CREDIT INFORMATION SHARING AND DEFAULT RATE OF LOANS ISSUED BY COMMERCIAL BANKS LISTED AT THE NAIROBI SECURITIES EXCHANGE

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DECLARATION

I pronounce that this project I personally developed it and is not a copy of any other work submitted to any institution for assessment.

Signature …………………………………….. Date……………………..

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Declaration by the supervisor

This research project has been submitted with my approval as University supervisor.

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DEDICATION

I dedicate the project to my lovely wife, Poisilah Lesilele, and my children, Ian Meingati, Ethan Matuni and Amelia Msayon, who encouraged and given me support throughout the process. I will always appreciate them.

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OPERATIONAL DEFINITION OF TERMS

Credit information sharing	:	Denotes to the process by which lenders provide licensed credit bureaus with information about borrowers and loan portfolios so that they can be made available to other lenders
Customer credit reports sharing	:	Entails the total number of customer credit reports shared by each commercial banks with the various credit referencing bureaus
Customer credit reports pulling	:	Entails the total number of credit reports pulled by every commercial banks from credit referencing bureaus before they advance credit to them
Costs of credit information sharing	:	Entails the amount every commercial bank incurs to pay for credit referencing services
Default rate	:	Entails the proportion of NPLs and the commercial banks portfolio at risk

ABBREVIATIONS AND ACRONYMS

CBK	-	Central Bank of Kenya
CIS	-	Credit Information Sharing
CRB	-	Credit Reference Bureau
DW	-	Durbin Watson
EU	-	European Union
FEM	-	Fixed Effects Method
GDP	-	Gross Domestic Product
GMM	-	Generalized Method of Moments
KCB	-	Kenya Commercial Bank
MFBs	-	Microfinance Banks
MRPs	-	Money remittance Providers
NIC	-	National Industrial Credit
NPL	-	Nonperforming Loans
NSE	-	Nairobi Securities Exchange
REM	-	Random Effects Method
ROA	-	Return on Assets
ROE	-	Return on Equity
SACCOS	-	Savings and Credit Co-Operative Society
US	-	United States

ABSTRACT

The strength of banking systems is key in the stimulation of economic growth and development, creation of employment, domestic and foreign investment and poverty reduction. The banking sector in Kenya has been earmarked as a core pillar for the realization of Vision 2030 of making Kenya a middle-income nation through the provision of financial services and promoting macro-economic stability. From 2013 to 2019, the default rate demonstrates a loan default increase in the Kenyan banking industry. The expanding level of default rate among Kenyan business banks has troubled different partners and general society generally. Increasing levels of credit default rates diminishes the liquidity of banks, their productivity and in this way their profitability. This investigation subsequently related credit data sharing contribution on default rates of credits given by banks in Kenya with reference to client credit reports sharing, client credit reports pulling and expenses of credit data sharing. The investigation is pegged on the information asymmetry hypothesis, the adverse selection hypothesis, moral hazard hypothesis lastly the hypothesis of credit information sharing. This research embraced an explanatory research plan targeting all 12 banks listed at the NSE and source data from their reports. Customer credit reports shared, customer credit reports pulled and costs incurred on credit information sharing explained 80.72% of default rates of loans issued by listed commercial banks. Panel regression of coefficients findings indicated that customer credit reports sharing is negatively and significantly related to default rates on loans (β =-0.0446, p=0.000). Customer credit reports pulling and default rates of loans issued by listed commercial banks have a negative and significant relationship (β =-0.03351, p=0.008) while costs incurred on credit information sharing has a positive and significant relationship (β =0.098018, p=0.000) with default rates of loans issued by listed commercial banks. Bank size has a moderating effect of bank size on credit information sharing and default rates of loans issued by listed banks in Kenya since R^2 rose from 0.8072 before moderation to 0.8615 after moderation. The study concluded that customer credit reports sharing, customer credit reports pulled and costs incurred on credit information sharing affects default rates of loans issued by commercial banks. This study recommends that commercial banks may need to adopt credit scoring methods to facilitate efficient pulling of credit information from potential loan borrowers. With the adoption of credit scoring, a bank is able to extract information from the main credit bureaus and apply a proprietary algorithm in assessing the risk profile of each applicant. Commercial banks may need to come up with an integrated information system for ensuring that customers get prompt notification on their loan status and any other information. All commercial banks management ought to put emphasis on operational efficiencies as a way of eliminating redundant operational cost and as a result improving financial performance. The study suggests the need for future studies to investigate other exogenous factors influencing default rates among borrowers in commercial banks

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The commercial banks role as financial intermediary cannot be understated irrespective of the size of banks which would varies in different nations (Ngang'a, 2015). Banks match deficit and surplus funds in the economy through acceptance of deposits and in turn giving these deposits out as loans to borrowers (Shekhar, 2015). However, the seeming questions lenders have in mind range from: will the borrowers pay the loans? Will the borrowers pay on time? Is the lending decision profitable? Lenders often do not have full knowledge of the historical behavior of customers when it comes to borrowing (Davel, Serakuane & Kimondo, 2012). As a result of this challenge, there exists moral hazard due to the fact that lenders use the general market behavior and not the specific borrowing behavior of customers when making decisions regarding lending (Chen, 2010).

Globally, banks' lending decisions are made usually under an environment characterized by high level of uncertainty (Mwangi, 2015). Several US financial institutions, such as Sanderson State Bank, Haven Trust Bank, First Georgia Community Bank, and others have collapsed or had financial problems due to loan default (Chen, 2010). Default rate of loans are have been predominantly high in some parts of Southern Europe, places such as Italy, Cyprus, Portugal and Greece are marred by severe levels of default rates (Shekhar, 2015). A number of financial institutions in economies such as Indonesia, China, Thailand, Japan, Malaysia and Mexico recorded high default rates with a number of banks were liquidated mostly during the 2008 financial and banking crisis (Balgova, Nies, & Plekhanov, 2016).

African countries are also characterized by increasing degree of default rates of loans. Most African markets are over the years struggling to address this similar challenges as regards to default rates (Balgova, Nies, & Plekhanov, 2016). For instance, in 2015 over twenty-six African countries, the level of loan default rates surpassed 10 percent (World Bank, 2017). Statistics from Nigeria showed that the default rate in Nigeria for the year 2015 grew by 78.8 percent year-on-year where N363.31 billion was reported at the end of year 2014 and N649.63 billion at the end of year 2015 (Balgova, Nies, & Plekhanov, 2016). In Uganda, the problem loans have increased among banking institutions, which has reduced their performance levels while in the Ghanaian banking sector has experienced numerous problems, such as poor loan non-repayment, despite technology adoption (World Bank, 2017).

In Kenya, high level of default rate is the key reason responsible for the demise of wound up banks (Waweru & Kalani, 2009). In Kenya, concerns of poor repayment of loans to banking institutions and other non-bank institutions are growing (Kwambai & Wandera, 2013). This has caused problems for both Kenyan banks and their clients. The CBK upon recognizing the high risks associated with the banking sector, published risk management guidelines to aid banking entities in mitigating various risk exposures arising from lending (Musyoka & Kiage, 2015). However, due to adverse selection, increased probability of default rate highly increases banks' cost to income ratio among Kenyan banks (Kimasar & Kwasira, 2014). Therefore, the need to assess how credit information sharing affects default rates of loans issued by listed Kenyan banks.

1.1.1 Credit Information Sharing

Credit information sharing (CIS) involves credit providers for example banks and other licensed creditors to authorized credit reference bureaus (CRBs) for other credit providers to access (Kusi & Ansah-Adu, 2015). CIS is an organization remedy to the problem of asymmetric information and the resultant dilemmas of adverse selection and weak incentives to repay loans in the banking sector (Kusi & Ansah-Adu, 2015). Credit information systems fill the knowledge gap amongst the borrower and the lender by providing the loan repayment history, total debt and overall creditworthiness of the borrower (Peria & Singh, 2014).

Sharing of credit information makes it simpler for contending banks to dismiss their great and bad debtors (Gietzen, 2016). Credit data sharing is key in minimizing information asymmetry that exists among banks and borrowers (Chen, 2010). Credit data sharing was introduced which serves as a middle playing ground for both lenders (banks) and borrowers (customers) (Kiage, Musyoka & Muturi, 2015). Credit information sharing entails customer credit reports sharing and customer credit reports pulling. In addition, sharing and pulling credit information attracts various costs incurred by banking institutions in credit information sharing.

Sharing of customer credit reports entails exchanging information about their customer's loan repayment status. Bank can share positive information, which indicates customers are properly paying their loan obligations, or negative information, which indicates that customers have deflated in paying their loan obligations (Sutherland, 2018). Customer data sharing about borrowers' qualities and their obligation can significantly affect credit markets movement. This improves the banks' learning of candidates' qualities and grants an increasingly exact expectation of their reimbursement probabilities. Secondly, it decreases the enlightening rents that banks could obtain from their clients (Jappelli and Pagano, 2005).

Customer credit reports pulling is the aggregation of credit reports pulled by every commercial bank from authorized credit referencing bureaus before they advance credit to them (Hajat, Ketley, Miano & Njeru, 2016). Banks can get information on borrowers' qualities and loan repayment history through pulling of credit reports from the available credit referencing bureaus (Gietzen, 2016). CRBs usually collect financial data, process the data, store it and at the request of lenders and other financial institutions, share or provide the credit worthiness status or report for lending decisions by the requesting institution (Kusi, Agbloyor, Fiador & Osei, 2016).

CRB usually provides banks with the enablement to easily identify or pick between defaulters from borrowers, those adversely listed as defaulters are rejected or stringent measure be applied in appraising them for loan qualification (Mugwe & Olweny, 2015). However, banks have to incur costs on information sharing and they normally incur cost on reporting and pulling credit information. Sutherland (2018) argues that lenders tend to share more information about their customers when benefits of information sharing outweigh or when the competition cost is low.

Credit information sharing was presented in the Kenyan financial industry to encourage the idea of credit data sharing, reduce information asymmetry and credit risk. There are three authorized credit reference bureaus in Kenya, namely; CRB Africa, Metropol Ltd and Credit Information CRB Ltd which were authorized in 2010, 2011 and 2015 respectively. Kenya's Credit Reference Bureaus play a complementary role to banks because CRB provides banks with the environment to lend more to lower risk customers (Hajat *et al.*, 2016). Due to the uncertainty involved in lending, commercial banks over time have come up with higher loan interest rates and stringent collateral terms which is a move or strategy to cushion themselves from the risk of loan default rates. The promoters of the credit information sharing managed to have the bill passed and assented to law requiring all financial institutions to share credit information to accredited credit reference bureaus (Kiage, Musyoka & Muturi, 2015).

1.1.2 Default Rate

Default rate is a key aspect in each and every bank in the determining its stability and also the level of its liquidity at all times (Wanjiru, 2013). Gitahi (2013) indicated that loan portfolios are among the largest bank assets as they are also their largest sources of revenue due to the financial intermediation role they play. Loan default is and continue being an issue of great concern not only for the lenders but also for policy makers. The cost forgone to provide for NPLs is fairly large as NPL to a great extent reduces the banking sector efficiency (Hanifan, 2017). High rate of defaults among the banks has contributed immensely in poor performance of banks (Kumarasinghe, 2017).

In the scenario of increasing default rate of loans, commercial banks tend to increasingly do internal consolidation, which aims at improving the quality of assets as against issuing of credit (Alloyo, 2013). Additionally, the high level of default rate necessitates commercial banks to increase the provision for loan loss and this in turn depletes bank revenue, thereby making funds unavailable for additional or new lending to customers. Thus, it is challenging for lenders to predict whether their creditors will pay back their loans in full leading to default risk (Hanifan, 2017).

In Kenya, for the year 2014, the percentage of default rate in Kenya captured as non-performing loans to total gross loans was reported as 5.5 percent which increased when compared to the 5.05 percent of the previous year in 2013 (World Bank Group, 2015). The percentage reported is the ratio between NPL and the total value of the loan portfolio. Table 1.1 shows the trend in percentage of default rate of commercial banks in Kenya.

Table 1.1 Trends in Default Rate

Year	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Default rate (%)	6.29	4.43	4.59	5.05	5.46	5.99	7.453	8.923	10.617

Source: World Bank (2017)

Table 1.1 provides the trend in loan default rate for Kenyan banks. The trend is shown to be on an increasing pattern. Default rate was reported at 4.59 percent in 2012, which indicates an increase in comparison to that of 4.43 percent in 2011. The default rate level in Kenya further rose to 5.99 percent in 2015 from 5.05 percent in 2013. Commercial banks default rate further increased to 7.453 percent in 2016, 8.923 percent in 2017 and 10.617 percent in 2018 (CBK, 2019).

1.1.3 NSE Listed Commercial Banks in Kenya

Kenyan banking industry entails the apex regulator which is the CBK, 42 financial institutions with 41 being commercial banks and 1 mortgage finance company, 13 microfinance Banks (MFBs), 9 representative offices of foreign banks, 19 Money remittance Providers (MRPs) 3 credit reference bureaus (CRBs), and 73 foreign exchange bureaus (forex) as at 31 December 2018. Among the 43 banking institutions, 40 are privately owned, Government of Kenya has majority of ownership in 3 institutions. In addition, 15 among the 43 commercial banks have foreign ownership and controlled while the remaining 28 are locally owned (Banking Sector Annual Reports, 2016). All the money remitters providers, Credit reference bureau, Microfinance banks, on-Operating Bank Holding Companies and representative offices are privately owned (CBK, 2017).

The twelve (12) commercial banks listed on the Nairobi Securities exchange include; Barclays Bank Ltd, I&M Holdings Limited, Co-operative Bank of Kenya, CFC Stanbic Holdings Ltd, HF Group Limited, KCB Group Ltd, Diamond Trust Bank Kenya Limited, National Bank of Kenya Ltd, Standard Chartered Bank Ltd, NIC Group plc, BK Group PLC and Equity Group Holdings (Capital Markets Authority, 2017). This study drew conclusion by studying all the 12 listed commercial banks. A number of commercial banks operating in Kenya have exhibited diminishing performance which has mostly been associated with inadequate credit information on the creditors. Lack of adequate credit information increases the likelihood of credit defaulters which in turn leads to loss of both principle and interest accrued (Oira & Wamugo, 2018).

1.2 Statement of the Problem

The banking sector in Kenya plays a central role for the realization of Vision 2030 of making Kenya a middle-income nation through the provision of financial services and promoting macro-economic stability (Ngang'a, 2015). However, Kenyan banks have experienced significant losses attributed to high loan default levels from the borrowers (Gachora, 2015). According to the CBK (2018), the gross NPL to gross loan rates increased to 12.3% in 2017 from 9.2% in 2016, mainly due to unfavorable business environment experienced in 2017 and the overall NPL also increased by 23.4%. In addition, three Kenyan banks among them Imperial bank, Chase bank and Charter house were placed under receivership in 2015 due to a number of factors, including liquidity, mismanagement and default risk (Oira & Wamugo, 2018). Despite various effort by government to ensure a sound banking systems through the creation of Credit Reference Bureaus, default rate among Kenyan banks is steadily increasing (CBK, 2017).

Although credit information sharing is viewed to be critical to improve performance for lenders through lessening of default rates, this relationship is less discussed (Cheng and Degryse, 2010). However, in majority of the developing countries particularly in Africa, credit information systems still are in the early stages, and information sharing amongst lenders is still weak (Grajzl & Laptieva, 2016). Africa for instance remains one of the regions with most inefficient credit information systems (Nkoma, 2018). Further, it is postulated that CIS is a costly affair to banking entities and unevenly distributed data and issues of adverse selection are attributable to bank loaning since borrowers are more informed about their financial status than the banks (González-Uribe & Osorio, 2014).

Empirically, researchers have examined the effect CIS in the banking sector among them Morscher, Horsch and Stephan (2017) and Hu, Gu and Zhou (2017) among EU banks. Others include Sahin (2017) in 55 countries, Grajzl and Laptieva (2016) in Ukraine and Guérineau and Léon (2019) in 159 countries however, most of the international studies use cross country data as opposed to bank level data on CIS and loans default. In Kenya, Otete, Muturi and Mogwambo (2016), Oira and Wamugo (2018) assessed CIS and banks profitability while Maina *et al.* (2016) and Mwangi (2015) focused on CIS and SACCOs performance. As per the reviewed studies, it is evident that the few studies done on CIS in Kenya focus more on CIS and financial performance. In addition, the studies focus on various financial institutions among them commercial banks, microfinance banks and SACCOs. Further, the studies provide contradictory results, with most oscillating from positive to negative, using different methodologies hence an empirical literature gap. This study assessed how does CIS contribute to changes in default rates of loans issued by listed commercial banks in Kenya?

1.3 Objectives of the Study

1.3.1 General Objective

The general objective for this research was to determine the effect of credit information sharing on default rates of loans issued by listed commercial banks in Kenya

1.3.2 Specific Objectives

These include:

1. To evaluate how customer credit reports sharing affects default rates of loans issued by listed commercial banks in Kenya.
2. To investigate influence of customer credit reports pulling on default rates of loans issued by listed commercial banks in Kenya.
3. To examine the effect of costs of credit information sharing on default rates of loans issued by listed commercial banks in Kenya.
4. To determine the moderating effect of bank size on credit information sharing and default rates of loans issued by listed banks in Kenya

1.4 Null Hypotheses

The null hypotheses for the study were:

H_{01}: Customer credit reports sharing does not significantly affect default rates of loans issued by listed commercial banks in Kenya.

H_{02}: Customer credit information pulling does not significantly affect default rates of loans issued by listed commercial banks in Kenya.

H_{03}: Costs of credit information sharing does not significantly affect default rates of loans issued by listed commercial banks in Kenya.

H_{04}: There is no significant moderating effect of bank size on credit information sharing and default rates of loans issued by listed commercial banks in Kenya.

1.5 Significance of the Study

The management of commercial banks will be one of the groups that may benefit from the outcome of the study. The study may provide them with suggestions as regarding credit reference bureaus and default rate of banks and how they can use CIS to reduce default rates and in essence enhance bank performance.

The government via the Central Bank of Kenya may also find this study useful as it may highlight relevant policy implications and recommendations which when followed will ensure the stability of the Kenyan banking industry. The legislators may come up with policies that will make CIS more effective leading to improved efficiency in the Kenyan banking sector.

This research contributes to the existing literature and sheds more light on the subject matter. Researchers who wish to carry out further investigations on loan default rate of banks may find this study as a form of foundation which they can use and expand on. The study will also help in theory development.

1.6 Scope of the Study

The researcher incorporated listed banks operating in Kenya between 2013 and 2017 and data analyzed using regression technique. The study only covered the 11 commercial banks listed at the NSE. The conceptual scope of the study was customer credit reports sharing, customer credit reports pulling and costs of credit information sharing. Panel data was collected from the selected banks and regression analysis applied for data analysis purposes.

1.7 Limitations of the Study

One of these study limitations is data quality. It cannot be ascertained from the investigation whether findings show accurate facts from the situation. An assumption is made that the data is accurate. The measures used may change from a year to the next based on current conditions. The research used secondary data, which was in the public domain had already been obtained, unlike the first-hand information associated with primary data. The study considered selected determinants and not every factor that determines default rate of Kenyan banks primarily due to unavailable data.

1.8 Organization of the Study

This research thesis is organized into five chapters. Chapter one covers the introduction, chapter two covers literature review, chapter three covers the research methodology, chapter four covers data analysis and interpretation while chapter five covers discussion, conclusion and recommendations. In chapter one, the researcher has discussed the study background, study objectives, study significance and ends with scope and limitations for the study. Under chapter two, relevant theories on which the study is anchored on and empirical reviews are discussed to shed more light on the research question. Chapter three depicted the research methodology used in this study. It gives more on details the research design, sampling, population, data collection methods, research procedures and how data collected was analyzed. Chapter four illustrates the results and findings of the study. Chapter five concluded the discussion and included the conclusion, and recommendations for further implementation and research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This section looks at a number of theories guiding the study under the theoretical review, carries out an analysis of related studies under empirical review. The chapter also presents a literature review summary, the research gaps arising from empirical review and the conceptual framework.

2.2 Theoretical Review

The study was pegged on four theories which include; Information asymmetry theory (Akerlof's, 1970); Adverse selection theory (Rothscild and Stiglitz, 1976), moral hazard theory (Suglitz, 1983) and finally the theory of credit information sharing by Pagano and Jappelli (1993).

2.2.1 Information Asymmetry Theory

This theory was developed by Akerlof (1970) and it explained a situation where some of the parties in an undertaking have more information than others (Fosu, 2014). As indicated by the hypothesis, when average quality of a product is predictable in a market with an unpredictable product quality, the above quality product will be forced out of the market by market forces hence affecting products viability (Cheng and Degryse, 2010). In credit markets, risk from borrowers can be related to a good bought by the lender (Turner and Varghese, 2010). The hypothesis demonstrates that data asymmetry and poor agreement implementation lead to a disequilibrium in credit market (González-Uribe and Osorio, 2014).

The theory indicates that during lending, information asymmetry is contributed by the inability for the lender to access borrower's information on likelihood to repay also referred to their risk profile (Dierkes et al., 2013). The major critique of the theory is that theory was developed on the assumptions of perfect capital markets among the no transaction costs, no taxes and rationality some of which have been contested in literature (Brown & Zehnder, 2010). The theory has also been criticized that capturing special borrower information has various disadvantages for example, it is expensive, time consuming, having limited scope and coverage and causing informational rent (Sahin, 2017).

According to the theory, one method of eliminating asymmetric information challenge is generating specific information from observing the past behaviors of borrowers during the bank relationship (Negrin, 2011). The theory supports that sharing information lessens information asymmetries among borrowers and lenders, which helps screening and checking, improves the match among money lenders and borrowers, and upgrades access to credit for reliable borrowers (Sutherland, 2018). The hypothesis is utilized in this investigation to clarify that coordination among moneylenders to share and force data about their customers' past conduct hence low information asymmetry challenges.

2.2.2 Adverse Selection Theory

This theory was developed by Rothscild and Stiglitz (1976) and it revealed that the buyer knows the possibility of the accidents exposed while the seller does not. This happens when a customer deliberately engages in financial risks provided the consequences will be catered for by a third party (González-Uribe & Osorio, 2014). The hypothesis is anchored on two fundamental viewpoints; one is that banks are unable to recognize loan applicants of various risk levels, and that credit agreements can be broken. The theory is further anchored on the assumption that borrowers can only payback the loans when they are financially stable. Loan fees influences the profits from borrowers with low risks scaring them away (Hu, Gu and Zhou, 2017).

The theory of adverse selection explains why the adequate information on the borrowers improves the efficiency of the credit markets (Cheng & Degryse, 2010). More information increases the ability of lenders to determine accurately the risk extent for the borrowers so as to set the appropriate loan terms. This allows for the accommodation of high risk borrowers by setting higher interest rates which in turn leads to few high risk borrowers (Dierkes et al., 2013). On the other hand, the lower-risk borrowers enjoy lower loan fees which increases the demand for loans (Barron & Staten, 2013). The adverse selection theory is however faced with the challenge of differentiating between the bad and good borrowers (Hu, Gu & Zhou, 2017).

The limitation of the adverse selection theory therefore poses a risk to the lenders who are unable to differentiate between the bad and good borrowers and end up charging a uniform interest rate to all based on the general experience (Hu, Gu & Zhou, 2017). The theory also posits that, exchange of borrowers' credit information among the commercial banks in order to establish the quality of foreign clients and loan them with more concern as the local clients (Cheng & Degryse, 2010). Lessening of information asymmetry amongst lenders and borrowers through the credit reference bureaus allows for allocation of loans to the low risk borrowers who had earlier been locked out hence increasing the higher lending rates (Dierkes et al., 2013). In this study, the theory supports that sharing and pulling information on the loan applicant history minimizes adverse selection and hold-up problems.

2.2.3 Moral Hazards Theory

This theory as developed Suglitz (1983) refers moral hazard as the risk involved when an exchange has not gone into the agreement in compliance with common decency or has provided misleading information or has a motive to deliberately undertake unusual risks so as to earn a benefit before the agreement settles (González-Uribe and Osorio, 2014). The hypothesis suggests a voidable agreement between two gatherings whereby; party undertaking the risks has more information than the party to bear the consequences (Negrin, 2011). This theory apply to lending scenario in that bad borrowers knowing well there are no consequences will not make any effort to service their loans leaving the lender disadvantaged (Bos, Haas & Millone, 2013).

According to moral hazard concept, a borrower will always intend to default except the cases where the applicant is aware of possible future consequences (Sahin, 2017). This leads to the challenge in assessing the borrowers' wealth accumulation at loan maturity, as opposed to the time of application. Inability of a lender to determine the borrowers' wealth will entice the borrower to default (González-Uribe & Osorio, 2014). The assumption of the theory that higher interest rates leads to a different problem, adverse selection, since high interest loans will only be accepted by high risk borrowers has been criticized by various authors (Negrin, 2011).

According to the moral hazard hypothesis, the low capital banks are more vulnerable to high rates of non-performing loans since they increase the riskiness of their loan portfolio as an attempt to deal with the moral hazard incentives (Bos, Haas & Millone, 2013).

According to the theory, pooling default data minimizes moral hazard issues only if the lender has adequate information about the borrower. Sharing data about borrowers' obligation presentation minimizes the specific type of moral hazard from borrowers' capacity to obtain loan from several lenders (Jappelli and Pagano, 2005). In this research, the moral hazard hypothesis clarifies that credit data pooling can expand borrowers' expense of defaulting, consequently expanding debt repayment.

2.2.4 Theory of Credit Information Sharing

This theory was developed by Pagano and Jappelli (1993) and they argued that credit data sharing decreases adverse selection in bank loaning (Fosu, 2014). Sharing of the information increases the customer base which in turn increases loaning profits. Without credit data, banks cannot recognize new borrowers who are probably going to repay and other people who are probably going to default (Brown & Zehnder, 2010). The hypothesis has been condemned that when banks focus on sharing credit data, the extraction of instructive lease is controlled and furthermore acquires extra costs henceforth rising default costs (Brown, Jappelli and Pagano, 2009).

The hypothesis thus argues, since the new loan candidates may have acquired from different banks before, data sharing can help the bank being referred to settle on the correct choice to loan securely to trustworthy new candidates. However, the general effect on loaning relies upon the degree to which expanded loaning to safe borrowers makes up for the diminished loaning to risky borrowers (Barron & Staten, 2013). The information sharing theory posits all credit information is available and accessible by all players. However, this can only happen with high levels of technology adoption but illiteracy and ignorance from other players may hinder effective credit information sharing (Cheng & Degryse, 2010).

The hypothesis underpins that data sharing can diminish adverse selection in business sectors where borrowers approach various moneylenders consecutively. Increasingly, data sharing can likewise have a significant disciplining impact on borrowers (Brown and Zehnder, 2007). Data sharing similarly motivates borrowers to perform in accordance with banks' expectations (Dierkes et al., 2013). As per the hypothesis, credit data sharing affects performance of credit markets by diminishing effects of adverse selection in loaning hence minimizing moral hazard with respect to borrowers, in this way expanding borrower intentions and decreasing credit apportioning in numerous bank loaning (Barron and Staten, 2013). In this investigation, the hypothesis clarifies that data sharing and pulling mitigates the hold-up issues in loaning connections, which emerge when banks have or produce private data about firms.

2.3 Empirical Review

2.3.1 Customer Credit Reports Sharing and Default Rates of Bank Loans

A study by Oira and Wamugo (2018) studied how commercial banks' credit information sharing influences their performance. Using regression analysis on the obtained data from the 43 commercial banks found that changes in performance of commercial banks were significantly contributed by the credit information sharing since rate of loan repayment was positively influenced by effective credit information sharing system.

Mwangi (2015) looked at how loan performance of SACCOs operating within Nairobi County is influenced by credit information sharing. A descriptive survey was utilized for the study and secondary data collect data of 42 SACCOs between 2013 and 2015. Using the regression model, results found a negative relationship between the numbers of credit reports accessed from CRB and default rate. In addition, a negative relationship was found between the loan credit reports forwarded to CRBs and default.

Fosu (2014) examined the contribution of CIS on bank lending. The study collected bank-level data from African countries during the period 2004 and 2009 and utilized a dynamic two-step system generalized method of moments (GMM) estimation. The study found that customer credit sharing increased bank lending. The study also found that the degree of banking market concentration moderates the effect of CIS on bank lending.

In their study, Giannetti and Jentzsch (2013) assessed credit reporting, financial intermediation and identification systems. The study employed the difference-in-difference regression to analyse data from 172 countries for the period 2000 and 2008. The results revealed credit reporting positively contributed to financial intermediation (bank credit to deposits, net interest margins) and financial access (private credit to GDP), more so in countries that have credit reporting systems.

Doblas-Madrid and Minetti (2013) explored the effect of moneylenders' data sharing on firms' exhibition in the credit market utilizing rich agreement level information from a U.S. credit authority. The investigation utilizing regression analysis uncovered that data sharing diminishes contract misconducts and defaults, particularly when firms are unable to access information. The outcomes additionally uncovered that data sharing does not decrease the utilization of guarantees, that is, it may not uphold the loaning principles.

2.3.2 Customer Credit Reports Pulling and Default Rates of Bank Loans

Morscher, Horsch and Stephan (2017) did the credit information sharing contribution to changes in financial inclusion and financial intermediation. Using several regression analyses the study found a positive relationship between information sharing mechanisms and financial inclusion (measured by account (at a financial institution), borrowed from a financial institution, and domestic credit). The study however found that CIS did not contribute to changes in bank performance significantly.

Hu, Gu and Zhou (2017) investigated the contribution of comprehensive customer information pulling on aggregate credit volume and the default ratio. The study used a three-stage game model developed by Dell'Ariccia and Marquez (2006) and data from the European Union (EU). The results indicated that when an information sharing system develops to a relatively high level, comprehensive information sharing improvements, for both the width and depth, are associated with the rise in macro credit access but also the aggregate default risk.

A study Sahin (2017) examined whether the variation in non-financial information sharing in different countries affected the proportion of non-performing loan. The study collected data from 55 countries from 2015 to 2017 and the Ordinary Least Squares Method used for data analysis. The results revealed that in a credit reporting institution the rate of non-performing loans of banks was reduced by there being non-financial credit information from retails and utilities companies, in addition to financial sources.

In Ukraine, Grajzl and Laptieva (2016) inspected the effect of data sharing on the volume of private credit utilizing bank-level board information. The investigation utilized the fixed-impacts system and dynamic board strategies for data analysis. The examination found that there was no credit volume impact of data sharing when data sharing happens through the national bank-regulated open credit registry. The investigation likewise found that data sharing through private acknowledge authorities was related to the expansion in the volume of bank loaning, specifically when a bank is accomplice of different private credit agencies.

In Kenya, Otete, Muturi and Mogwambo (2016) surveyed the impact of credit data sharing on the profitability of commercial banks. The investigation gathered information utilizing surveys from the 43 banks in Kenya in 2016. Utilizing the regression analysis, the investigation concluded that general volume of loaning among banks has expanded because of pulling of client data from credit referencing organizations. The outcomes likewise uncovered that the effect of client credit reports on performance estimated by ROA and ROE was measurably insignificant.

2.3.3 Costs of Credit Information Sharing and Default Rates of Bank Loans

Guérineau and Léon (2019) did impact of credit data sharing and profitability. The investigation embraced a probit estimation of budgetary stability and gathered information from 80 developed economies and 79 third world countries. The examination found that credit data sharing lessens money related delicacy for the two sets of nations where for less developed nations, the principle impact was the decrease of NPL proportion. The investigation likewise found that credit data sharing additionally mitigates the impeding effect of credit blast on money related delicacy and the expense of IS negatively affected performance.

In Ghana, Kusi, Agbloyor, Fiador and Osei (2016) assessed contribution of information sharing to changes in profits of banks. Using Prais-Winsten panel regression for data analysis from 25 banks the findings revealed that information sharing through CRBs positively affected banks profitability. The study further concluded that information sharing lowers adverse selection and moral hazard risks which in turn reduces information asymmetry.

Maina, Kinyariro, Muturi and Muriithi (2016) assessed how credit information sharing contributes to level of loan defaults among SACCOS. Through use a descriptive survey and questionnaire to collect data, it was analysed using the regression model. The study revealed costs of credit information sharing, credit scoring and level of loan default among SACCOs strongly relate. From the study finding, the conclusion stated that CIS significantly affected the loan default level.

Kinanga (2016) considered the relationship between client data sharing and the Kenyan banks’ performance. A correlational plan was embraced and questionnaires used to gather information from 20 banks and utilized a regression analysis. The outcomes set up that the expenses of credit data sharing essentially affected banks' profitability. The outcomes likewise exhibited a positive connection between client data sharing, attributes of borrowers and Kenyan banks’ profitability.

Dierkes *et al.* (2013) explored how credit data sharing affected expenses and default risks of private firms. The investigation dependent on a board dataset that including private firms from various enterprises uncovered that business credit data sharing considerably improves the nature of default expectations. The investigation found that the improvement was more grounded for more seasoned firms and those with constrained risk, and relies upon the sharing of firms' payment history and the quantity of firms secured by the local credit department office. The examination likewise found that high estimation of business credit risk brings down the acknowledged default rates.

2.3.4 Default Rate

Yeboah and Oduro (2018) examined the factors contributing to rising loan defaults among lending institutions in Ghana. The study utilized primary data which was obtained from 244 respondents using questionnaires and the logistic regression for data analysis. Monitoring, education level, marital status and loan diversion were found to significantly contribute to loan default. The study suggested that credit education and loan appraisal should reduce credit default.

Makri and Papadatos (2016) assessed the determinants of default rate using a multivariate regression and secondary data spanning from 2003 and 2014 in Greece. The study used the ratio of provisioning of loan loss as the proxy for credit default. The results revealed that unemployment, public debt, growth of the economy, the consumer price index and internal factors among them profitability, past loan repayment history were the major factors leading to high rates of default.

Louzis, Vouldis and Metaxas (2012) investigated the factors that enhanced NPLs on mortgage, corporate and consumer loans among banking institutions in Greek. The study using the dynamic panel data methods revealed that management quality a microeconomic factor and macroeconomic (external) factors mainly the rates of interest rate and levels of unemployment significantly impacted NPL levels. Further, it was evidenced NPLs on mortgage loans were the least affected by changes in macroeconomic conditions. The study however covered both the macro and microeconomic factors and their effect on NPLs and not on loan repayment by consumers.

Podpiera and Ötker (2010) examined the fundamental contributors to credit default among European large financial institutions. The study collected data from 29 institutions between 2004 and 2008 and dynamic panel data estimator for data analysis. The findings revealed that some of the key determinants of credit risk included earning potential, business models and economic uncertainty. More so, liquidity, earning potential, capital adequacy, assets quality and quality of management affected default rates.

2.4 Summary of Research Gaps

The studies above presents knowledge gaps to be filled. First, the reviewed studies provided mixed conclusions on the direct relationship between CIS and default rate. Further, very few studies have been conducted on the relationship between the two study variables in both developed and developing economies and therefore need to conduct studies on the relationship between CIS and default rate.

Previous studies also reveal conceptual and contextual gaps. Conceptually, the findings of previous studies have been inconsistent ranging from a significant positive relationship to no relationship at all. These differences can be explained by the fact that previous researchers have operationalized CIS differently and therefore findings are specific to the operationalized method used. Contextually, most of the existing literature focuses on emerging markets with little research on developed and less developed markets.

Further, most of the studies used different research designs with some basing on empirical literature review to come up with conclusions while others review relevant literature to measure the interrelationships among the study variables. Researchers provided mixed and inconclusive results and also failed to document evidence of the likelihood that further innovation will be necessary to generate a more reliable CIS model. The different views from different authors therefore necessitate intervention by future studies to fill the gap by conceptualizing how CIS influence default rate. These gaps have shown that research on CIS and default rate relationship still has several grey areas with no empirical consensus. This study highlights the glaring research gaps in the study area and forms the basis for future advancement on CIS and default rate studies.

The table below presents details of the variable indicators, method of measurement and the type of the variable.

Table 2.1: Summary of Research Gaps

Study	Objective	Methodology	Findings	Gaps
Guérineau & Léon (2019)	Credit information sharing on financial stability in 179 countries	Probit estimation	Credit information sharing reduces financial fragility and reduction of NPL ratio	The study used country level data and covered several countries thus a contextual gap. The study also used the Probit model hence a methodological gap
Oira & Wamugo (2018)	Credit information sharing and profitability of commercial banks in Kenya	Multiple regression analysis	Credit information sharing system significantly affect capability to repay loans	The study data was acquired using a questionnaire hence a methodological gap
Morscher, Horsch and Stephan (2017)	Credit information sharing on financial inclusion and financial intermediation in Europe	Regression analysis	Positive relationship between CIS mechanisms and financial inclusion	The study did not incorporate default rates but focused more on lending

Hu, Gu and Zhou (2017)	Customer information pulling on aggregate credit volume and the default ratio in the EU	Three-stage game model	Information sharing improvements, for both the width and depth, are associated with the rise in macro credit access	The study used a different approach of data analysis hence a methodological gap
Otete, Muturi and Mogwambo (2016)	Credit information sharing on commercial banks' profitability	Regression method	Customer credit reports insignificantly affected banks ROA and ROE	The study focused on profitability and not default rates
Study	**Objective**	**Methodology**	**Findings**	**Gaps**
Kusi et al (2016)	Information sharing and profitability of banks	Prais-Winsten panel regression	Information sharing through CRBs positively affected banks profitability	The study focused on profitability and not default rates
Maina et al (2016)	Credit information sharing and the level of loan default in deposit taking SACCOS in Kenya.	Regression model	Credit information sharing significantly influenced level of loan default	The context of the study was SACCOs and not commercial banks
Kinanga (2016)	Credit information sharing and commercial banks' performance in Kenya	Regression model	Costs of credit information sharing significantly influenced banks' profitability	The study focused on profitability and not default rates
Mwangi (2015)	Credit information sharing on the loan performance among SACCOs in Nairobi county	Regression model	Negative relationship between the numbers of credit reports accessed from CRB and default rate	The context of the study was SACCOs and not commercial banks
Fosu (2014)	Credit information sharing and bank lending in African Countries	Generalized method of moments (GMM)	Customer credit sharing increased bank lending. Market concentration moderates the effect of CIS on lending	The study was a cross country study which covered several countries thus a contextual gap
Giannetti and	Credit reporting,	Difference in	Credit reporting	The study used

Jentzsch (2013)	financial intermediation and identification systems in 172 countries	difference regression	had a positive effect on financial intermediation and financial access	country level data and covered several countries thus a contextual gap

2.5 Conceptual Framework

Conceptual framework has been defined as collection of standards and thoughts got from appropriate enquiry fields and utilized in organizing a resulting presentation. As depicted in the conceptual framework, the independent variables include; customer credit reports sharing, customer credit reports pulling and costs of CIS while the dependent variable is default rates of bank loans. Figure 2.1 below is the study conceptual model.

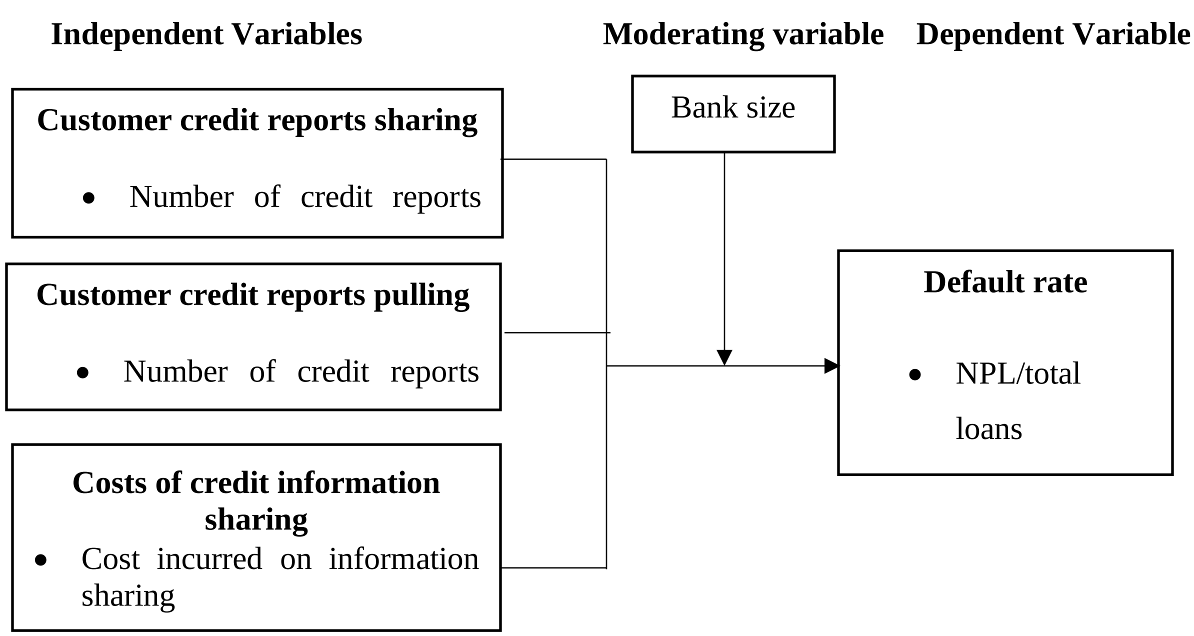

Figure 2.1: Conceptual Framework

Source: Author (2019)

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

A study methodology refers to the logical theoretic exploration of the approaches used in a study. This chapter thus consists the study research design, target population, sampling and sample size, the procedure of collecting data, and the process of data analysis.

3.2 Research Design

Burns and Burns (2008) define a research design as a blueprint or framework for collection, measurement and analysis of data, a plan or procedural outline that enables a researcher obtain answers to research questions. Khan (2008) opines that there are three major types of research design exist which are descriptive, exploratory and causal. He goes further to explain exploratory studies and say that they aim on providing understanding of a new knowledge and generation of new ideas to the researcher.

Explanatory and descriptive research designs were used for the study. Saunders *et al.* (2009), explains that explanatory research design establishes root association between variables. Researchers should be knowledgeable of the phenomenon in order to infer or detect pertinent root associations (Zikmund *et al.*, 2012). The researcher should be able investigate and understand how changes in one event influences another event of interest. In descriptive design, research emphasizes on the description of a set of elements or units (Robson, 2012).

Descriptive research design is in addition explained by Sreejesh *et al* (2014), who asserts that it ought to describe the features of specific groups for purpose of identifying certain behavior, to make specific forecasts and to assess the difference between groups. Hence the design for this study is both explanatory and descriptive since the researcher emphasizes the association of variables and purpose to identify their root effect.

3.3 Target Population

Kombo and Tromp (2006) describe population as group of elements, people, events or things that are being evaluated to infer results. The study undertook a census by studying all 11 commercial banks listed at NSE as attached in appendix I.

3.4 Sampling and Sample Size

Sampling entails random selection of elements from the target population to be included in the study (Saunders & Thornhil, 2007). A sample on the other hand is a lesser set of subjects acquired from the available study population. This study did a census which was the 11 listed commercial banks in Kenya. Cooper and Schindler (2007), indicates that a census is possible in the case of a small population and essential if the elements are very different. Therefore, since the population is small and the listed banks are assessable with certainty it was appropriate for to use census for this study.

3.5 Data Collection Techniques

This study relied on the secondary information from the available annual reports which were acquired from the three credit referencing bureaus in Kenya and the respective commercial banks' credit reports using a secondary data collection form. The data ranged on a 5-year period from 2014 to 2018. Information collected included; Data on the annual cost incurred on reporting and pulling credit information by every bank and data on the proportion NPL to total loans, aggregation of credit customers and credit reports.

3.6 Data Analysis

Raw data were classified and tabulated to summarize the results using descriptive statistics which consist of averages, standard deviations and frequencies. Tables and graphs presented data outcomes. To analyze the association between the study variables, the researcher employed Stata software. The connection amongst the variables, were determined using a multi-linear regression model. Inferential statistics and correlation testing were also carried out. The regression equations was formulated as follows

$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \varepsilon\text{it} \ldots\ldots$ *equation 3.1*

$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X * M + \varepsilon\text{it} \ldots\ldots$ *Equation 3.2*

Where;

Y_{it} = Default rate on loans measured using the proportion NPL to total loans for bank *i* at time *t*

X_{1it}- Customer credit reports shared by bank *i* at time *t*

X_{2it} - Customer credit reports pulling by bank *i* at time *t*

X_{3it} - Costs of credit information sharing by bank *i* at time *t*

M – Moderating variable (bank size for bank *i* at time *t*)

β_0 = Constant

$\beta_1 - \beta_4$ = Regression Coefficients

ε= Error term

All the variables have to be standardized using the moderating variable (M). The interaction terms (X_{1it} M, X_{2it} M, X_{3it} M and X_{4it} M) have to be calculated using the compute function as expressed in model (3.2). If $\beta_{1,}$ $\beta_{2,}$ β_3 and β_4 are significant, moderation effects exist in the four relationships. If only one is significant, moderation effect only exists in one of the relationship and if both $\beta_{1,}$ $\beta_{2,}$ β_3 and β_4 are insignificant, no moderation effect exists and M becomes just another independent variable (MacKinnon, 2011).

3.6.1 Definition and Measurement of Variables

The study comprises of explanatory variables, which include customer credit reports sharing, customer credit reports pulling and costs of CIS and the dependent variable default rates of loans issued by banks. Customer credit reports sharing entails the total number of customer credit reports shared by each commercial banks with the various credit referencing bureaus in Kenya. Customer credit reports pulling entails the total number of credit reports pulled by every commercial banks from credit referencing bureaus before they advance credit to them. Further, costs of credit information sharing entails the amount every commercial bank incurs to pay for credit referencing services. Default rate entailed the proportion of NPLs to total loans. Table 3.1 shows the variables operationalization

Table 3.1: Variables Operationalization

Variable	Operationalization	Measurement	Scale
Customer credit reports sharing	Entails the total number of customer credit reports shared by each commercial banks with the various credit referencing bureaus	Number of annual customer credit reports shared by every bank	Ratio
Customer credit reports pulling	Entails the total number of credit reports pulled by every commercial banks from credit referencing bureaus before they advance credit to them	Number of annual customer credit reports pulled by every bank	Ratio
Costs of credit information sharing	Entails the amount every commercial bank incurs to pay for credit referencing services	Annual cost incurred on reporting and pulling credit information by every bank	Ratio
Bank size	Denotes the size on an entity in terms of its assets	Natural log of total assets	Ratio
Default rate	Entails the percentage of unpaid loans and the commercial banks portfolio at risk	The proportion NPL to total loans	Ratio

Source: Author (2019)

3.7 Diagnostic Tests

3.7.1 Multi-collinearity

This means a form of very high inter-coalitions between the independent variables. Variables which are almost with absolute correlation coefficient give similar information and one should be dropped in approbation of the other to get rid multi-collinearity problem. Guajarati (2004), argues that correlation coefficients of less than 0.8 shows that the problem not serious and should be ignored. On the other hand, more than 0.8 alludes there is high degree of multi-collinearity and should be corrected. Multi-collinearity was tested with the help of Variance Inflation Factor (VIF).

3.7.2 Hausman Test

The decision to employ either random or fixed effects model in the study shall be made after, running the Hausman test whose hypothesis (null) is that the preferred model for purpose of data analyses shall be random effect viz-a-vis alternative model's with fixed effects. Saunders *et al*, (2009) cited in Belay (2012), assert that random and fixed effects models are stated as follows;

$Y_{it}= X_{it}\beta+\alpha+\mu_{it}\rightarrow$Fixed effects-- (3.3)

$Y_{it}= X_{it}\beta+\alpha+\mu_{it}+ \varepsilon_{it}\rightarrow$Random effects--- (3.4)

Where;

X_{it}=Variable vector

β= Coefficients vector

μ_{it}=Interference terms (between entities)

ε_{it}= Interference terms (within entities)

Random effects postulates interference term not having correlation with the predictor variables that permits for time-invariant variables to play the purpose of the control variables. In short, they permit general inferences outside the sample utilized in the model (Maddala, 2013). In addition, Maddala (2013) asserts that for fixed effects models they are planned to study the origin of the changes inside an entity. The Hausman test tested whether the unique disturbances (μ_{it}) have correlation with the regressors with null hypothesis being no correlation between the two. The test shall be carried out using Durbin–Wu–Hausman. If the *p*-value is less than 0.05, reject the null hypothesis (Chmelarova, 2007).

3.7.3 Normality Test

Normality test is often carried out to investigate if the standard errors are biased based on the conditional mean or not (Chmelarova, 2007). Jaque-Bera test statistc was used for the test. For a normally distributed data, the skewness is zero while kurtosis is about three.

In order to successfully test for normality, the null premise must be stated., that is, data has normal distribution while alternate premise is data does not originate from a normal distribution. When J-B value is large, it postulates that the standard errors are deficient of normal distribution while if the value is small, the researcher ought to refuse to accept the null hypothesis since the data is normally distributed (Zikmund *et al.,* 2012). Data that was not normal were transformed using logarithmic.

3.7.4 Stationarity Test

This is a feature of the data in a way that a set of variables, randomly selected for joint distribution in a series will always be the same irrespective of where the series is selected from (McKenzie, 2011). The mean for a data with a stationary series will always be constant even if the sample period is changed while that of a non-stationary series will vary and this causes panel data to be asymptotically biased (Crossman, 2003). This could lead to spurious regression i.e one in whose time-series elements are non-stationary and independent characterized by high coefficient of determination values and stunted Durbin-Watson scores (Saunders *et al*., 2009).

3.7.5 Heteroscedasticity Test

The study conducted heteroscedasticity test to investigate if the standard error term's variance will be static. If the results are to the contrary, then the assumption is violated. This was conducted using the white test of statistics whereby the researcher will express the sum of errors as a function of the predictors in the model and regress it through least ordinary square method. If there is no heteroscedasticity in the model it is expected that all the co-efficient will equal to zero (Pesaran, 2004). If heteroscedasticity is identified, a box –cox transformation is made.

3.7.6 Autocorrelation

Linear regression model is assumed to have zero autocorrelation (Roodman, 2006). Autocorrelation could either be positive or negative. If positive, the standard errors are small with the implication that the predictors' estimates are more accurate than in actual sense (Wang, 2013). The null hypothesis is rejected if serial is detected which would be incorrect. Autocorrelation errors results in inefficient coefficients giving rise to wrong forecasts

Autocorrelation was tested using the Pesaran test since it (autocorrelation) is similar to cross-dependence in panel data. Once the test is established to be significant, it would mean that autocorrelation (cross-sectional dependency) exists (Pesaran, 2004). Data that was discovered to have cross-sectional dependency was treated by lagging the dependent variable.

3.8 Ethical Considerations

The researcher was obliged to go by the terms and conditions of Kenyatta University. Upon approval by the university, the researcher obtained data from secondary sources as earlier identified. As a result, the researcher ensured the protection of data as consistent with the requirements specified by Kenyatta University and NACOSTI. The researcher observed integrity of all the institutions for data collection and analysis are kept secret to be utilized for purpose of this study only.

CHAPTER FOUR

DATA ANALYSIS AND INTERPRETATION

4.1 Introduction

The section presents data analysis and interpretation. The subsections presented in this chapter include the descriptive statistics, correlation analysis, diagnostic tests and panel regression. The results are presented in form of tables and figures.

4.2 Descriptive analysis

Descriptive results of the study are presented in this part. Averages, maximums, minimums and measure of variations are shown here. Refer to Table 4.1 for results.

Table 4.1: Descriptive Results

Variable	Obs	Mean	Std. Dev.	Min	Max
Default rate	55	0.1111448	0.1243743	0.013098	0.6584805
Number of customer credit reports shared	55	131,571	125,495	7,883	574,456
Number of customer credit reports pulled	55	199,721	185,927	12,447	847,558
Costs incurred on CIS	55	2,758,630	2,793,450	134,690	12,700,000
Bank size in '000 000	55	277,000	155,000	60,500	714,000

Source: Researcher 2020

Table 4.1 above indicates data collected described in terms of mean, standard deviation, minimum and maximum. The mean of default rate on loans operationalized as the proportion NPL to total loans was 0.1111448. The maximum and the minimum default rates on loans for the listed commercial banks were 0.0130983 and 0.6584805 in that order. The Std. Dev. was 0.1243743 indicating that default rate on loans was varying across the time scope of the study.

It was further established that the average number of client credit reports shared operationalized as the total number of client credit reports shared by each commercial banks with the various credit referencing bureaus was 131,571 shared credit reports. The min and the max of average number of customer credit reports shared are 7,883 shared credit reports and 574,456 shared credit reports respectively. The Std. Dev. was 125,495 shared credit reports indicating that the number of client credit reports shared across the measurement period.

Results in addition also shown that the average number of client credit reports pulled operationalized as the total number of credit reports pulled by every commercial banks from credit referencing bureaus before they advance credit to them was 199,721 pulled credit reports. The minimum and the maximum number of customer credit reports pulled were 12,447 pulled credit reports and 847,558 pulled credit reports respectively. The standard deviation was 115.8374 pulled credit reports indicating that number of customer credit reports pulled varied across the measurement period.

The average costs incurred on credit information sharing among the listed commercial was KES 2,758,630. The minimum and the maximum costs incurred on credit information sharing were KES 134,690 and KES 12,700,000 respectively. The standard deviation was 2,793,450 indicating that the costs incurred on credit information sharing varied across the measurement period.

The findings moreover showed that the average bank size operationalized using total assets was KES 277,000 million. The min and the max of bank size were KES 60,500 million and KES 714 000 million respectively. Its standard deviation was KES 155,000 million implying that bank size was varying across the time scope of the study. The efficiency and effectiveness of represented by profitability is strongly associated to total assets. Thus in the financial sector, the bank symbolizes economies of scale. The findings concur with Yoon and Jang (2011) that size of the firm had pronounced effect on ROE in comparison to debt, and irrespective of level of leverage, smaller firms were relatively riskier compared to bigger firms.

4.3 Correlation Analysis

In examining the degree of correlation amongst the study variables, the researcher embraced the Pearson's product-moment correlation coefficient (r) also the same was used in showing the strength of linear association amongst the variables. r ranges between ±1. If r= +0.7 and above, it shows a very strong relationship; r=+0.5 to below 0.7 is a strong association; r=0.3-0.49 is a moderate association while r=0.29 and below shows a weak association. Where r=0 it shows nonexistence of any association. The analysis aims at testing for existence of multicollinearity and it is ideal for eliminating variables which are highly correlated. The study conducted correlation analysis between to determine the effect of CIS on default rates of loans issued. Table 4.2 exhibits the correlation matrix of number of credit reports shared, credit reports pulled, cost of CIS, bank size and default rate.

The correlation results found that number of customer credit reports shared and default rates of loans have a negative and significant association ($r=-0.6303$, $p=0.000<0.05$). The results imply that number of customer credit reports shared and default rates on loans move in opposite direction. The associations between number of customer credit reports shared and default rates of loans is strong as illustrated by $r=-0.6303$. Sharing of customer credit reports entails exchanging information about their customer's loan repayment status. Customer data sharing about borrowers' qualities and their obligation can significantly affect credit markets movement. This improves the banks' learning of candidates' qualities and grants an increasingly exact expectation of their reimbursement probabilities. The results also conger with Mwangi (2015) who found a negative relationship was found between the loan credit reports forwarded to CRBs and default. According to Fosu (2014) who examined the contribution of CIS on bank lending, customer credit sharing increased bank lending.

Table 4.2: Correlation between credit information sharing and Default rate on loans

	Default rate on loans	Number of customer credit reports shared	Number of customer credit reports pulled	Costs incurred on credit information sharing
Default rate	1.000			
Number of customer credit reports shared	-0.6303	1.000		
	0.000**			
Number of customer credit reports pulled	-0.6727	0.6625	1.000	
	0.000**	0.000**		
Costs incurred on credit information sharing	0.5167	0.0668	-0.1359	1.000
	0.0001**	0.6282	0.3226	

**Significant at 0.05

Source: Researcher 2020

The results found that number of customer credit reports pulled and default rates of loans have a negative and significant association (r=-0.6727, p=0.000<0.05). The results imply that number of customer credit reports pulled and default rates on loans move in opposite direction. The associations between number of customer credit reports pulled and default rates of loans is strong as illustrated by r=-0.6727. Credit information pulling enables the use of proprietary algorithms to assess each applicant's risk profile and thus a bank is able to assess the probability of a borrower in defaulting loan repayment. The results agree with a study Sahin (2017) WHO examined whether the variation in non-financial information sharing in different countries affected the proportion of non-performing loan and revealed that presence of credit information from utilities and retail companies, in addition to financial sources, in a credit reporting institution reduces the NPLs rates of banks. Further, the results are in line with Otete, Muturi and Mogwambo (2016) who surveyed the impact of credit data sharing on the profitability of commercial banks concluded that general volume of loaning among banks has expanded because of pulling of client data from credit referencing organizations.

It was also established that costs incurred on credit information sharing and default rates of loans have a positive and significant association ($r=0.5167$, $p=0.0001<0.05$). The results imply that costs incurred on CIS and default rates on loans move in the same direction. The associations between costs incurred on CIS and default rates of loans is strong as illustrated by $r=0.5167$. In assessing cost of credit, banks charge a prices for the intermediation services rendered under uncertainty and sets the rates of interest for both loans and deposits. The differences between the gross cost of borrowing and the return on lending is the cost of intermediary and comprise of transactions costs, information costs, operational costs, default and administration costs. Banks have to incur costs on information sharing and they normally incur cost on reporting and pulling credit information. The results are in line with Maina, Kinyariro, Muturi and Muriithi (2016) who assessed how credit information sharing contributes to level of loan defaults and revealed that costs of CIS, credit scoring and level of loan default strongly relate. Further, Kusi, Agbloyor, Fiador and Osei (2016) who assessed contribution of information sharing to changes in profits of banks revealed that information sharing through CRBs positively affected banks profitability. Information sharing lowers adverse selection and moral hazard risks that as a result reduces information asymmetry.

4.4 Diagnostic Tests

4.4.1 Multicollinearity Test

Variance inflation factors (VIF) was employed to check for multicollinearity. Basing on Field (2009), VIF greater than 10 shows that multicollinearity is present.

Table 4.3: Multicollinearity Test

Variable	1/VIF	VIF
Number of customer credit reports shared	1.87	0.535987
Number of customer credit reports pulled	1.89	0.528448
Costs incurred on credit information sharing	1.07	0.937723
Mean VIF	1.61	

Source: Researcher 2020

The results in Table 4.3 indicated absence of multicollinearity since the VIF of all the variables were less than 10. The VIF values for number of customer credit reports shared, number of customer credit reports retrieved and costs incurred on credit information sharing were less than 10 indicating absence of multicollinearity.

4.4.2 Fisher-type test of unit root

Unit root test need to be checked before running any model for accuracy and consistency of the results. The study employed Fisher-type test in testing the stationarity of the data. Stationarity outcome is shown in Table 4.4. The hypotheses to be tested were;

Ho: All panels contain unit roots

Ha: At least one panel is stationary

Table 4.4: Fisher-type test of unit root

Variable		Inverse chi-squared(70) P	Inverse normal Z	Inverse logit t(179) L*	Modified inv. chi-squared Pm
Default rate on loans	test statistic	54.1043	21.0303	23.0045	4.8399
	p-value	0.0002	0.0088	0.0018	0.000
Number of customer credit reports shared	test statistic	49.1984	3.426	-6.4022	4.1003
	p-value	0.0008	0.0231	0.0045	0.0000
Number of customer credit reports pulled	test statistic	40.4347	-2.4033	-1.8012	2.7791
	p-value	0.0096	0.0203	0.0384	0.0027
Costs incurred on credit information sharing	test statistic	2.5875	5.188	5.1861	-3.0773
	p-value	0.041	0.002	0.003	0.021
Bank size	test statistic	57.7112	6.4381	-2.3661	5.3837
	p-value	0.0000	0.0093	0.0385	0.0000

Source: Researcher 2020

The stationarity results test for unit root revealed that, at level number of customer credit reports shared, number of customer credit reports pulled, costs incurred on CIS and bank size were stationary since p-value<0.05 at P, Z, L* and Pm. The phenomena imply that results are fit for running model (Gujarati, 2003) and so panel regression models could be generated.

4.4.3 Normality Test

Normality is undertaken to ensure data is normally distributed (Brooks, 2008). Table 4.5 presents the normality results using for skewness and Kurtosis test for the financial firms. Bera and Jarque (1981) check for normality were undertaken. If the p-value < 0.05, the null of normality at the 5% level is rejected. If the data is not normally distributed a nonparametric test are employed. Data was normally distributed with absence of extremes.

H_0: The data are not normally distributed

H_1: The data are not normally distributed

Table 4.5: Normality Test

Variable	Observation	Skewness	Kurtosis	p-value
Default rate	55	3.8054	0.8019	.302
Number of customer credit reports shared	55	4.0678	0.5527	.549
Number of customer credit reports pulled	55	1.4051	0.6281	.851
Costs incurred on credit information sharing	55	2.2974	0.3083	.063
		0.1427	0.9784	2.25
Bank size	55			

Source: Researcher 2020

Table 4.5 shows the normality results using for Skewness and Kurtosis test. The P-values were higher than the critical 0.05 and thus we conclude that the data is distributed normally. A general guideline for skewness is that if the number is greater than +5 or lower than –5, this is an indication of a substantially skewed distribution. For kurtosis, the general guideline is that if the number is greater than +1, the distribution is too peaked. Likewise, a kurtosis of less than –1 indicates a distribution that is too flat (Hair, Hult, Ringle & Sarstedt, 2017). The results therefore imply that the Skewness and Kurtosis statistics fall within the acceptable ranges therefore, the data can be considered not to be violating the normality assumption and is appropriate for linear regression.

4.4.4 Autocorrelation Test

Autocorrelation was undertaken to monitor standard correlation errors in the observations. Wooldridge test for serial correlation was utilized to test for serial correlation. The test tested for the following hypotheses and outcome shown in Table 4.6.

H_0: Residuals of this regression model does not have serial correlation

H_1: Residuals of this regression model have serial correlation

Table 4.6: Serial Correlation Tests

Default rate
Wooldridge test
H_0: no first-order autocorrelation
F(1, 10) =3.140
Prob > F = 0.1068

Source: Researcher 2020

The null hypothesis was not rejected. The test value showed a F-test of 3.140 and a p value of 0.1068>0.05. Serial correlation is thus absent.

4.4.5 Heteroscedasticity

Breusch-Pagan test employed to check heteroskedasticity. The null hypothesis was that error terms have a constant variance. Table 4.7 exhibit Heteroskedasticity Test Results.

Table 4.7: Heteroskedasticity Test Results

Breusch-Pagan / Cook-Weisberg test for heteroscedasticity Ho: Constant variance Variable: fitted values		
chi2(1)	=	0.19
Prob > chi2	=	0.6611

Source: Researcher 2020

The p value generated was greater than 0.05, 0.6611>0.05. Thus, heteroskedasticity was absent in the data set. All the variables, number of customer credit reports shared, number of customer credit reports pulled, costs incurred on credit information sharing and bank size were homoscedastic and thus could be further used to run a viable panel regression model.

4.4.6 Hausman Test

Hausman test is undertaken to determine the better model between fixed and random model. Hausman outcome results are shown Table 4.8.

H_0: Random effect is appropriate

H_1: Fixed effect is appropriate

Table 4.8: Hausman Results

Default rate on loans				
Column1	**(b)** fixed	**(B)** random	**(b-B)** Difference	**sqrt(diag(V_b-V_B))** S.E.
Number of customer credit reports shared	-0.02991	-0.0446	0.014692	0.003148
Number of customer credit reports pulled	-0.02082	-0.03351	0.012699	0.002134
Costs incurred on credit information sharing	0.099193	0.098018	0.001175	.
chi2(4)	1.36			
Prob>chi2	0.5099			

Source: Stata 14 computations
Source: Researcher 2020

The results showed that random effects model is favored compared to the fixed effects model. Hausman results had chi-square of 1.36 and significance value 0.5099 that is more than 0.05. Null hypothesis was not rejected and conclusion reached that random is better than fixed model. With fixed effects models, we do not estimate the effects of variables whose values do not change across time. Random effects models will estimate the effects of time-invariant variables, however the estimates may be biased because we are not controlling for omitted variables.

4.5 Panel Regression Results and Hypothesis testing

An overall panel regression model showing the relationship between the number of customer credit reports shared, number of customer credit reports retrieved and costs incurred on credit information sharing and default rate on loans among customers of listed commercial banks. The panel model output is exhibited in Table 4.9.

Table 4.9: Panel Regression Results

Default rate	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Number of customer credit reports shared	-0.0446	0.010978	-4.06	0.000**	-0.06611	-0.02308
Number of customer credit reports pulled	-0.03351	0.012711	-2.64	0.008**	-0.05843	-0.0086
Costs incurred on credit information sharing	0.098018	0.011342	8.64	0.000**	0.075789	0.120248
_cons	-0.11834	0.099031	-1.19	0.232	-0.31243	0.075762
R-squared:	within = 0.7857					
	between = 0.9942					
	overall = 0.8072					
Wald chi2(4)	120.92					
Prob > chi2	0.000					

**sig at 0.05

Source: Researcher 2020

The R squared checked the explanatory power of the variable. The study was supported by R square of 0.8072 as shown in Table 4.9. This means that number of customer credit reports shared, number of customer credit reports retrieved and costs incurred on credit information sharing explains 80.72% of default rates of loans issued.

4.5.1 Number of customer credit reports shared and default rates on loans

The outcome in Table 4.9 revealed that number of customer credit reports shared and default rates of loans issued by listed commercial banks have a negative and significant relationship (β =-0.0446, p=0.000). The model is also justified by z-statistic of 4.06>1.96. This suggest that an increment in the number of customer credit reports shared results to decline in default rates of loans issued by listed commercial banks measured using non-performing loans. Hypothesis was checked by employing p-vale technique. The hypothesis was that customer credit reports sharing does not significantly affect default rates of loans issued by listed commercial banks in Kenya

$Ho_1$was rejected since p-value is 0.000<0.05 and conclusion made that customer credit reports sharing significantly affect default rates of loans issued. Sharing of credit information makes it simpler for contending banks to dismiss their great and bad debtors. Credit data sharing is key in minimizing information asymmetry that exists among banks and borrowers. Credit data sharing was introduced which serves as a middle playing ground for both lenders (banks) and borrowers (customers). The results are in agreement with Oira and Wamugo (2018) who studied how commercial banks' credit information sharing influences their performance and noted that changes in performance of commercial banks were significantly contributed by the credit information sharing since rate of loan repayment was positively influenced by effective credit information sharing system. The results also conger with Mwangi (2015) who found a negative relationship between the numbers of credit reports accessed from CRB and default rate. However, the results do not concur with the study by Oira and Wamugo (2018) on commercial banks' credit information sharing influences their performance who found that changes in performance of commercial banks were significantly contributed by the credit information sharing since rate of loan repayment was positively influenced by effective credit information sharing system. Likewise, the results do not agree with Giannetti & Jentzsch (2013) who assessed credit reporting, financial intermediation and identification systems and revealed credit reporting positively contributed to financial intermediation (bank credit to deposits, net interest margins).

4.5.2 Number of customer credit reports pulled and default rates on loans

Results in Table 4.9 also showed that number of customer credit reports pulled and default rates of loans issued by listed commercial banks have a negative and significant relationship (β =-0.03351, p=0.008). The model is also justified by z-statistic of 2.64>1.96. This suggest that an increment in number of customer credit reports pulled results to a decline in default rates of loans issued by listed commercial banks measured using non-performing loans. Hypothesis was checked by employing p-vale technique. The hypothesis was that number of customer credit reports pulled does not significantly affect default rates of loans issued by listed commercial banks in Kenya $Ho_1$was rejected since p-value is 0.008<0.05 and conclusion made that the number of customer credit reports pulled significantly affect default rates of loans issued.

Customer credit reports pulling is the aggregation of credit reports pulled by every commercial bank from authorized credit referencing bureaus before they advance credit to them. Banks can get information on borrowers' qualities and loan repayment history through pulling of credit reports from the available credit referencing bureaus. However, banks have to incur costs on information sharing and they normally incur cost on reporting and pulling credit information. The results agree with Hu, Gu and Zhou (2017) who investigated the contribution of comprehensive customer information pulling on aggregate credit volume and the default ratio and indicated that when an information sharing system develops to a relatively high level, comprehensive information sharing improvements, for both the width and depth, are associated with the rise in macro credit access but also the aggregate default risk. Further, Otete, Muturi and Mogwambo (2016) who surveyed the impact of credit data sharing on the profitability of commercial banks concluded that general volume of loaning among banks has expanded because of pulling of client data from credit referencing organizations. However, the results fail to agree with Grajzl and Laptieva (2016) who inspected the effect of data sharing on the volume of private credit utilizing bank-level board information and found that data sharing through private acknowledge authorities was positively related to the expansion in the volume of bank loaning, specifically when a bank is accomplice of different private credit agencies.

4.5.3 Costs incurred on credit information sharing and default rates on loans

Further, the panel model in Table 4.9 revealed that costs incurred on CIS has a positive and significant relationship (β =0.098018, p=0.000) with default rates of loans issued by listed commercial banks. The model is also justified by z-statistic of 8.64>1.96. This suggests that an increment in the costs incurred on credit information sharing results to an increment in default rates of loans issued by listed commercial banks measured using non-performing loans. Hypothesis was checked by employing p-vale technique. The hypothesis was that costs incurred on CIS does not significantly affect default rates of loans issued by listed commercial banks in Kenya $Ho_1$was rejected since p-value is 0.000<0.05 and conclusion made that the costs incurred on CIS significantly affect default rates of loans issued. The capacity as well as the cost of filtering out riskier borrowers improves the performance of a portfolio and enables lenders to offer lower rates to borrowers that have low risk who would otherwise not have borrowed. Credit information sharing performs a major part in enhancing the financial institutions efficiency through reduction of cost of processing loans and also the time needed for processing the loan applications. A situation where there is increased and seamless CIS reduces operating costs and hence likely to result in lower cost of credit. The results agree with Owino (2014) that the operating cost and cost of funds as factors positively contribute to the cost of credit of commercial banks whereas credit information sharing and credit default risk made negatively insignificant contribution to determine the cost of credit. According to Dierkes *et al.* (2013) high estimation of business credit data brings down the acknowledged default rates. However, the results do not agree with Kusi, Agbloyor, Fiador and Osei (2016) who assessed contribution of information sharing to changes in profits of banks and revealed that information sharing through CRBs positively affected banks profitability. Likewise, the study by Kinanga (2016) in a study on the relationship between client data sharing and the Kenyan banks' performance exhibited a positive connection between client data sharing, attributes of borrowers and Kenyan banks' profitability.

4.6 Moderating effect of Bank size

The study determined the moderating impact of bank size on CIS and default rates of loans issued by listed banks in Kenya. All the independent variables (the number of customer credit reports shared, number of customer credit reports pulled and costs incurred) were interacted with bank size to give a composite (interaction term). Table 4.9 shows model the fitness for a regression model after moderation.

Table 4.10: Moderating effect of bank size on credit information sharing and default rates of loans issued

Default rate of loans	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Number of customer credit reports shared	-1.80411	0.412095	-4.38	0.000**	-2.6118	-0.99642
Number of customer credit reports pulled	0.010204	0.379992	0.03	0.979	-0.73457	0.754974
Costs incurred on credit information sharing	1.636709	0.364256	4.49	0.000**	0.92278	2.350638
Number of customer credit reports shared*M	0.213329	0.049705	4.29	0.000**	0.115909	0.31075
Number of customer credit reports pulled*M	-0.00155	0.045476	-0.03	0.973	-0.09068	0.087586

Costs incurred on credit information sharing*M	-0.18889	0.045251	-4.17	0.000**	-0.27758	-0.1002
_cons	-0.15639	0.107181	-1.46	0.145	-0.36646	0.053682
R-squared:	within = 0.7248					
	between = 0.9572					
	overall = 0.8615					
Wald chi2(4)	298.5					
Prob > chi2	0.000					

Sig ** 0.05

Source: Researcher 2020

M=Moderator/ Bank size

The outcomes in Table 4.10 indicate bank size has a moderating impact of bank size on credit information sharing and default rates of loans issued by listed banks in Kenya. Output results pinpoints that R^2 rose from 0.8072 before moderation (Table 4.9) to 0.8615 after moderation. Number of customer credit reports shared and default rates of loans issued by listed commercial banks had a negative and significant relationship both before and after introducing the moderator/bank size.

Number of customer credit reports pulled and default rates of loans issued by listed commercial banks had a positive but insignificant relationship before introducing the moderator/bank size, and negative and no significant connection with default rates of loans issued after introducing the moderator/bank size. The results imply that bank size has no moderating effect on the relationship between number of customer credit reports pulled and default rates of loans issued by listed commercial banks.

Results of moderation also showed that the number of customer credit reports shared and default rates of loans issued by listed commercial banks had a negative and significant relationship before introducing the moderator/bank size, and a positive and significant relationship with default rates of loans issued after introducing the moderator/bank size. The results imply that bank size has full moderating effect on the relationship between Number of customer credit reports shared and default rates of loans issued by listed commercial banks.

Further, it was also established that the costs incurred on credit information sharing and default rates of loans issued by listed commercial banks had a positive and significant relationship before introducing the moderator/bank size, a negative and significant relationship with default rates of loans issued after introducing the moderator/bank size. The results imply that bank size has full moderating effect on the relationship between costs incurred on credit information sharing and default rates of loans issued by listed commercial banks.

The hypothesis that there is no significant moderating influence of bank size on credit information sharing and default rates of loans issued by listed commercial banks in Kenya was rejected. The study accepted the alternative hypothesis that bank size has a significant moderating effect of bank size on the relationship between credit information sharing and default rates of loans issued by listed banks in Kenya.

Bank size describes the economies of scale of the bank. A large bank reduces cost because of economies of scale and scope. The size of a bank acts an essential role in determining the availability of loans for lending. The findings are in line with Yoon and Jang (2011) that bank size has pronounced correlation with performance of the banks. Larger banks have high lending power as the command sizeable amount of resources.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATION

5.1 Introduction

The chapter presents the summary of findings, conclusions and possible recommendations that commercial banks can implement or adopt so as to minimize high cases of loans defaults among borrowers. Areas for further research are also suggested in this section.

5.2 Summary of the Study

Although CIS is viewed to be critical to improve performance for lenders through minimization of default rates, this relationship is less discussed. However, in majority of developing countries particularly in Africa, credit information systems are still in the early stages of commencement and information amongst lenders continue being weak. The study sought to ascertain the effect of CIS on default rates of loans issued by listed commercial banks in Kenya. The study employed descriptive research designs targeting 12 commercial banks listed at the Nairobi Securities Exchange. Results were analyzed using descriptive statistics that included means, standard deviations, minimums and standards deviations, correlations and panel models. Hypothesis testing was done using p-value technique.

5.2.1 Number of customer credit reports shared and default rates on loans

The first objective was to evaluate how customer credit reports sharing affects default rates of loans issued by listed commercial banks in Kenya. The average number of client credit reports shared operationalized as the total number of client credit reports shared by each commercial banks with the various credit referencing bureaus was 131,571 shared credit reports. Pearson correlation results found that customer credit reports sharing has a negative association with default rates of loans listed commercial banks. Panel regression of coefficients findings indicated that customer credit reports sharing is negatively and significantly associated to default rates on loans. Research results rejected the null hypothesis that customer credit reports sharing does not significantly affect default rates of loans issued.

Sharing of credit information makes it simpler for contending banks to dismiss their great and bad debtors. Credit data sharing is key in minimizing information asymmetry that exists among banks and borrowers. Credit data sharing was introduced which serves as a middle playing ground for both lenders (banks) and borrowers (customers). The results are in agreement with Oira and Wamugo (2018) who studied how commercial banks' credit information sharing influences their performance and noted that changes in performance of commercial banks were significantly contributed by the credit information sharing since rate of loan repayment was positively influenced by effective credit information sharing system. The results also conger with Mwangi (2015) who found a negative relationship between the numbers of credit reports accessed from CRB and default rate. However, the results do not concur with the study by Oira and Wamugo (2018) on commercial banks' credit information sharing influences their performance who found that changes in performance of commercial banks were significantly contributed by the credit information sharing since rate of loan repayment was positively influenced by effective credit information sharing system. Likewise, the results do not agree with Giannetti & Jentzsch (2013) who assessed credit reporting, financial intermediation and identification systems and revealed credit reporting positively contributed to financial intermediation (bank credit to deposits, net interest margins).

5.2.2 Number of customer credit reports pulled and default rates on loans

The second objective was to investigate influence of customer credit reports pulling on default rates of loans issued by listed commercial banks in Kenya. The average number of client credit reports pulled from referencing bureaus before they advance credit to them was 199,721 pulled credit reports. Pearson correlation results revealed that customer credit reports pulling has a negative association with default rates of loans listed commercial banks. Panel regression results further indicated that customer credit reports pulling is negatively and significantly connected to default rates on loans. Research results rejected the null hypothesis that customer credit reports pulling does not significantly affect default rates of loans issued by banks and conclusion made that customer credit reports pulled significantly affect default rates of loans issued.

Customer credit reports pulling is the aggregation of credit reports pulled by every commercial bank from authorized credit referencing bureaus before they advance credit to them. Banks can get information on borrowers' qualities and loan repayment history through pulling of credit reports from the available credit referencing bureaus. However, banks have to incur costs on information sharing and they normally incur cost on reporting and pulling credit information. The results agree with Hu, Gu and Zhou (2017) who investigated the contribution of comprehensive customer information pulling on aggregate credit volume and the default ratio and indicated that when an information sharing system develops to a relatively high level, comprehensive information sharing improvements, for both the width and depth, are associated with the rise in macro credit access but also the aggregate default risk. Further, Otete, Muturi and Mogwambo (2016) who surveyed the impact of credit data sharing on the profitability of commercial banks concluded that general volume of loaning among banks has expanded because of pulling of client data from credit referencing organizations. However, the results fail to agree with Grajzl and Laptieva (2016) who inspected the effect of data sharing on the volume of private credit utilizing bank-level board information and found that data sharing through private acknowledge authorities was positively related to the expansion in the volume of bank loaning, specifically when a bank is accomplice of different private credit agencies.

5.2.3 Costs incurred on credit information sharing and default rates on loans

The third objective was to examine the effect of costs of CIS on default rates of loans issued by listed commercial banks in Kenya. The average costs incurred on credit information sharing among the listed commercial was KES 2,758,630. Pearson correlation results exhibited that costs of CIS have a positive association with default rates of loans listed commercial banks. Panel regression results further indicated that costs of credit information sharing has a positive and significant relationship with default rates on loans. Research results rejected the null hypothesis that costs of credit information sharing does not significantly affect default rates of loans issued by listed commercial banks in Kenya and conclusion made that costs of credit information sharing significantly affect default rates of loans issued.

The capacity as well as the cost of filtering out riskier borrowers improves the performance of a portfolio and enables lenders to offer lower rates to borrowers that have low risk who would otherwise not have borrowed. Credit information sharing performs a major part in enhancing the financial institutions efficiency through reduction of cost of processing loans and also the time needed for processing the loan applications. A situation where there is increased and seamless CIS reduces operating costs and hence likely to result in lower cost of credit. The results agree with Owino (2014) that the operating cost and cost of funds as factors positively contribute to the cost of credit of commercial banks whereas credit information sharing and credit default risk made negatively insignificant contribution to determine the cost of credit. According to Dierkes *et al.* (2013) high estimation of business credit data brings down the acknowledged default rates. However, the results do not agree with Kusi, Agbloyor, Fiador and Osei (2016) who assessed contribution of information sharing to changes in profits of banks and revealed that information sharing through CRBs positively affected banks profitability. Likewise, the study by Kinanga (2016) in a study on the relationship between client data sharing and the Kenyan banks' performance exhibited a positive connection between client data sharing, attributes of borrowers and Kenyan banks' profitability.

5.2.4 Moderating effect of Bank size on CIS and default rates of loans issued

The forth objective was determining the moderating effect of bank size on CIS and default rates of loans issued by listed banks in Kenya. The findings moreover showed that the average bank size operationalized using total assets was KES 277,000 million. The outcomes uncovered that the R^2 improved after introducing bank size as the moderator in the relationship between CIS and default rates of loans issued by listed banks. The hypothesis that costs incurred on credit information sharing does not significantly affect default rates of loans issued by listed commercial banks in Kenya was rejected and conclusion made that costs incurred on credit information sharing significantly affect default rates of loans issued. Bank size describes the economies of scale of the bank. A large bank reduces cost because of economies of scale and scope. The size of a bank acts an essential role in determining the availability of loans for lending. The findings are in line with Yoon and Jang (2011) that bank size has pronounced correlation with performance of the banks. Larger banks have high lending power as the command sizeable amount of resources.

5.3 Conclusion

Conclusions were generated based on the results of the research objectives. The study concludes that customer credit reports sharing affects default rates of loans issued by commercial banks. Credit information sharing involves credit providers such as banks and other licensed creditors to authorized credit reference bureaus for other credit providers to access. Credit information sharing is an organization remedy to the problem of asymmetric information and the resulting dilemmas of adverse selection and weak incentives to repay loans in the banking sector. Credit information systems fill the knowledge gap between the lender and the borrower by providing the loan repayment history, total debt and overall creditworthiness of the borrower.

The study also concludes that customer credit reports pulling negatively affects default rates of loans issued by commercial banks. Pulling credit information attracts various costs incurred by banking institutions in credit information sharing. Banks can get information on borrowers' qualities and loan repayment history through pulling of credit reports from the available credit referencing bureaus.

The study further that costs of credit information sharing positively affects default rates of loans issued by commercial banks. The capacity as well as the cost of filtering out riskier borrowers enhances the performance of a portfolio and enables lenders to provide lower rates to borrowers that have low risk who would otherwise not have borrowed. Credit information sharing performs a major part in enhancing the financial institutions efficiency through reduction of cost of processing loans and also the time needed for processing the loan applications. A situation where there is increased and seamless credit information sharing reduces operating costs and hence likely to result in lower cost of credit.

The study further concludes that bank size moderates the association amongst CIS and default rates of loans issued by listed banks in Kenya. Bank size describes the economies of scale of the bank. A large bank reduces cost because of economies of scale and scope. The size of a bank plays a very crucial role in determining the availability of loans for lending.

5.4 Recommendations

5.4.1 Recommendations for Practices

The study established that customer credit reports pulling affects default rates of loans issued by commercial banks. Commercial lending financial institutions may need to enhance their credit risk monitoring mechanisms by credit scoring to mitigate high cases of nonperforming loans in the banking sector. Credit scoring has the ability to predict the probability of loan defaults by fetching and mathematically analyzing customer background information. Incidences of non-performing loans may be minimized through proper monitoring of loans issued and closer scrutiny of borrowers. This may be facilitated by efficient pulling of credit information for potential loan borrowers. With the adoption of credit scoring, a bank is able to extract information from the main credit bureaus and apply a proprietary algorithm in assessing the risk profile of each applicant.

The study additionally makes a recommendation that ought to always utilize CIS for appraising loan applicants with an aiming of NPLs reduction since this will lead to improvement of their profitability. For purpose of ensuring effective CIS, it is necessary that the mechanism covers not only banks but also other credit providers. The reason is that a good number of people also obtain credits from other institutions that are not banks for example SACCOs, utility companies and other financial institutions. Commercial banks may need to come up with an integrated information system for ensuring that customers get prompt notification on their loan status and any other information. It is therefore imperative for strengthening of competitive information sharing amongst commercial banks as it will lead to improved financial performance. Strengthening CIS necessitate making sure that accurate and quality information of the borrowers is shared in all commercial banks.

All commercial banks management ought to put emphasis on operational efficiencies as a way of eliminating redundant operational cost and as a result improving financial performance. In efforts of reducing debt recovery and Research and Development costs, all lending institution in Kenya need to utilized CIS mechanism and this will possibly have a positive impact of financial performance.

Total assets controlled by a bank are vital in ensuring credit information sharing. Bank size describes the economies of scale of the bank. A large bank reduces cost because of economies of scale and scope. The size of a bank plays a very crucial role in determining the availability of loans for lending.

5.4.2 Contribution to Policy

There is need for the CBK to regulate the credit reference bureau so as to protect the borrower's information, accuracy and integrity of credit information. In the same way, commercial banks ought to develop system to monitor customers' behaviors and this will lead to reduction of credit track records, search cost and risk premiums charged to customers by banks. This would enhance customer monitoring while minimizing cases of loan defaults.

5.4.3 Contribution to Knowledge

The study customer credit reports sharing affects default rates of loans issued by commercial banks. Credit information sharing involves credit providers such as banks and other licensed creditors to authorized credit reference bureaus for other credit providers to access. The results contribute to body on knowledge on Information Asymmetry Theory. In credit markets, risk from borrowers can be related to a good bought by the lender (Turner and Varghese, 2010). The theory demonstrates that data asymmetry and poor agreement implementation lead to disequilibrium in credit market (González-Uribe and Osorio, 2014).

The theory indicates that during lending, information asymmetry is contributed by the inability for the lender to access borrower's information on likelihood to repay also referred to their risk profile. According to the theory, one method of eliminating asymmetric information challenge is generating specific information from observing the past behaviors of borrowers during the bank relationship (Negrin, 2011). The theory supports that sharing information lessens information asymmetries among borrowers and lenders, which helps screening and checking, improves the match among money lenders and borrowers, and upgrades access to credit for reliable borrowers.

The study established that customer credit reports pulling negatively affects default rates of loans issued by commercial banks. Pulling credit information attracts various costs incurred by banking institutions in credit information sharing. Banks can get information on borrowers' qualities and loan repayment history through pulling of credit reports from the available credit referencing bureaus. The results make significant contribution to the Moral Hazards Theory.

Moral Hazards Theory suggests a voidable agreement between two gatherings whereby; party undertaking the risks has more information than the party to bear the consequences (Negrin, 2011). This theory apply to lending scenario in that bad borrowers knowing well there are no consequences will not make any effort to service their loans leaving the lender disadvantaged (Bos, Haas & Millone, 2013). According to moral hazard concept, a borrower will always intend to default except the cases where the applicant is aware of possible future consequences (Sahin, 2017). This leads to the challenge in assessing the borrowers' wealth accumulation at loan maturity, as opposed to the time of application. Inability of a lender to determine the borrowers' wealth will entice the borrower to default. According to the theory, pooling default data minimizes moral hazard issues only if the lender has adequate information about the borrower. Sharing data about borrowers' obligation presentation minimizes the specific type of moral hazard from borrowers' capacity to obtain loan from several lenders.

5.5 Areas for Further Research

Despite effective credit risk management, loan defaults still exit even for those customers that had highest credit scores. Further research may be conducted on demographic factors that result to mortgage loan default.

The study relied on panel regression approach as the main method of analysis. However, multivariate regression has some limitations such as lack of precise coefficients especially where the strict assumptions of multivariate regression may not be achieved. Further research may adopt a different methodology to analyze data particularly structural equation modeling. SEM is a powerful multivariable analytical method that can allow models to test linkage among variables simultaneously while illustrating the relationship through structures and diagrams.

There are other exogenous factors affecting default rates among customers lending in commercial banks. The factors include inflation, interest rate and economic recession and political instability. Further research may include these variables to determine how these exogenous factors affect default rates among borrowers in commercial banks.

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APPENDICES

APPENDIX I: KU AUTHORIZATION LETTER

APPENDIX II: LIST OF NSE LISTED COMMERCIAL BANKS

Bank Name
1. Barclays Bank Ltd
2. Stanbic Holdings
3. I&M Holdings Ltd
4. Diamond Trust Bank Kenya Ltd
5. HF Group Ltd
6. KCB Group Ltd
7. National Bank of Kenya Ltd
8. NIC Group PLC
9. Standard Chartered Bank Ltd
10. Equity Group Holdings
11. Co-operative Bank of Kenya
12. ABSA Group PLC

Source: NSE (2019)

APPENDIX III: DATA COLLECTION SHEET

Bank	Year	credit reports shared	credit reports pulled	costs on credit information sharing	Bank Size	Default rate
Barclays Bank	2014	4.774654	6.080708	5.980707676	8.353811	0.036
Barclays Bank	2015	4.722775	4.921145	6.000326467	8.381795	0.027
Barclays Bank	2016	5.091862	5.283426	6.39736897	8.414459	0.052
Barclays Bank	2017	5.289148	5.471803	6.617931502	8.433253	0.056
Barclays Bank	2018	5.457217	5.626130	6.802221102	8.511669	0.061
Co-operative bank of Kenya	2014	4.792611	4.998665	5.998664665	8.455448	0.044
Co-operative bank of Kenya	2015	4.846941	5.045311	6.124492487	8.534684	0.038
Co-operative bank of Kenya	2016	5.269457	5.761021	6.574964403	8.546365	0.048
Co-operative bank of Kenya	2017	5.476994	5.659649	6.805777115	8.587551	0.074
Co-operative bank of Kenya	2018	5.688274	5.057187	7.03327776	8.616655	0.120
Diamond Trust Bank	2014	4.553735	4.759789	5.759788675	8.325391	0.013
Diamond Trust Bank	2015	4.602107	4.800477	5.879657747	8.433944	0.028
Diamond Trust Bank	2016	5.093768	5.285332	6.39927558	8.515933	0.032
Diamond Trust Bank	2017	5.205981	5.388636	6.53476378	8.560269	0.076
Diamond Trust Bank	2018	5.356573	5.525485	6.701576619	8.577169	0.071
Housing finance Company ltd	2014	3.923281	4.129335	5.129335353	7.785057	0.092
Housing finance Company ltd	2015	3.896695	4.095065	5.174245936	7.855273	0.077
Housing finance Company ltd	2016	4.366268	4.557832	5.671775251	7.856911	0.114
Housing finance Company ltd	2017	4.606397	4.789052	5.935179658	7.829568	0.165
Housing finance Company ltd	2018	4.807689	4.976602	6.152693395	7.782109	0.307
I&M Bank	2014	4.402654	5.608708	5.608707843	8.187692	0.019
I&M Bank	2015	4.470277	4.668647	5.747828034	8.217017	0.044
I&M Bank	2016	4.943779	5.135343	6.249285941	8.323340	0.061
I&M Bank	2017	5.134704	5.717359	6.463487159	8.380412	0.127
I&M Bank	2018	5.256623	5.425536	6.60162711	8.460179	0.143
KCB Bank	2014	4.946962	5.153016	6.153015637	8.690496	0.065
KCB Bank	2015	4.988747	5.187117	6.266298506	8.746707	0.068
KCB Bank	2016	5.394567	5.586131	6.700074746	8.774692	0.082
KCB Bank	2017	6.627337	5.009992	6.956120482	8.810682	0.089
KCB Bank	2018	5.759257	5.028169	7.104260687	8.853888	0.072
NIC Plc bank	2014	4.421721	4.627775	5.627775375	8.162280	0.040
NIC Plc bank	2015	4.400278	4.598648	5.677829517	8.219530	0.115
NIC Plc bank	2016	4.950885	5.142449	6.256392264	8.229065	0.114
NIC Plc bank	2017	5.148560	4.331215	6.477342688	8.314231	0.110

NIC Plc bank	2018	5.329882	4.498794	6.674885472	8.318913	0.126
Stanbic Bank Kenya Ltd	2014	5.551107	4.757161	5.757160596	8.233877	0.038
Stanbic Bank Kenya Ltd	2015	4.468793	5.667163	5.746344573	8.297931	0.048
Stanbic Bank Kenya Ltd	2016	4.975115	5.866679	6.280622071	8.311532	0.061
Stanbic Bank Kenya Ltd	2017	6.162852	6.345507	6.491635073	8.379138	0.079
Stanbic Bank Kenya Ltd	2018	5.343200	6.512113	6.688204401	8.448634	0.114
National Bank of Kenya	2014	3.989956	4.196010	5.196010287	8.090230	0.110
National Bank of Kenya	2015	3.052392	5.250761	5.329942694	8.098437	0.173
National Bank of Kenya	2016	1.528769	2.720333	5.834276339	8.061801	0.545
National Bank of Kenya	2017	2.735685	1.918340	8.064467723	8.040892	0.528
National Bank of Kenya	2018	1.847552	3.016465	9.192556303	8.060128	0.658
Standard Chartered Bank	2014	4.057340	4.863394	5.863394245	8.347322	0.088
Standard Chartered Bank	2015	4.689439	5.887809	5.966989774	8.369152	0.128
Standard Chartered Bank	2016	4.962863	5.854427	6.268370369	8.398777	0.123
Standard Chartered Bank	2017	6.224523	5.407178	6.553306415	8.455947	0.140
Standard Chartered Bank	2018	6.950645	5.619558	6.795648911	8.455460	0.183
Equity Bank	2014	6.790974	4.997028	5.997027965	8.537280	0.044
Equity Bank	2015	4.837436	6.035806	6.114987076	8.631507	0.034
Equity Bank	2016	5.242526	6.434090	6.548032991	8.675515	0.070
Equity Bank	2017	5.444201	5.626856	6.772984527	8.719717	0.064
Equity Bank	2018	5.567434	5.036346	6.912437556	8.758446	0.081

APPENDIX IV: RESEARCH WORK PLAN

ACTIVITY	**June 2020**	**July 2020**	**August 2020**	**September 2020**	**October 2020**
Proposal development					
Pilot Testing					
Data collection					
Data Analysis					
Report writing					
Submission					

APPENDIX V: RESEARCH BUDGET

ITEM	QUANTITY	UNIT COST Ksh	TOTAL- AMOUNT Ksh
STATIONERY			
-Photocopying	800 pages	15	12,000
-Foolscaps	8 rim	240	1,920
-Printing	20 copies@100	10	20, 000
DATA COLLECTION	-	-	50,000
DATA ANALYSIS	-	-	80,000
Binding copies	10	100	1000
TOTAL			164,920
CONTINGENCY			16,492
GRAND TOTAL			181,372

APPENDIX VI: NACOSTI APPROVAL LETTER