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Predicting Microfinance Credit Default: A Study of Nsoatreman Rural Bank, Ghana

Ernest Yeboah Boateng[1*] and Francis T. Oduro[2]

[1]Department of Basic Sciences, School of Basic and Biomedical Sciences, University of Health and Allied Sciences, Ghana.
[2]Department of Mathematics, Kwame Nkrumah University of Science and Technology, Ghana.

Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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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.

**Corresponding author: E-mail: eyboateng@uhas.edu.gh;*

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1 Introduction

Formal banking began in Ghana (then the Gold Coast colony) in 1896 with a local office of the Bank of British West Africa [1]. Barclays Bank DCO followed in 1917 [2]. The Gold Coast Cooperative Bank 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 [3].

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 [4].

Available data from the Registrar Generals Department indicates that 90% of businesses, registered in Ghana as of December 2016 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 [5].

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 and their developing partners in the recent decades have emphasised the need for microfinance.

It has been identified as one of the best means of providing small loans and other financial services to poor low-income households and microenterprises.

However, microfinance credit default constitutes a great hindrance to the smooth implementation of the microfinance policy in Ghana. According to the ARP Apex Bank 2016 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 [6].

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 [7].

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 [8].

Kwofie et al. [9] in their study identified the predictors of loan default in Ghana as marital status, number of years in business and base capital.

Awunyo-Vitor [4] investigated the determinants of loan repayment default among farmers in the Brong Ahafo region of Ghana using the Probit model. His results showed that farm size, larger loan amount, longer repayment period, access to training and engagement in off farm income generating activities reduces the likelihood of loan repayment default significantly.

Pollio and Obuobie [6] 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 Vojtek [10] 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.

Continuous default by borrowers affects the economic growth of every country and is therefore a major concern for governments and financial institutions.

To ensure that credit worthy customers do not carry the burden of default of other persons, the government of Ghana through legislative instrument, the Borrowers and Lenders Act 2008, has provided a legal framework to prohibit certain credit practices and also to promote a consistent framework related to credit.

But till date, the rate of credit default is high with the aggregate non performing loan ratio of the banking industry at 23.6% as at December 2015 [3].

One of the major barriers to the development of microfinance in Ghana is credit default. According to the ARP Apex Bank Report 2015, microfinance credit default accounted for the majority of bankruptcies of microfinance institutions in Ghana.

It is against this background that this paper presents a statistical validated model to predict the factors that contribute to microfinance credit default using logistic regression model.

2 Methodology

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 2015 Bank of Ghana ratings for community and rural banks.

2.1 Model specification

In this paper, the response variable, credit default, is a binary variable (whether the loan was repaid or not). 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 [11].

The logit, in this model, is 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;

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

Where;

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

Y is the dichotomous outcome which represents credit default (whether the loan was repaid or not) $X_1, X_2, \ldots, X_K$ are the predictor variables which are 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 $\beta_o, \beta_1, \beta_2, \ldots, \beta_k$ are the regression (model) coefficients

2.2 Determining the number of significant variables to retain

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

2.3 Assessing the goodness-of-fit of the estimated model

The analysis sample was assigned 89% of cases in the dataset in order to obtain a model. The hold-out sample was assigned 11% of cases in the dataset to give an "honest" estimate of the ability of the model to predict. The error computed across the two samples were approximately the same. This signifies that the model is a good fit in predicting credit default.

3 Empirical Results and Discussion

3.1 Model estimation

The estimated result for the final logistic regression model is reported in Table 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 (β=-1.5381, P<.001 and OR=0.2148) for group loan and (β=-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).

Table 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 Referei					
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
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			

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 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 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.

Table 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

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 4.

The Hosmer and Lemeshow test shows insignificance for the fitted model (0.650 from Table 3), indicating that insignificant differences remain between the actual and expected values. This is a strong signal of a good model fit.

Table 3. Hosmer and Lemeshow Test

Step	Chi-square	df	Significance
1	5.975	8	0.65

Table 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

3.2.2 Pseudo R^2 measures

From Table 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.

Table 5. Model summary

	Likelihood	Cox & Snell R square	Nagelkerke R square
1	273.175a	0.476	0.643

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 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.

Table 6. Classification table for analysis sample[a]

	Observed		Predicted		
			Did you pay		Percentage
			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

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 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.
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Table 7. Classification table for the holdout sample [a]

Observed			Predicted		
			Did you pay		Percentage
			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*

4 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.

Competing Interests

Authors have declared that no competing interests exist.

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