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Factors Affecting Default in the Loan Portfolio of Microfinance Institutions in Cameroon

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Authors' contributions:

This study was carried out with collaboration from all authors. Author PCC designed and initiated the study, performed the statistical analysis, wrote the protocol, and wrote the first draft of the manuscript. Authors FoAJ and OMYN managed the analyses of the study. Authors PCC and FAJ managed the literature related aspects of the study. All authors read and agreed on the final manuscript.

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ABSTRACT

The main objective of microfinance is to provide funds to those who are excluded from the banking system. But in order to attain this objective they have to deal with the issue of default in their loan portfolios. The aim of this paper is to analysis the factors that affect the default of borrowers in microfinance institutions. The discriminant analysis reveals that 96.6% of the bad borrowers are correctly classified and 92.1% of the good borrowers are correctly classified and that other debts, age of borrower, borrowers income and number of dependents significantly affect the likelihood of default. We suggest that credit officers in microfinance institutions should be keen on these factors when granting loans.

Keywords: Loan; default; discriminate; portfolio; microfinance.

1. INTRODUCTION

During the late two decades the landscape of microfinance has expanded in Cameroon despite the failure of some MFIs. Microfinance can be defined as a financial instrument such as loans, savings, insurance and other financial products that are tailored only to the poor. Microcredit has

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enabled the poor to raise income and improve their standard of living. Development is impossible without an efficient financial system. This paper deals with the repayment problems of borrowers of MFIs in Cameroon. In the present context with the need for funds for development projects in Sub-Saharan Africa several arguments justify the importance of this problem. A good repayment performance is essential for the sustainability of MFIs and the increase in access of credit to the poor. However due to the high level of information asymmetry loans granted by microfinance institutions are becoming more and more risky. According to several authors the problem of asymmetric information is more severe in developing countries [1,2]. The high degree of credit market imperfection and the importance of the informal sector [3] increase the costs of loan default and the vulnerability of the financial structure. The results from our finding will ease access to credit by the vulnerable. The microfinance sector in Cameroon has expanded tremendously in the last decades and according to the Central African Banking Commission (2008) it occupies a central position in The Central African Monetary and Economic Community. The quality of the loan portfolios of MFIs in Cameroon has also deteriorated in the last few years with doubtful debtors increasing from 23.114 billion FCFA to 35.553 billion FCFA in 2008 [4]. Cameroon hosts 67% of the microfinance institutions in the regions, has 69% of the deposits, 72% of the number of tellers and 82% of the loan advances. The series of bankruptcies in the microfinance sector in Cameroon such as COFINEST (Compagnie Financiere de l'estiaure), CAPCOL (la caisse Populaire Cooperative du Littoral) and FIFFA (First Financial investment Assistance) essentially caused by the low rate of repayment of loans necessitates the examination of factors that could be responsible for this.

2. LITERATURE REVIEW

There has been a growing consensus on the need for the liberalisation of the financial sector in the last few decades. In a transition economy such as that of Cameroon the cost of gathering information are very high and is a significant obstacle to the allocation of loans [5]. In MFIs the lender-borrower relationship can be considered as an agency relationship in which the lender (principal) give out part of his wealth to the borrower (agent) who pays back the principal with interest at a future date. Jensen and Meckling [6] define an agency relationship as a contract in which one or several persons (principal) hire another person to carry out a task on their behalf this implies some decision making power is delegated to the agent. Such a situation reveals the incomplete nature of the loan contract due to the existence of asymmetric information between the MFI and the borrower which makes it difficult to evaluate the quality of the borrower ex-ant and ex-post.

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2.1 Factors That Affect Loan Default in Microfinance Institutions

Several studies have highlighted a series of factors that affect loan default. They focus on the practices of stakeholders in financial institutions, borrower specific variables and loan granting procedures as well as other factors such as macro-economic factors and socio-demographical factors have also been suggested as causes of loan default and non-repayment.
Some of the outstanding determinants of loan repayment in microfinance institutions include outreach, shocks, training duration, loan size and credit officers experience [7].

Berger and De Young [8] indicate that managers in most financial institutions are faced with the problem of non-performing loans because they do not practice loan underwriting, monitoring and control appropriately. Mensah et al. [9] used ordinary least square regression to suggest that interest charged on loans and over borrowing by customers affect loan default. [10] showed that technical training of borrower has a significant effect on loan default in MFIs.

Goldstein and Turner [11] found out that loan default is generally due to economic depression and volatility, term of trade deterioration, high interest rate, excessive reliance on overly high-priced interbank borrowing, insider borrowing and moral hazard. Again, poor handing over from one loan officer to another, late disbursement of loan, delayed loan process, business or crop failure and sudden change in the market have been reported as some of the factors that drive loan default or non-performing loans. For instance, an unexpected change in the market such as increase in prices of items could affect loan market; how much people can take as loans and subsequently how much they can pay as instalment.

Bichanga and Aseyo [12] found out that loan repayment default was as a result of non-supervision of borrowers by MFIs and the inadequate training of borrowers on the utilisation of loan funds before they received loans. They equally suggest that most borrowers did not spend the loan amount on intended and agreed project. The unwillingness to pay loan, diversion of funds, wilful negligence and improper appraisal by credit officers as some of the factors that affect loan default [13]

Balogun and Alimi [14] indicated low supply of loan, delays in loan granting, small size of business, high interest rate, age of farmers and poor supervision as determinants of loan default. In addition, poor business practice and management such as record keeping, and assessing business performance over time also result in loan default. Many borrowers do not have the technical know-how to undertake their investment activities properly and as a result tend to generate low income which affects loan repayment and finally leading to loan default.

The study by Munene and Guyo [15] in Kenya showed that one of the causes of loan defaults is characteristics of the business. It was revealed that high cases of loan default were common in the manufacturing sector (67.9 percent) and was followed by the service industry (64.0 percent); agricultural sector (58.3 percent) and the trade sector recorded the least cases of loan default (34.9 percent). Felsovalyi and Hurt [16] found that corporate loan default leads to a fall in the real domestic product. They further reported that borrowers' repayment ability is directly affected by exchange rate depreciation and hence loans demanded tend to be delinquent.

Nishimura et al. [17] also highlighted that one of the underlying causes of Japan's prolonged economic stagnation is as a result of high non-performing or bad loans. They further explained that some of the loans disbursed to companies by financial institutions during the bubble era became non-performing when the bubble busted. This delayed structural reforms and affected the performance and proper functioning of the financial institutions. The authors finally asserted that most of the defaults were as a result of poor management procedures, loan diversion and unwillingness to repay loan.

Tuidui and Tuidui [18] averred that the higher the income of borrowers, the lower the default rate and that loan size increases with loan default. The findings are consistent to Roslan and Karim [19]; Zohair [20]; and Duy [21]. Pasha and Negege [22] on their part attributed timely disbursement of loan, loan usage on the intended purpose and time given to borrower as contributory factors of loan default. They said that timely disbursement of loan increases significantly the loan repayment performance and that there is a negative relationship between repayment and period of repayment.

Wongnaa and Awunyo-Vitor [23]; explained that the longer the period of repayment, the lower the rate of default and that high repayment leads institutions to lower their interest rate and cost of processing loan. Roslan and Karim [19] asserted that loan tenure is negative and significant with loan repayment implying that shorter repayment period leads to higher loan repayment. Interest rate featured prominently in works by Magali [24] and Ayogyam, Goddana, Mohammed and Boateng [25]. Whilst Magali [24] revealed that interest rate affect credit risk and profitability; Ayogyam, Goddana, Mohammed and Boateng [25] found that interest rate affect repayment of agricultural loans. Eze and Ibekwe [26]; Nawai and Shariff [27]; and Roslan and Karim [19] cited socio-demographical variables like age, gender and educational level as causes of loan default.

It can be inferred from the above review that age, sex, marital status, educational level, household size, income, diversion and monitoring are some of the determinants of loan default. These factors have positive and/or negative relationship with loan default.

The age variable is expected to have a positive relationship with loan default. That is because as one grows the ability to work reduces and therefore he/she cannot undertake much productive investment compared to younger counterparts. As a result, his/her ability to engage in diverse investment in order to earn more income also reduces and this may adversely affect their repayment capabilities hence the more likelihood of defaulting in loan repayment [14,19,27]. Eze and Ibekwe [26] said that age is positively significant to loan default and that younger people have better loan repayment performance.

The relationship between sex (being male) and loan default is expected to be positive. This is because, males often have more responsibilities as heads of family and as a result may use loan taken for productive investment for other purposes such as consumption, fees payment and other utility bills. This will result in difficulty in loan repayment because no income might be generated and hence the likelihood of not paying the loan on time as scheduled [26]. Roslan and Karim [19] and Wongnaa and Awunyo-Vitor [23] concluded that females have good loan repayment history than their male counterparts. They advanced the propensity of economic empowerment of females emanating from credit extension and behavioral characteristics of hard work and culture of discipline as the likely reasons of satisfactory loan recoveries from females. However, [28] and Nawai and Shariff [27] hold the view that either male or female borrower does not have any impact on loan repayment performance.

There is a negative relationship between being married and loan default. That is, married couples are more likely to receive support from their partners and as such loan received could be repaid on time. This may be the case in the sense that when loans are received and repayment is due the instalment can be paid without necessarily affecting the fulfilment of other family needs because the partner could supplement in the provision of these needs. Therefore married respondents are less likely to default in loan repayment compared to counterparts who are either single, separated or widowed who might not have any sup-port from anywhere [18,19,20] and [21].

Education variable is expected to correlate positively with loan default. That is, individuals with lower level of education are more likely to default in loan repayment compared to counterparts who have higher levels. This is because individuals with lower level of education are likely to lack managerial skills to guide their businesses and therefore loan received might not yield enough income to enhance loan repayment on time. On the other hand, individuals with higher level of education may possess some managerial skills which can help them manage their businesses and hence more income to repay the loan received on time all things being equal [14,19,26,27].

The household size is expected to correlate positively with loan default. That is, as the number of dependents increases the responsibility also increases. As a result the income that is supposed to be used for loan repayment would be used for the provision of social and economic needs and hence the probability of not repaying loan on time (defaulting) increases all things being equal [14,18,19,20,21].

The income variable is expected to have negative relationship with loan default. That is, individuals who earn relatively high income are expected to repay their loan on time and therefore not defaulting in loan repayment. This is so because, the substantial income earned facilitates loan repayment compared to counterparts who earn relatively low income who might find it difficult to repay their loan which may be attributed to the fact that the income is not even sufficient for the provision of social and economic need [14,18,19,20,21]. Cyrus Munyua [29] indicates that loan collection procedures, loan diversion, efficient financial management and amount of loan borrowed affect loan default in Microfinance Institutions.

Loan diversion is expected to have positive relationship with loan default. That is, all things being equal, if a person diverts loan received for productive investment to undertake unproductive investment, no income will be generated and this is likely to make loan repayment difficult [18,19,20,21].

It is expected that monitoring will have negative relationship with loan default. That is, borrowers are likely to use the loan for the intended purpose if they know Loan Officers will be monitoring their progress. As the loans are used for the intended purpose and are well managed more income will be generated and loan will be repaid on time all things being equal. On the other hand, if the borrowers are not monitored to ensure they are making progress with their business, loans received are likely to be misused and this will result in loan default [8]. This is confirmed by Wongnaa and Awunyo-Vitor [23,27,30] who held the view that loan repayment rate is higher in Micro Finance Institutions which pay frequent visits to the borrowers premises in a month. Using a sample of 244 credit unions in Ghana with the aid of a logistic regression model, Edward Yeboah and Irene Mirekuah Oduro [31] suggest that education, loan diversion, monitoring, marital status and income are significant factors that affect loan default.

In Cameroon Nzongang et al. [32] show that MFIs have put in place certain number of strategies with the aim of reducing default risk. Their empirical study demonstrates that collateral is rigid and do not lead to a reduction in loan default. Ntieche et al. [33] used the credit records of the Community Credit of Africa (CCA) in Cameroon to show that borrower characteristics such as level of education, awareness about the location of the business and/or home of the borrowers by the lender, sector of activity, availability of collateral, income stability and personal income of the borrower have a statistically significant influence on the microcredit repayment behaviour of borrowers. Lassin Kone [34] suggests that default could be caused by the quality of the selection of borrowers (corruption of credit officers and poorly constituted loan files), the hidden (post-ante) actions of the borrower (diversion of the objective of the loan, over indebtedness and bad faith) and natural hazards (natural disasters, government decisions).

3. METHODOLOGY

In this section the method of data collection is presented followed by the methods of data analysis.

3.1 Method of Data Collection and source of Data

The data used in this study is collected from microfinance institutions and their borrowers with the collaboration of credit officers. The survey is carried out with the aid of questionnaires and direct interviews with loan officers and borrowers of some selected MFIs in urban areas of Cameroon. It is carried out in the selected towns of Douala, Yaounde, Bamenda and Limbe. The sample used in this thesis was made up of 723 borrowers. The data was collected from microfinance borrowers and the administration of MFIs. The collected data refers to the operations of credit granted to borrowers of microfinance institutions in Cameroon in the period 2016 to 2017. All the credit granted in that period was analysed with the purpose of verifying the probability of default of the borrowers.

The customers selected through the process of random sampling had their business records obtained from the administration of the MFIs and the customers themselves. We identified the personal characteristics of the customer and economic-financial data related to the business or economic activity of the customers.

3.2 Linear Discriminate Analysis

The aim of linear discriminate analysis (herein after ''LDA'') is to classify a heterogeneous subsets and further the decision process on these subsets. We can assume that for each applicant there are a specific number of explanatory variables available. The idea is to look for such a linear combination of explanatory variables, which separates most subsets from each other. In a simple case of two subsets, the goal is to find the linear combination of explanatory variables which leaves the maximum distance between means of the two subsets.

In a general case we consider the distributions $p(x \mid G)$ and $p(x \mid B)$ which are multivariate normal distributions with the common variance are. Then the equation above reduces to

$A_G = \{x \mid \sum w_i x_i > c\}$

As it follows from the econometrics theory, here x_i are explanatory variables, w_i are associated coefficients (weights) in the linear combination of explanatory variables. If one takes $s(x) = \sum w_i x_i$ then it is possible to discriminate according to this score and thus to reduce the problem to only one dimension.

The discriminate analysis was introduced by Fisher [35] who searched for the best way to separate two groups using linear combination of variable [1]. Eisenbeis [36] criticised this method by stating that the rule is optimal only for a small class of distributions. However, Hand and Henley [37] claim that ''if the variables follow a multivariate ellipsoidal distribution (of which the normal distribution is a special case), then the linear discriminate rule is optimal''.

Other critics state that there is a selection bias due to the fact that a learning sample for a credit scoring system is made of applicants to whom credit has been granted. That means that results are biased when applied to the whole population. Eisenbeis [36] also saw problems in the definition of the bad and good groups in the case when no clear boundary is between them and under the assumption that the covariance matrices of the two distributions are equal. In this case the use of quadratic discriminate analysis instead of the linear case is appropriate. Problems also arise when one wants to test for the significance of individual variables as one does not have the assumption of normality and therefore cannot perform statistical inference [2]. (Altman [38], who was the first to apply discriminate analysis, constructed the so-called z-score which is a linear corporate credit granting problem [3]. He found the model to be extremely accurate in correctly predicting bankruptcy.

As we have mentioned, the advantages of the LDA method are that it is simple, it can be very easily estimated and it actually works very well; it is often used by financial institutions for credit scoring purposes. The disadvantage is that LDA requires normally distributed data but the credit data are often non-normal (and categorised).

3.3 Definition of Variables

The selection of variables is from the evaluation of the socio-economic and demographic environment of Microfinance institutions in Cameroon. It was equally based on the information available. A major element in the selection of variables was the information provided by credit officers. From the theoretical framework developed and the availability of information we have identified and collected information on the variables in the Table below (some of the variables are defined in the Tables).

The dependent variable in the two models is ''missed loan repayment''. It is a dummy variable in which 1 if the borrower did not miss any loan repayment and 0 if the borrower missed a loan repayment.

After review of literature [Schreiner [4]], the independent variables are arranged in three categories according to the factors affecting loan default. Characteristics of the borrower, characteristics of the loan and those related to the experience of the credit officer. The characteristics of the borrower provide insight into the likelihood of repayment. Knowing about the borrower's external conditions (socio-economic) is an important way of knowing what factors could reduce their willingness to repay. The characteristic of the loan is an important factor because of how the demanding contractual conditions of MFIs can induce or discourage borrowers to respect their obligations. The credit officer plays an important role in identifying a bad borrower by evaluating their credibility prior to granting the loan. The inclusion of all variables would make the model unnecessarily large and scare customers when confronted with the required number of questions.There are several approaches in selecting independent variables proposed by authors. Hand and Henley [37] describe three ways of selecting variables. First, expert knowledge is used to select the right variables. Secondly statistical procedures such

[1] Fisher (1936) suggested (under assumption of common sample variance) looking for the linear combination of explanatory variables which leaves the maximum distance between means of the two classes.

[2] Many of these issues are addressed in the review by Rosenberg and Gleit (1994)

[3] The variables used are Sales/Total Assets (TA), working capital/TA, Retained Earnings/TA, Earnings before Interest and Taxation/TA, Market value of equity/Book Value of total debt.

[4] Schreiner classified the explanatory variables affecting default into three categories the characteristics of the borrower, the characteristics of the loan and variables related to the experience of credit officer.

as forward and backward selection based on R^2 can be implemented.A combination of the forward and backward approaches the stepwise approach also exists. The technique of Discriminant Analysis was implemented in classification groups of default or no default in the loan portfolio.

4. ESTIMATED RESULTS AND DISCUSSIONS

This section begins by presenting and discussing the descriptive statistics of the data collected then is continues with the results of the discriminant analysis.

Table 1. Variables in the models

Variable	Definition
GENDER	Sex of the borrower
MARITAL	Marital Status of borrower
EDUCATION	Educational level of borrower
BUSTYPE	The type of business carried
EXINCOME	The extra income of borrower
EXLOAN	Extra loans received by the borrower
AGE	The age of the borrower
NUMDEPEND	The number of depends under the responsibility of the borrower
BUSREV	The amount of business revenue earned by the borrower
MISREPAY	The number of repayments missed by the borrower
OTHDEBTS	Other debts contracted by the borrower
REQUESTAMNT	The amount of loan requested by the borrower
AMNTACG	The amount of loan actually granted to the borrower
COTYPE	The type of collateral offered by the borrower
NUMLOANS	Number of loans granted by institution to borrower
REDURATION	The period of time required to refund the loan
EXLOANOFF	The number of years of experience of credit officer

Source: Authors

Table 2. Descriptive statistics of variables

Variables		Default	No default	Significance	S.E
Gender	Female	21.5%	25.6%	0.630	0.006
	male	28.4%	24.4%		
Educational level	Less than primary	27.3%	14.9%	0.002	0.037
	More than primary	20.7%	37.2%		
Extra income	Otherwise	30.6%	3.3%	0.000	0.073
	yes	17.4%	48.8%		
Age	18 to 25 years	8.6%	1.3%	0.000	0.058
	26 to 35 years	15.7%	1.7%		
	36 to 45 years	12.4%	20.7%		
	46 to 55 years	9.9%	21.5%		
	More than 55 years	0.7%	7.6%		
Marital Status	Unmarried	28.9%	9.9%	0.000	0.082
	married	19.0%	42.1%		
Type of activity	Agriculture	0.8%	5.0%	0.056	0.072
	Business	45.1%	49.1%		
Loan term period	Less than 1 year	37.2%	39.7%	0.856	0.091
	More than 1 year	10.7%	12.4%		
Extra loan	No	34.5%	23.5%	0.001	0.087
	Yes	26.8%	55.6%		
Number of	1 to 2 people	16.5%	8.3%	0.000	0.071

Variables		Default	No default	Significance	S.E
dependent	2 to 4 people	14%	17.4%		
	more than 4 people	9.1%	26.4%		
Revenue of borrower	Less than 500 000	18.2%	6.6%	0.014	0.020
	500 001 to 1 000 000	13.2%	19%		
	1 000 001 to 1 500 000	8.3%	18.2%		
	1 500 001 to 2 000 000	6.4%	6.8%		
	More than 2 000 000	1.5%	1.9%		
Other debts	No	12%	47%	0.000	0.063
	Yes	37.6%	3.4%		
Requested amount of lo	Less than 500 000	23.1%	11.6%	0.010	0.078
	001 to 2 000 000	14.9%	19%		
	2000 001 to 5 000 000	8.3%	14.9%		
	More than 5 000 000	1.7%	6.6%		
Amount granted	Less than 500 000	29.8%	24.8%	0.013	0.081
	001 to 2 000 000	11.6%	19%		
	2 000 001 to 5 000 000	3,3%	8,3%		
	More than 5 000 000				
Type of Collateral	Land	9.9%	24.8%	0.004	0.079
	Guarantor	19.8%	14.9%		
	Salary	9.6%	10.2%		
	Savings	2.7%	0.6%		
	house	5%	2.5%		
Number of loans received	1 only	35.5%	22.3%	0.000	0.085
	More than 1	12.4%	29.8%		
Repayment arrears	No	13.2%	40.5%	0.000	0.079
	Yes	34.7%	11.6%		
Requested duration	1 to 6 month	1.7%	9.9%	0.002	0.083
	7 to 12 months	18.2%	6.6%		
	13 to 18 months	14.2%	15.5%		
	19 to 24 months	8,3%	15.7%		
	More than 24 months	6%	4%		
Loan officer experience	Less than 1 year	11.6%	1,7%	0.000	0.050
	to 2 years	19%	9,9%		
	2 to 5 years	12,4%	17.4%		
	more than 5 years	4%	19.1%		

Source: Authors

Table 3. variables and coefficients for discriminant analysis

Independent variables	Wilks' Lambda	F	p-value	Canonical coefficients
Constant				-2.036
Marital status	0.747	35.543	0.000	-1.243
Level of education	0.906	10.958	0.001	0.177
Type of activity carried out by borrower	0.967	3.582	0.061	0.020
Extra income of borrower	0.611	66.762	0.000	0.335
Period of loan term	0.999	0.070	0.792	0.564
Weekly mode of repayment by borrower	0.966	3.698	0.057	0.894
Existence of borrower's extra loan	0.941	6.565	0.012	0.484
Age of borrower	0.625	62.942	0.000	-0.374
Number of dependents in borrower's family	0.735	37.812	0.000	0.107

Independent variables	Wilks' Lambda	F	p-value	Canonical coefficients
The income level of borrower	0.930	7.932	0.006	0.045
The repayment amount of the loan	0.921	9.064	0.003	0.116
Existence of other debts	0.546	87.181	0.000	2.433
The purpose of the loan	0.931	7.758	0.006	-0.118
Requested amount of loan	0.851	18.365	0.000	-1.004
Amount of loan actually granted	0.903	11.232	0.001	1.256
The amount of the collateral	0.910	10.324	0.002	-0.881
The type of collateral offered by borrower	0.892	12.690	0.001	0.521
Time between request and granting of loan	0.997	0.346	0.557	-0.596
The number of loans received by borrower	0.949	5.595	0.020	0.502
Existence of repayment arrears	0.808	25.000	0.000	1.210
The requested duration of the loan	0.989	1.207	0.274	0.454

Source: analysis of authors

4.1 Statistical Description of Variables

From Table 2 below 25,6% of the female borrowers did not default as against 21,8% who defaulted indicating that males in our sample are more likely to default than females thus gender affects loan default. The results are different from those of some authors who show that women are better credit risks than men especially in the African context [39]. 37.2% of the respondents who had an educational level more than primary school did not default suggesting that borrowers who are more educated are less likely to default than those who are more educated. This confirms the importance of education as a possible determinant of default. Most of the borrowers in our sample are married (61.1%) and 19% defaulted as against 42.1% who did not default. Seemingly, being unmarried increases credit risk.

4.2 Results

The Eigen value of 3.882, shows that a high proportion of the variance of the dependent variable is explained by the discriminant function. The canonical correlation (0.892) shows a high degree of association between discriminant function and dependent variable. The square of the canonical coefficient (0.795) equally indicates that a high proportion of the variance is explained by the dependent variable.

Wilk's Lambda of 0.205 shows that about 20.5% of the independent variables are explained by the discriminant function which is not significant and indicates that the group means differ. The model is therefore adequate for the prediction of good and bad borrowers.

It is seen that the discriminant analysis effectively predicts default by separating good and bad borrowers but it does not meet the underlying assumptions.

The sensitivity of the discriminant analysis is 96.6% which means that 84.5% of the bad borrowers are correctly classified and there are few false negative results (type II error). The model is highly specific (92.1%) meaning that 92.1% of good borrowers are correctly classified and there are few false positive results (type I error).94.2% of the originally group cases are correctly classified. The discriminant analysis successfully separates the groups (bad and good borrowers maximally

4.3 Discussion

The adequacy of the analysis was examined using the Eigen value of 3.882 which shows that a high proportion of the variance of the dependent variable is explained by the discriminant function. The canonical correlation (0.892) shows a high degree of association between discriminant function and dependent variable. The square of the canonical coefficient (0.795) equally indicates that a high proportion of the variance is explained by the dependent variable. This confirms the fact that the variables used in the analysis can explain loan default significantly.

Table 4. Adequacy of the discriminant analysis

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	3.882^{a}	100.0	100.0	.892

Source: Authors

Table 5. Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.205	149.836	21	.000

Source: Authors from SPSS analysis

Table 6. Classification table by discriminant function method

Actual group	Number of cases	Predicted group membership	
		No default	Default
No default	378	92.1%	7.9%
default	348	3.4%	96.6%
Overall percentage		94.2%	

Source: SPSS analysis

Wilk's Lambda of 0.205 shows that about 20.5% of the independent variables are explained by the discriminant function which is not significant and indicates that the group means differ. The variables are therefore adequate for distinguishing between good and bad borrowers.

The classification results Table evaluates how well the discriminant function classifies good and bad borrowers. The sensitivity of the model is 96.6% which means that 96.6% of the bad borrowers are correctly classified and there are few false negative results (type II error). The model is highly specific (92.1%) meaning that 92.1% of good borrowers are correctly classified and there are few false positive results (type I error).94.2% of the originally group cases are correctly classified. The discriminant analysis successfully separates the groups (bad and good borrowers maximally but it does not produce the probability of default.

From the values of Wilks' Lambda and f values of the variables we find that the most important variable to the discriminant function are the existence of other debts, age of the borrower, borrower's extra income and number of dependents. This corroborates with the study of Gonzalez-Vega [40] who suggests that age has a significant effects on the likelihood of loan default. This high lights the fact that younger persons are more likely to default since most of them tend to have fewer commitments. The descriptive statistics equally show that the highest number of defaulters (15.7%) is those between the ages of 26 to 35 years and the highest numbers of borrowers who do not default (21.5%) are those between the ages of 46 to 55 years old.

5. CONCLUSION

This paper investigates the factors influencing loan default in the loan portfolio of microfinance institutions in Cameroon. Using commonly used variables we find that age [41] other debts, borrowers extra income [41,33] and number of dependents [42] affect the likelihood of loan default more significantly than the other variables. Our analysis equally suggests that 96.6% of the defaulted borrowers are correctly classified thus it is less likely to make a type 2 error (that is selecting a bad borrower) and 92.1% of the borrowers who have not defaulted are correctly classified meaning that it is less likely to make a type 1 error (that is reject a good borrower). Therefore in order to improve the management of the loan portfolio of microfinance institutions it is necessary to examine these factors

DISCLAIMER

The products used for this research are commonly and predominantly use products in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company rather it was funded by personal efforts of the authors.

CONSENT

As per international standard or university standard, respondents' written consent has been collected and preserved by the author(s).

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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