

PREDICTING MICROFINANCE CREDIT DEFAULT: A STUDY OF NSOATREMAN RURAL BANK, GHANA

ABSTRACT:

This paper examined the factors predicting microfinance credit default in Northern Ghana. Data was collected from 409 microcredit beneficiaries of Nsoatreman Rural Bank who were located in urban, semi-rural and rural areas. Logistic regression was used to analyse the data. It was evident from the study that factors such as educational level, number of dependents, type of loan, adequacy of the loan facility, duration for repayment of loan, number of years in business, cost of capital and period within the year the loan was advanced to the client had a significant effect on credit default. To enhance the efficient management of microcredit, it is encouraged that Microfinance Institutions (MFI'S) adopt the group loan policy as the main mode of advancing micro loans to clients rather than the individual loan policy. Again, the MFI'S should team up with the Ministry of Education through the Non-Formal Education Division to organize functional literacy workshops for microcredit beneficiaries so as to equip them with the required knowledge to do successful business. Also, the MFI'S should consider giving loans with repayment duration of at least 12 months and at most 24 months.

Keywords: *Ghana, Microfinance, Credit Default, Predicting, Nsoatreman Rural Bank, Logistic Regression*

1.0 INTRODUCTION

Formal banking began in Ghana (then the Gold Coast colony) in 1896 with a local office of the Bank of British West Africa (Fry, 1976) with Barclays Bank DCO following in 1917 (Crossley and Blandford, 1975) and then the Gold Coast Cooperative Bank, which was established in 1945 as the first indigenous bank. But till date Ghana's commercial banking system, which has about twenty-three (23) major banks, reaches only about 5% of households and captures 40% of money supply (Sparks, 1995).

Most individuals, micro and small businesses in Ghana do not possess the documentary evidence required in the credit methodology such as long-standing bank-customer relationship and collateral which the traditional commercial banking principles demand (Quainoo, 1997).

Available data from the Registrar Generals Department indicates that 90% of businesses, registered in Ghana as of December 2012 were small and medium scale enterprises (SMEs). According to the 2010 population and housing census, 80% of the working population is found in the private informal sector while 63% of the populations live in rural areas and this group is characterised by lack of access to commercial credit facility. [\(who said this?, provide sources\)](#)

These observations indicate that a major barrier to the speedy development of the private sector which is the engine of growth of the economy is the lack of access to credit facility.

The core of Ghana's development strategy has focused on poverty reduction.

The foremost goal of Ghana's Growth and Poverty Reduction Strategy (GPRS) is to eradicate widespread poverty and growing income inequality, particularly among the productive poor who form the majority of the working population. These trends justify why governments in developing countries, which Ghana is no exception, and their developing partners in the recent decades have emphasised the need for microfinance as the means of providing small loans and other facilities like savings, insurance and transfer services to poor low-income household and microenterprises. [\(long sentence\)](#)

However, microfinance credit default constitutes a great hindrance to the smooth implementation of the microfinance policy in Ghana. According to the ARP Apex Bank 2012 annual report, the number of community and rural banks dropped from one hundred and eleven (111) to ninety-six (96) between the periods of 1993 and 2010 as a result of loan write-offs (Pollio and Obuobie, 2010).

None of the poverty alleviation programs through microcredit entered into by the Government of Ghana such as the Developing Cottage Enterprise Project (1989), National Board for Small-Scale Industries (NBSSI) revolving fund scheme (1992), NBSSI/DED credit scheme (1993) and NBSSI/NFED-Development Assistance (1994) being administered by the NBSSI (which charges 20% interest) has reached a 70% recovery rate (Quainoo, 1997).

As a consequence, these “revolving funds” are depleting in nominal as well as real terms, even without including the momentous costs to the government of operating them, with an insignificant outreach. [\(awkward sentence\)](#)

Empirical research shows that demographic, economic and financial ratios can help to predict company and individual credit default through the implementation of statistical techniques. Large and medium-sized enterprises have mainly been the focus of most literature (Brau and Woller, 2004).

The financial statements of Small Enterprises (SE'S) tend to disclose less information and are therefore thorny to interpret (Goddard and Jay, 1981). This prevents a widespread use of statistical models in countries like Ghana where there are large numbers of SE'S.

Empirical studies aimed at the prediction of credit default by financial ratios date back to the 1960s, when first Beaver (1966) used univariate statistical techniques and then Altman (1983) employed Multiple Discriminant Analysis demonstrated the success of these methods. After their pioneering work, similar studies were conducted for many firms in different countries.

Pollio and obuobie (2010) applied logistic regression on four factors and concluded that the probability of default increases with the number of dependents, whether the proceeds are used to acquire fixed assets, the frequency of monitoring, decreases with the availability of non-business income, years in business, the number of guarantors, whether the proceeds were used for working capital purposes and whether the client is a first-time borrower.

Kocenda and Vojtek (2009) developed a specification of the credit scoring model with high discriminatory power to analyse data on loans at the retail banking market. They were able to detect that the most important characteristics of default behaviour were the amount of assets the client has, the educational level, marital status, the use of the loan and the duration for which the client has had an account with the bank.

This paper presents a statistical analysis of the factors predicting microfinance credit default using logistic regression model.

This study is organised as follows: section 1 is the introduction followed by section 2 which describes the concept of methods employed. Section 3 presents the empirical analysis, results and discussion while Section 4 provides the concluding remarks.

2.0 METHODOLOGY

To develop a logistic regression model that identifies the factors predicting credit default, one needs a default and non-default data set. Data for this study was obtained from 409 clients from the Sunyani, Nsoatre, Jinijini, Yamfo and Techiman Branches of Nsoatreman Rural Bank who have benefited from Microfinance loans from 2008 to 2012. A questionnaire was administered to the customers through the help of the mobile bankers commonly called “susu” collectors of the said bank in order to obtain the data set for the analysis. In all, a total of 500 questionnaires were sent to the field, but 409 representing approximately 82% were received. The respondents were randomly sampled from each of the five branches which are located in rural, semi-rural and urban centres. Nsoatreman Rural Bank was selected for the study because it is one of the most successful rural banks in Ghana according to the 2012 Bank of Ghana ratings for community and rural banks.

2.1 Model Specification

In this paper, the response variable, credit default, is a binary or dichotomous variable. Therefore, the logistic regression is a suitable technique to use because it is developed to predict a binary dependent variable as a function of the predictor variables. The logistic regression model is widely used in credit default studies where the dependent variable is binary (Valent et al., 2002; Vallini et al, 2008; Jones & Whitfield, 1988; Lui et al.).

The logit, in this model, is the natural logarithm of the odds or the likelihood ratio that the dependent variable, credit default, is one (1) as opposed to zero(0), non-credit default. The probability, P, of credit default is given by;

The model form for Predicted Probabilities is given as;

$$\ln \left[\frac{P(Y)}{1 - P(Y)} \right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k$$

Where

$\ln \left[\frac{P(Y)}{1 - P(Y)} \right]$ is the log (odds) of the outcomes

Y is the dichotomous outcome

$X_1, X_2, \dots, X_K$ are the predictor variables

$\beta_0, \beta_1, \beta_2, \dots, \beta_k$ are the regression (model) coefficients

β_0 is the intercept.

2.2 Interpreting the Odds Ratio

With all other factors remaining constant, when an independent variable X_i increases by one unit, the odds of the dependent variable increase by a factor $\exp(\beta_i)$ which is called the odds ratio (OR) and ranges from zero(0) to positive infinity. It shows the relative amount by which the odds of the outcome (credit default) increase (OR > 1) or decrease (OR < 1) when the value of the corresponding independent variable increases by one (1) unit.

2.3 Determining the Number of Significant Variables to Retain

Since the estimates of the included variable may be sensitive to changes in the variable(s) omitted, some researchers have chosen to retain all the variables representing the same factor if at least one of them is statistically significant and refer to such a model as the full model (Jouault, and Featherstone, 2011; Kockelman and Kweon, 2002; Kim et al., 2008; Tay et al., 2008) while others chose to eliminate all insignificant variables from the model to increase efficiency of estimation and refer to such a model as the reduced model (Goddard and Jay, 1981; Odeh et al, 2006; Wang and Abdel-Aty, 2008). To enhance the efficiency of credit default prediction, the reduced model with only the statistically significant variables retained is used in this paper. In reducing the model, a stepwise reduction method using the backward reduction procedure in R- Console and SPSS version 17 is adopted.

The P-Value Criterion: Working with alpha-value of 5%, that is, confidence interval of 95%, variables with p-value less than or equal to 5% were treated as statistically significant.

The Z-test or Wald test Method: Variables with a Z-value of greater or equal to absolute value of two (2) were retained.

2.4 Testing for Significance of the Coefficients

151 The Wald statistic test is used to assess the significance of the logistic regression coefficients.
 152 Hypothesis

$$H_0: \beta_k = 0$$

$$H_A: \beta_k \neq 0$$

153 The test statistics is

$$Z = \frac{\beta_k}{SE_{\hat{\beta}_k}} \quad \text{where } z \text{ is } N(0, 1)$$

154 Critical z value for $\alpha = 0.05$ is 1.96 (two-sided). Reject H_0 if Z calculated is greater than the critical Z
 155 value.

156

157 **2.5 Assessing the Goodness-of-fit of the Estimated Model**

158 There are two ways to assess the goodness-of-fit for a logistic regression model. One approach is to
 159 assess the model estimation fit and the other method is to examine the predictive accuracy (like the
 160 classification matrix indiscrimination analysis). Although the two approaches examine model fit from
 161 different perspectives, they yield similar results and as such the study made use of both approaches.

162

163 **2.5.1 Model Estimation Fit**

164 The fundamental measure of how well the maximum likelihood estimation procedure fits is the
 165 likelihood value, similar to the sums of squares values used in multiple regression. The model
 166 estimation fit for L.R is measured by the value of -2 times the log of the likelihood value, referred to as
 167 -2LL or -2 log likelihood. The minimum value for -2LL is 0, which corresponds to a perfect fit
 168 (likelihood = 1 and -2LL is then 0).

169 Thus the lower the -2LL value, the better fitted the model.

170 The -2LL value can be used to compare between equations for the change in fit or used to calculate
 171 measures comparable to the R^2 measures in multiple regression.

172

173 **2.5.2 Between Model Comparisons**

174 The likelihood value can be compared between equations to assess the difference in predictive fit
 175 from one equation to another, with statistical tests for the significance of these differences.

176

177 Hypothesis Testing

178 Interested in testing

$$H_0: \beta_1 = \beta_2 = \dots = \beta_k = 0$$

$$H_A: \text{Not all } \beta_i = 0$$

179 The test statistic is given by

$$X^2_{\text{obs}} = -2 \ln \left[\frac{L_0}{L_1} \right] = -2 \ln L_0 - (-2 \ln L_1)$$

180

181 Where;

182 L_0 is the likelihood value of the reduced model or the model with no predictor variables.

183 L_1 is the likelihood value of the full model or the model with the desired predictor variables

184 The Rejection Region (R.R) is

$$X^2_{\text{obs}} \geq X^2_{\alpha, k}$$

$$P\text{-value: } P(X^2 \geq X^2_{\text{obs}})$$

185 Where X^2 is chi-square with degree of freedom equal to the number of extra parameters in full model.

186

187 **2.6 Pseudo R^2 Measures**

188 In addition to the statistical chi-square tests, the paper also used the pseudo R^2 value to assess the fit
 189 of the model. The value interpreted in a manner similar to the coefficient of determination in multiple
 190 regression is calculated as

$$R^2_{\text{LOGIT}} = \frac{2LL_0 - (-2LL_1)}{-2LL_1}$$

The logit R^2 value ranges from 0.0 to 1.0. A perfect fit has -2LLvalue of 0 and an R^2_{LOGIT} of 1.0. The Cox and Snell R^2 measure and Nagelkerke R^2 measure which are interpreted in a similar manner to the pseudo $-R^2$ measure and common in most statistical software packages were also used in this paper.

3.0 EMPIRICAL RESULTS AND DISCUSSION

3.1 Model Estimation

The estimated result for the final logistic regression model is reported in Table 3.1. It can be noticed from the table that educational level has a significant influence on Microfinance credit default. Compared to tertiary education and all other variables held constant, a client with secondary education (OR=4.121, $P=.05$) is four times more as likely to default while a client with primary education (OR=10.2677, $P<.001$) is almost eleven times more as likely to default. There is an increase of 312.1% in the relative probability of credit default by clients with secondary education and 926.77% for clients with primary education.

Also, it could be observed from the table that the number of dependents of a client is estimated to have a significant effect on credit default. Compared to customers with no dependents, customers with one dependent (OR=3.1861, $P=.05$), two dependents (OR=2.7865, $P=.05$) and three dependents (OR=3.1025, $P=.05$) are characterized by significantly higher probability of credit default. However, clients with more than three dependents, that is, four or more dependents (OR=5.4184, $P<.005$) are associated with a very higher probability of default. That is compared with customers with no dependents, and all other variables held constant, customers with four or more dependents are five times more as likely to default. The relative probability of default increases by 441.84% for clients with more than four dependents and approximately 210.25% for clients with one to three dependents.

The results also confirmed the type of loan to have a significant effect on credit default. Compared to Susu loan (individual), all the other types of loan were found to have a decreased probability on credit default. The negative sign of the estimated coefficients and the sign of the odds ratio being less than 1 ($\beta=-1.5381$, $P<.001$ and OR=0.2148) for group loan and ($\beta=-1.6042$, $P<.001$ and OR=0.2010) for Susu group loan show that the probability of credit default is higher for individual loan than group loan. That is the relative probability of credit default decreases by 78.52% for clients who take group loans and 79.9% for clients who take Susu (group loans).

The number of years a customer had spent in business was also found by the study to be negatively related to the likelihood of credit default. Compared with clients with less than one year in business, clients with 1-2 years in business (OR=0.3523, $P=.05$), 2-3 years in business (OR=0.3302, $P=.05$) and above four (4) years (OR=0.2883, $P=.05$) are found to have a decreased probability on credit default. That is the relative probability of credit default decreases by 64.77% for clients with 1-2 years in business, 66.98% for clients with 2-3 years in business and 71.17% for clients with above four (4) years in business.

Adequacy of the loan facility for the clients intended purpose was also identified to have a significant influence on the likelihood of the client to default or not. The probability of credit default significantly increases with the non-adequacy of the loan facility (OR=3.4021, $P<.001$). That is the relative probability of credit default increases by 240.21% for clients who stated the loan facility was not adequate for their intended purpose. All other variables held constant, a client who stated the credit facility was not adequate for his or her intended purpose is three times more as likely to default compared to a client who indicates the credit facility will be adequate.

Period for the repayment of the loan has a major effect on the likelihood of credit default. Compared to loans with repayment schedule of 1-6 months, loans with repayment period of 1-2 years (OR=0.1139, $P<.001$) is found to decrease the likelihood of default. That is the relative probability of credit default decreases by 88.6% for clients who take loans with repayment period of 1-2 years.

Cost of capital also influenced the probability of default. The likelihood of default is lower for clients who rank interest rate to be normal relative to clients who rank interest rate (cost of capital) to be high,

(OR=0.2556, $P<.001$). That is the relative probability of credit default decreases by 74.4% for clients who rank interest rate to be normal.

The period the loan was given to the client also have a significant influence on the likelihood of default. The likelihood of default is higher for loans advanced to clients during the last quarter of the year relative to the first quarter of the year (OR=4.8867, $P<.005$). All other variables held constant, a client who took loan during the last quarter of the year is almost five times more as likely to default to a customer who took the loan during the first quarter of the year. That is the relative probability of default increases by 388.67% for clients who take loans in the last quarter (October to December).

3.2 ASSESSING THE MODEL FIT

Three approaches were used in assessing the overall fit of the fitted model. These are the statistical measures of overall model fit, pseudo R^2 measures and classification accuracy.

3.2.1 Statistical Measures

The model with the minimum AIC was selected. To assess the fit of the model, the null hypothesis; the fitted model is not different from the null model was tested against the alternative hypothesis; the fitted model is different from the null model. This followed a chi-square test with one degree of freedom. It can be observed from Table 3.4 that the -2LL value reduced from the base model value of 508.44 to 273.17 for the fitted model, a decrease of 235.27. This increase in model fit was statistically significant at 0.000 level, hence, the null hypothesis was rejected and concluded that the fitted model was significantly different from the null model.

It can be observed from Table 3.2 that the fitted model is significantly different from the base (null) model since $P(0.000) < 0.05$. That is from the table, since $P(0.000) < 0.05$, the null hypothesis can be rejected in favour of the alternative hypothesis and conclude that the fitted model is significantly different from the null model.

The next statistical measure is the Hosmer and Lemeshow measure of overall fit. This statistical test measures the correspondence of the actual and predicted values of the dependent variable. A better model fit is characterized by a smaller difference between the observed and predicted classification as evident in Table 3.4 below.

The Hosmer and Lemeshow test shows insignificance for the fitted model (0.650 from Table 3.3), indicating that insignificant differences remain between the actual and expected values. This is a strong signal of a good model fit.

3.2.2 Pseudo R^2 Measures

From Table 3.5, it can be observed that the model has a relatively larger pseudo R^2 of 0.634 for the Nagelkerke R^2 and 0.476 for the Cox and Snell R^2 Square. That is the fitted model can explain or account for 63.4% of the variation in the dependent variable. This is an indication of a good model.

3.2.3 CLASSIFICATION ACCURACY

This represents the level of predictive accuracy achieved by the fitted model. It can be observed from the classification table in Table 3.6 that the fitted model predicted an overall percentage of 82.9% correctly. That is 83.6% of the outcome yes of the variable did you pay is predicted accurately while 82.2% of the outcome no of the variable did you pay is predicted accurately by the fitted model.

Together with the statistically based measures of model fit, the model is deemed acceptable regarding both statistical and practical significance.

3.3 Casewise Diagnostics

In addition to assessing the classification accuracy of the fitted model, individual cases were examined for their predictive accuracy and identify specifically the misclassified cases. It could be observed from Table 3.7 that out of forty respondents in the holdout sample, three were misclassified by the fitted model. It is also evident from the table that the fitted model achieved an overall

classification accuracy of 92.5% in the holdout sample indicating a high practical significance of the model.

4.0 CONCLUSION

The study showed that educational level, number of dependents, type of loan, adequacy of loan, duration for repayment of loan, number of years in business, period within the year the loan was acquired and how the customer ranks the interest charged on the loan were significant determinants of micro credit default. Based on the findings of this study, the following recommendations are suggested;

The Microfinance Institutions (MFI'S) should adopt the group loan policy as the main mode through which microcredit may be issued to suitable applicants. Considering the current value of the Ghana cedi relative to the exchange rates and the economy as a whole, the MFI'S should consider increasing the size of loan amounts. The government through the Ministry of Health should also collaborate with agencies such as the Planned Parenthood Association of Ghana to educate the populace, especially the rural and semi-rural folks, on the importance of family planning. This would help decrease household sizes and consequently decrease their expenditure levels which are a major determinant of default. The MFI'S should team up with the Ministry of Education through the Non-Formal Education Division to organize functional literacy workshops for microcredit beneficiaries to equip them with the required knowledge to do successful business. The government through Bank of Ghana and the ARP Apex Bank should come out with more stringent policies and if possible Acts to effectively control the cost of capital (interest rate) being charged by MFI'S. Finally, the MFI'S should give out long term loans preferably one to two years repayment period rather than one to six months repayment period which is typical of most micro loans and also MFI'S should be more cautious when issuing loans in the last quarter of the year.

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367 **Table 3.1: Parameter Estimates for the fitted Model**

Explanatory Variable	Co-efficient	Standard error	P-value	Z-value	Odds Ratio
Constant	-0.4217	0.6943	0.54362	-0.607	0.6559
Educational level (Tertiary as Reference)					
Middle/ Junior High	1.0855	0.5773	0.06006	1.880	2.9609
Primary	2.329	0.6726	0.00053	3.463	10.2677
None	2.425	0.6912	0.35265	0.929	11.302
Number of Dependants (None as Reference)					
One	1.1588	0.5700	0.04205	2.033	3.1861
Two	1.0248	0.5063	0.04296	2.024	2.7865
Three	1.1322	0.5273	0.03178	2.147	3.1025
Above Three	1.6898	0.6047	0.0052	2.794	5.4184

Type of loan (Susu Individual as Reference)

Group Loan	-1.5381	0.3988	0.00012	-3.857	0.2148
Susu Loan (Group)	-1.6042	0.5148	0.00183	-3.116	0.2010

Adequacy of loan (Yes as Reference)

No	1.2244	0.3302	0.00021	3.708	3.4021
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Loan Duration (1-6 Months as Reference)

1 – 10 months	-0.181	0.4294	0.67334	-0.422	0.8344
1 – 11months	-0.8188	0.4469	0.06691	-1.832	0.4410
1 – 2 years	-2.1725	0.5102	0.01388	-4.258	0.1139
2 years and above	-2.3946	1.2523	0.05586	-1.912	0.0912

Number of Years in Business(Less than One Year as Reference)

1 – 2 years	-1.0432	0.4809	0.03006	-2.169	0.3523
2 – 3 years	-1.1078	0.5612	0.04836	-1.974	0.3302
Above 4 years	-1.2436	0.5402	0.02132	-2.302	0.2883

Interest Rate Ranking (High as Reference)

Normal	-1.3641	0.3642	0.00018	-3.746	0.2556
Low	-0.4643	0.8751	0.59574	-0.531	0.6286

Period of Loan (First Quarter as Reference)

Second Quarter	0.2712	0.3972	0.49481	0.683	1.3115
Third Quarter	0.7173	0.504	0.15464	1.423	2.0489
Fourth Quarter	1.5865	0.5507	0.00396	2.881	4.8867

Null Deviance: 508.44 on 366 degrees of freedom

Residual Deviance: 273.17 on 343 degrees of freedom

AIC: 321.17

Number of Fisher Scoring iterations: 6

368

369

370 **Table 3.2 Omnibus Tests of Model Coefficients**

		Chi-square	Df	significance
step 1	Step	238.148	25	0.000
	Block	238.148	25	0.000
	Model	238.148	25	0.000

371

Table3.3 Hosmer and Lemeshow Test

step	chi-square	df	significance
1	5.975	8	0.65

372 **Table3.4 Contingency Table for Hosmer and Lemeshow Test**

did you pay = yes		did you pay = no		Total
Observed	Expected	Observed	Expected	

Step	11	36	36.425	1	0.575	37
2						
2		36	34.788	1	2.212	37
3		30	32.915	7	4.085	37
4		32	29.455	5	7.545	37
5		23	22.726	14	14.274	37
6		15	16.14	22	20.86	37
7		9	9.516	28	27.484	37
8		6	4.682	31	32.318	37
9		1	1.854	36	35.146	37
10		1	0.500	35	35.500	36

Table 3.5 Model Summary

	likelihood	Cox & Snell R Square	Nagelkerke R Square
1	273.175a	0.476	0.643

Table 3.6 Classification Table for Analysis Sample^a

			Predicted		
			did you pay	Percentage	
Observed			Yes	No	Correct
Step 1	did you pay	Yes	158	31	83.6
		No	32	148	82.2
	Overall Percentage				82.9

The cut value is .500

Table3.7 Classification Table for the Holdout Sample^a

			Predicted		
			did you pay	Percentage	
Observed			Yes	No	Correct
Step 1	did you pay	Yes	19	2	90.4
		No	1	18	94.7
Overall Percentage					92.5

a. The cut value is .50