Predicting Credit Default among Micro Borrowers in Ghana

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Abstract
Microfinance institutions play a major role in economic development in many developing countries. However many of these microfinance institutions are faced with the problem of default because of the non-formal nature of the business and individuals they lend money to. This study seeks to find the determinants of credit default in microfinance institutions. With data on 2631 successful loan applicants from a microfinance institution with braches all over the country we proposed a Binary logistic regression model to predict the probability of default. We found the following variables significant in determining default: Age, Gender, Marital Status, Income Level, Residential Status, Number of Dependents, Loan Amount, and Tenure. We also found default to be more among the younger generation and in males. We however found Loan Purpose not to be significant in determining credit default. Microfinance institutions could use this model to screen prospective loan applicants in order to reduce the level of default.
Keywords: Microfinance, Loan Default, Default Prediction, Logistic Regression

1. Introduction

In a bid to reduce poverty, the Government of Ghana has liberalized the non-banking financial sector. This development has led to the setting up of many microfinance companies. In Ghana, Bank of Ghana is charged with the responsibility of issuing licenses to Microfinance Companies. As at the end of March 2014 there were over 400 licensed microfinance companies (Bank of Ghana).

The intense competition among these microfinance institutions for customers has driven a lot of them to overlook critical details in assessing the credit worthiness of prospective borrowers. To be sustainable these microfinance companies need to adopt more effective and innovative ways to control credit risk.

Microfinance companies have traditionally targeted the non-formal sector. The non-formal sector in Ghana is generally not organized. In this country, most streets are not named, most houses are not numbered and most citizens do not have National Identity Cards. This makes it very easy for borrowers to abscond.

Interest rates charged by Microfinance Institutions (MFIs) in Ghana are so high that you ask yourself if they are really there to reduce poverty. The reason most MFIs give for high interest rate is that default rates are quite high. Bad loans generally prevent financial institutions from adequately providing loans to customers. In trying to arrest this situation the Bank of Ghana has granted three companies license to operate as credit reference bureaus. Unfortunately due to cost constraints most microfinance companies cannot afford the services of credit reference bureaus. Also these credit reference bureaus are unable to capture records of all loan defaults in the country since their database is made up of information that are provided to them by financial institutions. Until such a time when the database of credit reference bureaus are exhaustive enough to capture all loan defaults in the country, it is important for microfinance companies to develop their own models to screen prospective customers. The aim of this research is to provide a model for predicting whether or not a person would default so that an appropriate interest could charge based on information provided by the customer.

2. Literature Review

2.1 What is Microfinance

"Microfinance" is often seen as financial services for poor and low-income clients(Ayayi, 2012; Mensah, 2013; Tang, 2002). In practice, the term is often used more narrowly to refer to loans and other services from providers that identify themselves as "microfinance institutions" (MFIs) [Consultative Group to Assist the Poor (CGAP) 2010]. Microfinance can also be described as a setup of a number of different operators focusing on the financially under-served people with the aim of satisfying their need for poverty alleviation, social promotion, emancipation, and inclusion. Microfinance institutions reach and serve their target market in very innovative ways (Milana 2012).

Microfinance operations differ in principle, from the standard disciplines of general and entrepreneurial finance. This difference can be attributed to the fact that the size of the loans granted with microcredit is typically too small to finance growth-oriented business projects. The CGAP (2010) identifies some unique features of microfinance as follows;

- Delivery of very small loans to unsalaried workers
- Little or no collateral requirements
- Group lending and liability
- Pre-loan savings requirement
- Gradually increasing loan sizes

Implicit guarantee of ready access to future loans if present loans are repaid fully and promptly Microfinance is seen as a catalyst for poverty alleviation, delivered in innovative and sustainable ways to assist the underserved poor, especially in developing countries(Dixon, Ritchie, & Siwale, 2007; Spiegel, 2012). Economic development may be achieved by helping the underserved poor to engage in income-generating/poverty reduction activities through entrepreneurship (Milana 2012). On December 18, 1997, the United Nations (UN) passed a microcredit resolution, also known as the Grameen Dialogue of 1998 at its General Assembly. The resolution was adopted because of the importance of microcredit programs in poverty reduction (Elahi & Demopoulos 2004). The UN later declared the year 2005 as International Year of Micro Credit. Globally, Microfinance has become an important sector. It is estimated that more than 3,500 institutions are meeting the demands of 205 million clients with a volume that is still uncertain but substantial (Maes and Reed 2012). The global asset size of Microfinance institutions is estimated to be over US$70 billion (*Mix Market*). The independent microfinance think-tank housed by the World Bank, Consultative Group to Assist the Poor (CGAP) and Swiss manager and adviser *Symbiotics* estimate the global asset size at US$7 billion (Milana, 2012). Microfinance is the best known, most developed sector of the so-called 'impact investing' world of credit suppliers (Grene 2012).

2.2 Default in Microfinance

Default in microfinance is the failure of a client to repay a loan. The default could be in terms of the amount to be paid or the timing of the payment. MFIs can sustain and increase deployment of loans to stimulate the poverty reduction goal if repayment rates are high and consistent (Wongnaa 2013). MFIs are able to reduce interest rates and processing fees if repayment rates are high, thus increasing patronage of loans. A high repayment rate is a catalyst for increasing the volume of loan disbursements to various sectors of the economy (Acquah & Addo, 2011).

The agriculture sector is experiencing a decline in access to credit due to poor loan repayment performance. Poor management procedures, loans diversion and unwillingness to repay loans as well as other socioeconomic factors are likely causes of poor loan repayment performance (Wongnaa 2013).

Income, farm size, age of farmers, farming experience and level of education of farmers contribute positively to the credit worthiness of farmers (Arene 1993). A study conducted by Mashatola & Darroch, (2003) in Kwazulu-Natal, South Africa showed that the following factors affect loan repayment; farm size (proxied by annual gross turnover), access to off-farm income, and average annual gross turnover relative to loan size. These factors provide additional liquidity to fund future operations and debt repayment. Amount of loan obtained by farmers, years of farming experience with credit and level of education are major factors that positively and significantly influence loan repayment(Oladeebo & Oladeebo, 2008). Amount of loan received, age of beneficiary, household size, years of formal education and occupation are important predictors of loan repayment (Eze & Ibekwe 2007).

The age of borrowers have also been seen to be significant in determining default (Dunn, 1999). According to Wongnaa, (2013) borrowers, especially farmers who are younger (21-41 years) are very energetic and are likely to work effectively to increase their yield. They are therefore likely to raise more income and pay off their debt. A study conducted by Afolabi, (2010) on Loan Repayment among Small Scale Farmers in Oyo State, Nigeria confirms this.

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. Literate farmers will pay off their loans better than illiterate farmers because they understand the advantages of prompt loan repayment (Oladeebo & Oladeebo, 2008).

Wongnaa, (2013) further states that borrowers who are married are likely to spend much of their income on their families. Married borrowers are likely to have larger families than the ones that are not married. Borrowers that are single are therefore more likely to pay off their debts than the married ones. Although larger families are likely to have higher expenses, they tend to have a greater labour force than smaller families; hence they can produce more and raise more income and therefore have better repayment ability(Dinh & Kleimeier, 2007).

The number of years of experience in a particular occupation tends to have a positive effect on a borrower's repayment ability. The higher the number of years' experience, the better the repayment ability. Oladeebo & Oladeebo, (2008), state that the more the farming experience with credit use, the more the ability of the farmer to generate enough funds to repay agricultural loans. This might arise from better management of funds, thus resulting in increased productivity which in turn leads to higher farm income and high repayment of loans.

Number of supervisory visits by credit officers also affects repayment ability. Visits by loan officials to borrowers will motivate the borrowers to worker harder and make sure the loans given to them are not diverted to unintended purposes. Therefore borrowers who are visited frequently may have higher repayment rates. A case study of village credit institutions in Gianyar, Bali, showed that because of the high mobility of staff of the MFIs, loan repayment rates were high. They applied mobile banking techniques to collect savings deposits and loan repayments in person. It forced borrowers to repay their loans regularly and on time (Arsyad, 2006).

Profit motivates borrowers to repay their loans. Since profits are additions to principals, borrowers who are able to make substantial profits are expected to have higher repayment rates. A farmer who makes losses after production will not be able to repay loans.

Females are normally regarded as more disciplined when it comes to loans management. Therefore females may have higher repayment rates. From a study conducted at a Tunisian MFI, Baklouti, (2013)concluded that being female and married is likely to increase the borrower's repayment probability. Based on these findings, the study highly recommends targeting the female groups. They default less frequently on loans possibly because they are generally inclined towards the culture of financial discipline (Bhatt and Tang 2002). In addition, repayment rates may be expected to be higher for women because they are likely to choose the relatively less risky projects (Sharma & Zeller, 1997).

2.3 Default Prediction Techniques

Several Researchers have developed several models for prediction of default (H. Abdou, Pointon, & El-Masry, 2008a; Baklouti, 2013; Blanco, Pino-Mejías, Lara, & Rayo, 2013; Ciampi & Gordini, 2013a; C.-L. Huang, Chen, & Wang, 2007; KARAA & KRICHENE, 2012; Kocenda & Vojtek, 2009; Laitinen, 2010; Lugovskaya, 2010). These techniques can be broadly categorized as follows: (1) Statistical models: linear discriminant analysis, logistic regression, probit regression, *k* nearest neighbour, classification tree, etc. (2) Mathematical programming methods: linear programming, quadratic programming, integer programming, etc. (3) Artificial intelligence techniques: artificial neural networks, support vector machines, genetic algorithm and genetic programming, rough set, etc. (4) Hybrid approaches: artificial neural network and fuzzy system, rough set and artificial neural network, fuzzy system and support vector machines etc. (5) Ensemble or combined methods: neural network ensemble, support vector machine ensemble, hybrid ensemble etc.

3. Methodology and Data Estimation Techniques

3.1 Data Source and Sampling Technique

In this section we describe our data set and how we chose our samples. Our data was obtained from one of the leading microfinance companies in Ghana with branches in all the 10 regions of the country. Customers at the point of applying for the loan volunteer their personal data. The data was then extracted from applications filed from January 2009 to June 2013. Within this period the microfinance company received 42,548 loan applications from individuals across the country and approved 23,498. Our data contains information on only individuals that were granted the loan and does not contain those who were denied. The credit worthiness or Probability of Default of rejected applicants was therefore not considered. This may result in potential bias in the model developed but this is common with other researchers (Kocenda & Vojtek, 2009). Of those who were offered loans 5630 defaulted representing a default rate of about 24%. Also for those who had more than one loan the loans were aggregated. From the data we randomly selected 1100 defaulters and 1531 non-defaulters. Default was defined by the microfinance institutions as a loan that is overdue for 90 days with payments on interest and or principal, which is consistent with the literature.

3.2 Data Analysis Method

Several Researchers have developed several models for prediction of default (H. a. Abdou, 2009; H. Abdou, Pointon, & El-Masry, 2008b; Blanco et al., 2013; Ciampi & Gordini, 2009; T. Dinh & Kleimeier, 2007; J.-J. Huang, Tzeng, & Ong, 2006; Jacobson, Lindé, & Roszbach, 2005; Kocenda & Vojtek, 2009; Laitinen, 2010; Lugovskaya, 2010; Ribeiro, Silva, Chen, Vieira, & Carvalho das Neves, 2012). Among the models used are Multiple Discriminant Analysis, first proposed by Fisher (1936), with work pioneered by Altman (1968) and more recently Lugovskaya, (2010), Probit models (Zmijewski, 1984).

More recently several researchers have also applied advanced statistical techniques like Genetic Algorithm (H. a. Abdou, 2009; C.-L. Huang et al., 2007; J.-J. Huang et al., 2006; Ong, Huang, & Tzeng, 2005), Neural Networks (H. Abdou, Pointon, & El-Masry, 2008c; Atiya, 2001; Blanco et al., 2013; Ciampi & Gordini, 2013b; KARAA & KRICHENE, 2012) and Support Vector Machines in predicting default probabilities. (Chen & Li, 2010; KARAA & KRICHENE, 2012; Xu, Zhou, & Wang, 2009)

3.2.1 Logistic Regression Model

Logistic regression analysis was first used to predict default probability by Ohlson (1980) and since then several other researchers have also used Logistic regression to predict default (Altman & Sabato, 2007; Jain, Gupta, & Mittal, 2011; Laitinen, 2010; Lugovskaya, 2010; Westgaard & Wijst, 2001).

Comparing with MDA, Logistic Regression Analysis (LRA) does not make assumptions of multivariate normality also Variance-Covariance matrix of the independent variables can be different for defaulting and non-defaulting customers. The logistic regression model offer the following advantages (1) fits the problem of default prediction, that is, Logistic regression has a score between 0 and 1 conveniently giving us the probability of default. (2) LRA models allow us to model dichotomous dependent variable in our case default and non-default. Lastly (3) estimated coefficients of the LRA model can show the relative importance of particular independent variable.

The equation for Logistic Regression can be generalized as

$$E(y) = \frac{e^{(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_i x_i)}}{1+e^{(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_i x_i)}} \qquad (1)$$

Where

$$y = \begin{cases} 1, & \text{If default occurs} \\ 0, & \text{for non default} \end{cases}$$

$E(y) = P(\text{Default occurs}) = \pi$ and $X_1, X_2\ldots,X_i$ are independent variables

Estimating for the β parameters a non-linear model like this can be a tedious exercise and hence the logit transformation $\pi" = \ln\left(\frac{\pi}{1-\pi}\right)$ is employed ie.

$$logit\ P(y) = \ln\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i \qquad (2)$$

The logit form is now linear and hence the OLS method can be used to estimate the β parameters easily. The β coefficient can now be used to determine the relative importance of a particular variable in determining the probability of default. The researchers opt for LRA in their analysis because of its advantages.

4. Results and Discussion

4.1 Results

Table 1 below displays the results for the case processing summary. The minimum ratio of valid cases to independent variables for logistic regression is 10 to 1, with a preferred ratio of 20 to 1. In this analysis, there were 2631 valid cases and 13 independent variables. The ratio of cases to independent variables is 202.4 to 1, which satisfies the minimum requirement. In addition, the ratio of 202.4 to 1 satisfies the preferred ratio of 20 to 1.

Table 1: Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	2631	100.0
	Missing Cases	0	.0
	Total	2631	100.0
Unselected Cases		0	.0
Total		2631	100.0

a. If weight is in effect, see classification table for the total number of cases.

Table 2 displays the results for the omnibus tests of model coefficients. The presence of a relationship between the dependent variable and combination of independent variables is based on the statistical significance of the model chi-square at step 1 after the independent variables have been added to the analysis. In this analysis, the probability of the model chi-square (1093.715) was < 0.001, less than or equal to the level of significance of 0.05. The null hypothesis that there is no difference between the model with only a constant and the model with independent variables was rejected. The existence of a relationship between the independent variables and the dependent variable was supported.

Table 2: Omnibus Tests of Model Coefficients

	Chi-square	Df	Sig.
Step	1093.715	13	.000
Block	1093.715	13	.000
Model	1093.715	13	.000

Table 3:
Hosmer and Lemeshow Test

Chi-square	df	Sig.
9.025	8	.340

From Table 3, since the p – value, 0.340, is greater than the significance level, $\alpha = 0.05$, we fail to reject the null hypothesis (H_0) and conclude that there is enough evidence to show that the hypothesized model fits the data set used in predicting credit default among microfinance institutions in Ghana. Also from the Classification Table (Table 4) the model was able to classify with an overall correct prediction percentage of 76.1%

Table 4 Classification Table

Observed	Predicted		
	Non-Default=0	Default=1	Percentage Correct (%)
Non-Default= 0	1135	396	74.1
Default=1	232	868	78.9
Overall Percentage (%)			76.1

Cut-off value =0.50

Table 5: Model Summary

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
2482.701	.340	.458

Under Model Summary we see that the -2 Log Likelihood statistic is 2482.701. This statistic measures how poorly the model predicts the decisions, the smaller the statistic the better the model. The Model Summary table also tells us how much of the variance in the dependent variable is explained by the model. It can be observed from Table 5 that, between 34.0% and 45.8% of the variance in predicting default was explained by the independent variable

Table 6: Variables in the Equation

Variable	Estimated β	S.E.	Wald	df	Sig.	Exp(β)
Age	.170	.045	14.260	1	.000	1.185
Sex	-.772	.138	31.428	1	.000	.462
C_Residence_Status	-.101	.053	3.604	1	.058	.904
C_Marital_Status	-.234	.121	3.739	1	.053	.791
GrossMonthlyincome	-.560	.079	50.129	1	.000	.571
YearsNoCurrEmp	-.278	.043	41.467	1	.000	.757
Region	-.065	.026	6.533	1	.011	.937
Loan_Purpose	.002	.071	.001	1	.981	1.002
M_OrigLoanAmt	.235	.062	14.158	1	.000	1.265
I_OrigTenor	-.533	.069	58.867	1	.000	.587
No_Dependents	.039	.021	3.397	1	.065	1.040
M_Other_Income	-1.605	.086	348.108	1	.000	.201
M_other_Deductions	.385	.080	23.203	1	.000	1.470
Constant	5.553	.478	135.135	1	.000	258.092

Table 6 summarises the results for the variables in the logistic regression model. From the results it can be observed that the variables age, sex, gross monthly income, number of years with current employer, region, original loan amount, original tenor, other income and other deductions were all significant in predicting credit default. The result also depict that among the significant variables sex, gross monthly income, number of years with current employer, original tenor and other income were negatively associated with credit default. This implies that an increase in these variables would result in a subsequent decrease in default.

Table 7: Pearson's Correlation between default and some independent variables

	Default	
	Pearson's Correlation	Sig. (2-tailed)
Age	0.021	0.000**
Sex	-0.101	0.000**
Residential Status	0.089	0.000**
Marital Status	-0.081	0.000**
Gross monthly income	-0.301	0.000**
Years with current employer	-0.149	0.000**
Loan amount	-0.216	0.000**
Tenor	-0.168	0.000**

* $p< 0.05$ ** $p< 0.01$

Table 7 displays the results for the Pearson's Product Correlation between default and some independent variables. The results show that there is a positive relationship between default and the independent variables age and residential status. The results also depicts that there is an inverse relationship between default and the independent variables sex, marital status, gross monthly income, years with current employer, loan amount and tenor. The results further show that all the variables obtained an alpha value less than 0.01 in all cases in relation to their association with credit default. We can conclude from Table 7 that the null hypothesis that there is no association between default and the independent variables should be rejected

4.2 Discussions

On gender it can be seen that a greater percentage of the loans went to males (about 84%). This could be due to cultural influence and points to the fact that males have easier access to credit than females (Godquin, 2004). Our results showed that males were 2.16 time more likely to default than females. Default among Single borrowers was also seen to be 1.26 time more likely than in married borrowers, this is consistent with literature(Agarwal, 2008; T. Dinh & Kleimeier, 2007; Kocenda & Vojtek, 2009; Vogelgesang, 2003). We also found Income Status to be a significant predictor of default. This is consistent with Jacobson and Roszbach, (2003) and Agarwal, (2008) among others, who found that income has significant predictive power and those with high income and high wealth are less likely to default on their debt. Kocenda & Vojtek, (2009) however found that default behavior did not depend on absolute income (difference between Income and Expenditure) but rather relative income (ration of expenditure to income). A Client may have high income but may have such high expenditure that the client is considered a risky client. It can also be observed from the results that the variables residential status, marital status, loan purpose and number of dependents were not significant in predicting default. Findings from the study show that there is an inverse association between credit default and the number of dependents. However in the logistic regression model the number of dependents that a borrower has was also found not to be significant in predicting default. This results is consistent with Mensah, (2013) who also found number of dependents not to be a significant predictor.

5. Conclusion

Microfinance has been globally accepted as the preferred medium to reach out to the rural and productive poor with banking services which includes micro credit to help alleviate poverty which is one of the United Nations millennium challenge goals. Micro credit default has been identified to be one of the major drawbacks of this laudable initiative as it depletes these revolving funds and reduces investors' confidence. Therefore, it is important to understand the factors that influence a loan beneficiary to default so that appropriate countermeasures can be developed to prevent and reduce the incidents of default.

In this study, logistic regression was applied to identify the factors associated with the occurrence of micro credit default. The analysis showed that age, gender, gross monthly income, tenure with current employer, loan amount, tenor of loan, number of dependents, other income and other deductions were important determinants of default.

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