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DETERMINANTS FOR LOAN DEFAULTS IN FINANCIAL INSTITUTIONS: A CASE OF TWO SELECTED INSTITUTIONS IN SUMBAWANGA MUNICIPALITY

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Abstract: The study on determinants for loan defaults in financial institutions was carried in Sumbawanga Municipality in two selected financial institutions namely NMB and CRDB. Specifically, the study intended to: evaluate the extent of loan default rate for the selected financial Institutions (FIs) for the period between 2013 and 2018; analyse factors influencing the likelihood of loan default and determine effects of loan defaults to borrowers and FIs. The study used cross-sectional design to gather information at the study area. Non-purposive sampling technique was applied to select 158 loan groups to be the respondents under this study. Purposively, FIs and key informants were selected. Primary data were collected directly from the respondents using structured interview and semi - structured interview whereas secondary data were collected through a documentary review of sources including published and unpublished materials related to loan default in FIs. Data obtained were analyzed by descriptive statistics and logistic regression using SPSS version 20. Binary Logistic regression model was used to estimate the factors influencing the likelihood of borrowers to default. The findings show that, the loan default was existed in both institutions. However, the rate of loan default has been decreasing from year 2013 to 2018. In addition, Logistic regression model showed that age of borrowers and interest rate charged by FIs were significant at ($P<0.05$) while business type, business management education and loan uses were found to be significant at ($P<0.01$). Majority of respondents identified loss of collaterals and denial of future loan are major effects faced by loan defaulters. Loss of Interest incomes, reduction of operating profit through provision for bad debts and reduction of lending capacity are effects reported by FIs. Further, this study recommended that FIs should involve borrowers in reviewing loan repayment terms and conditions, effective monitoring of loan by loan officers from FIs, effective credit training programs and where necessary the use private debt collectors.

Key words: *Loan defaults, Loan Groups, Financial Institutions and likelihood of borrowers to default*

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1.0 Introduction

The long-term vision of Financial Institutions (FIs) is to provide sustainable financial services to the economically-active people who are able to services their loans (Nyamsogoro, 2010). In fulfilling this vision, FIs has managed to play an important role in micro, small, medium and large-enterprises (MSMLEs) development in Tanzania, particularly as instruments to emphasis the financial inclusion so as to achieve equity economic growth. Remarkably, FIs have become an economic development strategy that encourages income-generating activities; assists active business people and the entrepreneurs in stabilizing existing sources of income and enables micro, small medium and large -enterprises to grow. In the development of market-based, FIs have provided MSMLEs with loans and other financial services on a sustainable basis. The linking access to finance with business development assistance is an effective way to improve entrepreneurial behaviour and builds business integrity (URT, 2000). However, there are number of challenges facing these FIs which are: inadequate funds to cover the entire population, insufficient support from government, improper regulations, limited management capacity and loan defaults (Dahir, 2015). Among these challenges, loan default is the major problem that threatens the financial operations of many FIs (Aghion and Morduch 2005; Zeller and Johannsen, 2006).

Recent default rate statistics in developing countries show that out of the 25 FIs, 10 which represent 40% of FIs are experiencing a default rate of (1 - 3) % which is consistent with internationally accepted rate of default. 8 representing 32% have default rate of (3-6) %; 4 representing 16% experience default rate of (6-10) % and 3 representing 12% have a default rate of more than 10%. Since loan default weakens the financial operations of FIs, various efforts have been put in places to reduce the problem. These efforts are articulated in credit collection policies which are used to manage the accounts receivables and manage loan portfolio of FIs (Pandey, 1995). These policies put into operation various institutional mechanisms to reduce the rate of loan default. These include lending methodologies, screening mechanisms, pledging of collateral, third party credit guarantee, credit rating and use of collection agencies (Sewagudde, 2000).

In line to this, the selected FIs use various strategies to reduce the risks involved in unsecured lending. These include; group lending, mandatory savings deposit to the amount borrowed, rewards for on - time repayments in form of future access to higher loan amounts, penalties for late payment such as fees and denial of higher loan amounts (Mulema, 2011). In addition to this new loan applicants are scrutinized before the credit facility is granted to them. However, traditional methods of deciding whether to grant loan to an individual are based on human judgment and experience of previous decisions. These methods are not

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objective but very subjective. Thus, to determinate the likelihood of a borrower to default the lender must estimate borrower's ability to pay back from his current business characteristics and favorability of FIs credit policies to borrowers. Using a statistical approach in estimating the likelihood of default gives an objective and straight forward approach.

Despite all the mentioned strategies, loan defaults are alarming in FIs and Microfinance Institutions (MFIs). This is an alarming rate because it is more than the international acceptable default rate of 3% (Korankye, 2014). General information shows that default risk is associated with economic and social factors (Berharm, 2005; Agarwal, 2009; Marjo, 2010;Marjo, 2010; and Bichanga, 2013). However, there is limited information on how current business and FIs characteristics determine the likelihood of a borrower to default. It is in this regard that this study was designed to find the determinants for loan defaults in the selected FIs area. The selected FIs they offer both services, macro and micro finances, apart from servicing corporate customers they do also servicing micro finance customers, hence qualify for being MFIs and FIs as well, for example CRDB bank Ltd has established a subsidiary purpose for serving microfinance services, this is CRDB Microfinance Services Company Limited incorporated in the United Republic of Tanzania in 2000. The overall objective of the study was to determine factors for loan defaults in FI in Sumbawanga Municipality in Tanzania. Specifically the study intended to: evaluate the extent of loan default rate amongst the selected FIs at Sumbawanga Municipality for a period between 2013 and 2018, analyse factors influencing the likelihood of loan default among borrowers in the selected FIs in Sumbawanga Municipality and determine the effects of loan defaults to the selected FIs and borrowers.

2.0 Methodology

The study was conducted in Sumbawanga Municipality in Sumbawanga region which is located in Longitude 35^{o} 44' East and Latitude 6^{o} 10' South in the centre of the country. Sumbawanga Municipality covers an area of 2,669 square kilometer of which 625 square kilometers is urbanised. The estimated population for Sumbawanga for the year 2017, shows that the district had total population size of 359,008; out of the total population 174,972 people (48.7 percent) are male while 184,036 (51.3 percent) are female and the average household size is 4.4 people, (NBS, 2018)

Sumbawanga Municipality has others 4 registered MFIs (CDA, 2013). The criteria for selecting this study were based on the availability of MFIs and their beneficiaries and it employed both purposive and non-purposive sampling techniques. Purposive sampling technique was used to select NMB and CRDB out of 6 MFIs in Sumbawanga municipality. The criterion for selecting NMB and CRDB is because they are the

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biggest financial institutions (FIs) offering microfinance services in the study area, where by both individual and group-based lending models are offered by these MFIs. Similar technique was used to select 3 key informants from each selected FI. These were heads of credit unit and two loan officers from each FI, which makes a total of 6 key informants. Non-purposive sampling technique that is simple random was used for selecting loan groups borrows from those FIs (NMB and CRDB). This method was used to select 79 loan groups which were the respondents from each FIs under group lending model, and this make a total respondents of 158 from loan groups. Equal sample size was taken from each FIs because the group of borrowers did not differ much.

The target population of the study was loan groups borrowed from those FIs. The sampling frame of the study was a list of all loan groups borrowed from NMB and CRDB at Sumbawanga municipality which was obtained from respective FIs. The sampling unit in this study was an individual loan group from selected FIs.

This study uses borrowers under group lending model to gather the required information. Thus, the population used to calculate sample size was 784 loan groups borrowed from CRDB and NMB as shown in Table 1 below.

Table 1: Number of registered group of borrowers from selected FIs in 2018

MFI	Group Lending	Number of Borrowers	Percent
NMB	458	3,206	58
CRDB	326	2,282	42
TOTAL	**784**	**5,558**	**100**

Source: Field data, 2018

From each selected FIs, registered group was used and a total of 79 loan groups were purposively selected from each FIs to make a grand total of 158, out of 784 groups identified for both FIs. In average members to group have ranged from 3 to 10 members, this make a total of 5,558 members from 784 loan groups counted from both FIs. Equal sample size of loan group was taken from each FI. The sample size was obtained using formula as shown by Kothari, (2004) as presented hereunder;

$$n = \frac{z^2 * p * q * N}{e^2 (N-1) + z^2 * p * q}$$

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Where;

N= Number of loan groups; 784

n= Size of loan groups (sample size) - ?

e = Acceptable error (estimate should be within 5% of true value),

p= standard deviation of population; 0.02

z= 2.005 (area of normal curve for the given confidence level)

q= 1- 0.02

$$n = \frac{(2.005)^{\wedge}2(0.02)(1-0.02)(784)}{(0.02)^{\wedge}2(784-1)+(2.005)^{\wedge}2(0.02)(1-0.98)}$$

$$\frac{61.77}{0.39199}$$

$$n = 158$$

Thus, the appropriate sample size selected was 158 loan groups.

Primary data were collected directly from each groups borrowers and key informants, which were 3 informants from each FIs, makes a total of 6 key informants, during a field work structured and semi-structured interview was used respectively. Secondary data were collected through documentary sources including: FIs annual reports and other documents such as journals (published and unpublished), and websites related to loan default problem.

Structured interview method through questionnaire was chosen as important method of collecting data from the respondents. An in-depth interview conducted to key informants by using checklist.

Part of data collected were analysed by using descriptive statistics where means, frequencies, percentages composition and cross tabulations were employed. Logistic regression model was employed to determine the factors leading to loan default among borrowers in a group. This method uses maximum likelihood estimation method to estimate the value of parameters of the model. The dependent variable takes the value of 1 if the borrower defaults loan repayment for more than 30 days and takes the value of 0 if the borrower did not default (did not delay loan repayment for more than 30 days). In binary logistic model, this variable is the one that determines the likelihood of a borrower to repay the loan. This makes possible to estimate the

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likelihood of default as explained by the respondents and key informants, which include variables such as the age of a borrower, gender of a borrower, distance from FIs to business area, business type, business management knowledge, interest rate charged by FIs, marital status of the borrower, level of education of a borrower, loan uses, family problems, asset ownership, past business experience and weak legal actions to loan defaulters. The borrower's likelihood to default is determined by the utility derived from prompt loan repayment. The difference in utility levels between defaulting and not to defaulting is what determines the borrower's repayment decision.

Let utility derived be denoted by μ. This utility depends on borrower's characteristics including education level, age, marital status and gender of the borrower. Other factors that may affect the utility function include distance from FIs to business area, business type, business management knowledge, interest rate charged by FIs and other characteristics. For each borrower we can derive the utility difference denoted by $y*$ as a function of borrowers' characteristics and other factors denoted by X and the error term μ, which captures the influence of other factors not observed.

The following equation can be estimated, assuming a linear relationship

$$y* = X\beta + \mu \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \quad (1)$$

$y*$ is unobserved variable called the latent variable. The assumption is that the borrower may default when the utility difference exceeds a certain threshold level that can be set to 0 without loss of generality.

If y is the variable that represents the borrower's likelihood to default it takes the value of 1 if the borrower defaults and it takes the value of 0 if the borrower do not. Estimation of equation 1 is not possible because y* is unobserved, hence it is of little significance.

Consider the following situation:

$$y = \begin{cases} 1 \ if \ y* > 0 \\ 0 \ if \ y* < 0 \end{cases}$$

Therefore, instead of estimating equation (1) equation (2) is estimated.

$$P_i = E(Y = 1|X_i) = \beta_1 + \beta_2 X_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \quad (2)$$

Where:

$$Y = \begin{cases} 1 \ \text{If the borrower defaults (delay loan repayment for more that 30 days)} \\ 0 \ \text{If the borrower do not default (not delay loan repayment for more that 30 days)} \end{cases}$$

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Equation (2) can be estimated by Ordinary Least Squares method (OLS), hence called a Linear Probability Model (LPM). Since the dependent variable is binary, estimation by OLS will be inappropriate. Gujarati and Porter (2005) points out the weaknesses of estimating equation (2) by OLS method. First, it can lead to probabilities that are out of range, that is, either negative values or values greater than 1. Second, the error term will be heteroscedasticity therefore statistical inferences will lead to wrong conclusions. Third non-normality of the disturbance term and finally the measures of goodness of fit of the model will be questionable. To resolve the problems of LPM, it is necessary to make some assumptions on the distribution of the disturbance term µ. The logistic regression model assumes the disturbance term follows a standard logistic distribution with mean 0 and standard deviation of $\frac{\pi^2}{3}$ while the probit model assumes µ follows a standard normal distribution with mean 0 and standard deviation of 1. Both logit and probit models use Maximum Likelihood (ML) technique to estimate equation (1).

X is a set of explanatory variables explaining the dependent variable. Since logit model assumes that the error term follows a standard logistic distribution with mean 0 and standard deviation of $\frac{\pi^2}{3}$. Thus the probability that Y=1 is given as:

$$P_i = E(Y = 1|X_i) = \frac{1}{1 - e^{-(\beta_1 + \beta_0)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

For ease of exposition, equation (2) can be written as

$$P_i = \frac{1}{1+e^{-Z_i}} = \frac{e^z}{1+e^z} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Where $Z_i = \beta_1 + \beta_2 X_i$

The equation (3) represents what is known as the (cumulative) logistic distribution function of characteristics of the borrower, business and FIs. It was easy to verify that as Z_i ranges from $-\infty$to$+\infty$, P_i ranges between 0 and 1 and P_i is nonlinearly related toZ_i(i.e., X_i), thus satisfying two requirements considered earlier. In order to satisfy these requirements, we have created estimation problems because P_i is non-linear not only in X but also in β's as can be seen clearly from equation (2). This means that cannot use the familiar OLS procedure to estimate parameters Gujarati and Porter (2005). Therefore, the equation (2) can be liberalized as follows:

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If P_i, is the probability of a borrower to default is given by equation (3), then $(1 - P_i)$, is the probability of a borrower not to default given the equation (4)

$$1 - P_i = \frac{1}{1 - e^{Z_i}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4)}$$

Therefore, the above equation will be as follows

$$\frac{P_i}{1-P_i} = \frac{1+e^{Z_i}}{1+e^{-Z_i}} = e^{Z_i} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad \text{(5)}$$

Now $P_i/(1 - P_i)$ is simply the odd ratio1 in favour of a borrower to default, the ratio of the probability that loan default occurs. In order to obtain a good result the equation (5) must be in natural log as follow in equation (6)

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = Z_i$$
$$= \beta_1 + \beta_2 X_i \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad \text{(6)}$$

That is, L, the log of the odds ratio, is not only linear to X, but also linear in the parameters. L is called the logit, and hence the name logit model for model equation (6).

The estimation techniques

In order to estimate the logit model the equation (6) can be writern as follows;

$$L_i = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_1 + \beta_2 X_i + \varepsilon_i$$

To estimate the specified logit model the forced entry method was used in favour of the stepwise approach. This is because of the advantage that the forced entry method has over the stepwise method. The stepwise method removes the variables that do not meet the significance level condition specified, thus losing some important information regarding the effect of variables removed have on the dependent variable. By forced entry method, all the variables are entered together and none is removed from the specified model.

Empirical model

The following Empirical model was estimated

[1] Odds ratio refers to the ratio of the probability that something happens to the probability of it not happening. If p is the probability of occurrence 1-p is the probability of non-occurrence. Thus the odds ratio is given as $\frac{p}{1-p}$

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$P_i = E(Y = 1|X) = F(X\beta)$, ... (7)

Where; P_i is the probability that the dependent variable takes the value of 1, given the value of regressors

X is a vector of explanatory variables explaining the dependent variable

β is the coefficient

In terms of logarithm of the odds is the equation (7) is written as:

$$ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 AG + \beta_2 GND + \beta_3 MART + \beta_4 EDU + \beta_5 BUSTYP + \beta_6 BUSEDU + \beta_7 MFILOCAT + \beta_8 FAMPROB + \beta_9 LOANUSE + \beta_{10}\ WEAKLEG + \beta_{11}\ ASTOWN + \beta_{12}\ PASTEXP + \beta_{13} INTEREST + \varepsilon_i \quad \text{.......................} (8)$$

Where;

$Y_i =$ Dependent variable that takes the value of "1" if the borrower defaults and it takes the value of 0 if the borrower does not default

p Is the estimated probability that *Y* takes the value = 1.

AG	=	Age of the borrower
GND	=	Gender of the borrower takes "1" if respondent is male and "0" for female within a loan group
MART	=	Martial status of respondent takes "1" for married and "0" for otherwise within a loan group
EDU	=	Education level of respondent take "1" if attended formal education and "0" for otherwise
BUSTYP	=	Business type takes "1" if business generate frequent revenue weekly and "0" for otherwise
BUSEDUC	=	Business Education takes "1" if respondents acquired business education and "0" for otherwise
FILOCAT	=	FI Location takes "1" if distance to FI is within 1-3 km and "0" for otherwise
FAMPROB	=	Family problem take "1" if respondent had death in within a loan group, etc and "0" for otherwise
LOANUSE	=	Uses of loan take "1" if loan was used for business purpose and

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"0" for otherwise

WEAKLEG = Weak legal actions take "1" if FI has weak legal action toward loan defaulters and "0" for otherwise

ASTOWN = Borrowers Asset Ownership takes "1" if respondent own assets accepted as collateral and "0" for otherwise

PASTEXP = Past experience takes "1" if respondent has past experience of the business he/she owns and "0" for otherwise

INTEREST = Interest rate charged by FIs

By rearranging (7), the estimated probability of default P(Y=1) is given by

$$P(Y = 1) = \frac{1}{1+e^{-(\beta_0+\beta_1 X+\beta_2 X+\beta_3 X+\cdots+\beta_n\ xn+e}} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (9)$$

Where; β_0, β_1, β_2, β_3 ,…… β_n are the coefficients to be estimated and *e* is the error term

3.0 Results and Discussion

3.1 The extent of loan default rate in selected FIs for a period of 2013 to 2018

The extent of loan defaults rate for a period of 2013 to 2018 was ascertained using records of borrowers from a loan group. This extent was determined by calculating the ratio of the total borrowers served to the number of borrowers who have defaulted within a group. This ratio is expressed in terms of percentage as presented in Figure 1. In both FIs the rate of loan defaulter has been decreasing from year 2013 to 2018. The study revealed that in both FIs the default rate decreased between 11 percent to 2 percent for the period of five years, (from 2013 to 2018), although it was decreasing but still the borrowers default was there.

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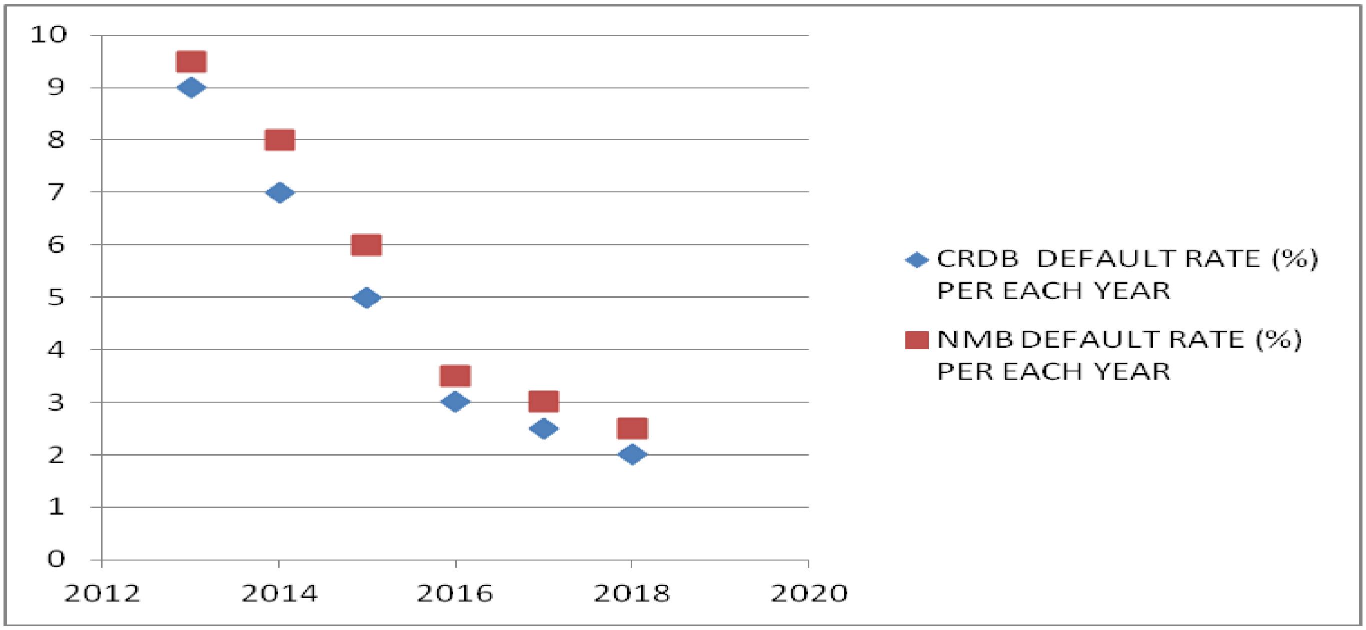
Figure 1: Trends of loan default in selected FIs for a period of 2013 to 2018



Source: Field data (2018)

The study shows a decrease in loan default rate for the period of five years, from 2013 to 2018 for both FIs this is due to various reasons such as improvements of lending process, loan screening and the conditions/terms for issuing a group loan, also the study shows the advancement in ICT technology enable the FIs to track loan repayment records report timely before the due date.

3.2 Factors influencing the likelihood of loan default in the selected MFIs

Logistic regression model was employed to estimate the likelihood of borrowers who obtained loan from selected FIs to default. Logistic regression estimates results are presented in Table 2. In the table, Column two with the heading "B" gives the coefficient of variables in the model. Column three with the heading "S.E" gives the standard error for the coefficient values. The column four with heading "wald" gives the Wald test values of the coefficient values. Df is the degree of freedom for the wald test values. The column "sig", show how significant the variables are to the model. A value less than 0.05 shows the variable is highly significant. Column "Exp (B)" gives the odds of each variable.

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Table 2: Logistic Estimated Parameters

PREDICTOR	B	S.E	Wald	Df	Sig	Exp(B)	
Constant	4.117	1.609	6.544	1	0.011	61.36	**
AGELOG	-0.761	0.361	4.432	1	0.035	0.467	*
GNDLOG	0.391	0.496	0.621	1	0.431	1.479	**Ns**
MARTLOG	0.156	0.477	0.108	1	0.743	1.169	**Ns**
EDULOG	0.514	0.378	1.847	1	0.174	1.672	**Ns**
BUSNTYP	-1.596	0.48	11.069	1	0.001	0.203	**
BUSEDUC	-1.409	0.507	7.734	1	0.005	0.244	**
MFILOCAT	0.633	0.868	0.532	1	0.466	1.883	**Ns**
FARMPROB	0.072	0.413	0.031	1	0.861	1.075	**Ns**
LOANUSE	-1.588	0.507	9.814	1	0.002	0.204	**
WEAKLEG	-0.344	0.652	0.279	1	0.597	0.709	**Ns**
ASTOWN	-0.423	0.668	0.401	1	0.527	0.655	**Ns**
PASTEXP	-0.631	0.856	0.543	1	0.461	0.532	**Ns**
INTEREST	-1.38	0.637	4.7	1	0.03	0.252	*

**** and * indicate significance at 1% and 5% respectively while (ns) shows not significant**

Source: Field data, (2018)

3.2.1 General analysis of the estimated Coefficients and Odds Ratio

General analysis of the odds ratio values shown in Table 2 indicate that GNDLOG, MARTLOG, EDULOG, MFILOCATION and FAMPROB have odd ratios greater than one (OR>1) with positive coefficients. This shows a positive relationship with likelihood to default. The odds ratios of AGELOG, BUSNTYPE, BUSEDUC, WEAKLEGAL, ASTOWN, PASTEXP and INTEREST are less than one (OR<1) with negative coefficients. This shows a negative relationship of these factors with the likelihood to default.

Further, Table 2 shows some factors were found to be significant at (P<0.05) including age (AGELOG), business education (BUSEDUC), interest rate charged by FIs (INTEREST), Business type (BUSNTYPE), and use of the loan (LOANUSE) were found to be significant at (P<0.01).

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The remaining factors were found to have insignificant effect in the likelihood of loan default. These factors are: Marital status (MARTLOG), level of education (EDULOG), gender of borrower (GNDLOG), distance/location of FIs (FILOCATION), family problems such as diseases (FAMPROBR), weak legal action to defaulters (WEAKLEGAL), asset ownership (ASTOWN) and past experience on business (PASTEXP).

3.2.2 Analysis of the significant factors

Age of the borrowers

Age measured the borrower's age in years. As the age of the borrower increases it reduces the likelihood of a borrower to default. The results show odds ratio of 0.467. This means that a unit increase in borrower's age lowers the likelihood of default by 53.3%. This suggests that borrowers in group between 18 to 34 years old are more likely to default than older age groups in the selected FIs. This finding is supported by Mokhtar (2012) where it was observed that the older borrowers would be more responsible and disciplined in repaying their loan than younger borrowers. Thomas (2000) and Boyle et al (1992) confirm that older borrowers are more risk adverse, and therefore the less likely to default. Thus banks are more hesitant to lend to younger borrowers who are more risk averse.

Business Management Education

Business management education among the borrowers was significant at 1% with odds ratio of (0.244) and a coefficient of (-1.409). This implies that borrowers who have management skills acquired through trainings or seminars manage their businesses more prudently and are less likely to default compared to borrowers managing their business without business education. Therefore an acquisition of business management education was associated with a reduction of the likelihood of a borrower to default by 75.6%. This result is supported by Awan (2015) who ranked lack of business education as the 4th important cause of loan default in the study conducted in Pakistan. Also Oladeebo (2008) found out that, borrowers that do not have formal education are likely to have inadequate knowledge of loan acquisition and management, thereby making them unable to repay the loans given to them. On the other hand, the borrowers' education level distinguished from post-graduate to non-high school graduate. Borrowers with high level of education are more likely to repay their loan since they occupy higher positions and with high income levels.

Type of Business

Business type was also significantly associated with the likelihood of loan default at 1%. The analysis showed a coefficient of (-1.596) with the odds ratio of (0.203), indicating that, businesses with frequent

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business transactions (Revenue can be obtained in daily basis) are likely to have reduction of odds in favour of default by 79.7% compared to businesses with less transactions. This means businesses which are able to generate enough revenue to meet the weekly repayment schedules reduce the likelihood of loan defaulting. This implies that borrowers involved in food vending, retail shops, and motorcycle operators (bodaboda) reduces the likelihood of loan defaulting compared to borrowers involved in businesses such as saloon and cloths selling. This finding is supported by Suraya et. al., (2012) where it was observed that the lower revenue cycle in businesses creates loan repayment problems to borrowers.

Loan Uses

Loan use was significantly associated with the loan defaulting likelihood at 1%. The odds ratio of (0.204) suggests that the use of loan for non business purposes is likely to increase loan default compared to business uses. Borrowers, who use loan for business purpose, reduce loan default likelihood by 79.6% compared to those who use loan for other non business purposes. The study revealed that most borrowers use loan to finance food, shelter, clothes and to meet their basic needs rather than for business activities. This result is supported by Bayang (2009) who reported that, at the time of loan disbursement, the poor borrowers are pre-occupied with addressing their social problems ranging from shortage of food, lack of seeds for planting and paying medical bills among others, a practice which makes loan repayment difficulty. Also Onchangwa et al (2013) asserted that misallocation of loans in unproductive activities by borrowers reduced their investments and this posed a high loan defaults in Kenya. ***Interest Rate***

Interest charged by FIs was also associated with influencing the likelihood of a loan borrower to default. This variable was statistically significant at 5% with an odds ratio of (0.252) which shows that the interest charged by FIs, as compared to those charged by other commercial banks, leads to about 74.8% reduction in the loan default likelihood. This means that high interest rates impose high cost to the borrowers, making loan repayment difficulty.

These findings concur with Vandel (1993) and Okpugie (2009) in their studies who found out that high interest rate charged by financial institutions is a major cause of default among the borrower

3.2.3 Assessment of the Model fit

In assessing the overall fitness of the model two approaches were used; statistical measures and pseudo R2 measures. The Hosmer and Lemeshow test measures the overall fit. The Hosmer and Lemeshow test shows insignificance for the fitted model is 0.614 as shown in Table 3, indicating that insignificant differences remain between actual and expected values. This is a strong indication of a good model fit.

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Table 3: Results of Hosmer and Lemeshow Test

Step	Chi-square	Df	Significance
1	8.288	8	0.614

***Pseudo R^2 Measures**

Source: Field data (2018)

It can be observed from Table 4 that the model has a relatively larger pseudo R2 of 0.521 for the Nagelkerke R Square and 0.452 for the Cox and Snell R Square. That is the fitted model is able to explain or account for 52.1% of the variation in the dependent variable. This is an indication of a good model.

Table 4: Model Summary

Steps	-2log likelihood	Cox and Smell R Square	Nagelkerke R Square
1	200.812[a]	0.452	0.521

Source: Field data, 2018

However, there were some other factors which were not statistically significant in the estimated model but had influence in the likelihood of loan default. These are Marital status (MARTLOG), level of education (EDULOG), gender of borrower (GNDLOG), distance/location of FIs (FILOCATION), family problems such as diseases (FAMPROBR), weak legal action to defaulters (WEAKLEGAL), asset ownership (ASTOWN) and past experience on business (PASTEXP).

3.3. The effects of loan defaults to borrowers within a loan group and to FI,

3.3.1 Effects of loan default to borrowers within a loan group

Loss of properties

The study identified loan defaults effects to loan borrowers. Collateral are valuable items that are to be acquired in case a borrower defaults to compensate for the loss. Table 5 shows that majority of respondents (76%) accepted that loan defaulters lose their properties in case the borrower fails to repay the remaining loan balance. 24% reported that defaulters do not lose their property instead are denied to acquire next loan and be rejected by group members.

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Table 5: Response of borrowers on Loss of Properties set as collateral

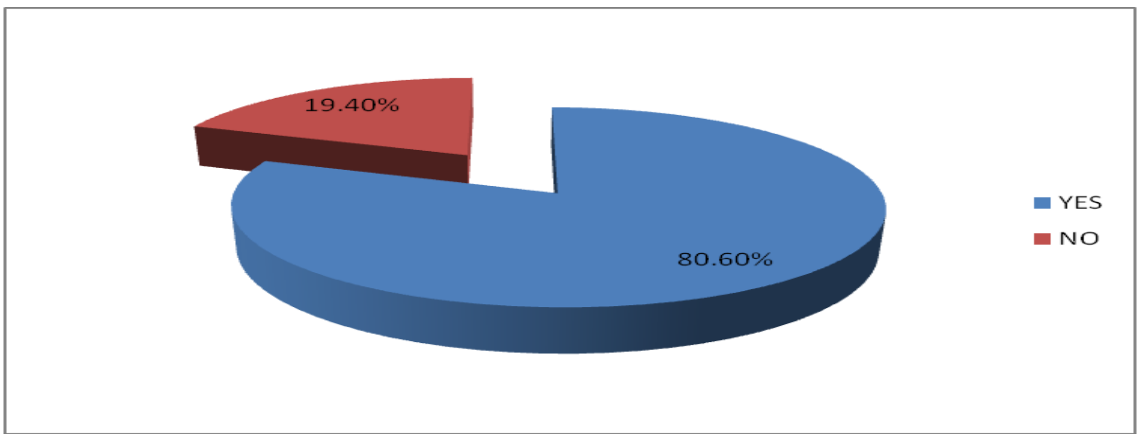
Loss of property	Frequency	Percent
YES	120	76.0
NO	38	24.0
Total	158	100.0

Source: Field data (2018)

Rejection of borrowers to the next Loan opportunity

The respondents were required to comment whether the individual borrowers rejected for the next loan opportunity or not. The responses are shown on Figure 2.

Figure 2: Response of borrowers on Denial for next Loan opportunity



Source: Field data (2018)

The information provided in Figure 2 shows that 80.6% of respondents accepted that loan defaulters are denied for next loan opportunity. These findings revealed that FIs had strong measures to control defaults.

3.3.2 Effects of Loan defaults to FIs

Data obtained from the field shows that, in average of 3.2% and 4.1% of interest incomes for both FIs are used to provide for bad debts for the period of five years starting from 2013 to 2018. This implies that, the FIs dilute its capital and reduce its operating income. The principal amount unpaid from the borrowers it affect the capital of the FIs, this force the FIs to borrow from others FIs or to cut down its profit from other sources to compensate for the principal amount unpaid, also on the unpaid interest from loan defaulted it reduce the net profit of the FIs. Although the FIs making follow up to all loan defaulters but the study shows that, it took time for the FIs to complete the follow-up process, since the process involves legal issues in

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confiscating the collateral pledged during the loan applications, this needs time and hence affect the financial statements of the FIs.

The study reveals that, these two FIs (CRDB and NMB) are the public companies, that means they have raised their capital from the public, who are the investors, if it happen that there is default of any rate, the investor are becoming worried for their money and hence they trade their equity stakes in the secondary market (Dar-Es Salaam Stock Exchange), this process undermine the ability of the FIs to raise any additional capital from investors who are mostly concerned about the health of the loan portfolio of the FIs. In addition, the study shows that, the entire amount spent for recover the bad debts for a period of five years, is very huge, it could be used to create new loans and expanding FIs capital. This had a negative impact on the liquidity of the FIs.

4.0 Conclusion and Recommendation

4.1 Conclusion

The findings show that, the loan default was existed in both FIs. Generally, the rate of loan default has been decreasing from year 2013 to 2018 due to proper screening of borrowers as well as credit rationing. Age and interest rate charged by FIs found to be significant at ($P<0.05$). Factors such as Business type, business management education and use of the loan were found to be significant at ($P<0.01$). Borrowers with default history are affected negatively through, denial of subsequent loan opportunities, bad image to the loan group and loss of properties pledged as collateral and bad relationship with FIs officers. Also, the study revealed adverse effects to the respective FIs as loss of the expected interest, reduction of operating profit and capital expansion.

4.2 Recommendations

The FIs should review their policies so as to establish stringent lending and debts collection regulations. It should also involve to a great extent competent loan officers and customers in formulating professional lending and other loan processing terms.

The FIs should have access to credit insurance that will ensure loans issued to borrowers are free from the risk of loan defaulting and review their interest rates they charge on loans.

The FIs should involve borrowers in reviewing loan repayment terms, effective monitoring of loans, frequent credit training programs, and the institutions should use credit referencing agents which is a current requirements issued by the Bank of Tanzania (BoT) and where necessary they have to use private debt collectors to ensure loan default rate is minimal.

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