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Credit Risk Management Practices and the Profitability of Selected Microfinance Institutions in Bamenda

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Abstract

Purpose: This article examines the effect of credit risk management practices on profitability of microfinance institutions in Bamenda which host majority of credit unions in Cameroon.

Methodology: After exploring the related concepts and theories, the study adopts a mixed research design where data were collected mainly with the use of questionnaires from a sample of 41 credit unions in the area, analysed using multivariate regression technique.

Findings: The results of the findings show that the data are normally distributed, not prone to any problem of multicollinearity, and that the model is globally significant at one percent following Fisher test, with the four dimensions of CRM practices explaining over 92 percent of variation in the MFIs' profitability. The influence of all the variables were positive as hypothesized. The coefficients of the variable for credit scoring was 0.783 and significant at 1 percent, for collateral requirement was 0.232 and equally significant at 1 percent, for loan monitoring was 0.172 and significant at 5 percent, meanwhile for limiting credit exposure was 0.081 and insignificant in contributing to the profitability of the MFIs.

Unique Contribution to Theory, Policy and Practice: Finding of this paper suggest that, MFIs can better manage its credits risks by enhancing the practice of credit scoring, limiting credit exposure, loan monitoring, and collateral requirement in that decreasing order of importance.

Keywords: *CRM practices, profitability, MFIs, Bamenda*

INTRODUCTION

Micro finances are exposed to varied types of risks, which affect the performance and activity of these institutions, since the primary goal of the management is to maximize the shareholders' wealth. According to Holland (2010), one of the primary reasons of the crisis is thought to be a failure in risk management. Through the sale of liabilities with a certain combination of liquidity risk and return, microfinance generates profits. The revenues are then used to purchase assets with a variety of characteristics, a process known as asset transformation. The business of the financial system is defined by modern financial management as assessing, controlling, and embracing risks. Given that providing loans is one of the primary revenue streams for microfinance institutions, credit risk is among the biggest threats they face. Consequently, profitability is impacted by how that credit's risk is managed (Harcourt, 2017).

Since credit risk management (CRM) is an essential component of the loan application process, financial institutions place a high value on it. By preserving exposure to credit risk, it reduces bank risk and adjusted risk rate of return while protecting the company from the negative consequences of credit risk. MFIs are spending a lot of money on modelling credit risk management. Both the risk associated with individual credits or transactions and the credit risk inherent in the entire portfolio must be managed by MFIs. Given that credit risk exposure is the primary cause of issues in financial institutions globally, MFIs and their supervisors ought to be able to learn valuable lessons from the past. MIFs ought to be acutely aware of the necessity of recognising, quantifying, tracking, and managing credit risk in addition to making sure they have enough capital to cover these risks and that they are fairly reimbursed for the risks they take. According to Sarkar and Alvari (2018), there is a need for more research and analysis on the topic of credit risk and its management because the current methods for managing it are insufficient to meet the current financial and economic difficulties.

Microfinance has demonstrated poor financial performance in several nations, as seen by rising loss ratios, including return on capital employed, quick, net profit, and current ratios. Low net interest margins, inflation, exchange rates, sound managerial concepts, credit risk management, and other reasons have all been blamed for this subpar performance. In his article on the factors influencing risk management in Indian banks, Singh (2015) made the case that improper lending practices that exposed banks to various risks and losses were one of the causes of bank collapse. As a branch of risk management, risk management has become a unique field of study. It combines concepts and methods from other fields to offer a solid conceptual basis and a collection of instruments for risk analysis and management. Due to political, economic, social, and cultural reforms, Cameroon's financial sector has liberalised, increased the use of information technology, and improved the business environment (IMF country report 2009).As a result of these developments, the degree of competition has peaked, and MFIs have implemented efficient risk management procedures as a result of more knowledgeable consumers and more regulatory scrutiny.

Bamenda is one of the cameroon town with ponponderance number of credit unions (Category one MFI). For the past seven years, the zone's restive nature has exposed the institutions to a wide range of threats. Due to their diverse structure and functions, microfinance institutions are vulnerable to a wide range of risks, particularly credit and liquidity risk, which is the possibility that the organisation and its clients won't be able to pay their debts on time. Liquidity risk affects the institution itself, whereas credit risk primarily affects the clients that obtain credit from the organisation. The causes and/or effects of credit risk have received a lot of attention (Baklouti Ibtissem & AbdelfettahBouri, 2013; Asad Abbas1 et al., 2014; Adamu et al., 2014; Harcourt, 2017), while the CRM's remediation procedures have received less attention. Oduya (2014) focused exclusively on commercial banks in his study on credit risk management practices in Kenya. In other countries, MFIs received less attention than banks in recent research on credit risk management, including Boahene et al. (2012), Singh (2015), Aykut (2016), Adebayo and Oluwaremi (2017), and Kaicer (2020). Many credit officers in Bamenda town, the birthplace and headquarters of the majority of MFIs in Cameroon, are ignorant of the proper credit risk management procedures to pursue due to the lack of rigorous empirical research of this kind. Once more, considering that MFIs require profit in order to be viable, the issue that must be asked is: What impact do credit risk management procedures have on MFI profitability? In order to address this problem, the paper's objectives are:

- To investigate how credit scoring affects MFI profitability
- To ascertain how loan monitoring affects MFI profitability
- To gauge the degree to which limiting credit exposure will affect MFI profitability
- To assess how much collateral requirements may impact MFIs' profitability

To attain these objectives, the rest of the sections are structured as follows; Section two discusses the literature review and theoretical framework. Section three describes data and econometric techniques used in investigating the relationships between the variables. The empirical results are presented in section four while section five focuses on the conclusion and policy implications emanating from the study.

LITERATURE REVIEW

Theoretical Reviews

In order to challenge and expand on current knowledge, theories are developed in this section to explain, forecast, and comprehend phenomena pertaining to credit risk management practices and their relationships to microfinance institutions' performance, all while staying within the bounds of critical limiting assumptions.

Woolcock's Theory

According to Woolcock's theory, the way banks screen potential borrowers and deal with opportunistic behaviour, which is promoted by loan contracts, greatly influences the credit or loan markets. In the year 2000, the theory was formed. As a result, lenders typically raise borrowing prices to a point where they anticipate the highest possible profits. This frequently leaves out small, expensive, and hazardous borrowers. Interest rates and the amount of collateral needed are typically inversely correlated with credit consumption. Applying the credit management philosophy, MFIs frequently take advantage of opportunistic behaviour displayed by prospective borrowers. Individual banks may use a variable interest rate pricing policy, and credit consumption is correlated with collateral requirements (Alshatti, 2015).

Information Asymmetry Theory

According to Akerlof's information asymmetry hypothesis, buyers often utilise market statistics to ascertain the value of items in 1970. Auronen (2003) As a result, while the seller employs a deeper understanding of a specific item, the clients simply see an average of the entire market. According to Akerlof, information asymmetry presents a seller with a huge opportunity to sell goods or services that are of lower quality than the market as a whole. As a result, both the market's size and the average quality of its goods or services will decline. For every agent, information is provided. Nonetheless, there is a significant knowledge imbalance between the investors and the managers. A situation where all people involved in an undertaking are unaware of the pertinent knowledge that is accessible is explained by this hypothesis. Auronen (2003) has suggested that intertemporal links play a role in competitive behaviour in these kinds of markets. According to the hypothesis, there are two issues with financial institutions' perceived knowledge asymmetry. That's moral hazard and adverse selection. According to the notion, MFIs can reduce loan repayment rates if they are able to share client information, particularly regarding creditworthiness. Credit reference bureaus will be able to create credit risk management strategies, including credit rating, through a decrease in the information asymmetry between lenders and clients. As a result, institutions will be able to offer loans to creditworthy borrowers, increasing aggregate lending and lowering default rates.

The Theory of Adverse Selection

According to the adverse selection theory developed by Stiglitz and Weiss (1981), adverse selection happens when customers possess traits or attributes that the bank cannot see when making a loan and that could result in loan repayment default, which would have a detrimental impact on the bank's profitability. According to the hypothesis, all bank loan contracts given to borrowers are subject to limited liability, and lenders will not be able to differentiate between bank loan clients with varying levels of risk. The scenario where a bank is unable to differentiate between safe and dangerous borrowers is described by the adverse selection hypothesis. According to this idea, the lender in this instance, microfinance, does not have enough information about the loan recipients. In order to compensate for a larger default risk, riskier loan consumers should pay higher interest rates than safer loan clients, whose default chances are extremely low. Therefore, safer loan customers should pay slightly less as long as they can be reliably distinguished from other loan customers or borrowers. High average interest rates are typically passed on to all loan clients without taking into account variations in their risk profiles since MFIs, as the lender, do not have complete knowledge about borrowers' risk profiles (Kauffman & Riggins, 2012). Credit providers put their loan applicants through a rigorous screening process before making a loan offer in order to prevent adverse selection issues; yet, this has been able to lower loan default rates in microfinancial institutions.

Empirical Literature

Credit risk management practices have been extensively in the empirical literature, specifically in the context of microfinances. Various studies have focused on understanding the impact of these practices on the profitability of microfinances. Some important findings such as Kauffman and Riggins (2012).examined the effectiveness of credit risk assessment practices in microfinance institutions (MFIs) and found that conducting thorough credit risk assessments using quantitative models, such as credit scoring, reduces default rates and improves MFI profitability. Similarly, a study by Afriyie and kotey (2013) and Vandeputte, and De Toffol (2017) showed that MFIs that use more sophisticated credit assessment techniques have lower portfolio at risk (PAR) and higher profitability. Afriyie and Akotey (2012) investigated the effect of Client monitoring and support on profitability of MFIs and noted that the effective client monitoring and support mechanisms have been shown to positively impact microfinance profitability. The results revealed that frequent client visits and follow-ups help in early identification of potential credit risk issues, leading to improved loan recoveries and profitability. Additionally, Ejoh et al. (2014) conducted a study to examine the effects of financial literacy on the performance of MFIs and found that financial literacy training to borrowers improves their repayment behavior and reduces credit risk. Findings from the study reveaved that MFIs offering financial education programs have lower default rates and significantly raises profitability.

Aigbomian and Akinlosotu (2017) noted that the adoption of risk-based pricing models, where the interest rates offered to borrowers reflect their creditworthiness. It was found that risk-based pricing helps align loan pricing with credit risk, reduces adverse selection, and improves the profitability of microfinances. By charging higher interest rates to higher-risk borrowers, MFIs can compensate for the additional credit risk they bear. A study by Djan et al. (2015) on the impact of loan portfolio diversification on the profitability of microfinances was investigated using primary data collected from selected MFIs and it was reported that MFIs with diversified loan portfolios across sectors have lower credit risk exposure and are more profitable. The results of these findings suggest that diversification reduces the likelihood of concentration risk, enhances risk-adjusted returns, and reduces credit losses.

Kaicer (2020 investigated the impact of adopting technology-driven solutions in credit risk management and found that microfinances utilizing digital credit scoring tools often have more accurate risk assessments and lower default rates, leading to improved profitability. These findings were similar to those of Sarkar and Alvari (2018) who highlighted how the automation of loan portfolio management processes using information technology improves efficiency and reduces operational costs, ultimately enhancing microfinance profitability.

These studies provide valuable insights into the relationship between credit risk management practices and the profitability of microfinances. However, it is important to note that the empirical findings are not always consistent, reflecting differences in methodologies, sample characteristics, and contextual factors. Nonetheless, the overall evidence emphasizes the importance of implementing effective credit risk management practices to enhance microfinance profitability and sustainability.

METHODOLOGY

Data collection and sources

Contextually, the study was restricted to reviewing microfinance institutions' credit risk management procedures and their impact on their profitability. Primary data from 41 credit unions was gathered through questionnaires given to portfolio managers. Structured questions on a Likert scale from 1 to 5 were included in the surveys. SIMA has duly recognised the RAINBOW Cooperative League, CAMCCUL, and RECUCAM as the umbrella organisations for the chosen microfinance institutions in Bamenda municipality. The city of Bamenda was chosen for this study due to the presence of diverse microfinance in an area where credit risk is prevalent. The city of Bamenda is located in Cameroon's northwest. In order to gather information from microfinance institutions regarding their perspectives and opinions regarding the impact of credit management practices on microfinance profitability, a survey design was employed. The optimum approach, according to Ajala (1996), is a descriptive survey when people's opinions, experiences, values, and impressions about a problem need to be recorded. This is why the descriptive survey research approach was used in the study that evaluated the impact of credit risk management on MFI profitability. The data was sorted both qualitatively and quantitatively.

Method of Analysis

The link between the independent variables (credit scoring, loan monitoring, limiting credit exposure, and collateral requirements) and the dependent variable (profitability) was examined using multivariate regression analysis.

The following was the multiple regression model.

$$\mathbf{PROFITi} = \beta_0 + \beta_1\mathbf{CRSCOi} + \beta_2\mathbf{LOMOi} + \beta_3\mathbf{LICRi} + \beta_4\mathbf{COLREi} + \mu_i$$

Where:

PROFITi = Profitability of MFIs

CRSCOi = Credit scoring

LOMOi = Loan monitoring

LICRi = Limiting credit exposure

COLREi = Collateral requirement

β_0 = Constant term

β_1 = Sensitivity of Credit scoring to Profitability of MFIs

β_2 = Sensitivity of Loan monitoring to Profitability of MFIs

β_3 = Sensitivity of Limiting credit exposure to Profitability of MFIs

β_4 = Sensitivity of Collateral requirement to Profitability of MFIs

μ_i = error term

The reliability test was conducted to measure the internal consistency of the reliability of the questionnaire used for the collection of survey data for this study.

Table 1. Reliability Statistics

Cronbach's Alpha	Number of items
0.816	5

Source: Ccomputed by author (2024) using SPSS

Table 1 above shows the results of the overall reliability of the items in the questionnaire used for the collection of survey data for this study. As sown above a Cronbach alpha of 0.816 for a total of 5 items (credit scoring, loan monitoring, collateral requirements, limiting credit exposure and profitability) was arrived at indicating that the research was an exploratory one. In that effect, the reliability scale for each item was also calculated as illustrated on table 2 below.

Table 2: Scale Reliability

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha
Credit Scoring	15.1463	5.028	.853	.793
Loan Monitoring	15.1707	7.495	.375	.840
Limiting Credit Exposure	14.0732	8.470	.209	.868
Collateral Requirement	14.7561	6.289	.719	.750
Profitability	15.0976	4.690	.923	.743

Source: Ccomputed by author (2024) using SPSS

Table 2 above presents the results of the scale reliability test for the measuring index used in the questionnaire and the results revealed tha all the values are highly reliable as results from the reliability scale showed an alpha value of 0.743. Therefore, the above results indicates statistical consistency of the responses obtained across the multiple items measures as seen on the table above and the presence of a high correlation among the four constructs of credit risk management practices (credit scoring, loan monitoring, limiting credit exposure, collateral requirements) that the measure the dependent variables profitability of MFI and employee turnover.

PRESENTATION AND DISCUSION OF FINDINGS

Results in table 3 showed that 08 (19.5) of the Credit Unions were affiliated to network, RAINBOW Cooperative League, 29 (70.7) were under CAMCCCUL network and 4(9.8) were allied to RECUCAM network.

Table 3: Frequency Distribution of Credit unions based on the network

MFIs Network	Frequency	Percent	Cumulative Percent
RAINBOW CAM	08	19.5	19.5
CAMCCUL	29	70.7	90.2
RECCUCAM	04	09.8	100
	41	100	

The results respondents' perception are based on the means and standard deviation for the data that was collected through the 5-point likert scale measuring the extent of agreement of the respondents with respect to the given aspects. Table 4 summarises the descriptive statistics for the variables included in the model.

Table 4: summary of the descriptive statistics

VARIABLE	N	Min	Max	Mean	Std. Dev
Credit Scoring	41	2.60	5.00	4.1233	0.73073
Loan Monitoring	41	2.00	5.00	3.1975	0.35101
Limiting Credit Exposure	41	2.00	5.00	3.9259	1.16341
Collateral Requirement	41	3.10	5.00	4.5833	0.23291
Profitability	41	3.20	5.00	4.2160	0.63598

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It is observed from the table that the mean value of profitable inices of MFIs is 4.2160 with a standard deviation of 0.63598, while the minimum and maximum values are 3.20 and 5 respectively. The result shows that there is a moderate deviation of profitability from the mean as the standard deviation is not far from the mean and also, the mean is closer to the maximum value than to the minimum thus indicating that profit of MFIs in Bamenda was relatively high during the period under study. Furthermore, the mean value for Credit Scoring stands at 4.1233 with a standard deviation of 0.73073, while the minimum and maximum values are 2.6 and 5 and this indicates a moderate deviation of the variable for Credit Scoring from the mean. The mean value of Loan Monitoring stands at 3.1975 with a standard deviation of 0.35101. The minimum and maximum values are 2.00 and 5.00, respectively for Loan Monitoring. This indicates a low deviation of Loan Monitoring from the mean indicating some level of stability of the variable. The mean value for Limiting Credit Exposure stands at 3.9259with a standard deviation of 1.16341 while the minimum and maximum values are 2.00 and 5.00 and this indicates a high deviation of the variable for Limiting Credit Exposure from the mean. This indicates a very low level of stability in the variable. Finally, the mean value of Collateral Requirement was found to be 4.5833 with a standard deviation of 0.23291. Collateral Requirement have a minimum and maximum values of 3.00 and 5.00 which indicates low deviation from the mean and high level of stability in the variable.

Table 5 indicates a statistical test for normality with actual calculated probability values using two different test models that is the Kolmogorov_smirnov and shapiro-wilk. The test was to calculate the probability that the sample of this study was drawn from and normal population. It carries on with the assumption that, probabilities >0.05 indicates that the data are normal, while probabilities <0.05 indicates that the data are not normal.

Table 5: Test for Normality

Variables	obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2
Credit Scoring	41	0.2754	0.0297	5.62	0.0602
Loan Monitoring	41	0.2646	0.7474	1.42	0.4907
Limiting Credit Exposure	41	0.0624	0.6032	3.96	0.1383
Collateral Requirement	41	0.2520	0.5765	1.72	0.4228
Profitability	41	0.2644	0.0353	5.44	0.0658

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Table 5's results demonstrate that the profitability index, collateral requirements, credit scoring, loan monitoring, and limiting credit exposure are all normally distributed as their probability values are greater than 0.05 or 5% based on the outcomes of the skewness and Kurtosis tests.

In this work, two multicollinearity tests were employed. The correlation matrix between the independent variables (credit scoring, loan monitoring, limiting credit exposure, and collateral requirement) is based on a multicollinearity test.

Table 6: Multicollinearity test based on correlation matrix

Independent variables	Credit Scoring	Loan Monitoring	Limiting Credit Exposure	Collateral Requirements
Credit Scoring	1.000			
Loan Monitoring	0.3706	1.000		
Limiting Credit Exposure	0.2964	- 0.1025	1.000	
Collateral Requirements	0.6153	0.3676	0.1623	1.000

A bivariance of each pair of variables is observed in the correlation matrix in table 6 above. The correlation coefficient relationship between loan monitoring and credit scoring is low, with an R-value of 0.3706, that between limiting credit exposure and credit scoring is 0.296, that between collateral requirements and credit scoring is 0.6153, and that between limiting credit exposure and loan monitoring is negative, with an R-value of -0.1025. Since none of the variables exhibit a level of high correlation or close to that which would have been deemed problematic to the outcome, this indicates that there is a weak positive correlation relationship among the constructs of the independent variables used in predicting the dependent variables and also accounts for the absence of multicollinearity.

Table 7: Results of multicollinearity based on variance inflation factor

Model		Collinearity Statistics	
		Tolerance	**VIF**
1	(Constant)		
	Credit Scoring	.432	2.313
	Loan Monitoring	.796	1.256
	Limiting Credit Exposure	.859	1.165
	Collateral Requirement	.475	2.103

As per the working rule of thumb, which states that VIF values below 1 and above 10 are problematic, all of the VIF values are less than 10, indicating the absence of multicollinearity in the data. Additionally, auxiliary regression was created for each variable, and the Variance Inflation Factors (VIF) were calculated for all constructs for the independent variable.

Additionally, each independent variable has a tolerance result that spans from 0 to 1. Although there isn't a precise threshold for tolerance, Allison (1999) proposed that a tolerance of less than 0.20 indicates significant multicollinearity in a model, while a tolerance of 0.84 indicates low multicollinearity. According to table 4.23's findings, the tolerance values for flexible work schedules, employee support programs, and limiting credit exposure were 0.678, 0.889, and 0.908, respectively. This displayed a high tolerance value, which suggests that multicollinearity is either low or nonexistent.

Therefore, the outcome has demonstrated from all indications that each variable in the linear regression calculation for this study can be used to explain its own prediction of the dependent variable.

Multiple Regression Results of the profitability model of MFIs

A multiple linear regression model was developed utilising likert scale data gathered from the 41 category 1 Microfinance Institutions in order to better understand the degree to which credit risk management strategies impact the profitability model of MFIs in Bamenda.

A regression model was estimated using Likert scale data gathered from the chosen category one Microfinance Institutions in Bamenda, Cameroon, in order to examine the impact of credit risk management practices (as measured by credit scoring, loan monitoring, limiting credit exposure, and collateral requirements) on MFI profitability. The analysis's findings are then displayed.

Table 8: **linear regression results for model**

Profitability of MFIs	**Coefficient**	**Standard Error**	**T**	**P<[t]**
Credit Scoring	.782	.068	11.440	.000
Loan Monitoring	.172	.065	2.659	.012
Limiting Credit Exposure	.079	.077	1.028	.311
Collateral Requirement	.232	.082	2.811	.008
_ Cons	-1.026	.423	-2.423	.021
R-squared	0.932			
Adjusted R-squared	0.924			
F(4,36)	122.642			
Prob >F	<0.001			
Root MSE	0.26933			

Note: ∗∗∗=1%, ∗∗=5% and ∗= 10% level of statistical significance

With the profitability of MFIs as the dependent variable and the four aspects of credit risk management methods as predictors, a multivariate linear regression model was run. As can be seen in table 16 above, a measure of explained variance revealed that credit risk management methods, which include credit scoring, loan monitoring, limiting credit exposure, and collateral restrictions, account for more than 92% of the overall variation in MFI profitability. Factors not included in the model are responsible for the remaining 8%. Additionally, the value of standard error 0.26933 is produced as the measure of unexplained variance.

Since the computed F-value is higher than the critical value, the model's significance was assessed using the Fisher statistic, which indicates that the F-value of 122.642 is highly significant at p = 0.01. This suggests that the regression model is appropriate for use in the study and that it matches the data. The table above displays the regression coefficients for the test of how credit risk management procedures affect MFI profitability. According to the regression equation above, other factors affecting MFI's profitability will rise by 3.937 units while keeping all independent variables (credit scoring, loan monitoring, limiting credit exposure, and collateral requirements) constant. The test statistic, which is marked by a t-value of 13.373 and a standards error of 0.294, is significant at p = 0.01.

The variable showed the predicted indications in the regression, and the most significant factor in determining the profitability of category 1 microfinance institutions in Bamenda was the coefficient of credit risk management techniques as measured by credit scoring. The variable had a very high significant force in adding to the organization's profitability and was positive as predicted. With a coefficient of 0.783 and a p-value of 0.000 ($pv < 0.01$), the regression results demonstrate that credit scoring has a significant impact on the profitability of MFIs in the region at the one percent level. According to these findings, an MFI's credit score can be raised by more than 0.78 points for every unit increase in credit scoring procedures.

The regression results also show that loan monitoring, a proxy for the variable for credit risk management methods, was a significant factor influencing the profitability of Bamenda's category 1 microfinance institutions. The variable contributed significantly to the profitability of MFIs in the study area and was positive as predicted. According to the regression results, loan monitoring has a substantial five percent impact on the profitability of MFIs in Bamenda, with a coefficient of 0.172 and a p-value of 0.012 ($pv < 0.05$). This finding suggests that MFIs can enhance their credit scores by more than 0.172 points per unit.

The regression results also show that, although the variable for credit risk management techniques, as evaluated by restricting credit exposure, was positive as predicted, it did not significantly contribute to the profitability of Bamenda's category 1 microfinance institutions. Limiting credit exposure is not a significant correlate of the profitability of MFIs in Bamenda, according to the regression results, which show that the coefficient of limiting credit exposure is 0.081 with a p-value of 0.311 ($pv > 0.05$). This finding suggests that, despite being relatively less important, reducing credit risk has a favourable impact on increasing a company's profitability.

Another important factor influencing the profitability of Bamenda's category 1 microfinance institutions was the coefficient of collateral required. In the regression, the collateral requirement variable showed the anticipated signals. The variable had a very high significant force in adding to the institution's profitability and was positive as predicted. With a coefficient of 0.232 and a p-value of 0.000 ($pv < 0.01$), the regression results demonstrate that the collateral requirement has a significant impact on the profitability of MFIs in the region at the one percent level. According to these findings, an improvement of one unit in the way MFIs handle their collateral requirements can raise the institution's score by more than 0.232.

We can so determine the regression equation as follows using the results above:

$$PROFITi = -1.026 + 0.783\ CRSCOi + 0.172\ LOMOi + 0.079\ LICRi + 0.232\ COLREi$$

Where PROFITi is Profitability of MFIs, CRSCOi is Credit scoring, LOMOi is Loan monitoring, LICRi is Limiting credit exposure COLREi is Collateral requirement

Results of the Pearsons correlation of credit risk management practices and profitability of MFIs

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The variables were subjected to Pearson Correlations for additional investigation. Utilising information efficiently gathered from 41 MFIs in Bamenda 2023 through questionnaires, Pearson Correlations between the independent factors and profitability were performed. The second parametric method in the current study was Karl Pearson Product Moment Correlation, and the following are the findings from SPSS version 25.

Table 9: Correlation between firms' performance and indicators of credit risk management practices

		Profitability
Credit Scoring	Pearson Correlation	.948**
	Sig. (2-tailed)	.000
	N	41
Loan Monitoring	Pearson Correlation	.471**
	Sig. (2-tailed)	.002
	N	41
Limiting Credit Exposure	Pearson Correlation	.289
	Sig. (2-tailed)	.067
	N	41
Collateral Requirement	Pearson Correlation	.776**
	Sig. (2-tailed)	.000
	N	41

**. Correlation is significant at the 0.01 level (2-tailed).

According to the results of the t-tailed testing procedure, all of the variables in Table 9 are significant correlates of the profitability of the chosen category 1 microfinance institutions in Bamenda (p-value or sig <0.05). According to Saunders' (2003) analysis, the credit score and collateral requirement Pearson correlation coefficients both surpass 0.7, indicating a positive and significant relationship with MFI profitability. According to the same logic, the loan monitoring correlation coefficient ranges from 0.4 to 0.7, with a correlation coefficient of 0.471 suggesting a positive and moderate relationship with MFI profitability. Limiting Credit Exposure has a correlation coefficient of less than 0.3, which suggests a weak but favourable relationship with

MFI profitability.As a result, the Pearson correlation result agrees with the previously described regression analysis result.

Results of Post Estimation Tests (Robustness Test)

All of the factors presented in table 9 are significant correlates of the profitability of the selected category 1 microfinance institutions in Bamenda, as indicated by the results of the t-tailed testing technique (p-value or sig <0.05). The credit score and collateral requirement Pearson correlation coefficients both exceed 0.7, demonstrating a positive and significant association with MFI profitability, per Saunders' (2003) investigation. Using the same reasoning, the correlation coefficient between loan monitoring and MFI profitability is between 0.4 and 0.7, with a correlation coefficient of 0.471 indicating a moderately good association. The correlation coefficient between Limiting Credit Exposure and MFI profitability is less than 0.3, indicating a modest yet positive association.Consequently, the results of the regression study previously mentioned are consistent with the Pearson correlation result.

Table 10: Test for heteroscedasticity

Models	ANOVA (F) statistics	P-(values)
Residual of organisational perforance	**0.671**	0.412[b]

[b] is the residual term

According to the Goldfield-Quandt test of 1965, assumptions of heteroscedasticity are problematic if the probability value is less than 5% (p-0.05), which indicates the presence of heteroscedasticity. Accordingly, the probability value for the institution has p-values greater than 5%, showing the lack of heteroscedascity, based on the analysis of table 18 above.

Discussion of Findings

This study's primary goal was to investigate how credit risk management strategies affect MFI profitability. The results of this study showed that loan monitoring, credit exposure limitation, and credit scoring are three ways that credit risk management techniques impact organisational performance. These align with the three research hypotheses that were examined in this investigation.

Both descriptive and inferential statistics were used to test the four hypotheses that were developed from the particular goals that served as the study's compass. Among other things, the mean and standard deviation were employed for the descriptive statistics. The bulk of the likert scale questions utilised to capture the various dependent variables (profitability) and independent variables (indicators of credit risk management techniques), according to the mean and standard deviation results. With the exception of the index designed to reflect restricting credit exposure, the majority of the means were judged to be strong since they surpassed three and the standard deviation was less than one, indicating little departure from the mean and high levels of stability in the variables. The data gathering questionnaires were as dependable as alpha. The data are normally distributed according to the multiple normality tests that were performed, and Cronbach's coefficient exceeded 0.7 for all of the variables included in the study. This is the sole justification for employing parametric testing procedures to validate the various research hypotheses.

Since credit scoring was very important in determining the profitability of category 1 MFIs in Bamenda and the variable showed the predicted signals in the regression, the first research hypothesis about the impact of credit scoring on profitability of category 1 MFIs was realised. This suggests that the variable contributes significantly to the profitability of category 1 MFIs in the region at the one percent level. This result contradicts Jonathan Morduch's but is consistent with Hand and Henley's (1997) findings. The variable showed the predicted indications in the regression, and the most significant factor in determining the profitability of category 1 microfinance institutions in Bamenda was the coefficient of credit risk management techniques as measured by credit scoring. The variable had a very high significant force in adding to the organization's profitability and was positive as predicted. With a coefficient of 0.783 and a p-value of 0.000 ($pv < 0.01$), the regression results demonstrate that credit scoring has a significant impact on the profitability of MFIs in the region at the one percent level. This suggests that an improvement of one unit in MFIs' credit scoring practices can raise the institution's score by more than 0.78. The findings of this study are comparable to those of Asfaw and Veni's (2015) research in Ethopia.

Due to the fact that loan monitoring significantly increased the profitability of category 1 MFIs, the second research hypothesis about the impact of loan monitoring on MFI profitability was realised. The findings of the regression show that loan monitoring is beneficial. According to the study's findings, loan monitoring significantly increases the profitability of category 1 MFIs in Bamenda at the five percent level. According to these findings, an increase of one unit in MFI loan monitoring can increase the MF institution's profit by more than 0.43. Similar findings have been documented in previous studies (Aykut, 2016 & Harcourt, 2017).

Although it is not entirely satisfactory, the third research hypothesis on the impact of limiting credit exposure on MFI profitability has also been met. Reducing credit exposure had no discernible effect on the profitability of Bamenda's category 1 MFIs, but it did have a favourable effect on their profitability, and the variable showed the predicted regression signals. According to these findings, an MFI's profit margin might increase by more than 0.67 for every unit improvement in its credit exposure limitation services. The outcome is consistent with Adebayo and Oluwaremi's (2017) findings.

Although it is not entirely satisfactory, the fourth study hypothesis about the impact of collateral restrictions on MFI profitability is also met. Another important factor influencing the profitability of Bamenda's category 1 microfinance institutions was the coefficient of collateral required. In the regression, the collateral requirement variable showed the anticipated signals. The variable had a very high significant force in adding to the institution's profitability and was positive as predicted. With a coefficient of 0.232 and a p-value of 0.000 ($pv < 0.01$), the regression results demonstrate that the collateral requirement has a significant impact on the profitability of MFIs in the region at the one percent level. According to these findings, an improvement of one unit in the way MFIs handle their collateral requirements can raise the institution's score by more than 0.232. This outcome agrees with the findings of Boahene et al. (2012).

CONCLUSIONS

Drawing inspiration from Woolcock's theory, the idea of asymmetry information, and the theory of adverse selection, this paper examines how credit risk management techniques affect the profitability of microfinance companies in Bamenda. Both descriptive and inferential statistics were included in the mixed research design. Questionnaires were the primary tool used to collect data. Regression and product moment correlational analyses were employed, and the empirical results demonstrate that the model is globally significant, with the four CRM practice variables accounting for more than 92% of the variation in MFI profitability. With corresponding coefficients of 0.783, 0.232, 0.172, and 0.081, the variables for credit scoring, collateral requirements, loan monitoring, and limiting credit exposure were all positive as predicted.

Since credit scoring significantly increased the profitability of category 1 MFIs in Bamenda, the first research hypothesis on the impact of credit scoring on category 1 MFI profitability was realised. Since loan monitoring had a major role in boosting category 1 MFIs' profitability, the second research hypothesis about the impact of loan monitoring on MFI profitability was also realised. In the same vein, the third research hypothesis, which examined how restricting loan exposure affected MFI profitability, was also met, albeit not to a high degree. The fourth research hypothesis, which examined how collateral requirements affected MFI profitability, was likewise favourable and extremely significant in raising MFI profitability.

Based on the findings, it might be recommended that in order to improve credit risk management by category one MFIs, particularly in Bamenda, the credit scoring method be improved, loan monitoring be closely monitored, and credit exposure be limited. In order to successfully reduce credit risk and pursue higher profits, MFIs are also encouraged to implement collateral requirements. This study's primary limitations are related to its small sample size, geographic scope, data type, data collection tool, and operationalisation of certain variables. Increasing the sample size, expanding the study area, utilising panel data, and adding additional aspects of credit risk management (CRM) can all broaden the study's scope.

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