000	6.000000	1.000000	1.000000	500.0000	250.0000
Minimum	0.000000	50.00000	25.00000	0.000000	0.000000	0.000000	50.00000	20.00000
Std. Dev.	2.360391	55.31283	8.029533	1.410523	0.449539	0.290636	87.15203	43.76097
Skewness	2.008601	1.518915	0.918675	0.264349	1.002972	-2.824228	0.996300	1.450787
Kurtosis	7.525930	8.135221	3.675206	2.385295	2.005952	8.976266	4.436134	5.483345
Jarque-Bera	132.7546	129.0461	13.89012	2.383014	18.16828	245.1255	21.86940	52.87474
Probability	0.000000	0.000000	0.000963	0.303763	0.000113	0.000000	0.000018	0.000000
Sum	163.8000	11575.00	3311.000	210.0000	24.00000	79.00000	15115.00	6440.000
Sum Sq. Dev.	479.1441	263117.8	5544.713	171.1034	17.37931	7.264368	653210.9	164692.0
Observations	87	87	87	87	87	87	87	87

Appendix 2: White Test for Heteroscedasticity

Heteroskedasticity Test: White

F-statistic	3.845269	Prob. F(7,79)	0.0012
Obs*R-squared	22.10950	Prob. Chi-Square(7)	0.0024
Scaled explained SS	26.88485	Prob. Chi-Square(7)	0.0003

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 06/04/23 Time: 06:53
Sample: 1 100
Included observations: 87

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.181884	2.161801	2.859599	0.0054
AMT^2	9.44E-05	3.63E-05	2.599315	0.0111
AGE^2	6.25E-05	0.000760	0.082213	0.9347
SOB__SITEOFBUSINESS_^2	-5.476916	1.788394	-3.062478	0.0030
DEP__NUMBEROFDEPENDENTS_^2	0.057881	0.067692	0.855067	0.3951
GENDER^2	-0.098023	1.126519	-0.087014	0.9309
VOS__VALUEOFFINANCEDSTOCK_^2	-0.000218	8.45E-05	-2.574904	0.0119
VOC__VALUEOFCOLLATERAL_^2	2.40E-05	1.66E-05	1.440230	0.1538

R-squared	0.254132	Mean dependent var	2.982861
Adjusted R-squared	0.188043	S.D. dependent var	5.152464
S.E. of regression	4.642818	Akaike info criterion	5.995968
Sum squared resid	1702.905	Schwarz criterion	6.222718
Log likelihood	-252.8246	Hannan-Quinn criter.	6.087273
F-statistic	3.845269	Durbin-Watson stat	2.478691
Prob(F-statistic)	0.001200		

Appendix 3: Regression Results

Dependent Variable: DR
Method: Least Squares
Date: 06/03/23 Time: 12:24
Sample: 1 100
Included observations: 87

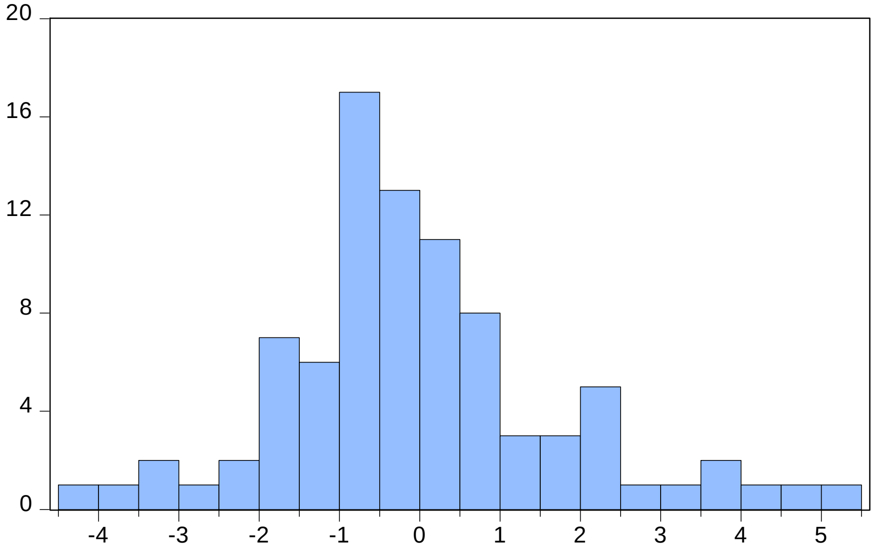
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.676903	1.239071	3.774523	0.0003
AMT	0.025006	0.005440	4.597070	0.0000
AGE	-0.030993	0.025331	-1.223547	0.2248
SOB__SITEOFBUSINESS_	-3.000661	0.712190	-4.213286	0.0001
DEP__NUMBEROFDEPENDENTS_	0.074658	0.145767	0.512172	0.6100
GENDER	-0.015900	0.439631	-0.036166	0.9712
VOS__VALUEOFFINANCEDSTOCK_	-0.032802	0.006708	-4.889809	0.0000
VOC__VALUEOFCOLLATERAL_	0.000204	0.002719	0.074863	0.9405

R-squared	0.458391	Mean dependent var	1.882759
Adjusted R-squared	0.410400	S.D. dependent var	2.360391
S.E. of regression	1.812436	Akaike info criterion	4.114668
Sum squared resid	259.5089	Schwarz criterion	4.341418
Log likelihood	-170.9881	Hannan-Quinn criter.	4.205973
F-statistic	9.551656	Durbin-Watson stat	2.342545
Prob(F-statistic)	0.000000		

Appendix 4: Correlation Matrix

	DR	AMT	AGE	DEP	GENDER	SOB	VOC	VOS
DR	1.000000	0.171628	-0.018353	0.095069	-0.053545	-0.507446	0.004584	-0.269606
AMT	0.171628	1.000000	0.231957	0.180387	-0.090302	-0.061939	0.499031	0.698641
AGE	-0.018353	0.231957	1.000000	0.138530	-0.072093	-0.057501	0.050951	0.126408
DEP	0.095069	0.180387	0.138530	1.000000	0.001265	-0.019562	0.263954	0.081978
GENDER	-0.053545	-0.090302	-0.072093	0.001265	1.000000	0.107413	-0.036997	-0.057070
SOB	-0.507446	-0.061939	-0.057501	-0.019562	0.107413	1.000000	0.041263	0.175704
VOC	0.004584	0.499031	0.050951	0.263954	-0.036997	0.041263	1.000000	0.471331
VOS	-0.269606	0.698641	0.126408	0.081978	-0.057070	0.175704	0.471331	1.000000

Appendix 5: Residuals' Normality Histogram



Series: Residuals	
Sample 1 100	
Observations 87	
Mean	1.99e-16
Median	-0.322004
Maximum	5.229550
Minimum	-4.105761
Std. Dev.	1.737108
Skewness	0.635900
Kurtosis	3.949464
Jarque-Bera	9.131220
Probability	0.010404