

Credit Default Risk and its Determinants of Microfinance Industry in Ethiopia

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Abstract

Despite the current enthusiasms in applying the concept of microfinance as a poverty alleviation tool in many countries, the risk management aspects of micro-financing should not be overlooked. This paper highlights several incidences of default risks in microfinance institutions. The problem identified was that microfinance programs perform scantily because of delay in repayment and high default rates. Hence, it was important to establish if these limitations prevailed in the selected 6 MFIs in Ethiopia schemed by determining the default rate and the grounds of the observed trends. Therefore, in order to address those issues, the researcher used primary data collected through structured questionnaire and referred to secondary sources of data. As a result, the collected data and information were compiled and analyzed for possible indications of problem areas. So, the outcomes revealed that the MFIs default rate increased over the review period and averaged 27.1 per cent as well. The core factor of default was found to be poor business performance. Besides, credit diversion to unprofitable uses, domestic problems, numerous dependents, and tenancy problems were other factors that caused credit default. Further, the inference results of the descriptive statistics and the probit model show that education, income, loan supervision, suitability of repayment period and availability of other credit sources are important and significant factors that enhance the credit repayment performance, while credit diversion and credit/loan size are found to significantly increase credit default. There were serious problems observed in the screening mechanism the institutions employed, i.e. borrowers who are good payers like literate were rationed more, while those who contribute to the default problem like male and who apply for larger loan amounts were rationed less. So, the lending institutions are particularly recommended to improve these problems observed in its rationing mechanism. Moreover, the processes should be worked out to identify borrower capacity and any obligations that may interfere with repayment. Finally, the selected MFIs should intensify recovery of outstanding balances from defaulters through increased borrower follow-up.

Keywords: MFIs, credit default, credit diversion, loan rationing, impact, creditworthy.

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1. Introduction

Microfinance has evolved as an approach to economic development intended to benefit low income women and men. It expanded enormously in 1990s (Ledgerwood 1999). Policy makers, donors, practitioners and academics underline the role of microfinance as a powerful tool for poverty alleviation and economic development.

Ethiopia is a land of contrast. Poverty is the main challenge and a fundamental issue of economic development in Ethiopia. The solutions to poverty are multifaceted as are its causes. Many argue that an inadequate supply of credit can affect production negatively. Alleviation of poverty and promotion of economic development can therefore be facilitated through providing credit to the poor.

The formal financial sector has failed to reach the majority of the rural as well as urban poor. This has forced the poor to turn to the informal and semi-formal financial sources. However, credit from such sources is not only inadequate, but also exploitative and costly.

In Ethiopia, microfinance services were introduced after the demise of the Derg¹ regime following the policy of economic liberalization.

Currently, 31² MFIs have been licensed by the NBE and started delivering microfinance services since the issuance of the proclamation. These MFIs aim at poverty alleviation through targeting specific groups (reaching the poor) and group-based lending.

Regarding delivery of financial services access to institutional credit was very limited in Ethiopia. Because of this limited access, the majority of the poor get

¹ The term *Derg* is equivalent to a committee in Amharic Language referring to a group of junior military officers that took over political power in 1974.

² As per the database of National Bank of Ethiopia, there are 31 MFIs in Ethiopia as of December 31, 2011.

financial services through informal sources like moneylenders, Iqqub³, Iddir (mutual aid society, burial society), merchants, friends and relatives, etc.

2. Background of the study

An overwhelming majority of the world's poor live in the third world countries. Various approaches have been employed in alleviating poverty of which provision of credit that targets the poor is one. Many are now of the opinion that allowing the poor to have command over resources through credit can contribute towards poverty alleviation. Gibbons (1992) argues that the best way to do something about poverty is to let the people do their own thing. Nobody will have more motivation to change his/her situation than the sufferer himself/herself.

According to Hunte (1996), default problems destroy lending capacity as the flow of repayment declines, transforming lenders into welfare agencies, instead of a viable financial institution. It incorrectly penalizes creditworthy borrowers whenever the screening mechanism is not efficient. Credit⁴ default may also deny new applicants access to credit as the bank's cash flow management problems augment in direct proportion to the increasing default problem.

Despite its remarkable achievements, there remained several weaknesses in microfinance that need to be improved to ensure its continuous development and successful implementation. A critical aspect of microfinance that needs to be focused on is the risks management aspect. Microfinance is entrapped by various types of risks, such as default risk (Goetz et, al. 1995), disaster risks (Karlán, 2005), currencies risk, and interest rate risk and commercialization risk. However, this study focused on the issue of credit default risk in the specific context of microfinance. Default risk is chosen instead of other types

³Traditional credit and saving institution with rotating fund. System of saving whereby people form groups and pay periodically a fixed amount of money, which will be collected in a common pool, so that, in rotation, each member of the group can receive one large sum, i.e. the sum of money paid by all in one period.

⁴ Credit risk is one of the most significant risks from a MFIs perspective.

of risks because default risk has severe negative repercussions on the success of microfinance. A series of defaults could lead to liquidity problem in the MFIs and would consequently limit the ability of the MFIs to extend credit/loan to other recipients. As would be revealed later, due to the serious consequences of defaulted credits, the MFIs might resort to various ways to reduce the possibility of default among the borrowers.

3. Objective of the Study

The principal aim of this study is to inspect the foundations of credit default from making on-time repayment of their debt in the microfinance institutions of Ethiopia scheme, with particular reference to borrowers in the selected 6 credit and saving institutions.

4. Research Hypotheses

In order to achieve the problem statement and objective above, the study develops the following research hypotheses:

The bond flanked by credit default and credit/loan rationing and the factors affecting them are hypothesized based on matter-of-fact experiences. For that reason, borrowers' socio-economic distinctiveness, the outlook of the lending agency in properly screening borrowers and other economic state of affairs are hypothesized to explain credit repayment recital of borrowers.

H₁: credit default has positive relationship with borrowers' socio-economic distinctiveness.

H₂: Default risk has positive relationship with credit repayment performance.

Further, it is hypothesized that alike variables that are thought to elucidate credit repayment performance explain the credit rationing mechanism to be employed by the lending or credit and saving institutions.

H₃: credit repayment performance has positive relationship with credit rationing mechanism of lending institutions.

Finally beneficiary's livelihood is expected to improve because of involvement in the credit scheme provided that the credit/loan is utilized effectively on activities that are income generating.

H₄: credit scheme has positive relationship with the method credit/loan is utilized.

5. Literature Review

Credit is the pivot on which the development of any sector rests. The Microfinance Institutions (MFIs), which are targeted towards providing smaller loans to the masses, have been operating in the country for long towards satisfying the credit demand of the lower class of the economy, mainly composed of the informal sector. Meanwhile, credit risk is the most important of the risk categories. It is the potential loss resulting from the poor quality of the MFIs assets, particularly its credit/loan portfolio. The most obvious manifestation of risk in credit projects is poor portfolio quality that leads to bad debt losses that erode the capital of the lending microfinance institution. The major variables that should determine a MFI's risk classification system are: past and present experience with overdue payments and type of methodology used in delivering loans.

5.1. Types of Risks Faced by Microfinance Institutions

There are a number of risks that a MFI has to face. These risks could be of delinquencies, frauds, staff turnover, interest rate changes, liquidity, regulatory, etc. but all these risks can broadly be classified into four major categories. These are credit risk, operational risk, market risk and strategic risk (Rangan 2010).

Of the above four categories, Credit risk and Market risk are directly of financial nature and hence are called Financial risks while Operational risk and Strategic risk are of non-financial character and result mainly from human errors, system failures, frauds, natural disasters or through regulatory environment, weak board, and poor strategy.

Credit risk is directly related to the portfolio of the organization and is one of the most significant risks from a MFI perspective. Whenever an MFI lends to a client, there is an inherent risk of money not coming back, i.e. the client turning into a defaulter, this risk is called a credit risk. Credit risk is simply the possibility of the adverse condition in which the clients do not pay back the loan amount (Rangan 2010).

MFIs try to have an objective view of their credit risk and want to measure the extent of credit risk, which is the risk on their portfolio. There are various indicators, which help in measuring the credit risk profile of a MFI. Of these indicators, portfolio at risk (PAR) is considered to be the most effective and is now a very common indicator across MFIs. Apart from PAR, Repayment rate and Arrear rate are other ratios, which also provide information about the portfolio quality of a MFI.

Portfolio at risk or PAR tries to measure the amount of loan outstanding that the MFI can lose in case an overdue client does not pay a single installment from the day of calculation of PAR. PAR is the proportion of loan with overdue clients to the total loan outstanding of the organization. $PAR\% = (\text{Loan outstanding on overdue loans} / \text{Total loan outstanding of the MFI}) \times 100$. PAR is further refined by MFIs to make it meaningful by including ageing in it. So MFIs often calculate PAR 30, PAR 60, and PAR 90, etc. PAR 30 means outstanding of all loans, which have overdue greater than 30 days as a proportion of total outstanding of the MFI. Besides, arrear rate equals total overdue over total loan outstanding times hundred.

Causes of High Credit Risk and managing them are (1) poor MIS, (2) poor screening of borrowers, (3) weak appraisal of loans, (4) unclear communication about product and methodology, (5) lack of immediate follow-up, (6) mixing with other social activities, (7) poor product, (8) natural disasters, (9) corruption at field staff level such as taking bribe for loans or frauds that can result in delinquencies, (10) and demotivated employees.

5.2. Real Incidences of Defaults in Microfinance

According to Kassim, Salina and Rahman (2008), it can be concluded that the MFIs are only concerned about extending finance without much effort being made to provide any form of post disbursement supervision. Post-disbursement supervision is highly relevant in ensuring the success of a microfinance project due to the fact that around 80 per cent of the recipients of microfinance are illiterate women. Furthermore, around 82 per cent of these women had no business experience before joining the microfinance program, while the rest 18 per cent had some basic business experiences. The illiteracy of the recipients is

rather serious to the extent that some do not even know how to count the amount of money that they received from the MFIs.

Commonly, the MFIs provide loan without any technical assistance except for some briefing of around five to ten minutes to the recipients. It should be emphasized that the technical assistance is just as important and should complement the financial assistance in ensuring the success of the business project.

Several incidences of default happened due to: case 1: lack of post-disbursement supervision leading to moral hazard, case 2: lack of training on basic business skills and knowledge, case 3: lack of health awareness resulting in the need to spend on medical expenses, case 4: burdensome immediate repayment schedule, case 5: lack of motivation to improve standard of living, case 6: multiple borrowings from different MFIs.

6. Methodology

Given the above points in the mind of the researcher, this study adopted a mixed type of approach in collecting and analyzing data in order to better understand the research problem. A Mixed approach was implemented sequentially, in which the researcher started with gathering qualitative data and then gathered quantitative data.

There are 31 MFIs in Ethiopia that have been founded since the commencement of microfinance institution service in Ethiopia in 1996. This study, however, focused on and selected 6 MFIs based on credit default, size and status of the share company, i.e. categories⁵ of the microfinance institution. Hence, the author selected 6 MFIs by using simple random sampling from the list of the categories, namely Amhara Credit and Saving Institution (ACSI) (S.C.), and Addis Credit and Saving Institution (AdCSI) S.C. from large MFIs; Gasha Microfinance Institution (GMI) S.C. and Wisdom Microfinance

⁵ The National Bank of Ethiopia (NBE) categorizes Microfinance Institutions of Ethiopia as Large, Medium, and Small MFIs.

Institution (WMI) S.C. from medium MFIs; Ghion Microfinance Institution (GMI) S.C. and Metemamen Microfinance Institution (MMI) S.C. from small MFIs in order to represent the whole population which covers more than 19 per cent of the 31 MFIs found in Ethiopia. A representative sample can only be guaranteed by drawing a sample methodically, thus enabling the researcher to obtain reliable results (De la Rey 1978:16). A sample of 240 clients were also selected using random sampling in order to manage the study effectively concerning the reasons for default among those who did not repay and those who repaid slowly, and concerning the factors influencing timely repayment by the regular borrowers.

The main sources of data for this work were primary sources and document review. The selected 6 MFIs have conducted more than 5 rounds of credit/loans since they began their operations in the districts. Nonetheless, the author of this work only included five year round of credit disbursement the maturity of which has passed at the time of data collection, i.e. credit extended during the last 5 years of rounds from 2006 through 2010.

6.1. Determinants of Credit Default

The methodologies used in this study to investigate the determinants of credit default, credit/loan screening mechanism and assessing impact of the credit scheme are presented in detail hereunder.

The credit default equation is precisely based on the assumption that the verdict of the i^{th} borrower whether to repay the credit in full or not depends on an unobservable utility index, U_i , explained by a set of independent variables. This utility index, which designates that the probability of repaying credit in full will be greater if its value is larger, can be defined by a regression relationship as:

$$U_i = \beta'X_i + \varepsilon_i \text{-----} (1)$$

Where: U_i = Utility index, β = Vector of parameters, X_i = Vector of explanatory variables (Maddala 1983).

The reason why the study uses a utility index for the analysis of repayment performance is that, under normal circumstances, a borrower repays if he/she derives benefits from repaying. For example, if a borrower expects to get another round of credit, he/she will repay the current credit/loan.

In order to narrate this unobservable utility index (precisely a utility derived from repaying) to the verdict of repaying credit in full, the study assumes that:

$CD_i = 1$, if $U_i > 0$ (borrower repaid credit in full); or
 $CD_i = 0$, if $U_i \leq 0$ (borrower did not repay credit in full)

Where CD_i = credit default for the i^{th} borrower.

Assuming U_i are normally distributed with a zero mean and variance δ^2 , the probability that

$U_i > 0$ can be computed as:

$$P_i = \text{Prob}(U_i > 0) = F(U_i) = F(\beta'X_i) \text{-----} (2)$$

Where: F is the CDF – Cumulative Distribution Function.

Hence the likelihood function (the joint probability) is given by Maddala (1983).

$$C/L = \prod_{LR_i=1} P_i \prod_{LR_i=0} (1 - P_i) \text{-----} (3)$$

To glance whether a borrower has repaid his/her credit or not, it needs to categorize borrowers into two to address the issue of determinants total credit default. So, it has to look for an appropriate model that enables us to analyze the determinants of credit default and probability of falling in either of the two groups. Application of Ordinary Least Squares (OLS) which in this case is the Linear Probability Model (LPM) - since the dependent variable is dichotomous- will be incorrect because of the following major problems: 1) non-normality of error terms; 2) heteroscedasticity of error terms; and 3) possibility of estimated probabilities lying outside the [0,1] range.

In practice, the probability of repaying credit in full is expected to be non-linearly related to a set of explanatory variables, the estimated probabilities lying in the [0, 1] range. Such a specification would provide us with a Cumulative Distribution Function (CDF) from which the two commonly chosen distributions; namely, the logistic and the normal CDFs emerge. These

CDFs give rise to the logit and the probit models respectively (Gujarati, 1995, Pindyck and Rubinfeld, 1981).

The logistic and the normal CDFs are very similar in their shape except that the former is slightly fatter around the tails than the latter (Maddala 1983). Although the choice between either of these models is difficult based on theory, the probit model is chosen for the purpose of this study because of the simplicity of getting the marginal effects of the coefficients.

On the other hand, credit/loan diversion rate, which is included as one explanatory variable in the repayment equation, is itself dependent on some of the other explanatory variables in the same equation. This necessitates the use of its fitted values to avoid interdependence between the variable and the error terms. The values of credit/loan diversion rate (ratio of amount of credit/loan diverted to total credit received) are limited between zero and one. Although the use of OLS is possible here, the two-limit Tobit⁶ is a commonly applied model, in cases when the outcome is a probability or a percentage (Long 1997). This model is specified as:

$$CDR_i^* = \gamma X_i + \epsilon_i \text{-----} (4)$$

Where: CDR_i^* is a latent variable and X_i and ϵ_i are set of explanatory variables and error terms respectively.

If CDR_i is the observed variable, the Tobit model will be:

$$\begin{aligned} CDR_i &= 0, \text{ if } CDR_i \leq 0 \\ &= CDR_i^*, \text{ if } 0 < CDR_i^* < 1 \\ &= 1, \text{ if } CDR_i^* \geq 1 \text{-----} (5) \end{aligned}$$

Where: 0 and 1 are the lower and upper limits respectively. Thus, the models for credit default and credit/loan diversion can be given as follows:

$$CD = f(AG, GEN, EDU, CSZ, TM, CDR, INCOM, INCA, SRP, SPV, AREA, NDP, \epsilon_j) \text{---} (6)$$

⁶ The model is called *Tobit* because it was first proposed by *Tobin* (1958), and involves aspects of Probit Analysis, see Tobin J (1958), "Estimation of Relationships for Limited Dependent Variables", *Econometrica* 26, 24-36.

Where: CR = Credit Default

$$CDR = f(NDP, SPV, EDU, FR, INCA, CSZ, NTB, SRP, \epsilon_j) \text{ ----- (7)}$$

Where CDR = Credit Diversion Rate

But since the variable education is qualitative in nature, it is required to deem the mutually exclusive levels of education unconnectedly. In view of that, the study classifies borrowers into illiterate, primary, and high school and above high school. As a result, it needs dummies to be initiated so as to take care of levels of education. The study investigated in the subsequent section since the majority of the respondents are primary level and only very few are in the first, third and fourth category, it is better to classify them as those who are illiterate and those who are literate. Hence, the study needs one dummy to take care of these two categories. That is why equations (6) and (7) become:

$$CD = f(D, AG, GEN, EDU, CSZ, TM, CDR, INCOM, INCA, SRP, SPV, AREA, NDP, \epsilon_j) \text{ -- (8)}$$

$$CDR = f(D, NDP, SPV, EDU, FR, INCA, CSZ, NTB, SRP, \epsilon_j) \text{ ----- (9)}$$

Underneath are given the list of the variables jointly with their definitions:

1. D = 1 if a borrower has gone to school and zero otherwise
2. CD = Credit Default (CD = 1 if fully repaid, zero otherwise)
3. AG = Age of borrower
4. GEN = Gender of borrower
5. EDU = Educational level of borrower
6. CSZ = Credit/loan size in Ethiopian Birr (ETB)
7. TM = Timeliness of Credit/loan release
8. CDR = Credit/loan Diversion Rate (ratio of credit/loan diverted to total credit received)
9. INCOM = Income from activities financed by credit/loan (annual)
10. INCA = Annual income from other activities (not financed by the credit/loan).
11. SRP = Suitability of Repayment Period
12. FR = Use of Financial Records
13. SPV = Adequacy of Supervision visits made to a borrower
14. AREA = Location of residence of borrower (1= urban 0= rural)
15. NDP = Number of Dependents

16. NTB = Number of Times Borrowed

17. ϵ_i = Error terms

3.2. Credit Screening (rationing) Mechanism

The method of analysis employed by Hunte (1996) stands appropriate for this section of the study unlike the credit repayment equation, the dependent variable for the credit/loan rationing equation is continuous and limited between 0 and 1, i.e. the study has some who are rationed credit and others who are not. The appropriate model is Tobit (Maddala 1983). But for the purpose of this study, since it is going to use a dummy variable by defining credit rationing to be equal to 1 if a borrower is not rationed and zero otherwise. Thus, the study used the logit model, which is given as:

$$CRAT_i^* = \alpha X_i + \epsilon_i \text{-----} (10)$$

Where: $CRAT_i^*$ = is credit/loan rationing ($CRAT = 1$ if a borrower is not rationed and zero otherwise).

X_i = Set of explanatory variables

ϵ_i = Error terms

NB: $CRAT_i^*$ are latent variables like the CR_i^* 's. All the explanatory variables of credit repayment equation are to be employed by the $CRAT_i$ equation as well. Comparison of the sign and level of significance of the estimates in the two equations, i.e. credit repayment and credit/loan rationing equations, will accomplish the task of evaluating the accuracy of the screening mechanism as done in Hunte (1996).

7. Results and Discussion

This section presents Descriptive Statistics and Econometrics Analysis of the study's findings on the credit default risk in the selected 6 MFIs of Ethiopia. The average repayment delay period and default rates are calculated and factors and/or determinants that contributed to credit default, slow repayment and credit screening mechanism are also presented in separate sections.

Table 1 Number of clients being served by the selected 6 MFIs

Name of MFIs	Operations of selected MFIs				Number of Clients		
	Head office	Main Branch	Sub Branch	Districts	Male	Female	Total
ACSI	Bahir Dar	10, 13 ⁷	188	411	228,412	431,218	659,630
AdCSI	A.A.	7	17	116	82,801	109,760	192,561
Wisdom	A.A.	23	27	5	19,858	36,877	56,735
Gasha	A.A.	N.A.	6	17	6,444	4,467	10,911
Metemamen	A.A.	N.A.	5	15	419	10,056	10,475
Ghion	A.A.	N.A.	3	13	980	730	1,710
Total	---	40	246	577	338,914	593,108	932,022

Note: A.A. stands for Addis Ababa the head office location of MFIs. And N.A. stands for not available.

Source: compiled from author's survey, April 15, 2011.

In this stage the method of model estimation will be offered and the estimation outcomes will be discussed in detail.

As discussed in the methodology part, one of the explanatory variables that thought to influence the credit default equation is credit/loan diversion rate. Since this variable was identified dependent on some variables that are included in the credit default equation, credit diversion equation was estimated first and the fitted values were used in the equation of credit repayment performance, in order to avoid endogeneity.

During the estimation process, the equation for loan diversion was detected to have problem of heteroscedasticity. Hence, this method employs the estimation of interval regression. According to the procedure interval regression is

⁷ There are 13 Micro Banks in the operation of Amhara Credit and Saving Institution (ACSI) other than main branches. Besides, 7 micro banks are also found in AdCSI.

estimated using variables generated from the dependent variable and was shown how such a regression is used to obtain the same results as the Tobit regression. Thus, to obtain the robust standard errors, it is only a matter of adding the robust option to the interval regression. Accordingly, an interval regression is estimated using the variables generated from the dependent variable in the same way as explained above and on the other hypothesized explanatory variables. Next, the robust option is used on the same regression to correct for the problem of heteroscedasticity. The final estimates so obtained are given below.

Table 2: Maximum likelihood estimation for credit/loan diversion

Number of obs = 210
Wald chi2(8) = 15.64
Log likelihood = -106.99844
Prob > chi2 = 0.0478

	Coefficients	Robust Std. Err.	Z-value	Sig.
D	-0.2056432***	0.113016	-1.81	0.067
CSZ	0.0000411	0.0001404	0.29	0.770
SRP	-0.3266075*	0.1147342	-2.85	0.004
INCA	-0.0000298	0.0001758	-0.17	0.865
FR	0.1500751	0.1702739	0.88	0.378
SPV	-0.0172498	0.0985662	-0.18	0.861
NDP	0.0004972	0.0191063	0.03	0.979
NTB	0.0754362***	0.0481348	1.57	0.117
Cons	-0.2642259	0.2515055	-1.05	0.293
/sigma	0.5177089	0.0467682		

*significant at 1%

***significant at 10%

The estimated model is significant at the 5% level. As shown in table 2, credit diversion is positively related to number of dependents supported by the borrower, use of bookkeeping, credit/loan size and number of times borrowed from the same source. Education, income from other sources, loan supervision and suitability of credit repayment period were found to be negatively related

to loan diversion. Suitability of repayment period was found to be significant at 1%, while education and number of times borrowed were found to be significant at 10%.

The sign of the variable representing the use of financial recording systems has an unexpected sign, i.e. positive however insignificant. The reason for this could be the fact that, even the few educated ones are unable to use modern and accurate methods of keeping financial records. The rest of the variables have exhibited the expected signs. Further, the results indicate that education, number of times borrowed and suitability of repayment period are significant determinants of credit diversion. The positive sign for education indicates that, literate borrowers have effectively used the loan for the intended purposes. But those who borrowed for more years on the average have contributed to the increase in the probability of diversion, may be due to the fact that they no more need further credits from the same source.

Imminent to the discussion of the estimates of the probit model for credit default equation, the existence of problem of heteroscedasticity has been detected. This has necessitated the estimation of robust model. The estimation results are presented in table 3. Nevertheless, the overall goodness of fit indicates that it is significant at 1%, implying that the explanatory variables used in the regression equation explain the variation in the dependent variable quite well.

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Table 3: Maximum likelihood estimate of a probit model for credit default

Probit estimates

Number of obs = 210

Wald chi2(10) = 53.07

Prob>chi2 = 0.0000

Pseudo R² = 0.8070

CD	Coefficients	Robust Std. Err.	Z- value	Sig.
D	1.218347***	0.6817127	1.79	0.074
GEN	-0.1295234	0.6335709	-0.2	0.838
AG	0.0077951	0.1234208	0.06	0.95
AGSR	-0.00043	0.0013922	-0.31	0.757
INCOM	0.0346739	0.0145101	2.39	0.017
SRP	2.166316*	0.6107892	3.55	0.000
NDP	-0.0415804	0.1120186	-0.37	0.710
CSZ	-0.0020723**	0.001014	-2.04	0.041
SPV	0.9705793***	0.5811818	1.67	0.095
FITCDR	-9.794303**	4.710661	-2.08	0.038
Cons	-3.491235	2.933985	-1.19	0.234

*significance at 1%

**significance at 5%

*** significance at 10%

Among the variables that were thought to affect credit repayment performance, variables like use of financial recording methods, income from other sources and area are dropped because they were inestimable using the software.

Explanatory variables used in the estimation of credit repayment performance equation were found significant. According to the estimates, credit diversion fitted value of credit/loan diversion rate (FITCDR) is significant and negatively related to credit repayment performance as expected. The negative sign probably implies the use of diverted funds for non-income generating purposes, and it is significant at 5%.

Consequently, gender, credit/loan size and number of dependents are all negatively related to the probability of credit repayment, none being

inconsistent with prior expectation. Only credit/loan size is significant at 5% level. This shows that the higher the credit/loan size, the lower the probability of repaying the credit/loan. The negative sign for gender indicates that female borrowers are better payers of credit than their male counterparts, although it is not significant. On the other hand, age was found to be positive, while age squared turned out to be negative. This shows that, as age increases, the probability of credit repayment increases up to a certain level of age beyond which performance will decline, i.e. there is a non-linear relation. Both these variables are statistically insignificant.

Moreover, incomes from activities financed by the credit/loan, suitability of repayment period and loan supervision literacy are positively and significantly related to loan repayment performance. The coefficient of the dummy for education above grade zero or literate is significant 10% level of significance, indicating that with more education borrowers can use the credit efficiently and invest on more productive and income generating activities enabling them to settle their credit/loan obligation in time.

Harmonizing table 4 below, 6 variables included in the model were found to be significant. According to the estimates presented in the table, credit diverters, borrowers supporting larger number of dependents, borrowers earning more income and literate borrowers are more rationed, i.e. the probability of such borrowers being rationed is high. On the other hand, borrowers who are older, male, apply for larger loan size, perceive supervision as adequate, and perceive the repayment period as suitable. Literacy level, age, suitability of repayment period, number of dependents and credit diversion are found to be significant in the model.

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Table 4: Maximum likelihood estimate of a logit model for loan rationing

Probit estimates

Number of obs = 210

Wald chi2(10) = 22.95

Prob > chi2 = 0.0180

Log likelihood = -72.055849

Pseudo R² = 0.1246

CRAT	Coefficients	Robust Std. Err.	Z- value	Sig.
D	-0.5928361**	0.2545076	-2.33	0.020
GEN	0.1747426	0.2897258	0.6	0.546
AG	0.1202621***	0.064093	1.88	0.061
AGSR	-0.0013319***	0.0007051	-1.89	0.059
INCOM	-0.0073434	0.0050361	-1.46	0.145
SRP	0.5073275***	0.3421386	1.78	0.108
NDP	-0.1135034**	0.0502756	-2.26	0.026
CSZ	0.0002257	0.0004294	0.53	0.599
SPV	0.0408717	0.2420632	0.17	0.866
FITCDR	-2.878546***	1.72271	-1.67	0.095
Cons	-1.534739	1.475238	-1.04	0.298

significance at 5% *significance at 10%

With this brief description of the estimation result, the evaluation of the loan rationing (screening mechanism), according to Hunte (1996), if a variable is positively signed in both equations, then the borrower with such a characteristic is correctly identified as creditworthy. If it is negatively signed in both equations, then the borrower with such a characteristic is correctly identified as non-creditworthy and hence should be rationed.

Meanwhile, if on the other hand, a variable is positive in the credit repayment equation and negative in the rationing equation, then the screening technique is incorrectly rationing a creditworthy borrower. Likewise, if a variable is negative in the repayment equation but positive in the rationing equation, it implies that the borrower having such a characteristic that results in poor credit

recovery is less rationed while he/she must have been rationed more. In view of that, borrowers who are aged perceive the repayment period as suitable and perceive credit/loan supervision as adequate are correctly identified as being creditworthy and were not rationed or are less rationed. Correspondingly, borrowers who are credit diverters and support larger number of dependents are correctly identified as being non-creditworthy, and hence are rationed.

8. Conclusion

The findings of the econometric analysis presented in section 4 reveal that, education, suitability of repayment period and numbers of times borrowed are significant determinants of the probability of loan diversion.

Factors that are found to be significant determinants of credit default performance were education, credit/loan size, and credit diversion, availability of other credit sources, credit/loan supervision, and suitability of credit repayment period and income. All of these factors except credit diversion and credit/loan size increase the probability of credit default. The number of dependents and being male reduce the credit repayment performance in addition to credit diversion and credit/loan size.

Coming to the screening technique, the empirical evidences show that although there were some problems of separating between creditworthy borrowers and those who are not, in most of the cases the technique was found to be good. Factors like income, level of education were incorrectly used to ration creditworthy borrowers, while the selected lending institutions wrongly used credit/loan size and gender to identify borrowers who shouldn't be rationed despite their being non-creditworthy. The rest gender variables were used efficiently and accurately to identify borrowers into creditworthy and non-creditworthy.

Particularly, credit diversion was found to be one of the important and significant factors influencing credit default negatively, i.e. it increases default risk significantly. This variable is itself influenced by many factors, of which loan supervision, education and suitability of repayment period were found to

reduce the probability of diverting credit to non-productive uses that ultimately lead to reduced recovery rate. So, there is a need for a continuous supervision on credit/loan utilization and training so as to reduce both the problem of using credit/loan for non-income generating activities as well as lack of skill observed because of the wide-scale illiteracy on the customers of MFIs in Ethiopia.

Sustainable microfinance programs, such as the Grameen Bank, were found to have low default rates (roughly an average of 3 per cent). On the contrary, this study observed that credit default risk in Ethiopian Microfinance Industry is an average 27.1 per cent, which is very high. Therefore, reducing the selected MFIs default rate is a survival priority for the credit/loan program. Sufficient repayment rates are necessary to facilitate re-disbursement of financing, and they contribute to achieving the MFIs objectives. Borrowers' major source of income was found to be the business enterprise particularly in urban area, and the predominant cause of default was poor business performance. Therefore, it can be concluded that borrowers who depend on their poorly performing businesses default.

References

- De La Rey, R. P 1978. 'Statistische Methoden in Seilkundige nalisierung', Manual for Psychology students. Pretoria:: University of Pretoria.
- Gibbons, D. S. 1992. 'The Grameen Reader', 2nd edition. Dhaka: Grameen Bank.
- Goetz, A. M. and R, Sen Gupta. 1995. "Who takes the Credit? Gender, power and control over loan use in rural credit programmers in Bangladesh." *World Development. Vol. 24.*
- Gujarati D. N. 1995. 'Basic Econometrics', 3rd Edition, New York: McGraw Hill.
- Hunte, C. K. 1996. 'Controlling Loan Default and improving the lending Technology in Credit Institutions', *Savings and Development. Vol. xx, No.1*, available at www.gdrc.org/icm/grameen-ref.html, viewed on March 07, 2011.
- Karlan, D. and Zinman, J. 2005. 'Observing unobservable: Identifying information asymmetries with a consumer credit field experiment', *CEPR Discussion Paper. London.*
- Kassim, Salina and Rahman, Md. Mahfuzur. 2008. 'Microfinance.' Malaysia: International Islamic University. available at <http://mpra.ub.uni-muenchen.de/16123/> accessed on March 4, 2011.
- Ledgerwood, J. 1999. 'Microfinance Handbook': An Institutional and Financial Perspective. Washington: the World Bank.
- Maddala, G. S. 1983. 'Limited Dependent and Qualitative Variables in Econometrics'. New York: Cambridge University Press.
- Pindyck, R. S. and Rubinfeld, D. L. 1981. *Econometric Models and Econometric Forecasts*, 2nd Edition, New York: McGraw Hill.
- Rangan, V. Kasturi. 2010. 'types of risks faced by microfinance institutions', *India. Microfinance Business News, Available at* <http://indiamicrofinance.com/types-risks-faced-microfinance-institutions.html> accessed on May 10, 2011.