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ABSTRACT

This study purposed to determine effect of credit referencing on loan performance of deposit taking MFIs in Mombasa, Kenya. In Kenya, despite CRBs introduction into the financial system, recent statistics of CBK indicate increasing microfinance non-performing loans over the years. According to Central Bank of Kenya (CBK) 2017 report, Kenya's microfinance sector loss hit to $7.31 million as at December 2017, compared to 2016, which recorded $ 3.77million thus contributing to huge reduction of financial income. The study utilized descriptive research design. The target population of the study was management staff of the 6 deposit taking MFIs which are licensed by CBK and have fully-pledged branches in Mombasa County. The study adopted stratified sampling technique. The study used primary and secondary data. A structured questionnaire was used to collect the primary data. Descriptive and inferential statistics was used to analyze information generated from respondents. Descriptive statistics included responses mean and standard deviation. Inferential statistics was composed of bivariate correlation analysis and multiple regression analysis. The data analysis tool to be used was Statistical Package for Social Science (SPSS) version 25. Analyzed data was presented in frequency tables to facilitate ease of interpretation and discussions. The study revealed that credit scoring has a positive effect on loan performance. The study established that the MFI uses credit information sharing as a basis for setting better loan pricing for the borrowers and that the MFI's knowledge of applicants' characteristics, easing adverse selection problems. Also the credit reference bureaus have led to improved default rate of borrowers. The study concluded that credit risk assessment has a positive effect on loan performance. The analysis comes to the conclusion that the MFIs are prone to experience bad actors who apply and get loans based on misleading information. Credit reference bureaus have led to enhanced loan delinquency in our MFIs. The study recommended that the deposit taking microfinance should promptly report policy exceptions and that these banks should conduct collection enforcements. The deposit taking microfinance should recover default amount from the guarantor. This would be made possible by setting up of a dynamic client follow-up procedures.

Key Words: *Credit Information Sharing, Moral Hazard, Credit Risk Assessment, Credit Scoring, Loan*

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INTRODUCTION

World over, loan performance remains the highest detrimental factor to development of the financial sector (World Bank, 2018) and impacts on financial institutions' ability to lend (Doriana, 2018). Lending decisions are made under the environment of uncertainty; information asymmetry therefore remains a key challenge that leaves credit practitioners having a lenders puzzle during the process of loan application appraisal (Kiage, Musyoka & Muturi, 2017). Consequently, over the past three decades, microfinance has eased liquidity constraints for millions of low-wealth people around the developing world.1 In making loans to low-wealth borrowers, microfinance lenders face not inconsequential problems of moral hazard and adverse selection given that small loan sizes and fixed information costs make it expensive to select and monitor borrowers.

Micro finance institution is a kind of financial organization that provides financial benefits to the low-income peoples, unemployed or group of individuals who have no access to financial benefits of commercial banks (Perways & Krishna, 2017). MFIs function in an environment where customers are without credit histories or unavoidably expected borrowing behaviors. In many emerging markets, micro finance institutions have significant outreach, providing financial services to thousands of small and micro enterprises. Since their primary relationship with these entrepreneurs often involves an enterprise loan, they could theoretically use that leverage to encourage improvements to conditions in the business.

Credit risk exposure continues to be a significant basis of problems for the microfinance banks. This issue is even more imperative with reference to microfinance institutions. Risk is inherent to any business and microfinance institutions are no exception. What makes microfinance special is absence or near absence of traditional risk mitigation mechanisms like collaterals and guarantees. Management of credit risk, therefore, becomes extremely important for microfinance institutions (Ewool & Quartey, 2021).

In Central and Eastern European nations, Škarica (2018) study on NPLs determinants found that the implementation of the CIS system reduced IA. As a result, microfinance institutions received information about borrowers' loan repayment characteristics, reducing tendencies to credit bad borrowers. Latin America boasts of the highest coverage of public Credit Registries where seventeen countries have established PCRs, including all the largest economies of Argentina, Brazil, Chile, Colombia and Mexico (World Bank Public credit registry report, 2018). Public Credit Registries (PCRs) contain information on the performance of borrowers in a financial system and are administered and maintained by the Central Bank as bank supervisor.

In Africa, the region has least developed credit information systems thus the rapid setting off financial sectors in many African countries have immensely gained interest in the feasibility of the creation of credit bureaus to help them manage borrower risk under heightened competition (World Bank Public credit registry report, 2018). The MFIs showed ROA of 3.1% with low portfolio quality (Microfinance Barometer Report, 2018). According to a 2007 Microfinance Information eXchange (MIX) publication, African MFIs reported higher percentages of portfolios at risk, as well as lower percentages of risk coverage and higher percentages of non-earning liquid assets (Ewool & Quartey, 2021). In the Sub-Saharan Africa (SSA) MFIs have been growing rapidly at a yearly rate of 10 percent in the last two decades (Chikalipah, 2017). Markedly, not only is microfinance the industry that is increasingly becoming the core of financial inclusion, but also it is an important instrument of consumption smoothing among the poor in the SSA region.

In Malawi, moral hazard is common occurrence among credit groups. Diagne (2016) note that peer monitoring rarely occurs in credit groups from Malawi and that when it occurs it does not lead to

improvements in repayment because the main reason for default in the Malawi Rural Finance Company (MRFC) credit groups is the unwillingness to repay (moral hazard) and not the inability to repay. The unwillingness to repay was found to be the first cause of default among the MRFC credit groups.

In Kenya, microfinance institutions have experienced significant growth from the period 2013 to 2018 (Kinyua, 2017). According to AMFI (2021), net loan portfolio in the MFI sector increased by 13.3% in 2018 however, there was a decrease before tax that decreased by 19% between 2017 and 2018. However, In Kenya, Manyauanda (2020) argues that Kenyan MFIs have experienced rapid increase in the level of NPLs hence leading to liquidity problems. The liquidity problem has led to performance issues of MFIs in Kenya such as declined deposits. In a survey conducted by AMFI in late May 2020 MFIs faced constrained working capital due to low repayment hence affecting the liquidity levels. According to AMFI (2021) as at 31st December 2020 the loan loss reserve stood at Ksh4.75B and write offs stood at Ksh395.91M with 6,998 number of loans written-off during the period. In the same period there was Ksh65.99B total liabilities. In Mombasa, there are 16 fully-pledged branches with an outstanding loan portfolio of Kshs. 2,031,554,311.77 (AMFI, 2021).

Statement of the Problem

Higher proportion of credit risks by financial institutions arises imminently from credit default risk bringing about non-performing loans in banks (Koros, 2018). Inadequate information sharing system on borrowers' history on credit and their exiting ability in terms of finances results in extreme difficulty of lending institutions to determine correctly borrowers' credit worthiness as well as the likelihood of their loan repayment (Wanjiru, 2017). Therefore, credit information sharing performs a strategic role in the enhancement of efficiency in the financial sector by addressing the issues of loan defaults.

Despite CRBs introduction into the financial system, recent statistics of CBK indicate increasing microfinance non-performing loans over the years. According to Central Bank of Kenya (CBK) 2017 report, Kenya's microfinance sector loss hit to $7.31 million as at December 2017, compared to 2016, which recorded $ 3.77million thus contributing to huge reduction of financial income. The sector which posted profits in 2015/2016 period also had nonperforming loans increase by 25.6% from $73.71 million to $99.1 million. Deposits by customers dropped to $394.16 million from $401.98 million for previous period 2015/2016. The increased NPLs affected the capital base which had risen to $104 million as at December 2016, dropped to $98.1 million this pushed CBK to put a requirement of $600,000 as the core capital. In Mombasa MFIs have continued to record high rate of non-performing loans with an outstanding loan portfolio of Kshs. 2,031,554,311.77 as of December, 2020 (AMFI, 2021).

A plethora of empirical literature has been done on credit reference and MFIs performance. Ndungo (2019) researched on credit reference bureaus effect on financial performance in SACCOs. Wangai and Mungai (2019) investigated the effects of financial management practices on loan performance in microfinance institutions in the Starehe constituency Nairobi County, Kenya. Kitonyi and Muriithi (2019) did an investigation on non-performing loans and financial performance of microfinance institutions in Kenya. Mburu, Muathe and Mwangi (2020) did a study on the credit management practices and loan performance of commercial banks in Kenya. Njeru (2021) conducted a study on credit reference bureau functions and loan performance of commercial banks in Kenya. However, majority of the studies done in the past have posed many gaps worth filling. Some of the studies have been focused on commercial banks (Mburu, Muathe & Mwangi, 2020) and SACCOs (Ndungo, 2019) and few studies have focused on credit referencing in the context of loan performance Microfinance institutions. The current

study sought to answer the research question: What is the effect of credit referencing on loan performance of deposit taking Microfinance institutions in Mombasa County, Kenya?

Objectives of the Study

The general objective of the study was to investigate the effect of credit referencing on loan performance deposit taking Microfinance Institutions in Mombasa County, Kenya. The specific objectives were;

- To establish the effect of credit information sharing on loan performance of deposit taking Microfinance Institutions in Mombasa County, Kenya
- To determine the effect of moral hazard on loan performance of deposit taking Microfinance Institutions in Mombasa County, Kenya
- To examine the effect of credit risk assessment on loan performance of deposit taking Microfinance Institutions in Mombasa County, Kenya
- To establish the effect of credit scoring on loan performance of deposit taking Microfinance Institutions in Mombasa County, Kenya

The research was guided by the following hypotheses;

- **$H_0$1:** There is no significant effect of credit information sharing on loan performance of deposit taking Microfinance Institutions in Mombasa County, Kenya
- **$H_0$2:** There is no significant effect of moral hazard on loan performance of deposit taking Microfinance Institutions in Mombasa County, Kenya
- **$H_0$3:** There is no significant effect of credit risk assessment on loan performance of deposit taking Microfinance Institutions in Mombasa County, Kenya
- **$H_0$4:** There is no significant effect of credit scoring on loan performance of deposit taking Microfinance Institutions in Mombasa County, Kenya

LITERATURE REVIEW

Theoretical Framework

Asymmetric Information Theory

Asymmetric Information theory was propounded by George Akerlof, Michael Spence and Joseph Stiglitz in 1970's. Information asymmetry exists when a client usually the borrower who applies for loan usually poses superior knowledge on the potential risks and returns regarding the business or investments for which the loan is being applied for (Arora & Kumar, 2016). The lender usually doesn't have complete of information about the borrower and the intended project. In the context of financial institutions, information asymmetry problems are generally categorized into two, that is, moral hazard and adverse selection (Rukwaro, 2017). Microfinance institutions encounter challenges in addressing these dominant problems because it is not rational to commit financial resources for monitoring and appraisal of small amounts of loans. This is because the data needed to screen applicants and monitor borrowers may have some costs attached to it (Ali, 2015). Therefore, MFIs face a problem of information asymmetry in their operations.

Asymmetry theory relates to this study in that it explains how borrowers outsmart lenders by taking advantage of the superior knowledge which they have over them (commercial banks) by not making available all vital information. Particularly, information that may increase the rate of interest to be charge or that which will jeopardize the chances of securing a loan. The theory was associated to credit terms and conditions variable.

Adverse Selection Model

Adverse selection model was introduced by Rothscild and Stiglitz in 1976 who revealed that the buyer knows the possibility of the accidents

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exposed while the seller does not. It is a situation where there is a tendency to take undue risks because the costs are borne by the party taking the risk. The model is mainly used in economics and it refers to a process in which undesired results occur when buyers and sellers have access to different or imperfect information, also known as asymmetric information. The party that knows less about the same specific item to be transacted is therefore in a position of making either right or wrong decision concerning the transaction (Mabvure, Gwangwava, Faitira, Mutibvu & Kamoyo, 2016).

Adverse selection arises when some information about borrowers‟ characteristics remain hidden to the lender and can lead to an inefficient allocation of credit. The imbalance of power or information in transactions sometimes causes credit transactions to go awry (Jagongo & Kerage, 2015). This uneven knowledge causes defaults and bad debts. Credit reference bureaus are essential for sharing credit information to mitigate defaults. Adverse Selection Theory rests on the view that one party is in possession of superior information as compared to the other party, where the more informed party takes advantage of this scenario to benefit from the agreement. This is a risk model which is utilized risk control for lending institutions when selecting who to give out credit to which is depending on borrowers' repayment capacity. The prepositions of adverse selection theory support the linkage between the study variables, that is credit information sharing and loan performance.

Moral Hazard Theory

Introduced by Akerlof in 1970, the theory is concerned with financial transactions and the parties involved. A situation whereby a party to a contract does not enter into the contract on a good note or a situation whereby misleading information is provided by a party concerning his or her creditworthiness for his or her personal gains (Mirrlees, 1999).

The theory of moral hazards refers to the possibility of a person being less concerned about negative consequences of undertaking a risk as a result of having some form of insurance. The problem may arise when individuals or institutions do not alone bear the full risk of a transaction and therefore will not act as carefully as they would if that was the case. This, in turn, may jeopardize the returns of the transaction, i.e. the investment- or project return. Armendáriz de Aghion and Morduch (2015) states that moral hazard in lending refers to situations where lenders cannot observe either the effort made or action taken by the borrower, or the realization of project returns.

The theoretical model by Stiglitz in 1990 shows how peer monitoring under joint liability lending can help to mitigate ex-ante moral hazard. In his work, he argues that the group-lending contract circumvents ex ante moral hazard by inducing borrowers to monitor each other's choice of projects and to inflict penalties upon borrowers who have chosen excessively risky projects. The author further asserts that the repayment rate decreases with the interest rate and the size of the loan. In both cases, success becomes a less attractive outcome compared to the case in which the project fails; therefore, an increase in the interest rate or in the size of the loan causes the risky project to dominate the safe project. Banerjee et al. (1994) also studies how joint liability lending can help to overcome the problem of ex ante moral hazard. The authors introduce monitoring and demonstrate how local information facilitates the role of borrowers as monitors since they can impose higher penalties on their peers in case of default.

This theory is relevant since a good culture of credit is established especially to borrowers in ensuring they invest loans obtained in the rightful or earlier presented projects without partial diversion of the loan from productive investment to consumption; and lenders should also scrutinize borrower's credit ability before granting a loan. The postulations of this theory support the linkages between moral hazard function and loan performance.

Conceptual Framework

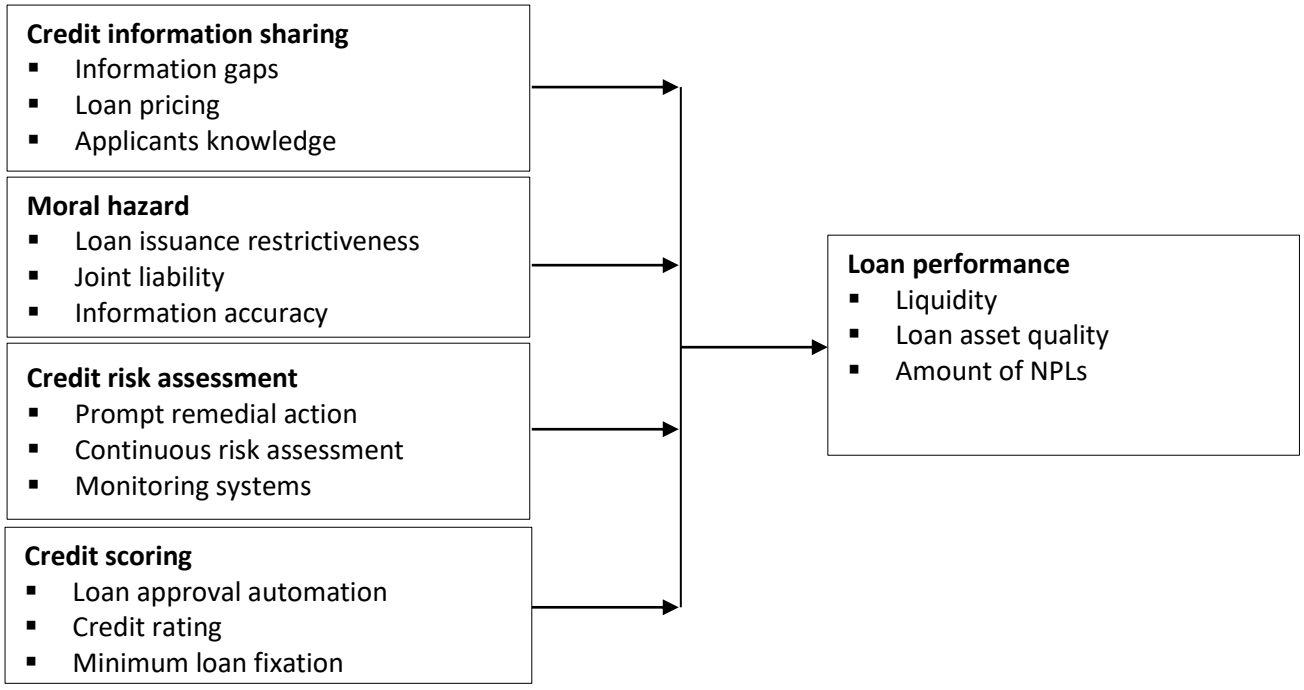

Figure 1: Conceptual framework

Review of Literature on Variables

Credit Information Sharing

Credit information sharing is a process where banks and other credit providers submit information about their borrowers to a CRB so that it can be shared with other credit providers. It enables the banks to know how borrowers repay their loans. Information sharing helps lenders assess credit worthiness, the ability to pay back a loan, and can affect the interest rate and other terms of a loan. Tchamyou and Asongu (2017) present credit data sharing as the regular passing of information about borrowers' creditworthiness. Bos, De Haas, and Millone (2016) view it as the sharing of knowledge about a customer's borrowing indebtedness and characteristics that bears significant implications to the activities of the credit market. Moreover, Tchamyou (2019) describes its passing on customers' borrowing information as a means of protecting creditors from crises related to excessive lending as well as no repayments.

Credit information sharing has a negative connection with the nonperforming loans since loan beneficiaries are encouraged to repay. Loan beneficiaries are likely to pay since sometimes they are forced to repay (Omukhokho, 2017). Sharing credit information also lowers the level of nonperforming loans as it discourages serial defaulters from failing to pay their dues. When credit information is shared on such defaulters, other microfinance institutions, digital lenders, and commercial banks would deny such a loanee credit (Koros, 2018).

In Kenya, the CIS system has not worked as expected, requiring a refresh. For instance, it was seen as a punitive “blacklisting” tool that bars Kenyans from getting loans, instead of helping borrowers take advantage of their credit history to get better pricing of loans. There are 378 million records in CRBs, of which, 42 million are blacklisted. Of these, 13 million are being blacklisted for amounts less than Ksh. 1,000 (CBK, 2018).

Moral Hazard

Moral hazard occurs in credit markets if raising the interest rate induces borrowers, who have a choice of projects, to invest in a project that yields the

bank a lower return than another project in which the borrowers could have invested. Moral hazard can occur under a type of information asymmetry where the risk-taking party to a transaction knows more about its intentions than the party paying the consequences of the risk and has a tendency or incentive to take on too much risk from the perspective of the party with less information.

Moral hazard is widely reported as a problem in credit and insurance markets, mainly arising from information asymmetry. Bester (2016) finds that also moral hazard can be eliminated if banks can vary both the interest rate and the collateral requirement. However, while collateralization can be an effective screening and incentive device that helps reduce adverse selection and moral hazard in lending, its effectiveness is limited both by borrowers' collateralizable wealth and by their risk preferences. Ghatak and Guinnane (2016) discuss how joint liability contracts can mitigate asymmetric information by shifting some risk to borrowers. Such contracts introduce risk sharing through cross-accountability where failure of one member to repay affects all others.

Besley and Coate (2015) argue that social sanctions by group peers increase the likelihood of repayment. The cost of failure of one member motivates peers to monitor and punish each other. The main tool used by the individual lenders to prevent the clients from moral hazard behavior is the regular repayment schedule. Armendariz and Morduch (2015) argue that regular repayment schedules screen out undisciplined borrowers; give loan officers early warning about emerging problems; and provide bank staff with valuable information about clients' behavior over time.

Credit Risk Assessment

Credit risk assessment is the heart of account management. It's what lets credit managers know when it's time to perform a periodic credit assessment and account review. Credit administration is a critical element in maintaining the safety and soundness of financial institutions (Armendariz & Morduch, 2015. An important tool in monitoring the quality of individual credits, as well as the total portfolio, is the use of an internal risk rating system. Once a credit is granted, it is the responsibility of the business unit, often in conjunction with a credit administration support team, to ensure that the credit is properly maintained. This includes keeping the credit file up to date, obtaining current financial information, sending out renewal notices and preparing various documents such as loan agreements.

For the various components of credit administration to function appropriately, senior management must understand and demonstrate that it recognises the importance of this element of monitoring and controlling credit risk. The credit files should include all of the information necessary to ascertain the current financial condition of the borrower or counterparty as well as sufficient information to track the decisions made and the history of the credit (Caire, 2017). Microfinance institutions need to develop and implement comprehensive procedures and information systems to monitor the condition of individual credits and single obligors across the bank's various portfolios. These procedures need to define criteria for identifying and reporting potential problem credits and other transactions to ensure that they are subject to more frequent monitoring as well as possible corrective action, classification and/or provisioning.

Internal risk ratings are an important tool in monitoring and controlling credit risk. In order to facilitate early identification of changes in risk profiles, the bank's internal risk rating system should be responsive to indicators of potential or actual deterioration in credit risk. Credits with deteriorating ratings should be subject to additional oversight and monitoring, for example, through more frequent visits from credit officers and inclusion on a watchlist that is regularly reviewed by senior management. Microfinance institutions need to manage risks on a daily basis, especially relating to financial controls and integrity (Bailey, 2016). These financial institutions need to guard against

falling prey to managing risks in a haphazard and unsystematic manner.

Credit Scoring

The use of statistical methods to convert pertinent data into numerical measures that monitor credit decisions is branded as credit scoring. Credit scoring is also defined as the conversion of qualitative information into numerals using statistical strategies. Credit rating is the opinion of the creditworthiness of an obligor with respect to a specific financial obligation. Credit scores and rating are generally categorized into two classifications founded on the technique used to acquire scores, i.e. judgmental or deductive credit scoring and statistical or empirical credit scoring (Caire, 2017).

So as to decrease the risk of credit, it is one of the imperative techniques used by financial institutions to categorize borrowers as bad or good clienteles. It is also the method of modeling the creditworthiness of borrower by the financiers (Anderson, 2016). It is used to know the probability that borrowers would default on the individual finance products by means of statistical strategies in order to appraise borrower loans. Lenders use credit scoring, among other things, to arrive at a decision on whether to extend credit and to evaluate the probability that a person repays his debts. They use credit scoring in risk-based pricing in which the terms of a loan, including the interest rate, offered to borrowers are based on the probability of repayment.

Loan Performance

Loan performance constitutes a huge proportion of the credit risk of a bank as it accounts for more than ten times of the equity (Barth *et. al*., 2016). The total amount of money issued out as loans is referred to as loan portfolio to different borrowers as different loan products. The loan products could be in form of individual loans, corporate loans, salary loans or group guarantee loans. Loan performance accesses the rates of payment, number of borrowing clients, security pledged and rate of arrears recovery (Mburu, Mwangi, & Muathe, 2020).

Non-performing Loans (NPLs) generally seen as those loans that for a long period of time are no more producing any yield; thus, the interest or principal for such loans has not been paid for minimum of 90 days at least. Performing Loans decreases bank liquidity, credit expansion, hampers the growth of the real sector which directly impacts on banking performance, the firm which is in default and the entire economy at large (Klein, 2016).

Empirical Review

Kusi and Ansah-Adu (2015) undertook research on the impacts of credit information sharing to access banks' credit in income bracket categories. Secondary data was obtained from the World Development Indicators from 2000-2012. Using OLS robust standard errors regression model, the research established that those who earn high levels of income can easily access bank credit relative to those with low-income earnings. The study similarly shows that CIS allows every person access credit from banks across the categories employed in this research.

Ngeno (2020) researched on the relationship between credit information sharing and MFIs Non-performing loans in Kenya. The research adopted a descriptive research study. The research population comprised all 13 MFI's registered by the CBK. The period of study ranged from the year 2014 to 2018. Secondary data was put to use for this study. Information gathered was analyzed via inferential statistics and descriptive statistics. Descriptive statistics such as standard deviation and mean kurtosis, and skewness were utilized to present analyzed data. The multiple regression was introduced as per the analytical model. The results indicated that the model fit with credit reports pulled, inflation rate, and interest rates were statistically significant in predicting non-performing loans. The coefficient table revealed that an increase for credit cards pulled resulted in It was also established that an increase in inflation rate and interest rate led to an improvement in the number of non-working loans.

Kiage and Muturi (2017) researched to examine the effect of positive credit information sharing determinants among CBs in Kisii Town, Kenya. A sample of 34 managers in the credit sector and 17 commercial banks was used for the study, where information was collected through questionnaires. Findings from this study reveal that costs associated with CIS adversely affect the FP of CBS and that protection privacy was adversely linked with the FP of CBS. This study recommends that financial establishments and credit bureaus protect private information in their care to ensure that sensitive data is not leaked to malicious people

Njeru, Mohammed and Wachira (2017) study investigated the relationship between effectiveness of credit appraisal on loan performance of Commercial Banks in Kenya. Descriptive research design was used. Data was collected using a self-administered questionnaire. Credit appraisal was found to be very important in influencing performance of commercial banks. Findings also revealed that lending placed much reliance on use of past information and thus credit referencing and credit history were applied more in credit appraisal.

METHODOLOGY

This research adopted the descriptive research design. Descriptive research design is a type of research design that aims to obtain information to systematically describe a phenomenon, situation, or population. The target population of the study was management of the 6 deposit taking MFIs which were licensed by CBK and had fully-pledged branches in Mombasa. The sampling frame was deposit taking MFIs which were licensed by CBK and had fully-pledged branches in Mombasa. The study employed stratified sampling technique whereby the target population was divided into different groups and those with similar characteristics were grouped in the same stratum then sample for the study was selected at random from each stratum. The sample size of 60 was selected at 95% confidence level and margin error/precision level of 0.05 which means there was 95 chances in 100 that the sample size represents the true population, and was calculated using Slovin's formula.

Research data for this study comprised the primary data. The primary data was collected by use of close ended questionnaires which were structured based on the research objectives. The researcher used questionnaires because they are easier to analyze as they are in immediate usable form, easier to administer and lastly they are economical to use in terms of time and money (Cooper & Schindler, 2016). Collected data was analyzed using Statistical Package for Social Sciences (SPSS) software version 25. Descriptive statistics in the form of mean and standard deviation (SD) was utilized to provide meanings to data collected. Inferential statistics such as linear regression and Pearson's correlation was used to establish the correlation between financial performance (dependent) and credit risk management (independent). The following linear regression model was adopted to test the statistical significance of the study predictor variables on dependent variable;

$$Y= \beta_{\theta} +\beta_1X_1+\beta_2X_2+\beta_3X_3+ \beta_4X_4+\varepsilon$$

Where:

Y= Loan performance

$\boldsymbol{\beta_{\theta}}$ = Regression intercept

$\boldsymbol{\beta_1}$-$\boldsymbol{\beta_4}$ are the coefficient of the regression model

$\boldsymbol{X_1}$= Credit information sharing

$\boldsymbol{X_2}$= Moral hazard

$\boldsymbol{X_3}$= Credit risk assessment

$\boldsymbol{X_4}$= Credit scoring

$\boldsymbol{\varepsilon}$= Error term

FINDINGS AND DISCUSSION

Descriptive Results

Descriptive analysis was conducted on the study variables to check the mean and standard deviation.

Credit Information Sharing

The researcher asked respondents to rate their agreement or disagreement on the various aspects of credit information sharing. They did this on a 5 point Likert scale where 1 represented Strongly

disagree while 5 represented Strongly agree. The results were presented in Table 1.

Table 1: Credit Information Sharing

	Mean	Std deviation
Credit information sharing plays a pivotal role in reducing the information asymmetry that exists between banks and borrowers	4.79	1.306
Information sharing has helped bridge the info gap about borrowers creditworthiness	4.40	.955
The MFI uses credit information sharing as a basis for setting better loan pricing for the borrowers	4.28	.295
The MFI's knowledge of applicants' characteristics, easing adverse selection problems	4.99	.374
Credit reference bureaus have led to improved default rate of borrowers	4.15	.916

The results in Table 1 showed that respondents agreed that credit information sharing plays a pivotal role in reducing the information asymmetry that exists between banks and borrowers and that information sharing has helped bridge the info gap about borrowers creditworthiness as indicated by a mean of 4.79 and mean of 4.40 respectively. Respondents also agreed that the MFI uses credit information sharing as a basis for setting better loan pricing for the borrowers (mean=4.28) and that the MFI's knowledge of applicants' characteristics, easing adverse selection problems (mean=4.99). Credit reference bureaus have led to improved default rate of borrowers (mean=4.15).

Moral Hazard

The researcher asked respondents to rate their agreement or disagreement on the various aspects of moral hazard. They were required to do this on a 5 point Likert scale where 1 represented Strongly disagree while 5 represented Strongly agree. The results are presented in Table 2.

Table 2: Moral Hazard

	Mean	Std. Deviation
The MFI lends to groups to enjoy peer monitoring that deals with moral hazard	4.65	.677
The MFIs are prone to experience bad actors who apply and get loans based on misleading information	4.09	.496
The moral hazard problem has made MFIs more restrictive in issuing loans	4.89	.505
The MFIs have adequate systems to help in reviewing new loans applications	4.90	.661
Credit reference bureaus have led to enhanced loan delinquency in our MFIs	4.15	.559

The results in Table 2 showed that respondents agreed that the MFIs are prone to experience bad actors who apply and get loans based on misleading information as indicated by a mean of 4.65 and mean of 4.09 respectively. Respondents agreed that the moral hazard problem has made MFIs more restrictive in issuing loans (mean=4.89). Respondents were in agreement to the statement that the MFIs have adequate systems to help in reviewing new loans applications (mean=4.90). Credit reference bureaus have led to enhanced loan delinquency in our MFIs (mean=4.15).

Credit Risk Assessment

The researcher asked respondents to rate their agreement or disagreement on the various aspects of credit risk assessment. They were required to do this on a 5 point Likert scale where 1 represented Strongly disagree while 5 represented Strongly agree. The results are presented in Table 3.

Table 3: Credit Risk Assessment

	Mean	Std. Deviation
Microfinance promptly reports policy exceptions	4.69	.402
Microfinance conducts collection enforcements	4.66	.229
Microfinance recovers default amount from the guarantor	4.75	.540
The microfinance has dynamic client follow-up procedures	4.50	.613
Credit reference bureaus have led to improved credit risk assessment in our MFI	4.28	.611

The results in Table 3 showed that respondents agreed that microfinance promptly reports policy exceptions and that microfinance conducts collection enforcements as indicated by a mean of 4.69 and mean of 4.66 respectively. Respondents also agreed that microfinance recovers default amount from the guarantor (mean=4.75) and that the microfinance has dynamic client follow-up procedures (mean=4.50). Credit reference bureaus have led to improved credit risk assessment in our MFI (mean=4.28).

Credit Scoring

The researcher asked respondents to rate their agreement or disagreement on the various aspects of credit scoring. They were required to do this on a 5 point Likert scale where 1 represented Strongly disagree while 5 represented Strongly agree. The results are presented in Table 4.

Table 4: Credit Scoring

	Mean	Std. Deviation
The credit score standardized loan screening procedures	4.64	1.078
Credit scoring enhanced loan approval procedures to be more automated	4.79	.308
A good credit score mean less underwriting Needed	4.80	.619
Credit scoring is a risk based pricing model	3.97	.456
Credit reference bureaus help lenders fix minimum loan to be granted to a borrower in our MFI	4.25	.604

The results in Table 4 revealed that respondents agreed that the credit score standardized loan screening procedures and that credit scoring enhanced loan approval procedures to be more automated as indicated by a mean of 4.64 and mean of 4.79 respectively. Respondents also agreed that a good credit score mean less underwriting needed (mean=4.80) and that credit scoring is a risk based pricing model (mean=3.97). Credit reference bureaus help lenders fix minimum loan to be granted to a borrower in our MFI (mean=4.25).

Regression Analysis

The primary objective of the following regression analysis is to determine the relationship between explanatory variables and the response variable. Data was regressed to determine the extent of the effect between explanatory variables and response variable as shown in the following sections.

Table 5: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.734[a]	.539	.499	1.856742

a. Predictors: (Constant), Credit scoring, Credit risk assessment, Moral hazard, Credit information sharing

The regression results in Table 5, showed a moderate regression between debt recovery techniques and loan performance. In the model summary, the R^2 is 0.539 indicating that predictors explain 53.9% change in loan performance.

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Table 6: Model Validity (ANOVA)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	113.458	4	28.365	15.209	.000[b]
	Residual	97.014	52	1.865		
	Total	210.472	56			

a. Dependent Variable: Loan performance

b. Predictors: (Constant), Credit scoring, Credit risk assessment, Moral hazard, Credit information sharing

An F-test was used to test the statistical significance of the regression equation. The regression was statistically significant (F=15.209, p <.005).

Table 7: Regression Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	.289	.984		.294	.000
Credit scoring	.150	.174	.143	.863	.004
Credit risk assessment	.063	.160	.065	.396	.036
Moral hazard	-.184	.141	-.223	-1.301	.022
Credit information sharing	.254	.242	.219	1.047	.006

a. Dependent Variable: Loan performance

From Table 7, the model would appear as follows:

$$Y = 0.289 + 0.150X_1 + 0.063X_2 + -0.184X_3 + 0.254X_4$$

The regression model indicates that loan performance would increase by 0.289, given that all the other factors are held constant at zero. Further in the regression model it shows that a unit increase in credit scoring would lead to an increase in DTMFIs loan performance by 0.150. A unit increase in credit risk assessment would lead to a positive increase in loan performance of DTMFIs by 0.063, and a unit increase in moral hazard would lead to a decrease in DTMFIs loan performance by 0.184. Further, regression results showed that a unit increase in credit information sharing would lead to an increase in DTMFIs loan performance by 0.254.

Discussion of Key Findings

The regression coefficients served as the foundation for achieving the study objectives. This was achieved by considering the p-values that are associated with the relevant regression coefficients and t-values. The first objective of the study was to investigate the effect of credit scoring on loan performance of DTMFIs. The regression results for credit scoring was β1=0.150, t=.863, and p<0.05 showing that there was a positive and significant relationship between credit scoring and loan performance. It is therefore concluded that a unit change in credit scoring would lead to 0.150 unit change in loan performance.

The second objective was to establish the effect of credit risk assessment on loan performance. According to the regression analysis's results β2 was = 0.063, t=0.396, p<0.05), credit risk assessment significantly affected loan performance. According to the study, a unit increase in credit risk assessment would lead to a positive increase in loan performance of DTMFIs by 0.063

Third objective of the study was to find out the effect of moral hazard on loan performance of DTMFIs in Mombasa. Regression results revealed that moral hazard had a significant and negative effect on loan performance as shown by β3 = -0.184, t=-1.301, and p<0.05. According to the

findings, a unit increase in moral hazard would lead to a decrease in DTMFIs loan performance by 0.184.

Fourth objective of the study was to determine the effect of credit information sharing on loan performance of DTMFIs in Mombasa. According to regression analysis results, credit information sharing had significant and positive effect on loan performance ($\beta 4 = 0.254$, $t=1.047$, and $p<0.05$), which implied that a unit increase in credit information sharing would lead to an increase in DTMFIs loan performance by 0.254.

CONCLUSSIONS AND RECOMMENDATIONS

The study concluded that credit scoring has a positive effect on loan performance. Also it is concluded that credit information sharing is pivotal to reducing the information asymmetry that exists between banks and borrowers and that information sharing has helped bridge the info gap about borrowers creditworthiness. The study concludes that the MFI uses credit information sharing as a basis for setting better loan pricing for the borrowers and that the MFI's knowledge of applicants' characteristics, easing adverse selection problems. Also the credit reference bureaus have led to improved default rate of borrowers.

The study concluded that credit risk assessment has a positive effect on loan performance. The analysis comes to the conclusion that the MFIs are prone to experience bad actors who apply and get loans based on misleading information. Credit reference bureaus have led to enhanced loan delinquency in our MFIs. Also the study concludes that the moral hazard problem has made MFIs more restrictive in issuing loans. The MFIs have adequate systems to help in reviewing new loans applications.

The study concluded that moral hazard has a positive effect on loan performance. The study concludes that microfinance promptly reports policy exceptions and that microfinance conducts collection enforcements. It is concluded that credit reference bureaus have led to improved credit risk assessment in our MFI. Microfinance recovers default amount from the guarantor and that the microfinance has dynamic client follow-up procedures.

The study concluded that credit information sharing has a positive effect on loan performance. The study comes to the conclusion that the credit score standardized loan screening procedures and that credit scoring enhanced loan approval procedures to be more automated. Credit reference bureaus help lenders fix minimum loan to be granted to a borrower in the MFI. Also a good credit score mean less underwriting needed and that credit scoring is a risk based pricing model.

The study recommended that the deposit taking MFIs should prioritize credit information sharing as it was revealed to reduce information asymmetry existing between MFIs and borrowers. The sharing of the information should help bridge the info gap about borrowers creditworthiness. The MFIs should use credit information sharing as a basis for setting better loan pricing for the borrowers.

The study recommended that the deposit taking MFIs should take notice of the high probability of bad actors who apply and get loans based on misleading information hence minimize the success rate of such incidences. The deposit taking MFIs should utilize credit reference bureaus as they have been found to lead to enhanced loan delinquency. In addition, the MFIs should invest in information systems to help in reviewing new loans applications.

The study recommended that the deposit taking microfinance should promptly report policy exceptions and that these banks should conduct collection enforcements. The deposit taking microfinance should recover default amount from the guarantor. This would be made possible by setting up of a dynamic client follow-up procedures.

The study recommended that the MFIs should standardized loan screening procedures as it was revealed that credit scoring enhanced loan approval procedures to be more automated. Credit reference bureaus should be approached to help deposit

taking MFIs fix minimum loan to be granted to a borrower.

Suggestions for Further Research

The study was limited to credit referencing and loan performance in the context of deposit taking MFIs. Nonetheless, the researcher advises that further research be done on other credit referencing aspects that can affect loan performance of other financial institutions because only 53.9% of the results were explained by the independent variables in this study. Additional research could concentrate on different industries such as insurance industry.

REFERENCES

Anderson, R. (2016). *The credit scoring toolkit: Theory and practice for retail credit risk management and decision automation*. Oxford, United Kingdom: Oxford University Press.

Association of Microfinance Institutions Kenya (AMFI) (2020). *Microfinance Sector Report of 2020* (6th edition.). Retrieved from https://amfikenya.com on 10th July 2021.

Bailey, J. A. (2016). *Strengthening control and integrity: A checklist for government managers*. [online] Available at: http://www.businessofgovernment.org/sites/default/files/BaileyReport.pdf. Accessed: 30 September 2021

Byaruhanga, I. (2017). *Credit terms, credit accessibility and performance of agricultural cooperatives in Rwanda* (Doctoral dissertation).

Central Bank of Kenya (2020). *Directory of licensed Microfinance Banks in Kenya.* Retrieved from https://www.centralbank.go.ke/wp-content/uploads/2016/06/Directory-of-Licenced-Microfinance-Banks.pdf on 10th July, 2021.

Cooper, D. R., & Schindler, P. S. (2013). *Business research methods,* (12th, edition). McGraw-Hill Publishing, Co. Ltd. New Delhi-India.

Creswell, J.W. (2014), *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. Sage publications, London.

Emilios C. C Galariotis, Christophe Villa, Nurmukhammad Yusupov. Recent advances in lending to the poor with asymmetric information. *The Journal of Development Studies, Taylor & Francis (Routledge)*, pp.1. ff10.1080/00220388.2010.527956ff. ffhal-00722838f

Ewool, L. M., & Quartey, J. A. (2021). Evaluation of the Effect of Risk Management Practices on the Performance of Microfinance Institutions. *International Journal of Academic Research in Accounting Finance and Management Sciences*, *11*(1), 211-240.

Jagongo, A. O., & Kerage, P. M. (2015). Credit Information Sharing and Performance of Commercial Banks in Kenya. *Global Journal of Commerce & Management perspective*, 3(6), 18-23

Kagoyire, A. (2018), Effect of credit management on the financial performance of commercial banks in Rwanda. *International Journal of Business and Management Review,* .6(1), pp.57-69

Kinyua, A., (2017). Effects of Credit management practices on loan performance of commercial banks in Nyeri County, Kenya. *European Journal of Economic and Financial Research* 2(2).

Klein, N. (2013). *Non-Performing Loans in CESEE: Determinants and Impact on Macroeconomic Performance.* Washington DC: International Monetary Fund.

Kitonyi, J. M., Sang, W., & Muriithi, D. (2019). Non-performing loans and financial performance of microfinance institutions in Kenya. *The Strategic Journal of Business & Change Management,* 6 (3), 840 – 848.

Kothari, C. R. (2014). *Research Methodology: Methods and Techniques*. New Delhi, New Age International (P) Ltd Publishers.

Ledgerwood, J., Earne, J., & Nelson, C. (2017). *The new microfinance handbook*. Washington, DC: World Bank.

Lin, C., Ma, Y., & Song, F. (2012). What Drives Bank Operating Efficiency? The Role of Bank Competition and Credit Information Sharing. *Research Handbook on International Governance*, 87.

Mabvure, T., Gwangwava, E., Faitira, M., Mutibvu, C., & Kamoyo, M. (2012). Non-Performing Loans in Commercial Banks: A case of CBZ Bank Limited In Zimbambwe. *Interdisciplinary Journal of Contemporary Research in Business*, 4(7), 1-22.

Mburu, I., Mwangi, L., & Muathe, S. (2020). Credit Management Practices and Loan Performance: Empirical Evidence from Commercial Banks in Kenya. *International Journal of Current Aspects in Finance, Banking and Accounting*, *2*(1), 51-63. https://doi.org/10.35942/ijcfa.v2i1.105

Microfinance Barometern Report. (2018). *Microfinance Barometer 2018.* Paris, France : Convergences Publication.

MicroSave (2018), *Market led solutions for financial services.* MicroSave publication.

Ndongo, J. M. (2019), Effect of credit reference bureau on financial performance of Savings and Credit Cooperative Societies in Kenya. *Journal of Finance and Accounting, 3*(3), Pp. 187

Ngeno, G. K. (2020), Relationship between credit information sharing and MFIs Non-performing loans in Kenya. Unpublished Thesis, University of Nairobi, Kenya.

Njanike, K. (2016). The impact of effective credit risk management on bank survival. *Annals of the University of Petroşani, Economics*, *9*(2), 173-184.

Njeru, D. G. (2021), *Credit reference bureau functions and loan performance of commercial banks in Kenya.* Unpublished Thesis, Kenyatta University, Kenya.

Perways, A., & Krishna, P. M. (2017). *The role of microfinance in empowerment of women: An empirical study in Somali regional state in Ethiopia.*

Saba, I., Kouser, R., & Azeem, M. (2012). Determinants of Non-Performing Loans: Case of US Banking Sector. *The Romanian Economic Journal*, 44 (6), 1-12.

Slama, J. (2018), Risk management for African Microfinance Institutions. The Global Treasurer publication. Retrieved from https://www.theglobaltreasurer.com/2008/11/18/risk-management-for-african-microfinance-institutions/ on 7th July, 2021.

Wambugu, M. K. (2017). *The effect of debt collection strategies on financial performance of local authorities in Kenya* (Doctoral dissertation).

Wangai, P. M. & Mungai, J. N. (2019). Financial management practices and loan performance of micro finance institutions in Starehe Constituency, Nairobi County, Kenya. *International Academic Journal of Economics and Finance*, *3*(3), 117-135.

World Bank Public credit registry report (2018). https://data.worldbank.org/indicator/IC.CRD.PUBL.ZS