THE RELATIONSHIP BETWEEN CREDIT INFORMATION SHARING AND NON-PERFORMING LOAN AMONG MICROFINANCE INSTITUTIONS IN KENYA

BY

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DECLARATION

This research project is my original work and has not been presented for a degree in any other university.

Signature.......................... Date...25/11/2021..................

Gilbert Kiplangat Ngeno **D61/6272/2017**

This research project has been submitted for examinations with my approval as the university supervisor.

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DEDICATION

To my family and all those who supported me in completing this project, I dedicate this work to you

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LIST OF ABBREVIATIONS AND ACRONYMS

CB Central Bank

CBK Central Bank of Kenya

CIS Credit Information Sharing

CPI Consumer Price Index

CRB Credit Reference Bureaus |

FP Financial Performance

GDP Gross Domestic Product

IA Information Asymmetry

MFIs Micro Finance Institutions

NPLs Non-performing Loans

OLS Ordinary Least Square

SPSS Statistical Package for Social Sciences

VIF Variance Inflation Factor

ABSTRACT

The purpose of the research was to realize the link between credit information sharing and Nonperforming Loans of Micro Finance Institutions in Kenya. The research adopted a descriptive research study. The research population comprised all 13MFI'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. The study determined that credit report pulling had a positive impact on the reduction of non-working loans. Thus, the study recommends that all microfinance organizations implement the use of CRB reports. This will aid in the identification of frequent defaulters and guide the microfinance institutions in their lending. Findings from the study also displayed that the inflation rate harmed the reduction of nonperforming loans. Thus, the research recommends that the Central Bank of Kenya set up policies that will help cushion the economy from high inflation rates. Results of the study also established that interest rates harmed the reduction of nonperforming loans. The study thus recommends that the Central Bank of Kenya offer lower interest margins to loans advanced to the microfinance institutions. This would, in turn, lead to the microfinance institutions lowering their interest rates to their customers, thus reducing the number of nonperforming loans.

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CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

Non-performing loans (NPLs) have been a consistent challenge no commercial banks (CBs) band When individuals do not pay back loans, and credit institutions lose the interest that earns them money to avail for future borrowers. Tchamyou (2019) identifies several factors causing NPLs and classifies them into economic factors, bank-related factors, and customer-related factors. Among these factors include; disillusion of borrower's companies, borrowers' death, ineffective control and monitoring of loans by financial institutions, and debtor's bankruptcy. Similarly, factors such as loan securities, inter-firms competitions, mergers, and knowledge of customers were also identified as other significant causes of nonperforming loans. Loan information-sharing systems have been identified and implemented to reduce

Moral Hazard Theory borrowed a few concepts from the Adverse Selection hypothesis and the Asymmetric information theory. As explained in Guerrieri and Shimer (2014), the asymmetric information theory identifies the difficulty in distinguishing between good and bad borrowers. According to work, these difficulties lead to adverse selection and challenges related to moral problems. Pagano and Jappelli (1993) proposed the opposing selection theory regards CIS to reduce opposing selection challenges. It improves financial institutions' capabilities to get information about their loan applicants (Bruhn, Farazi, & Kanz, 2013).

The problem of NPLs has persisted for many years, especially in Kenya. The industry has historically ailed and suffered from the disintermediation of financial systems and erosion of their profitability. The persistence of problems related to non-performance loans consequently led to the closure of 37 microfinance institutions by 1998 (Kwambai & Wandera, 2013). Although the microfinance industry in Kenya suffered from some issues, understanding lending practices stood out as one of the significant factors. Sharing credit information system was consequently implemented in 2010.

1.1.1 Credit Information Sharing

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.

There is no doubt about the significance of sharing a borrower's credit information in improving the quality of the collection of borrowers. The practice enhances the bank's understanding of their applicant's payment tendencies. It also reduces the costs involved in getting first-hand credit information directly from the borrowers. Similarly, it helps customers in controlling their borrowing discipline. Lastly, it discourages borrowers from getting over-indebted by simultaneously acquiring several loans from different institutions (Tchamyou & Asongu, 2017). However, Tchamyou (2019) identified the following theoretical challenges related to the concept of credit information Sharing. First, he noted the difficulty in accessing credit information of non-local borrowers that makes it difficult to decrease defaults related to non-local borrowers. As per the work, the implied raise of safe borrowing cannot reimburse for the reduced lending to the dodgy borrowers. Similarly, credit information sharing compromised the trust-building process between banks and their customers. The informational advantage grants financial institutions greater market power over their clients, generating a future hold-up crisis.

Various indicators have been used to measure credit information sharing. One of the research indicators includes the number of reports pulled by credit providers/ microfinance institutions or financial institutions (Fosu, Danso, Agyei-Boapeah & Ntim (2020); Thuo, 2016).

1.1.2 Non- Performing Loans

Klein (2013) defines the term as the sum of money borrowed by a debtor who has not paid as scheduled for a specified period. Messai and Jouini (2013) regard it as a debt either in default or almost becoming defaulted. Makri, Tsagkanos, and Bellas (2014) further define it as those debts in which 90 days have passed without the debtor having paid either the interest or installments as agreed.

Banks lend money to their debtors, hoping that the borrowers will pay their debts as agreed. However, debtors do not always meet the agreement. Sometimes they run out of cash to pay back their debts or might just decide not to submit any payment. Nonperforming loans are generally considered bad loans since they have a low probability of being repaid. Klein (2013) notes that the higher the number of unpaid loans on a bank's books, the more the negative impacts on its stock price. The magnitude of such loans can be measured by determining their fraction in all the total loans. The ratio of unpaid loans to the gross loan is found by having the gross value as the denominator and delinquent loans as the numerator (Messai & Jouini, 2013).

Many bad loan loans can negatively impact both the bank and the yet-to-be borrowers; since banks lose money, they would have collected from the interests and lack money to avail for new borrowers. Similarly, a high percentage of nonperforming loans negatively affects its stock investments as it might cause the stock price to reduce (Makri, Tsagkanos, & Bellas, 2014).

1.1.3 Credit Information Sharing and Non-Performing Loans

When credit data on unpaid credit is shared to information exchange institutions like the public credit registrars and the credit bureaus, it avails the identities of individuals with bad debt records to commercial banks and other microfinance institutions. Such individuals are barred from accessing simultaneous loans from other banks or might even be punished upon the repayment of an overdue loan. Wairimu (2013) regards information sharing as an efficient means for financial institutions to distinguish between bad and good borrowers. As a result, individuals with Good Credit History are granted access to credit facilities more efficiently and at a lower cost than those at a high risk of defaulting.

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, 2015). 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, 2015).

1.1.4 Micro Finance Institutions

A microfinance institution is a business organization that serves to provide financial assistance to an economically marginalized population. Their principal duty is to open credit facilities to low-income families, consequently providing low-income earners with the much-required financial services. However, they also offer services like insurance, deposits, payment services, and money transfer services. Such a firm that provides its services at a great scale with branches operating in various geographical regions is termed a microfinance institute (Copestake et al., 2016).

Globally, the structure and practices of microfinance institutions have primarily evolved over the decades. These institutions began as a means of serving a greater social purpose of fighting poverty. Since they could not sufficiently fund themselves, they received financial assistance from non-governmental organizations and microfinance institutions. These institutions were initially non-profitable, concentrating on helping poor populations out of poverty rather than making profits. However, the situation has changed over time, with most non-profit microfinance institutions turning into profit-making business enterprises. Copestake et al. (2016) observe that most such institutions turned into business investment not only to attain market penetration but also for sustainability. Taiwo, Agwu, and Benson (2016) note that they thought they still serve marginalized populations to help them come out of poverty; they work more to sell their financial product and attain broader customer coverage. In Kenya, the procedures and activities of the microfinance entities are monitored and controlled by CBK.

Similarly, the CBK works to provide larger credit facilities to the microfinance institutions, and Given the 21st century pedagogical and technological advancements, the future is bright for microfinance institutions; since their capacities to reach broader populations and lend and collect efficiently are continuously improving.

1.2 Research Problem

Most financial institutions have and are still facing nonperforming loans related challenges, following both the difficulty in understanding borrowers creditworthiness, and Ahmad (2013) maintains that nonperforming loans result from debtor's inability to repay a loan as agreed either due to lack of funds or being overwhelmed by several simultaneous loans. One of the measures taken to understand a borrower's creditworthiness is credit information sharing. Credit information sharing provides the opportunity to financial institutions to lend persons the ability to repay their credit. This involved looking at the cash generated over time, previous credit is taken, the performance of existing loans, and their overall credit score from credit bureaus. The lending institutions use this information to determine how much borrowers qualify if they are eligible (Škarica, 2014).

In Kenya, microfinance institutions have continued to experience the problem of bad debts since the 1990s and even led to the closure of more than 36 banks in 1998 (Kisengese, 2014). According to Wairimu (2013), bad borrowers who had learned that institutions were operating alone took advantage of information asymmetry (IA) to acquire numerous credits from different microfinance institutions, consequently distorting credit business and negatively impacting the performance of microfinance institutions. The phenomenon threatens the stability of the MFIs and slows the growth of the microfinance industry following the subsequent high-interest fee charged to curb the loan-related risks. Whereas the problems faced by the microfinance institutions in Kenya may be attributed to several other factors, availability of records on an individual's borrowing history can be identified as one of the leading causes of such problems. Therefore, the significance of basing credit decisions on extensive assessment of risk factors of borrowers' lending practices should not be overlooked.

Škarica's (2014) study on NPLs determinants in Central and Eastern European nations 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. Similarly, Dhar and Bakshi's (2015) study on loan losses determinants of Indian commercial banks observed the arrangements for sharing credit information to help develop an information capital about borrowers characteristics, thus saving cost and inconveniences related to getting first-hand knowledge from the customers. Ahmad's (2013) study on information sharing and corruption as the determinants on the extent of NPLs in Pakistan found the practice significant in broadening the information shared to financial institutions beyond banks and microfinance institutions while simultaneously reducing the NPLs share. Moreover, Beck, Jakubik, and Piloiu's (2013) study on matters surrounding NPLs done on 75 countries of the European Union found CIS helpful to lenders as it provided a faster way of making more accurate lending decisions.

In Kenya, a few studies on this link were done in 2011, 2012, and 2013. Boyana's (2012) study on the impacts of CIS on lousy debt to the functioning of commercial banks in Kenya found loan performance to relate negatively to information sharing.

Similarly, Wairimu (2013), on the function of loan reference bureaus on nonperforming credits in Kenyan commercial banks, found a significant estimated reduction of bad credits by 4 percent between 2010-2012. Wandera and Kwambai (2013), on impacts of sharing loan information to nonperforming loans in Kenyan commercial banks, found observed credit information sharing to impact the profitability of financial institutions positively. Moreover, Kisengese (2014), on the impact of distributing insufficient debt data in Kenyan financial institutions, established that all banks struggled with the issues of bad credits.

Similarly, the research found that sharing credit information assisted banks in refusing to lend chronic defaulters; consequently, reducing default rates. Although most of those studies agree that sharing data on bad debt reduced the occurrence of bad credits, they are few and failed to investigate the negative impacts of the practice. Five years down the line, there is a need for up-to-date empirical findings on this relationship and identity arising challenges. This research hopes to fill in the gaps by assessing the connection between information sharing and the level of bad debts by answering the question; What is the link between credit information sharing and Nonperforming Loans of Kenyan microfinance institutions?

1.3 Research Objective

The research aimed to base the link between credit information sharing and Nonperforming Loans of Micro Finance Institution's in Kenya.

1.4 Value of Study

The findings of this study might assist the management of microfinance institutions in strengthening lending practices and policies. As a result, they would attain long-term objectives of identifying potential customers with the capacity for timely payment.

Similarly, the study would add empirical and up-to-date data on the already existing information; consequently, creating reference material for researchers and scholars wanted in this research region. Similarly, findings in this research would highlight the gaps that require further research study.

The study hopes to educate the policy-making organs/bodies on the impacts and consequences of credit information shared to the reference bureaus. The understanding would clear up the misunderstanding and the misconceptions surrounding the sharing of credit information.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

A review of the determinants of NPLs, theories and a review of literature will be discussed. To conclude, a literature review was summarized and research gap presented.

2.2 Theoretical Review

Moral hazard theory, asymmetric information theory, and adverse selection theory supported the study. The relevance of the theories were explained with respect to the variables, non-performing loans, and credit information sharing.

2.2.1 Moral Hazard Theory

Suglitz (1983) and Strauss (2017) suggests that borrowers will naturally default on loans if they are not aware of the immediate future consequences of default. Barbosa and Markle (2011) stated that moral risk is a problem that arises from situations with unequal information. The fact that borrowers can default on a loan if they are unaware of future consequences makes it difficult to know the amount of money the lender has earned until they can pay their payment obligations. Should be respected and not the date of application (Mwengei, 2013). This hypothesis argues that NPLs have lower capital growth than their loan portfolio risk in response to ethical risk incentives that may potentially increase the number of future NPLs (Clean, 2013).

According to Mehrteb (2015), there is a moral catastrophe in the credit markets. Higher interest rates directly affect borrowers with alternative projects, which bring lower returns to the banking sector as investors invest in projects. In addition, in cases where an individual or organization fails to take responsibility for its actions and the consequences of its conduct, moral danger may arise even in situations where the other party tends to experience the effects of such activities. Survives (Zappelli and Pagano, 2013).

The issue of moral risk is that in financial activities, one party engages in undesirable activities to the other party following the agreement between the two parties. The power of incentives is determined by information on the past credit behavior of borrowers provided by credit bureaus, which helps them generate motivation to divert their investments to profitable projects. Therefore, it is evident that borrowers credit information can help lenders reduce the moral hazard problem, resulting in

This theory is criticized because one of the parties to a transaction has more information about the other party. In the case of lender and borrower Mehrteab (2015), the lender may rely on insufficient or misrepresented information of the borrower.

2.2.2 Adverse Selection Theory

This paradigm proposed in Pagano and Jappelli (1993) regards CIS to reduce challenges related to adverse selection. It improves the capabilities of financial institutions to get information about their loan applicants (Bruhn, Farazi, & Kanz, 2013). This theory posits that risky borrowers tend to be offered incentives to make more payments and be provided credit compared to the unrisky loanees. The adverse selection problem is associated with asymmetric information and which commonly arises before undertaking a transaction. A harmful selection problem occurs when an invisible characteristic challenge exists where the informed party in a market self-select in a manner that harms the party with poor knowledge of the problem. This implies a situation of IA, where the uninformed party chooses selections that have unattractive characteristics (Tumay, 2015).

In microfinance organizations, borrowers may keep sensitive credit information about their past and intend to carry out an investment of their loans which causes the adverse selection problem before commencing with the credit relationship. As much as the lending institution may have comprehensive knowledge about the characteristics of potential borrowers, it may fail to collect all the essential information as regards every borrower's features and how risky are the projects borrowers intend to invest in. the relevance of adverse selection to microfinance institutions is crucial considering that provision of funding cannot be fulfilled for all borrowers and applicants; however, lack of complete information for all borrowers by microfinance institutions makes it hard in decision making for the creditworthiness of borrowers. Therefore, CIS between microfinance institutions and credit agencies reduces the problem of adverse selection. Moreover, microfinance institutions must reduce IA between those providing credit and borrowers, which will give safe borrowers and access to loans, which will also enhance aggregate lending (Grajzl & Laptieva, 2014).

This theory is criticized for assuming the existence of asymmetric information in the contract. Asymmetric information may fail to exist between two parties as both parties could be having sufficient material information about each other (Tumay, 2015.

2.2.3 Asymmetric Information Theory

As explained by Guerrieri and Shimer (2014), this paradigm identifies the difficulty in distinguishing between good and bad borrowers. According to work, these difficulties lead to adverse selection and challenges related to moral problems. The work done by Akerlof (1970), Stieglitz, and Rothschild (1976) is the origin of this hypothesis. Asymmetric information happens when there is a party with poor knowledge about the other party's economic activity, adversely affecting its decisions. The entry of intermediate goods and services into a market soon gets thrown out by introducing better quality goods and services; this is the same case for credit markets where the riskiness of a borrower is seen as the good purchased by the lender. Lack of adequate information awareness and sharing can adversely affect both parties in a market.

In a credit market, IA arises from a lack of precise information by the lender on the ability of a borrower to pay back a loan at the given time, which forces the lender to make a lending decision based on the available information. To directly solve the asymmetric information appraisal method is used while indirectly can be solved by signaling, screening. Information collection by financial intermediaries is a crucial activity to help in making a credit decision. Using credit bureaus to acquire important information can help microfinance institutions reduce the problem of asymmetric information and credit markets' moral hazard. When the credit provider can access a potential borrower's creditworthiness information, they can make an informed decision by imposing incentives that assist the borrower pay loans on the agreed date in the form of restricting the ability of the borrower in the future to get loans from different lending organizations.

The theory has faced criticism for not distinguishing the information imbalance between the borrower and the creditor (Turner & Varghese, 2013). The imbalance in communication can be seeking out more information from the internet or regulatory bodies

2.3 Determinants of Nonperforming Loans

The existence of NPLs is a significant challenge for microfinance institutions and generally for all financial institutions. In their study, Saba, Kouser, and Azeen (2015) identify the low repayment ability of borrowers as the reason behind high rates of loan default. Therefore, this section will cover credit information sharing, interest rates, economic growth, and inflation as NPLs determining factors.

2.3.1 Credit Information Sharing

Credit information about a borrower's behavior in repaying loans is accumulated and kept in the credit reference bureau. Credit information can be sourced from the borrower, data suppliers, and any other body that consistently provides credit to borrowers, sponsors, or other parties entitled to a credit. Kusa and Okoth (2013) state that sharing information helps reduce interest rates and costs associated with data collection from the clientele and helps to enhance the speed at which the credit market can grow. Some of the credit information shared are; the total amount of loans that are yet not paid, the time taken to complete repayment of each loan, and number and amount of installments paid, kind of credit facilities given to the borrower, among other factors.

Application of credit sharing information can help most financial establishments reduce IA between them and the borrowers because the lender is able to get a clear insight of the borrower's credit worthiness. The reduction of asymmetric information plays a significant role in ensuring that only credit-worthy clients are awarded credit. However, there are several disadvantages associated with credit information sharing. One of them is most of the information provided by credit bureaus is based on debtors who failed to repay their loans; this situation prevents financial institutions from acquiring credit information from the good borrowers.

2.3.2 Rates of Interest

Interest rates can be defined as the amount of money or price the borrower pays for using money granted to them by a financial organization. It is the fee a borrower pays on assets given to them. Where floating-rate loans are involved, rates of interest influence the difficulty of servicing debts. Louzis, Vouldis, and Metaxas (2014) posits that the fact above, which has the effect of causing high rates of bad debt because as interest rates increase, the number of NPLs also increases. Saba, Kouser, and Azeem (2015) contends that high rates of loan provided to borrowers and high rates of interest are the main reason behind the rising number of NPLs in financial institutions, specifically the banking industry in the US. Thus, this implies that interest rates influence the servicing of debts capability, precisely where floating-rate loans are involved Klein (2013).

Rizvi and Khan (2015) postulate that interest rates that the banking sector applies to take account of a premium in case the risks of loan default occur. Highly risky clientele are charged high interest rates by the commercial banks since. However, when high-interest rates are imposed on borrowers with substandard credit records, there is a high possibility of them defaulting on loans, thus causing high rates of nonperforming loans. It is evident that when interest rates are increased, this tends to reduce the borrower's capacity to repay their loans which posits that there is a substantial positive. Higher rates of interest or discount rates also reduce the cash flows' present value, lowering investment attractiveness (Koskija & Turan 2014).

2.3.3 Inflation Rate

It is a persistent and extreme rise in the total price of commodities and services, which lowers the purchasing power of money (Gezu, 2014). Rizvi and Khan (2015) further define inflation as the increment rate of an index of reference (CPI), representing the general basket of commodities and services. High inflation levels ease the servicing of debt by lowering the actual outstanding loan value; however, it similarly results in lower income for the borrower when wages become sticky. Klein (2013) states that where there exist variable rates of borrowing, higher inflation results in higher rates that cause the monetary policy actions to reduce inflation.

Inflation rates tend to reduce the capacity of debtors in loan servicing because lenders will tune lending rates to fit their actual returns. Thus, the correlation between inflation and NPLs can turn out positively or negatively, determined by the existing economic environment (Farhan, 2012). Turan and Koskija (2014) say that there exists a positive correlation tween inflation and NPLs. A surge in inflation rates compels monetary policymakers to introduce regulations that bring high-interest rates so that inflation can be combated, which implies that borrowing costs have increased. According to Rizvi and Khan (2015), when unexpected high inflation rates occur, the borrowers rips benefits at the expense of the borrowers.

2.3.4 Economic Growth

According to Beck, Ubik, and Piloiu (2013), the growth in Real Domestic products (GDP) is a significant cause of NPLs rates. A slight decrease in the worldwide economic activity is a substantial and crucial risk for bank asset quality. Klein (2013) observes that a high rate of growth in real GDP impacts increased income inflow, which enhances the borrower's debt-servicing capacity; hence, this has the effect of reducing rates of bad debt and vice versa. Therefore, when the global economic activities are poor, this results in losses associated with loans. Skarica (2013) also presents an argument based on the GDP as the primary driver of NPLs, and that high NPLs ratios result from lots of crises.

Turan and Koskija (2014) state GDP has an adverse link with NPLs, and high rates of real GDP growth impact economic development to the country involved, which points out that a surge in economic growth lowers NPLs level. Alternatively, a decline in economic growth results in a rise of NPLs, which have the bearing of increasing unemployment rates, which causes borrowers to go through tough times in repaying off their credit Klein (, 2013). Rizvi and Khan (2015) contend a substantial adverse link between GDP and NPLs. This points out that high rates of economic development result in lower rates of nonperforming loans.

2.4 Empirical Studies

There have been several global studies on this concept of study. Sorge and Zhang (2014) suggest that pre-expanded credit information may be considered an alternative to reasonable lender advance protection when extending corporate debt maturities in developing countries. The study also revealed the imposed policies that require positive and negative information on credit before providing it to the relevant parties.

Brown and Zehnder (2014) investigated the Impact of IA and a competitive credit market have on voluntary information sharing among lenders. The study experimented on an actual credit market where CIS can differentiate worthy and unworthy borrowers since borrowers can exogenously move to different locations. The study also established that IA in lending markets tends to increase the frequency of sharing information among lenders significantly and the competitive environment between creditors lowers the CIS practice. However, the influence of competition tends to be just of second-order priority.

Kusi and Ansah-Adu (2015) undertook research on the impacts of CIS 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. The research equally ascertained an upbeat link between CIS and gross domestic savings in accessing banks' credit. In contrast, gross capital formation, inflation rates, and NPLs had a substantial adverse link when accessing banks' credit.

In their research, Bos, Millone, and Haas (2015) examined borrower information sharing in a lending market that exists in a very competitive environment in Herzegovina and Bosnia. This study suggests that making CIS compulsory strengthens the giving of credit at the extensive margin since the refection of many applications occurs, specifically for areas with robust competition in the credit market. The findings further suggest that standards of giving credit can similarly become tight at the intensive margin; registry causes shorter, more minor, and quite costly credits. Moreover, this study shows that when lending is made to be tight in both margins, the quality of loans improves significantly, and the rates of defaulted loans also decrease.

Local studies conducted in this area include Oliweny and Mugwe (2015), focusing on the effects of CIS on the performance of the Kenyan commercial banking sector. Data was sourced from 43 Kenyan commercial banks from 2005-2014 annually. The data source was from the profit soon before tax and the number of credit reports banks could access from 2010-2014 every quarter. Using correlational research design, the study found that equity returns, assets returns, and net concern margin had a growing trend after licensing of Credit Reference Bureaus (CRB) for the period between 2010 to 2014 linked with a decreasing trend for the period before CIS was started between 2005-2009.

Toroitich and Omwono (2015) examined the correlation that exists between NPLs and the financial performance (FP) of Equity Bank (K) Ltd, Eldoret Town. Using a correlation research design, the study revealed that a surge in the number of NPLs negatively affected the financial performance of Equity banks generally. The research recommends that the staff credit department have more significant loan goals as this impacts the bank's profit margins significantly. The study similarly suggests that banks should strive to keep nonperforming loans at minimum levels.

Kiage and Muturi (2015) researched to examine the effect of positive CIS 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.

Osoro et al. (2015) carried out research to investigate CRB and how it impacts the FP of the banks in Eldoret Town, Kenya, between 2005-2011. Ninety-seven respondents were used in this study, where random sampling was used to select them, and data collection sheets were issued to collect information. Findings from this study realized that in 2008 the number of loans defaulted was relatively high compared to 2010, where only a percentage of 15.9 loans defaulted. The study further shows that wholesalers consisted of the highest number of loan defaulters amounting to 41,6%. In contrast, mining firms and gas, water, and electricity supply firms both had the lowest rates of defaults amounting up to 0.9 %. This study recommends that it is time that creditors accept the need to come up with more adequate strategic control systems, which will also improve the efficiency and effectiveness of CRB.

Koros (2015) researched the impacts of CIS on the credit market performance of Kenyan commercial banks. A sample of 34 managers in the credit sector and 17 commercial banks was used for the study, where data sourcing was sourced 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.

2.5 Conceptual Framework

The pictorial presentation noted below presents a pictorial illustration between the study variables. The predictor variable is represented by credit information sharing, control variables defined by capital adequacy, asset quality, interest rate, and inflation rate, while NPLs represent the dependent variable.

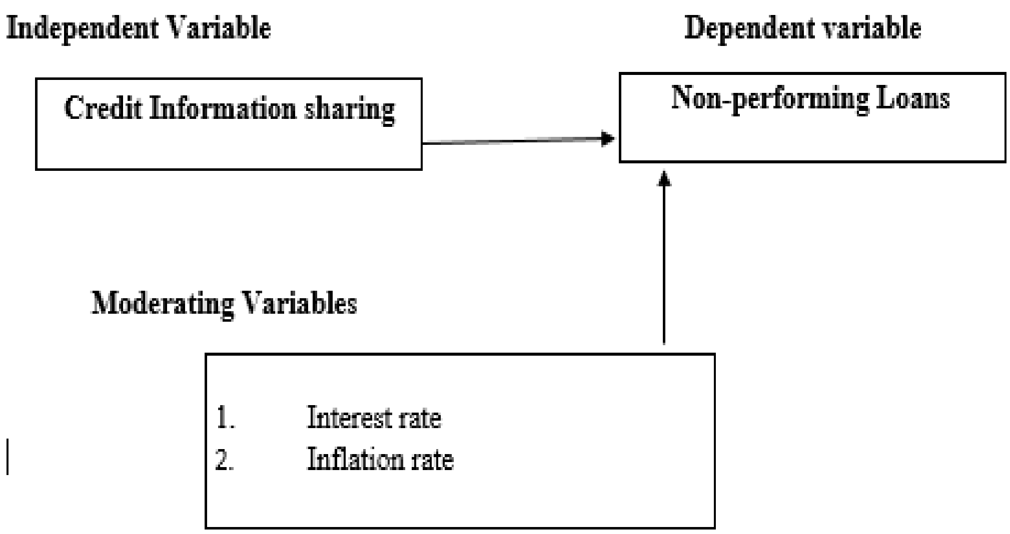

Figure 2.1: Conceptual Framework

2.6 Summary of Literature Review and Research Gap

The literature provided on past studies conducted on this area posits that sharing of credit information aids banks with informed data about borrowers characteristics by giving credit history, which makes it possible for banks and other financial establishments to accurately predict the capabilities of those applicants to repay loans they have applied for, reduces the costs associated with sourcing information's from the clientele and also acts as a control for the discipline of borrowers. Additionally, the empirical literature review has established that symmetric use of credit reports in determining applicants' creditworthiness is one of the most crucial revolutionary phases in retail banking.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

The methodology of the study is presented in this section. It clearly outlined how the study was executed? The chapter presented the research design, study population, data gathering process and instruments, diagnostic tests and analysis, and presentation of data.

3.2 Research Design

The study adopted a detailed research study. According to Mitchell and Jolly (2012), the detailed research design is the process of obtaining information without changing position, meaning that nothing is manipulated. It is appropriate to adopt a clear research design as the phenomenon is researched in general and unaffected settings. Similarly, descriptive research is a precursor to study further because it is valuable in establishing measurable variables.

3.3 Target Population

The aimed populace is one entire team of individuals or units the investigator wants to take a broad view of the study result. The study population comprised all the 13MFI's registered by the CBK. The period of study ranged from the year 2014 to 2018.

3.4 Data Collection

Secondary data was put to use for this research. Secondary data included information on the Inflation rate and interest rates as the moderating variables. Annual total Nonperforming Loans was also gathered to represent the dependent variable.

Secondary data was gathered from Annual Central Bank Supervisory Report. This report was available on the Central Bank of Kenya Website. The information to be collected covered a period of 5 years, that is, 2014 through 2018, due since this was the data that has been published.

3.5 Diagnostic Tests

Normality tests, homoscedasticity, autocorrelation, Linearity, and variance inflation factor (VIF) will be used to perform diagnostic tests. The usual test of data was measured through a P-P plot. Data is normally distributed if the P-P plot is always horizontally grouped. This aided in noting outliers. Homoscedasticity was tested using be tested using Levene test, and this is a measure of the existence between the predictor and the dependent variable. Levene test at $\alpha=0.05$ indicates that the data group lacks equal variances. Autocorrelation used Durbin Watson statistics which ranges between 0 to 4. The VIF is used to measure multicollinearity. This is a situation where two or three predictor models are highly correlated, which effectively makes it hard to establish the contribution of each predictor. The multicollinearity assumption has a VIF value of a Maximum of 10. A linearity test was utilized to test the association between the dependent factor and the predictor variable. Linearity was detected via P-P Plot.

3.6 Data Analysis

The quantitative data from this study was organized using multiple regression analysis since it entailed various predictor variables and one output variable. The multiple regression was presented as per the analytical model below.

3.6.1 Analytical Model

The multiple regression models to examine the impacts of credit information sharing on NPLs are presented below. The model adopted comprised of :

$$Y \; -= \; \alpha + \; \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

Where: Y = (Non-performing Loans measured as log of annualNPL's)

X_1: CIS determined by the natural record of the number of credit reports pulled

X_2: Interest rate determined by annual interest rate,

X_3: Inflation rate determined by the annual inflation rate,

α = Constant, ϵ = error term; β_1, β_2, β_3, = Regression coefficients

CHAPTER FOUR

DATA ANALYSIS RESULTS AND DISCUSSION

4.1 Introduction

This study examines the association between CIS and nonperforming loans among microfinance institutions in Kenya. Specifically, the study examined credit information sharing among microfinance institutions in Kenya and their impact on interest rates, inflation rates, and nonperforming loans.

4.2 Diagnostic Tests

Among the diagnostic tests conducted by the survey include normality tests, homoscedasticity, autocorrelation, and multicollinearity. The study used a P-P plot as a test for normality. A P-P plot looks into the normality distribution of the data by checking if the data points cluster along the line of best fit for a normal distribution. The study employed the Homoscedasticity test to examine variances by assessing if the error term is the same across all the independent variables. Levene's test has used a measure of homoscedasticity. Levene uses an *F*-test to test the assumption that the variances across the groups under investigation are equal. A *p-value* of less than 0.05 indicates a violation of the premise, while a p-value greater than 0.05 indicates that the assumption is holding. Autocorrelation is used to assess the extent of correlation between the variables. The study utilized the Durbin Watson statistic to test for autocorrelation. The Durbin Watson statistic values range between 0 to 4. Values ranging from 0 to less than 2 imply positive autocorrelation, and values above two and less than 4 points to negative autocorrelation. Values close to 2 or equal to 2 indicate the absence of autocorrelation in the data. Findings from the study areas are presented in the figure and tables below.

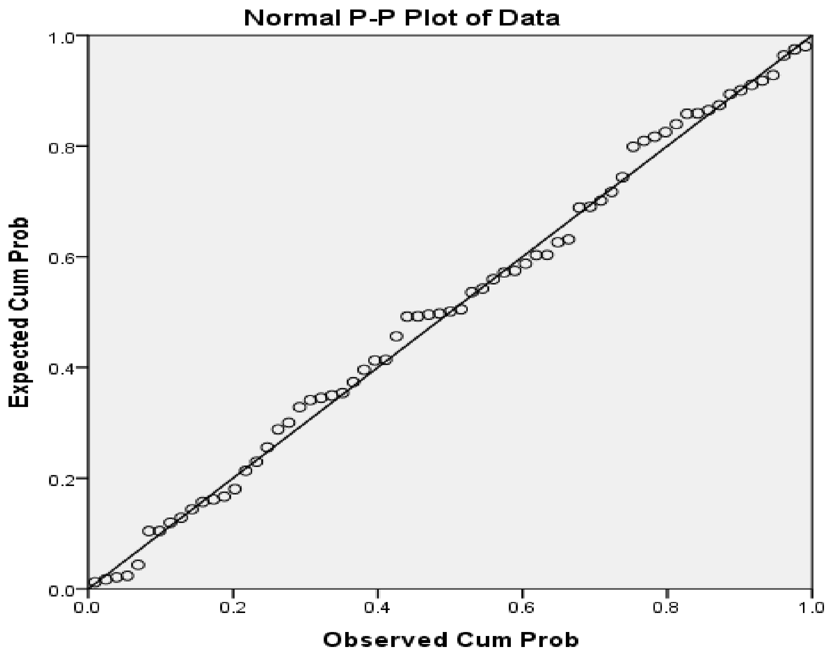

Figure 4.1 Normal P-P Plot

Source: (Secondary Data, 2020)

From the standard p-p plot, it was clear that the data from the study clustered around the standard line of best fit with no significant departures and outliers. Thus, it was noted that the data utilized for the study came from a normal distribution.

Table 4.1 Autocorrelation

Autocorrelation	
Durbin-Watson Statistic	2.14

Source: (Secondary Data, 2020)

The autocorrelation table revealed the Durbin-Watson Statistic to be at 2.140. This value is approximately 2. Thus it was interpreted to mean that autocorrelation was absent in the variables under investigation.

Table 4.2 Collinearity statistics

	Tolerance	**VIF**
Non-performing loans	0.169	5.917
Credit reports pulled	0.933	1.072
Interest rate	0.932	1.073

Inflation rate	0.998	1.002

Source: (Secondary Data, 2020)

Findings from the collinearity statistics table it was shown that credit report pulled, interest rate, and inflation rate all had VIF factors of approximately 1. This was an indication that no correlation was present in these data sets. However, nonperforming loans had a VIF factor of 5.917, indicating that it was highly correlated with other variables.

Table 4.3Levene's test

	Levene Statistic	df1	df2	Sig.
Based on Mean	0.662	12	3	0.69
Based on Median	0.425	12	3	0.787
Based on Median and with adjusted df	0.89	12	3	0.918
Based on trimmed mean	0.986	12	3	0.105

Source: (Secondary Data, 2020)

The Levene's test based on the mean had a fundamental level of 0.69. This level of importance was more significant than 0.05. This suggests that the variances across the groups under investigation are equal, and thus the data is drawn from a normal distribution.

4.3 Descriptive Statistics

Descriptive statistics are useful summaries that help give meaning to the raw data. In the study descriptive statistics that were explored included maximum, minimum, standard deviation and mean. The minimum points out the lowest data point in a data set, the maximum points out the highest point in the data se. The mean shows the average value in a dataset while the standard deviation shows how far a data point is away from the mean. Standard deviation below mean also act as indicators of consistency in the data set. Findings from the study are as shown below.

Table 4.4 Descriptive Statistics

	Minimum	Maximum	Mean	Standard Deviation(SD)
Non-Performing Loans	0.057	0.064	0.047	0.029
Credit Reports Pulled	5.4083	5.5219	5.4682	0.4476
Interest Rate	8.5	11.5	9.8333	0.684
Inflation Rate	4.69	7.99	6.492	0.183

Source: (Secondary Data, 2020)

From table 4.4 it was revealed that NPL had a mean of 0.047 and SD of 0.029. Credit report pulled had a mean of 5.4682 and SD of 0.04476. Interest rate had a mean of 9.8333 and SD of 0.684 while inflation rate had a mean of 6.492 and SD of 0.183.

4.4 Regression Analysis

The research carried out the regression interpretation to access if a relationship existed between the dependent variable and the predictor variables. The results of the regression analysis were summarized in model summary, coefficient and Anova tables. The model summary displays the variation of the dependent variable that is as an outcome of predictor variables. The Anova assess if the model fit with independent variable is statistically significant to predict the independent variables. The coefficient table gives beta values that show the impact of every predictor variable on dependent variable. It is this beta values that are used to fit a regression model. The outcome of the findings are as shown in the tables below.

Table 4.5 Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of Estimate
1	.794^{a}	0.63	0.5072	0.02484

Source: (Secondary Data, 2020)

It was determined that R^2 was 0.63. This meant that 63% of variation in nonperforming loans could be expounded by the model fitted with credit reports pulled, inflation rate and interest rates.

Table 4.6: ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	2.163	3	0.721	3.4382	.000[b]
Residual	2.097	10	0.2097		
Total	4.26	13			

Source: (Secondary Data, 2020)

Results from the Anova show that the F value was established at 3.4382 with a important level of 0.000. This significance level less than the p-value of 0.000. Thus it was sign that model fit to survey nonperforming loans based on credit reports pulled, inflation rate and interest rates was statistically significant.

Table 4.7: Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	0.406	0.058		6.962	0
	Credit Reports Filled	-0.053	0.172	0.038	-0.307	0
	Interest rate	1.099	0.454	0.353	2.42	0
	Inflation rate	0.7216	0.5113	0.215	1.412	0

Source: (Secondary Data, 2020)

Findings from the coefficient table the model fit for the data is;

$Y=0.406-0.0503X_1+1.099X_2+0.7216X_3$

Where: Y = Nonperforming Loans

X_1: Number of credit reports pulled

X_2: Interest rate

X_3: Inflation rate

4.5 Discussion of the Findings

From regression analysis it was shown that 63% of variation in nonperforming loans was due to the model fitted with number of credit cards pulled, interest rate and inflation rate as independent variables. This was also an indication that 36% of variation in nonperforming loans was either due to error or other variables that were not investigated by the study.

The constant value from the coefficient table is shown as 0.406. This meant that the value of NPLs is 0.406 if all other variables are kept constant. Draw credit report beta value -0.053. This means that with a unit increase in the number of credit reports, the unit value of nonperforming loans will decrease by 0.053. The interest rate beta value is 1.099. This is an indication that the number of arrears with a value of 1.099 will increase as a result of the unit increase in the annual interest rate. The inflation rate beta value is 0.7216. This means that a unit increase in the inflation rate would increase the value of nonperforming loans by 0.7216.

The results of this findings are in agreement with those of Omukoko (2016) who investigated the effect of CIS on nonperforming loans of commercial banks in Kenya.

In his study he concluded that an increase in the amount of credit reports shared led to a decrease in the number of nonperforming loans.

The results of this study also coincided with Ombaba (2013), which estimated the factors contributing to arrears in Kenyan banks. Their research shows that sharing credit information has a positive effect on reducing arrears. Their research further demonstrated that inflation rates and interest rates could significantly contribute to the growth of nonperforming loans in Kenya's commercial banks.

CHAPTER FIVE: SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The chapter summarizes the results, conclusions, and recommendations of the study in line with the study objective of sharing credit information and assessing the relationship between microfinance institutions in Kenya. The study additionally provides limitations and suggestions for further study.

5.2 Summary of the Findings

Based on the normality tests, homoscedasticity, autocorrelation and multicollinearity diagnostic tests that were carried out it was revealed that the data utilized for the study came from normally distributed data sets.

Findings from the descriptive statistics showed that nonperforming loans had an average of 0.047 and std. of 0.029. Credit report pulled had an average of 5.4682 and std. of 0.04476. Interest rate had an average of 9.8333 and std. of 0.684 and inflation rate had an average of 6.492 and std. of 0.183.

Results from the regression analysis established that a model fitted with credit reports pulled, inflation rate and interest rates as variables explained the variation in nonperforming loans. The outcome further indicated that model fit with credit reports pulled, inflation rate and interest rates was statistically significant to predict non-performing loans. From the coefficient table it was revealed that an increase in the number of credit cards pulled caused a reduction in nonperforming loans. It was also established that an increase in inflation rate and interest rate led to an increase in the number of nonperforming loans.

5.3 Conclusion

From the research results it was finalized that CIS possessed a negative impact on nonperforming loans. This implied that the more credit reports were pulled and shared among institutions it leads to a higher chance of spotting defaulters. Thus, this information pool will lead to a decrease in incidence of nonperforming loans.

From the outcome of the analysis, it can be concluded that inflation rate possessed a positive effect on NPLs. This implies that an increase in the inflation rate would lead to an increase in the number of NPLs that the microfinances experiences.

The study further concluded that interest rate had a positive impact on nonperforming loans. It is a show that an increase in the interest rate charged by the microfinances in the loans they advanced would result to an increase in the default of those loans.

5.4 Recommendations

From the research it was determined that credit report pulling had a direct impact on the reduction of nonperforming loans. Thus the study recommends that all microfinance institutions implement the use of CRB reports. This will aid in the identification of frequent defaulters and guide the microfinance organisation in their lending.

Findings from the research also displayed that inflation rate had a indirect effect on the reduction of nonperforming loans. Thus the research recommends that Central Bank of Kenya sets up policies that will help cushion the economy at large from high inflation rates.

Results of the study also come up with the interest rate that had a negative impact on the reduction of NPLs. The research thus, directed that that the Central Bank of Kenya to offer lower interest margins to loans advanced to the microfinance institutions. This would in turn lead to the microfinance institutions lowering their interest rates to their customers thus reducing the number of nonperforming loans.

5.5 Limitations of the Study

The research was limited in time frame that was investigated. The research specifically looked into nonperforming loans between 2014 to 2018. Thus the outcome of this research may only be inferred to this time period only.

The research was also limited to the use of secondary data. Thus the study cannot verify the validity of the data used for the research. Thus the researcher had to rely on the accuracy of the information as presented.

The researcher was also limited in the time set aside to carry out the study. However, researcher utilized the time to the best of his ability and carried out the research in the stipulated time frame.

5.6 Suggestions for Further Research

From the research it was concluded that 63% of variation in nonperforming loans was expounded by the number of credit reports pulled, interest rate and inflation rates. Consequently, it is significant for other researchers to look into the other factors that account for the remaining 36% variation in nonperforming loans.

The study looked into nonperforming loans between the years 2014 and 2018. Thus it is important for other researchers to look into nonperforming loans for a different time period. This will help establish if the results will hold for those other years as well and help establish a knowledge base of various factors affect nonperforming loans.

The study was limited to MFIs only. Thus it is paramount for other researchers to look into commercial banks as well as other financial institutions. This will help establish a knowledge base of what factors exactly help contribute to the issue of nonperforming loans.

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APPENDICES

Appendix I: Data Collection Sheet

Indicators	2018	2017	2016	2015	2014
Non-performing Loans					
Number of credit reports pulled					
Interest rates					
Inflation rate					

APPENDIX II: List Micro Finance Institutions

1. Caritas Microfinance Bank Limited
2. Century Microfinance Bank Limited
3. Choice Microfinance Bank Limited
4. Daraja Microfinance Bank Limited
5. Faulu Microfinance Bank Limited
6. Kenya Women Microfinance Bank Limited
7. Rafiki Microfinance Bank Limited
8. Remu Microfinance
9. SMEP Microfinance Bank Limited
10. Sumac Microfinance Bank Limited
11. U & I Microfinance Bank Limited
12. Uwezo Microfinance Bank Ltd
13. Maish Microfinance Bank Limited