

Determinants of Loan Defaults in Microfinance Institutions in Tanzania: A case of two Selected Microfinance Institutions in Dodoma Municipality

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ABSTRACT

The study on determinants of loan defaults in Microfinance Institutions in Tanzania was carried in Dodoma Municipality in two selected branches namely PRIDE and FINCA. Specifically, the study intended to: assess the default rate of the selected MFIs for the period between 2004 and 2014; determine factors influencing the likelihood of loan default and identify measures that have been taken to reduce loan defaults problems. The study used cross-sectional design to gather information at the study area. Non-purposive sampling technique was applied to select 196 respondents. Purposively, Micro-finance institutions 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interview whereas secondary data were collected through a documentary review of sources including published and unpublished materials. Data obtained were analyzed by descriptive statistics and logistic regression using SPSS version 11.5. Logistic regression model estimated the factors influencing the likelihood of borrowers to default. The findings show that, the loan default existed in both branches. However, the rate of loan default has been decreasing from year 2004 to 2014 . In addition, Logistic regression model shows that age of borrowers and interest rate charged by MFIs 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 and key informant reported that holding of defaulters' property, rejection of borrowers to the next loan opportunity, frequent communication and capacity building were measures undertaken by MFIs to reduce default problem. Further, this study recommended that MFIs should involve borrowers in reviewing loan repayment terms, effective monitoring of loans, credit training programs and where necessary the use private debt collectors.

Keywords: Loan, microfinance, defaulter

1.0 INTRODUCTION

The long-term vision of Microfinance Institutions (MFIs) is to provide sustainable financial services to the economically-active poor who are unable to access these services from the mainstream of financial services (Nyamsogoro, 2010). In fulfilling this vision, Microfinance institutions has managed to play an important role in micro-enterprise development in Tanzania compared to commercial banks, particularly as instruments to reduce the financial exclusion so as to achieve equity economic growth. Remarkably, MFIs have become an economic development strategy that encourages income-generating activities; assists entrepreneurs in stabilizing existing sources of income and enables micro-enterprises to grow into small businesses. In the development of market-based, microfinance institutions have provided SMEs with micro-loans and other financial services on a sustainable basis with more flexible terms than those offered by traditionally risk-averse banks. 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 Microfinance Institutions which are: inadequate donor funding, 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 these MFIs (Cull et al, 2009, Aghion & Morduch 2005; Zeller & Johannsen, 2006).

Recent default rate statistics in developing countries show that out of the 25 MFIs, 10 which represent 40% of MFIs 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 MFIs, various efforts have been put 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 MFIs (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 MFIs 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 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 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 MFIs 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 MFIs. In Tanzania, the Foundation for International Community Assistance (FINCA) and Promotion of Rural Initiative and Development Enterprises (PRIDE) reported to experience high defaults that is 3.4% and 3.8% respectively. 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; Vasanthi and Rajab, 2006 Marjo, 2010; and Bichanga, 2013). However, there is limited information on how current business and MFIs characteristics determine the likelihood of a borrower to default. It is in this regard that this study was designed to find the determinant factors for loan default in the selected Microfinance Institutions in Dodoma Municipality. The overall objective of the study was to determine factors for loan defaults in Microfinance Institutions in Tanzania. Specifically the study intended to: assess the level of loan default amongst the selected MFIs in Dodoma for a period between 2004 and 2014, determine factors influencing the likelihood of loan default among borrowers in the selected MFIs in Dodoma and identify measures have been taken by MFIs to solve the problem.

2.0 METHODOLOGY

The study was conducted in Dodoma Municipality in Dodoma region which is located in Longitude 35 ° 44' East and Latitude 6° 10' South in the center of the country. The town is 486 kilometers West of the former capital at Dar es Salaam and 441 kilometres South of Arusha, the headquarters of the East African Community. Dodoma Municipality covers an area of 2,669 square kilometer of which 625 square kilometers is urbanised. The Population Census of 2012 shows that the district had total population size of 410,956; out of the total population

199,487 people (48.5 percent) are male while 211,469 people (51.5 percent) are female and the average household size is 4.4 people.

Dodoma Municipality has a total of 6 MFIs including PRIDE, FINCA, VISION FUND, WORLD VISION and BRAC (CDA Report, 2013). The criteria for selecting this study area based on the availability of MFIs and their beneficiaries.

The study employed both purposive and non-purposive sampling techniques. Purposive sampling technique was used to select PRIDE and FINCA out of 6 MFIs in Dodoma municipality. The criteria for selecting PRIDE and FINCA is because they are the biggest MFIs in the study area which use both individual and group-based lending models. Similar technique was used to select 2 key informants from each selected MFI. These were Branch Managers, credit officers and loan officers who make 6 key informants. Non-purposive sampling technique that is simple random was used for selecting loan borrowers from PRIDE and FINCA. This method was used to select 98 respondents from each MFI and make a total of 196 respondents. Equal sample size was taken from each location because the population did not differ much.

The target population of the study was loan borrowers from MFIs. The sampling frame of the study was a list of loan borrowers from FINCA and PRIDE in Dodoma municipality which was obtained from respective offices. The sampling unit in this study was a loan borrower who have obtained loan from selected MFIs.

Due to unavailability of the loan borrowers using individual lending model, this study uses borrowers of group lending model to gather the required information. Thus, the population used to calculate sample size was 328,765 borrowers obtained from FINCA and PRIDE as shown in Table 1.

Table 1: Number of registered borrowers in selected MFIs in 2014

MFI	Number of Borrowers	
	Group lending Model	Individual lending Model
FINCA	173,530	3873
PRIDE	155,235	4603
TOTAL	328,765	8476

From each selected MFIs, register was used and names of 98 borrowers were selected randomly to make a grand total of 196 out of 328,765 borrowers. Equal sample size was taken from each MFI because the population did not differ much. The sample size was obtained using formula as shown by Kothari, (2004) as presented hereunder:

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

Where;

n = size of sample; N= size of population – 328,765; e = acceptable error - (since the estimate should be within 2% of true value); p= sample proportion = 0.02; z= 2.005 (area of normal curve for the given confidence level of 95.5%); q= 1-0.02

$$n = \frac{(2.005)^2(0.02)(1 - 0.02)(328765)}{(0.02)^2(328765 - 1) + (2.005)^2(0.02)(1 - 0.02)}$$

$$\frac{25904.21}{131.58}$$

Thus, the appropriate sample size was 196 borrowers.

Primary data were collected directly from the borrowers and key informants during a field survey using structured and semi-structured interview respectively. Secondary data were collected through documentary sources including: MFIs annual reports related to loan default problem, journals (published and unpublished) and websites. Structured interview method through questionnaire was chosen as important method of collecting data from 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, percentage composition and cross tabulation were employed. Logistic regression model was employed to determine the factors leading to the likelihood of borrowers to loan default. 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 Likelihood of default as explained by business and MFIs characteristics, which include variables such as the place of residence, age of a borrower, gender of a borrower, distance from MFIs to business area, business type, business management knowledge, interest rate charged by MFIs, marital status of the borrower, level of education of a borrower, asset ownership, past business experience and weak legal actions to 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 u . 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 MFIs to business area, business type, business management knowledge, interest rate charged by MFIs 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

$$y^* = X\beta + \mu \dots\dots\dots (1)$$

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:

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

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

$$P_i = E(Y = 1|X_i) = \beta_1 + \beta_2 X_i \dots\dots\dots (2)$$

Where:

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

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 (2004) 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:

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

For ease of exposition, we write equation (2) as

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

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 MFIs.

It is 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 to Z_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 (2004). Therefore, the equation (2) can be liberalized as follows:

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)

$$1 - P_i = \frac{1}{1 + e^{Z_i}} \dots\dots\dots (4)$$

Therefore, the above equation will be as follows

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

Now $P_i/(1 - P_i)$ is simply the odd ratio² 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)

$$L_i = \ln \left(\frac{P_i}{1 - P_i} \right) = Z_i$$

$$= \beta_1 + \beta_2 X_i \dots\dots\dots (6)$$

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 as follows

² 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 $\frac{p}{1-p}$

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

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 logistic model was estimated

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

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:

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

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

- MART* = Martial status of respondent takes “1” for married “0” and otherwise
- EDU* = Education level of respondent take “1” if attended formal education and “0” otherwise
- BUSTYP* = Business type takes “1” if business generate frequent revenue weekly and “0” otherwise
- BUSEDUC* = Business Education takes “1” if respondents acquired business education and “0” otherwise
- MFILOCAT* = MFI Location takes “1” if distance to MFI is within 1-3 km otherwise “0”
- FAMPROB* = Family problem take “1” if respondent had death in family, etc and “0” and otherwise
- LOANUSE* = Uses of loan take “1” if loan was used for business purpose and “0” and otherwise
- WEAKLEG* = Weak legal actions takes “1” if MFI has weak legal action toward defaulters and otherwise “0”
- ASTOWN* = Borrowers Asset Ownership takes “1” if respondent own assets accepted as collateral and otherwise “0”
- PASTEXP* = Past experience takes “1” if respondent has past experience of the business he/she owns and “0” otherwise
- INTEREST* = Interest rate charged by MFIs

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

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X + \beta_2 X + \beta_3 X + \dots + \beta_n x_n + e)}} \dots \dots \dots (9)$$

Where; $\beta_0, \beta_1, \beta_2, \beta_3, \dots, \beta_n$ are the coefficients to be estimated and e is the error term

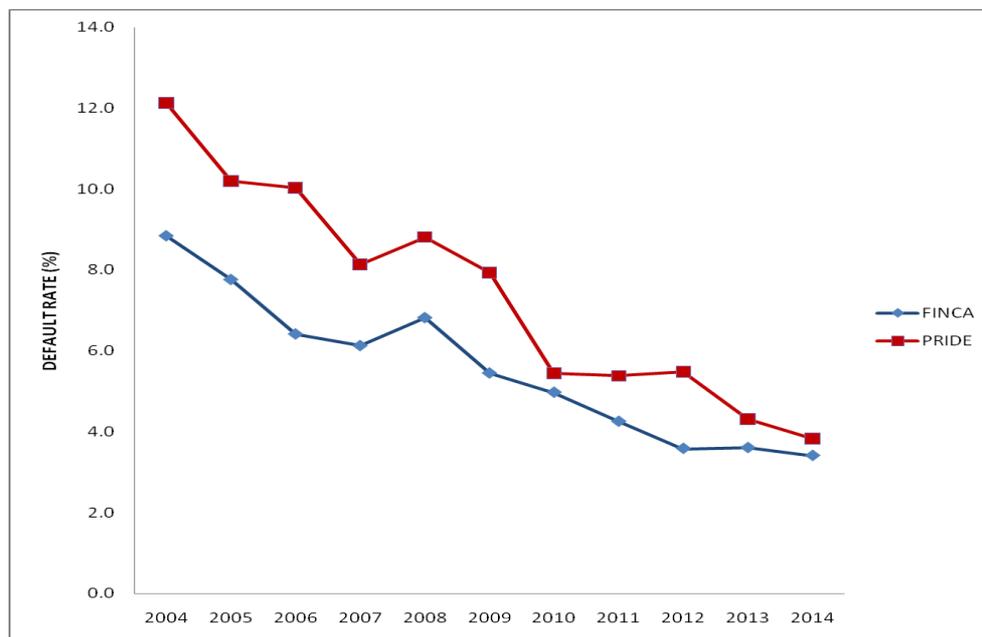
3.0 RESULTS AND DISCUSSION

3.1 Assessment of the Extent of Loan Default in Selected MFIs for a Period of 2004 to 2014

The extent of loan defaults for a period of 2004 to 2014 was ascertained using records of borrowers who were in individual lending model. This extent was determined by calculating the ratio of the total borrowers served to the number of borrowers who have defaulted. This ratio is expressed in terms of percentage as presented in Figure 1.

In both MFIs the rate of loan defaulter has been decreasing from year 2004 to 2007. However, in 2008 to 2009 there was a sharp increase of default rate in PRIDE microfinance institution. Information from the institution shows inadequate close monitoring and less supervision of new borrowers' businesses due to few loan supervisors. Thereafter, there was a massive decline of default rates due to increase loan supervisors, close monitoring of borrowers' business, high screening and credit rationing for new borrowers.

Figure 1: Trends of loan default in selected MFIs for a period of 2004 to 2014



Source: Field data, 2015

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 MFIs 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.

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	**
AGLOG	-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

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 (AGLOG) and interest rate charged by MFIs (INTEREST). Factors such as Business type (BUSNTYPE), business management education (BUSEDUC) and use of the loan (LOANUSE) were found to be significant at ($P < 0.01$).

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 MFIs (MFILOCATION), 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 borrower

Age measures 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 MFIs. 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 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 MFIs 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 MFIs, as compared to those charged by 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 Vandell (1993) and Okpugie (2009) in their studies who found out that high interest rate charged by microfinance institutions is a major cause of default among the microfinance borrowers.

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.

Table 3: Results of Hosmer and Lemeshow Test

Step	Chi-square	Df	Significance
1	8.288	8	0.614

Pseudo R² Measures

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 & Smell R Square	Nagelkerke R Square
1	200.812 ^a	0.452	0.521

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 MFIs (MFILOCATION), family problems such as diseases (FAMPROBR), weak legal action to defaulters (WEAKLEGAL), asset ownership (ASTOWN) and past experience on business (PASTEXP).

3.3 Measurers Undertaken to Solve the Problem of Loan Defaults in Microfinance Institution

3.3.1 Loss of properties

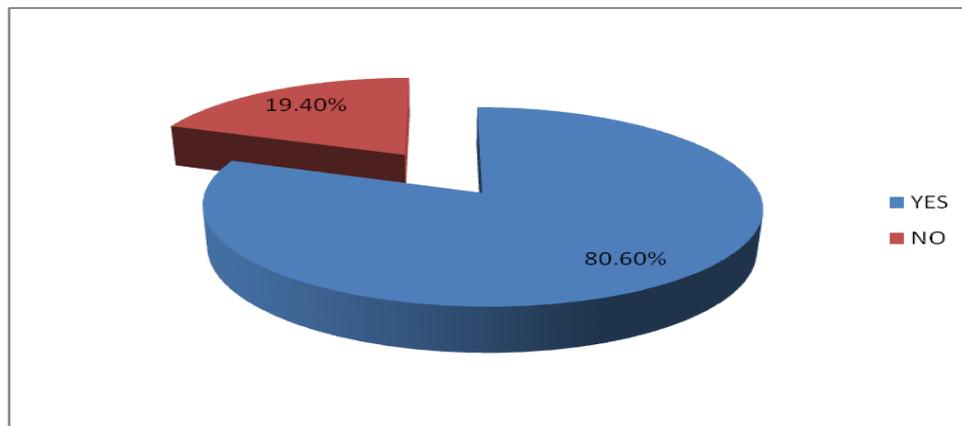
The study identified loan defaults measures to loan borrowers. Table 5 shows that majority of respondents (76%) accepted that loan defaulters lose their properties when the borrower fails to repay the remaining loan balance. This study findings revealed that loan defaulters had to loose their properties to debt collectors. Similar results were obtained by Katunga (2014) in Zimbabwe, that hundred of microfinance institutions loan defaulters loose their properties including houses.

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

Loss of property	Frequency	Percent
YES	149	76.0
NO	47	24.0
Total	196	100.0

3.3.2 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

The information provided in Figure 2 shows that 80.6% of respondents accepted that loan defaulters are denied for next loan opportunity. The study concurred with Gerhard (2012) that *defaulters* are frequently *denied a loan* and, if not, they have to pay a higher *loan*. These findings revealed that IMFs had strong measures to control defaults.

3.3.3 Capacity in terms of human resources

The information obtained from the key informant explained that the Institution have made effort on providing training to their staff. However, 69% of respondents reported that trainings were conducted once per year. The study revealed that more training are needed to reduce business risks.

3.3.4 Frequent communication

The key informant responded that the office ensures efficient communication, continuity and speedy processing of loans. The process is largely coordinated by the Product Officer from sign up to post disbursement.

CONCLUSION AND RECOMMENDATIONS

The findings show that, the loan default was existed in both branches. Generally, the rate of loan default has been decreasing from year 2004 to 2007 due to proper screening of borrowers as well as credit rationing. Age, interest rate charged by MFIs, Business type, business management education and use of the loan were found to be significantly influencing decision to default among borrowers. Borrowers with default history are affected negatively through, denial of

subsequent loan opportunities, bad image to the society and loss of properties pledged as collateral and bad relationship with MFIs officers. Also, the study revealed MFIs hold the defaulters property, rejection of borrowers to the next Loan opportunity, frequent communication and capacity building. Therefore, the MFIs should review their policies so as to establish stringent lending and debts collection regulations. It should also provide trainings to loan officers and customers to reduce loan risks. The institutions 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. Also, loan officers should ensure that the loan funds are invested directly into the business to assist entrepreneurs to overcome self-control problems or the diversion of cash into non-business activities.

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