Amity Journal of Finance
4 (1), (30-43)

A Framework for Developing Credit Scoring Models from Zimbabwe's Sensitive Data

Corelleta Kaseke
G-Telecoms Zimbabwe, Harare, Zimbabwe

Stanley Murairwa
Africa University, Mutare, Zimbabwe

Abstract

The research explores the determinant factors of creditworthiness in Zimbabwe's credit market and develops a credit scoring model. The research was prompted by increasing the levels of non-performing loans in the lending sector. The research investigated several factors that affect creditworthiness in Zimbabwe. Statistical tests were conducted to determine the significance of the different independent variables in the espoused credit scoring model. It is found that marital status, installment amount, loan amount, age and terms of the loan were very crucial determinant factors of creditworthiness in Zimbabwe. The country should increase the pace towards the development of the national credit registry in order to bring stability in the lending sector. The use of hybrid credit score models that can provide timely and relevant information should be encouraged so that the credit providers can view holistically their credit applicants before granting credits. The policies that encourage the growth of credit in a rational and civilized manner should be encouraged if the economy is to realise long-term stability of the lending sector.

Key words: Credit Scoring Model, Creditworthiness, Credit Market, Debt Repayment, Zimbabwe

JEL Classification: G21

Paper Classification: Research Paper

Introduction

With old ways and a dynamic market, will Zimbabwe's credit market improve? This could be one of the questions credit providers are asking themselves as the market is taking a nosedive with no hope of improvement for the better. Organisations like the World Bank stated that Zimbabwe required a comprehensive credit bureau system that can enable sound risk management measures for all credit providers (Dhliwayo, 2015). In Zimbabwe, commercial banks were believed to be the most dominant financial intermediaries, however, there was an increase in the emergence of Micro-Finance Lenders who constituted 4.41% of the financial sector (Dhliwayo, 2015). A poor credit culture has been observed in Zimbabwe's credit market which has been one of the inherent weaknesses of the failing financial sector (Dhliwayo, 2015). A good credit culture

is a prerequisite for the stable functioning of any financial system. Though some private credit bureaus (CBs) have been operating in the market to help mitigate the credit risk, the absence of a comprehensive credit reference system has seen the economy turning for the worst.

Credit is a term that has always existed and in Zimbabwe, it has turned out to be one of the fastest-growing trends with some of the highest returns. Not only has the Zimbabwean market adopted this trend with an increase in total loans for banks and micro-finance institutions from US$3.957 billion in 2014 to US$4.163 billion in 2015, but it has also made it be one of the reasons for its downfall. The sector has been experiencing more than 20% in non-performing loans (NPLs) when the acceptance rate is 5% (Dhliwayo, 2015). Credit Scoring is a term that only came into being about 50 years ago with the first score model being built by Fair Isaac Corporation in the 1950s (Smith, 2006). Over the years, credit providers in Zimbabwe have been making use of an applicant's payment history, if not just a mere applicant's income, in order to determine creditworthiness (Dhliwayo, 2015). This has been done through the use of private CBs in the market. The private CBs make it their mandate to collect individual data from credit providers and then process it into credit reports that can then be used for credit risk assessment. The CBs compile data (such as credit repayment records, court judgments and bankruptcies) on individuals and corporations and create comprehensive credit reports that are availed by lenders for use.

The current Zimbabwe financial regulations and supervisory architecture were inherited from the colonial government in 1980. The Minimum Disclosure Requirement requires that all financial institutions disclose fully their credit risk management policies, strategies, objectives, models, effectiveness and validation. This regulatory and supervisory regime served Zimbabwe well until 1990 as the financial sector was stable; without financial crisis and bank failures. The Government of Zimbabwe, in 1991, embarked on an Economic and Structural Adjustment Programme (ESAP), which included the effectuation of financial reforms through liberalisation and deregulation (Mabvure, Gwangwava, Faitira, Mutibvu, & Kamoyo, 2012). In 2000, the Banking Act was improved to make it possible for financial establishments to transmute into commercial banks by acquiring additional functions on their licences and of significant importance was the relaxation of new entry players into the banking sector (Mabvure et al., 2012). The financial sector experienced an upswing emergence of microfinance institutions (MFIs) when the sector grew massively around 2003 with at least 1600 registered MFIs. The MFIs' total loans of US$162.20 million constituted 4.41% of total banking sector loans of US$43.98 billion in 2015. Thus, there is a need for a major initiative towards building a strong credit culture, through improving the credit risk management systems and practices in Zimbabwe. Most credit providers have been exposed to high credit risk due to inadequate information on borrowers' creditworthiness.

Research Objectives

The objectives of the research were to establish the explanatory variables of creditworthiness, determine the relationship among the explanatory variables that affect the creditworthiness in Zimbabwe and propose a framework for developing the credit scoring models from sensitive data.

Literature Review

The Nature of Credit Scoring Models

The pragmatism and empiricism of credit scoring imply that any characteristics and environments of the borrower that has obvious connections with default risk should be used in the scoring system (Lewis, 1992). The Credit Scoring Models' (CSMs) aim is to minimize the credit

risk and default rates by preventing the granting of loans to bad customers and avoiding a false rejection of good customers. The CSMs use a statistical technique to analyse historical data in order to identify the variables or features that can distinguish between bad and good customers (Horkko, 2010). Despite the fact that the concept of credit is five thousand years old, the concept of credit scoring has only been around for about fifty years (Samreen & Zaidi, 2012). According to Siddiqui (2006), the new Basel 11 Capital Accord defined default as ninety days past due (delinquent). Kanwar (2005) defined credit risk as a risk that arises when the borrower is either unwilling or unable to repay the loan granted, which results in economic loss to the lender.

The CSMs can be both qualitative and quantitative in nature (Chijoriga, 2011). The qualitative technique is judgmental and subjective. The weakness of the qualitative method is that there is no target base for deciding the default risk of a loan applicant. The quantitative method is a systematic way to categorise loan performance into performing loans or non-performing loans. The technique addresses the defects of the qualitative method and it has proved to be a more reliable and accurate method. The credit applicants are granted credit after assessing their creditworthiness such that when the credit applicants meet the cutoff score, they are considered as good credit applicants; otherwise, they are bad credit applicants and their applications are rejected. (Lieli & White, 2010). According to Steenackers and Goovaerts (1989), the most primal use of credit scoring prototypes is the evaluation of new individual loans. There are many research studies done on granting loans to old customers, but less literature was available on loans given to new customers (Orgler, 1971).

Barefoot (1996) depicted various fundamental benefits of credit scoring and noted that credit scoring method reduces the cost of lending as it reduced the participation of humans in evaluating a loan application. The CSMs have also enhanced the precision of forecasting the credit risk of debtors. According to Ponicki (1996), the CSMs have provided a standard technique of loan evaluation and efficient ways of executing the transactions in the credit market. The CSMs offer benefits to clients by providing a simple application process, results of credit approval in a short space of time and quick access to financial credit. The experiments conducted in Bolivia and Colombia concluded that scoring for microfinance can enhance the judgment of risk and also reduce costs (Schreiner, 2000). Despite these benefits, statistical scoring cannot, however, replace the loan officers because ultimately, it is the duty of the credit analysts to make the credit decision and these scoring models can act as helpful guides. The statistical scoring model reminds the credit managers of the elements of risks that they may have ignored (Schreiner, 2003).

Research Gap

The economy of Zimbabwe has been steadily growing with an increase in the availability of credit lines which complement constrained or uncertain incomes. However, the lending sector has experienced a huge accumulation of non-performing loans (NPLs) that was crippling its operations tremendously, due to the inability to effectively forecast the creditworthiness of the credit applicants. High risk always translates into the high cost of borrowing making it impossible for borrowers to access credit, thus, crowding out effect. As a result, private firms are unable to afford available credit lines, inhibiting the expansion of multiple sectors in the economy. This inability to determine creditworthiness has led to the failure of some banks due to NPLs as shown in Table 1.

Table 1: Banks closed in Zimbabwe

Bank	Year closed	Number closed
Renaissance Merchant	2011	1
Interfin and Royal	2012	2
Afrasia	2015	1

The banking sector in Zimbabwe witnessed a closure of three banks in two years. The country has been trying to put in place policies aimed at reducing the NPLs. In 2012, the Zimbabwe Minister of Finance stated that the upward trend in NPLs that has led to the recent failures of banks was a cause for concern (Biti, 2012).

Research Contribution

The research explains the phenomena of creditworthiness and how a number of factors affect it in Zimbabwe's credit market. Thus, the research results will improve the understanding of how the selected variables are great determinants of creditworthiness in Zimbabwe. This will assist the relevant bodies in Zimbabwe to formulate policies that help in reducing the number of NPLs in the country. The consumer creditworthiness is a relatively new area of research in Zimbabwe mainly due to a less matured consumer credit market and the unavailability of sensitive data. Therefore, research of that nature has not been conducted in Zimbabwe. Thus, this research will provide interesting results and a framework for developing credit scoring models from sensitive data. The credit providers will have access to an up-to-date credit scoring prototype that has been formulated with real historical customer data. The research provides a cost-effective way of assessing credit-worthiness of credit applicants by providing a basic credit scoring model that can be employed by credit providers. The society will understand the variables that affect the creditworthiness and how to develop credit scoring models. The research results will affect the way credit providers in Zimbabwe view and understand the degree to which economic and demographic variables are included in the assessment of the credit application. The research provides a step towards addressing the problem of selecting variables for developing credit scoring models.

Research Methodology

Type of Study

A cross-sectional study was used to explore the factors that affect credit worthiness in Zimbabwe's credit market.

Variables of the Research

The variables of interest were creditworthiness (CRW), marital status (MS), employment status (EMPS), income level (Y), number of dependents (ND), gender (GNDR), age of borrower (AGE), loan amount (LAMT), installment amount (INST), terms of the loan (TML) and number of accounts (NACC). Thus, the researchers used both nominal and ratio data.

Population

The population was made up of all 7 983 credit applicants and 15 credit providers comprising micro-finance institutions and retailers. All the applicants were at least 18 years old as only adults are allowed to access credit lines in Zimbabwe.

Sample

The research used a sample of 13 volunteered credit providers who were randomly selected to provide relevant data for the research. The research also used all the 7 983 credit applicants' data.

Sampling Technique

The Voluntary Sampling Design (Murairwa, 2015) was used to select the 13 credit providers who participated in the research.

Data Collection Instrument

A customised Data Recording Table (DRT) (Murairwa, 2010) was developed and implemented to collect the research data from the 13 volunteered credit providers.

Method of Data Collection

Each of the 13 volunteered credit providers was given the DRT to complete while the data collector was waiting to take back the completed DRT.

Data Analysis Tools Used

The Pseudo R^2 (Cox and Snell R^2 and Nagelkerke R^2) values were computed to examine the goodness of fit. The Cox and Snell R^2 value was calculated with the formula:

$$R^2_{CS} = 1 - \left(\frac{L(M_{intercept})^{\frac{2}{n}}}{L(M_{full})}\right), \quad (1)$$

where L is the estimated likelihood, Mfull is the model with predictors, Mintecept is the model without predictors, LM is the conditional probability of the outcome variable given the predictor variable and μ is the error term. The Nagelkerke R^2 was calculated with the formula:

$$R^2_N = \frac{1 - \left(\frac{L(M_{intercept})}{L(M_{full})}\right)}{1 - L(M_{intercept})^{\frac{2}{n}}}, \quad (2)$$

The value of the Wald test was computed with the formula:

$$W_j = \frac{B_j}{SE_{B_j}}, \quad (3)$$

where W_j is the j^{th} Wald statistic, B_j is the estimated coefficient of the j^{th} explanatory variable, SE_{Bj} is the standard error of the j^{th} explanatory variable. The hypothesis is H_0: The explanatory variable has no effect on creditworthiness versus H_1: The explanatory variable has an effect on creditworthiness. The null hypothesis (H_0) is rejected if and only if $|W_j| > \chi^2\frac{\alpha}{2}$ at a 5% level of significance. The omnibus test of the coefficients of the model was used to test the general implication of the proposed credit score framework. The Chi-square statistic is the change in -2 log-likelihood from the previous step, block or model. The presence of a correlation between the outcome and predictor variables is based on the statistical implication of the framework's X^2

at step I after the predictor variables have been added to the analysis and with a hypothesis, H_0: the model is not valuable versus H_1: the model is valuable. If p-value is smaller than α=0.05, H_0 is rejected. The Pearson's product-moment correlation coefficient (r) was computed with the formula:

$$r = \frac{n(\sum xy) - (\sum x \sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}}, \qquad (4)$$

where r ranges from -1 to 1. The correlation value was used to ascertain the relationships of the independent variables. The hypothesis used to determine the presence of multicollinearity in the data is H_0: there is multicollinearity in the data versus H_1: there is no multicollinearity in the data. The multicollinearity in a logistic regression solution is discovered by analysing the standard errors (SEs) for the beta (β) coefficients. The standard error (SE) was computed with

$$SE = \sqrt{Var\,\acute{\beta}_i}, \qquad (5)$$

A standard error that is greater than 2.0 shows numerical problems such as (a) multicollinearity among the predictor variables, (b) zero cells for a dummy-coded predictor variable and (c) complete separation whereby the two groups in the outcome variable can be perfectly separated by scores on one of the predictor variables. The results that show numerical problems should not be interpreted. The probability (P_r) function is given by

$$P_r = \frac{e^y}{1+e^y}, \qquad (6)$$

where P_r is the probability of creditworthiness and y is the summation function from the econometric model.

Research Results

Of the targeted 15 credit providers, only 13 volunteered to provide data for the research, constituting a response rate of 86.67%. All the 7 983 credit applicants' data were analysed for the research. Table 2 shows the percentage distribution of the research participants by gender, employment status and marital status.

Table 2: Respondents' gender, employment status and marital status

Category		Percentage
Gender	Male	68.80
	Female	31.20
Employment status	Employed	97.11
	Unemployed	2.89
Marital status	Married	58.09
	Not Married	41.91

Table 2 shows that more males (68.80%) than females (31.20%) participated in the research. This indicates that more males are active financial borrowers than females in Zimbabwe. Of the credit applicants, 97.11% were employed. This indicates that most credit providers were disbursing loans to employed credit applicants as a way of attempting to lower the default risk. Of those who participated in the research, 58.09% were married while 41.91% were unmarried.

The Explanatory Variables of Creditworthiness in Zimbabwe

Table 3: Explanatory variables of creditworthiness in Zimbabwe

								95% Confidence Interval	
Variable		B	S.E.	Wald	df	Sig.	Exp(B)	Minimum	Maximum
Step I(a)	MS(1)	0.532	0.204	6.778	1	0.009	1.702	1.140	2.540
	EMPS(1)	0.869	0.473	3.369	1	0.066	2.384	0.943	6.030
	Y	0.001	0.001	0.446	1	0.504	1.001	0.999	1.002
	ND	-0.055	0.067	0.655	1	0.418	0.947	0.830	1.081
	AGE	0.019	0.010	3.970	1	0.050	1.019	1.000	1.038
	GNDR(1)	0.274	0.190	2.085	1	0.149	1.315	0.907	1.907
	LMT	0.020	0.001	229.927	1	0.000	1.020	1.017	1.023
	INST	-0.238	0.009	667.196	1	0.000	0.788	0.774	0.803
	TML	-0.435	0.061	51.586	1	0.000	0.647	0.575	0.729
	NACC	-0.137	0.089	2.392	1	0.122	0.872	0.733	1.037
	Constant	6.956	0.939	54.914	1	0.000	1049.543		

The estimated logistic regression equation of all the explanatory variables for CRW was

CRW = 6.956 + 0.532MS + 0.869EMPS + 0.001Y - 0.055ND + 0.019AGE + 0.274GNDR + 0.02LMT - 0.238INST - 0.435TML - 0.137NACC…….…….....……(7)

In Table 3, the Wald statistic was compared with χ^2_{Tab} = 3.8415. The probabilities of the coefficients were used to verify the significance of the predictor variables as determined by the relationship between the Wald statistic and Wald critical value. The results imply that only the MS, AGE, LMT, INST and TML were significant in explaining the creditworthiness in Zimbabwe. Therefore, EMPS, Y, GNDR, NACC and ND were insignificant in determining the creditworthiness in Zimbabwe.

Table 4: Chi-square test of the explanatory variables

Model		χ^2	Degrees of freedom	Sig.
Step I	Step	3799.255	10	0.0000
	Block	3799.255	10	0.0000
	Model	3799.255	10	0.0000

The probability of the framework's χ^2 (3799.255) was less than the α=0.05 at 0.0000. The null hypothesis that there is no difference between the prototype with only a constant and the prototype with predictor variables was rejected. This meant that the variation explained by the framework is not merely by chance. The research results indicate that there was sufficient evidence to show that the framework was valuable and that at least one of the predictor variables co-efficient was non-zero. Therefore, a change in one of the predictor variables will result in a change in creditworthiness of the credit applicant.

Table 5: Cox and Snell and Nagelkerke R Squares of explanatory variables

Step	-2 Log-likelihood	Cox and Snell R^2	Nagelkerke R^2
I	1040.878(a)	0.662	0.884

The value of R^2_{CS} was 0.662 (66.20%). In addition, R^2_N was also computed and the value was found to be 0.884 (88.40%). This means that 88.40% of the variations in creditworthiness was explained by the fitted credit score model. It should be noted, however, that in binary regression models, the goodness of fit is of secondary importance. What matters are the expected signs of the regression coefficients and their statistical and/or practical significance (Gujarati, 1995). None of the independent variables in this analysis had a standard error greater than 2.0 and the null hypothesis that there was multicollinearity in the data was rejected.

Effectiveness of the Selected Explanatory Variables to Determine Creditworthiness in the Credit Market of Zimbabwe

Table 6: Effectiveness of the selected explanatory variables to determine creditworthiness

								95% Confidence Interval	
Variable		B	S.E.	Wald	df	Sig.	Exp(B)	Minimum	Maximum
Step I (a)	MS(I)	0.428	0.183	5.456	1	0.019	1.534	1.071	2.197
	INST	-0.238	0.009	677.386	1	0.000	0.788	0.774	0.803
	LMT	0.020	0.001	233.281	1	0.000	1.020	1.017	1.023
	TML	-0.442	0.060	54.392	1	0.000	0.642	0.571	0.723
	AGE	0.016	0.009	3.977	1	0.049	1.016	0.998	1.035
	Constant	8.003	0.744	115.643	1	0.000	2989.458		

Table 7: Chi-Square (χ^2) test of the effectiveness of the explanatory variables

Model		χ^2	Degrees of freedom	Sig.
Step I	Step	3791.989	5	0.0000
	Block	3791.989	5	0.0000
	Model	3791.989	5	0.0000

Table 8: Cox and Snell R^2 and Nagelkerke R^2 of the effectiveness of the explanatory variables

Step	-2 Log-likelihood	Cox and Snell R^2	Nagelkerke R^2
I	1048.144(a)	0.662	0.883

In testing for the significance of the explanatory values, the Wald test was used at 5% level of significance. In Table 6, the Wald statistic was compared with χ^2_{Tab}= 3.8415. All the Wald statistic values are greater than the Wald critical value. Thus, MS, AGE, LMT, INST and TML were effective in determining the creditworthiness of a credit applicant in Zimbabwe. The suggested creditworthiness logistic regression model is

$$CRW = 8.003 + 0.428MS(I) + 0.020LMT - 0.238INST - 0.442TML + 0.016AGE \ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Results, Discussion and Interpretation

Most Zimbabweans were not formally employed due to the harsh economic conditions the country was experiencing. Thus, companies were closing down. Most individuals were employed in the informal sector. This could be the reason why employment status failed to be a significant factor in determining creditworthiness. Therefore, the income level comprised formal and informal employment salaries. As a result, the credit applicant's salary level was not correctly reflecting his/her actual ability to repay the required loan. Thus, a person may have a low salary but may be able to repay the loan because of the additional income he/she may be acquiring from informal activities. Gender in most industrialised countries is no longer included in credit-scoring models as it is deemed discriminatory. However, due to dynamism in the socio-cultural factors, the inequality between men and women even in less developed countries seems to be disappearing. The emancipation of women has risen to empower women to be more financially included. As a result, gender may be an insignificant factor (as obtained by Hussein (2009)) in determining the creditworthiness.

Most people applied for loans in order to repay other pressing loans. As a result, the borrower is able to keep up with the loan monthly obligations until he/she can find enough money to clear the loan. However, in most cases, it's the lender at the end of the cycle who usually suffers. The research shows that employment status, income level, gender, number of accounts and number of dependents were not significant in determining creditworthiness in Zimbabwe. The variables had their Wald statistics less than the Wald critical value and probability values greater than 0.05. The research reveals that there are other variables besides employment status, income level, gender, number of accounts in the market and number of dependents that can determine the creditworthiness in Zimbabwe. The research presents the relationships of the independent variables in Table 9.

Table 9: Relationships of the independent variables that affect creditworthiness in Zimbabwe

Variable		Constant	AGE	LMT	INST	TML
Step 1	Constant	1.000	-0.319	0.201	-0.320	-0.850
	AGE	-0.319	1.000	0.070	-0.094	-0.060
	LMT	0.201	0.070	1.000	-0.737	-0.383
	INST	-0.320	-0.094	-0.737	1.000	0.238
	TML	-0.850	-0.060	-0.383	0.238	1.000

The results in Table 9 show that there was a correlation between the independent quantitative variables. In order to target elderly individuals who were deemed to be more creditworthy, a credit provider should focus on high loan amounts, reduce installment amounts and improve repayment terms of the loan. The low installment amount will be fostered by high terms of the loan. Therefore, depending on the objectives of the credit provider, a targeted mix can be fostered.

Proposed Zimbabwe's Credit Scoring Model

Considering all the explanatory variables used in this research, the proposed Zimbabwe credit scoring model is

$$CRW = f\,(MS,EMPS,Y,ND,GNDR,AGE,LMT,INST,TML,NACC), \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

The maximum likelihood estimation model was used to judge the association between the creditworthiness and some explanatory variables (Gujarati, 1995). The model is specified as follows:

$$Logit\ \pi = log\left(\frac{\pi}{1-\pi}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots \ldots \beta_i X_i + \mu, \quad (10)$$

where π= P(Y=1|X_i). Therefore, the Zimbabwe credit scoring model can be presented as follows:

$$CRW=\alpha+\beta_1 MS+\beta_2 EMPS+\beta_3 Y+\beta_4 ND+\beta_5 GNDR+\beta_6 AGE+\beta_7 LMT+\beta_8 INST+\beta_9 TML+\beta_{10} NACC+\mu, \quad (11)$$

where $\beta_1,\beta_2,\ldots\ldots\ldots,\beta_{10}$ are parameters that measure the slope of the model. However, further statistical analysis of the model indicated that MS, AGE, LMT, INST and TML were the only significant variables in determining the creditworthiness of the credit applicant in Zimbabwe. This implies that Equation 9 can be reduced to

$$CRW = f\ (MS,AGE,LMT,INST,TML), \quad (12)$$

and Equation 11 also reduced to

$$CRW = \alpha + \beta_1\ MS + \beta_2\ AGE + \beta_3\ LMT - \beta_4\ INST - \beta_5\ TML + \mu \quad (13)$$

where $\beta_1,\beta_2,\ldots\ldots\ldots,\beta_5$ are parameters that measure the slope of the model.

Application of the Zimbabwe Credit Scoring Model

The research suggests an acceptance region of a credit score of at least 0.50 in line with other researchers such as Hussein (2009). The null hypothesis of the credit applicant is not creditworthy is not accepted if the probability function value is smaller than 0.50; otherwise, it is not rejected. Thus, a low probability value leads to the rejection of H_0, while a high probability value leads to the non-rejection of H_0. The research used two credit applicants' data to test the proposed model to compute the credit scores and presented the results in Table 10.

Table 10: Calculating the credit scores

	Variable	First credit applicant	Second credit applicant
Data	MS	Single	Married
	AGE	46	25
	LMT	US215.00	US$500.00
	TML	12	12
	INST	30	58
	CRW Summation Function	0.835	0.187
Results	Probability Function	0.6974 (69.74%)	0.5466 (54.66%)
	Creditworthiness	Yes	Yes

The results in Table 10 show that both credit applicants were eligible for the credit because their probability values were greater than 0.50. The first credit applicant's probability value was 0.6974 while the second credit applicant was 0.5466. The proposed Zimbabwe credit score model can successfully determine the creditworthiness of the credit applicants.

Conclusion and Recommendations

The Zimbabwe credit score model was developed. The effectiveness of the identified independent variables was tested. The socio-demographic and economic factors were important in developing the model. Mundi (2016) reported that 32.30% of the population in Zimbabwe was made up of the age group of 25 – 54 years and that indicates a very young nation. This may be the reason why Zimbabwe is experiencing huge defaults due to low creditworthiness within this age group. Zimbabwe was estimated to have 50.70% of its population being females (Zimstat, 2016) who have been found to be less creditworthy to males. In most developing economies like Zimbabwe, men are the ones who are high earners and/or only earners in most households. Most of the credit applicants in this research had borrowed twelve months of term loans. This may imply that a lot of the credit providers in the country were disbursing loans with high credit terms and this could be the reason for many defaulters. Horkko (2010) stated that those who performed well with their loan repayments needed short-time financing to survive sudden costs but they were solvent in the long-term. The MS, AGE, LMT, INST and TML were the significant variables in determining the creditworthiness of the credit applicant.

Zimbabwe is a low income earning country at the moment and therefore disposable incomes are very low. The higher the number of dependents that an applicant has, the greater the obligations that they may have and the riskier they are in terms of default. The rate of formally employed individuals in Zimbabwe is very low as more and more people were losing their jobs. Unemployed individuals are considered very risky as their monthly income is considered unstable. Employed individuals have a constant flow of income which may make them less risky. Some of the credit providers can easily have direct deductions from the borrower's salary thereby reducing the chances of default. There are other variables that affect creditworthiness in Zimbabwe and these are explicated by the explanatory power of the prototype of 88.30%.

The development of a centralized credit registry system is of paramount importance to the lending sector of Zimbabwe. The Reserve Bank of Zimbabwe (RBZ) should make it mandatory for all credit providers to submit data to the national credit registry. The application of credit scoring prototypes can significantly reduce the costs associated with assessment of credit applications as there is reduced time and effort. Avery, Robert, Brevoort and Canner (2009) asserted that credit scoring models increase the availability and affordability of credit. The study also stated that credit scoring models increase the efficiency of consumer credit markets by helping creditors establish prices that are more consistent with the risks and costs inherent in extending credit. The policies that encourage only the growth of credit in a rational and civilized manner should be encouraged. A range of lending sectors prudential tools such as tightening or loosening loan eligibility criteria and credit growth for certain credit portfolios could be used to achieve a desired balance in the credit composition. A credit portfolio towards young individuals should be reduced. A sliding scale on the amounts that individuals can borrow should be implemented and it should depend on the credit applicant's score. A credit terms ceiling should be put in place to ensure that all credit terms are kept low.

Limitations of the Research

A new and reliable data is, however, a major problem in Zimbabwe. In some areas the data found was incomplete and in some, it was actually unavailable, which is why this report may not paint a comprehensive picture of the current situation and trends or use the same baseline, as

would otherwise be desirable. Limited literature was a problem for the study. This was a first time that such research was carried out in Zimbabwe, therefore, the literature was insufficient.

Suggestions for Future Studies

This research only focused on some of the variables that could determine the creditworthiness. However, future studies could focus on other variables such as the purpose of loan, education level and ownership of the residential place. A number of techniques can be employed in the formulation of the credit scoring frameworks which include neural networks, decision trees and general programming. Further studies could focus on employing these techniques in improving the developed credit scoring model. However, income from informal activities can also be considered in developing an improved credit scoring model.

References

Avery, R., Robert, B., Brevoort, P., & Canner, G. (2009). Credit Scoring and Its Effects on the Availability and Affordability of Credit. *The Journal of Consumer Affairs*, 43(3), 516–530.

Barefoot, A. (1996). Credit Scoring at a Crossroads. *Journal of Banking and Commerce*, 27 (4), 615–633.

Biti, T. (2012). Zimbabwe Mid-Term Fiscal Policy Statement, "From Crisis to Austerity: Getting Back to Basics". Retrieved from https://www.zimra.co.zw/index.php?option=com_phocadownload&view=category&id=15:budget-statements&download=360:2012-mid-year-fiscal-review-policy-review&Itemid=112

Chijoriga, M. (2011). Application of multiple discriminant analysis (MDA) as a credit scoring and risk assessment model. *International Journal of Emerging Markets*, 6 (2), 132-147.

Dhliwayo, C. (2015). Conference and Exhibition for the Banking, Finance and Insurance Sectors held at the Harare International Conference Centre, Harare, Zimbabwe. Retrieved from https://www.rbz.co.zw/documents/publications/speeches/remarks-by-dr-dhliwayo-at-the-banking-finance-and-insurance-expo-29-july-2015(1).pdf

Gujarati, D. N. (1995). *Econometrics*. (3rd Ed.). New York: McGraw-Hill, Inc.

Horkko, M. (2010). The determinants of Default in Consumer Credit Market. (Master's thesis, School of Economics, Alto University). Retrieved from http://epub.lib.aalto.fi/en/ethesis/pdf/12299/hse_ethesis_12299.pdf

Hussein, A. A. (2009). An evaluation of alternative scoring models in private banking. *The Journal of Risk Finance*, 10(1), 38 – 53.

Kanwar, A. (2005). Risk Management for Banks. *Journal of Market Forces*, 1 (1), 1-7.

Lewis, E. (1992). *An Introduction to Credit Scoring*. California: Fair, Isaac & Co., Inc.

Lieli, R. P., & White, H. (2010). The Construction of Empirical Credit Scoring Models Based on Maximization Principles. *Journal of Econometrics*, 157 (1), 110 – 119.

Mabvure, T. Gwangwava, E., Faitira, M., Mutibvu, C. & Kamoyo, M., (2012). Non-Performing loans in Commercial Banks: A case of CBZ Bank Limited in Zimbabwe. *Interdisciplinary Journal of Contemporary Research in Business*, 4(7), 467 – 488. Retrieved from https://pdfs.semanticscholar.org/b696/13a430cdbdbb5f3f51e042827cb10dc64781.pdf?_ga=2.16115574.1146304287.1562150390-516612544.1559660723

Murairwa, S. (2010). *A Hybrid Heuristic Research Framework: The Travelling Salesperson Problem*. (PhD Thesis, Universiti Utara Malaysia (UUM), Kedah, Malaysia). Retrieved from http://etd.uum.edu.my/cgi/search/simple?q=murairwa&_action_search=Search&_action_search=Search&_order=bytitle&basic_srchtype=ALL&_satisfyall=ALL

Murairwa, S. (2015). Voluntary Sampling Design. *International Journal of Advanced Research in Management and Social Sciences*, 4(2), 185 – 200.

Orgler, Y. (1971). Evaluation of Bank Consumer Loans with Credit Scoring Models. *Journal of Bank Research*, 2 (1), 31 – 37.

Ponicki, C. (1996). Case Study: Improving the Efficiency of Small-Business Lending at First National Bank of Chicago. *Commercial Lending Review*, 11(2), 51 – 60.

Samreen, A., & Zaidi, F. (2012). Design and Development of Credit Scoring Model for the Commercial banks of Pakistan: Forecasting Creditworthiness of Individual Borrowers. *International Journal of Business and Social Science*, 3 (17), 155 – 166.

Schreiner, M. (2000). Credit Scoring for Microfinance: Can It Work? *Journal of Microfinance Risk Management*, 2 (2), 105-118.

Schreiner, M. (2003). Scoring: The Next Breakthrough in Microcredit? CGAP (Occasional Paper No.33477). Retrieved from http://documents.worldbank.org/curated/en/625281468182661244/pdf/334770rev0OccasionalPaper107.pdf

Siddiqi, N. (2006). *Credit Risk Scorecards Developing and Implementing Intelligent Credit Scoring*. Hoboken, New Jersey: John Wiley & Sons, Inc.

Smith, M. (2006). Recent developments in credit scoring : A Summary Federal. Retrieved from https://www.philadelphiafed.org/-/media/community-development/publications/conference-summaries/cca_credit-scoring_summary.pdf?la=en

Steenackers, A., & Goovaerts, M. (1989). A Credit Scoring Model for Personal Loans. *Journal of Insurance, Mathematics and Economics*, 8(1), 31-34.

Zimstat. (2012). Zimbabwe Population Census 2012: Women and Men Profile Summary Report. Retrieved from http://www.zimstat.co.zw/sites/default/files/img/publications/Health/Women_and_Men_Summary_Report_2012.pdf

Authors' Profile

Corelleta Kaseke holds an Executive Masters in Business Administration and a Bachelor of Science in Economics Honors from Africa University, Mutare, Zimbabwe. She has been employed as an Accounts Relationship Manager at GTel Zimbabwe and a Client Relations Officer at Expert Decision Systems Zimbabwe (Credit Bureau). Over the years, she has acquired vast expertise in credit risk management, credit analysis and relationship management. She is passionate about data science and has acquired the IBM Professional Certificate in Data Science and the Applied Data Science Specialist Certificate. She is currently studying for a Bachelor of Arts in Germany and during this period has worked as a Research and Evaluation Intern at Kon-Tiki Lüneburg, Germany.

Stanley Murairwa is a Senior lecturer at Africa University (AU) in the College of Business, Peace, Leadership and Governance (CBPLG) in Zimbabwe. He is the Head of Business Sciences department. He obtained a Ph.D. degree in Decision Science from Universiti Utara Malaysia (UUM), Malaysia, M.Sc. degree in Operations Research (Distinction) from National University of Science and Technology (NUST), Zimbabwe, B.Sc. Special Honours degree in Statistics (Upper Second Division) from University of Zimbabwe (UZ), Diploma in Statistics (Pass) from University of Zimbabwe (UZ), Diploma in Management Information System from The Institute for the Management of Information Systems (IMIS), United Kingdom and a two year In-House Statistical Training Programme (ISTP) Part-A and Part-B certificates from Zimbabwe National Statistics Agency (ZIMSTAT). His areas of research interest include Heuristics, Production/Operations Management and Applied Statistics. His publications appear in Global Scientific Journals (GSJ), LAP Lambert Academic Publishing, Amity Journal of Marketing (AJM), Amity Journal of Operations Management (AJOM),

International Journal of Research and Development Organisation (IJRDO), International Journal of Advanced Research in Management and Social Sciences, Serial Publications, Publishers and distributors, European Journal of Scientific Research (EJSR), International Journal of Statistics And Systems (IJSS), Publishers and Subscription Agents of International and Indian Journals, International Conference on Mathematics, Statistics, and Their Applications and International Conference on Quantitative Sciences and Its Applications (ICOQSIA2010).