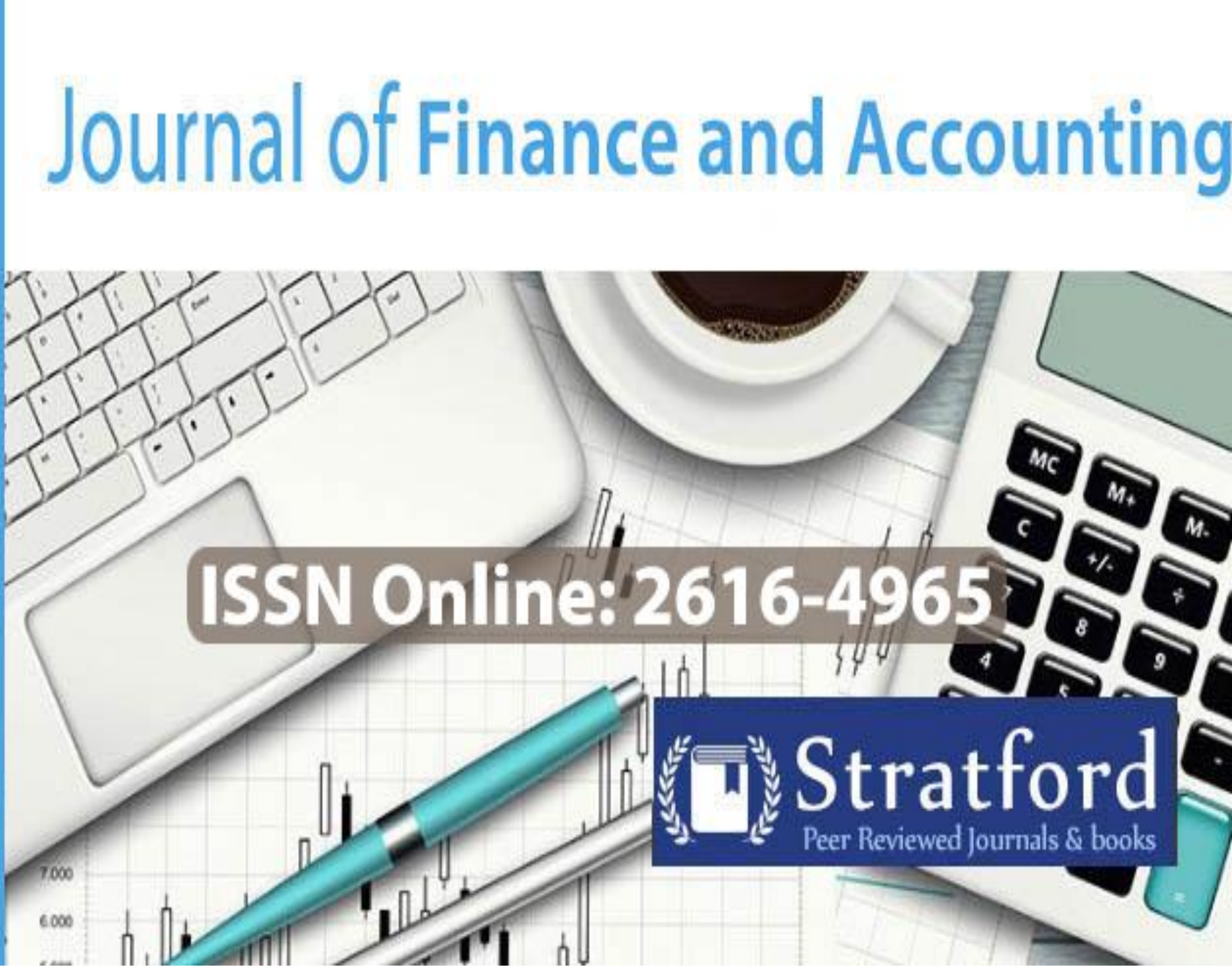

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Lelaono Alois Saruni and Dr. Jeremiah Koori

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Credit Information Sharing and Default Rate of Loans Issued by Commercial Banks Listed at the Nairobi Securities Exchange

[1*]Lelaono Alois Saruni & [2]Dr. Jeremiah Koori

[1]Post Graduate Student, Graduate Business School
School of Business, Kenyatta University

[2]Lecturer, Department of Accounting and Finance, School of Business,

Kenyatta University

[*]Corresponding Author's Email address: saruni.lelaono@gmail.com

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Abstract

The strength of banking systems is critical 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 while 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 study investigates the effect 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 study is pegged on the information asymmetry theory, the adverse selection theory, moral hazard theory lastly the theory 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.

Key words: *customer credit reports sharing, customer credit reports pulling, costs of credit information sharing, bank size, default rates of loans*

1.0 Introduction

The commercial banks role as financial intermediary cannot be understated irrespective of the size of banks which would vary 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).

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, there is need to assess how credit information sharing affects default rates of loans issued by listed Kenyan banks.

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 continues 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 shows the trend in percentage of default rate of commercial banks in Kenya.

Table 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 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).

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 & Pagano, 2005).

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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). There are 12 listed commercial banks at the Nairobi securities exchange (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 efforts 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. 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.

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2.0 Literature Review

2.1 Theoretical Review

2.1.1 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 & Degryse, 2010). In credit markets, risk from borrowers can be related to a good bought by the lender (Turner & Varghese, 2010). The theory demonstrates that data asymmetry and poor agreement implementation lead to disequilibrium in credit market (González-Uribe & 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, Erner, Langer & Norden, 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.

2.1.2 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 thoery 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 & 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.

2.1.3 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 & 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 & Pagano, 2005). In this research, the moral hazard theory clarifies that credit data pooling can expand borrowers' expense of defaulting, consequently expanding debt repayment.

2.1.4 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 thoery 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 & 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 theory, 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 & 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.

2.2 Empirical review

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 that 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.

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.

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 reduce 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.

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

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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.

2.3 Conceptual Framework

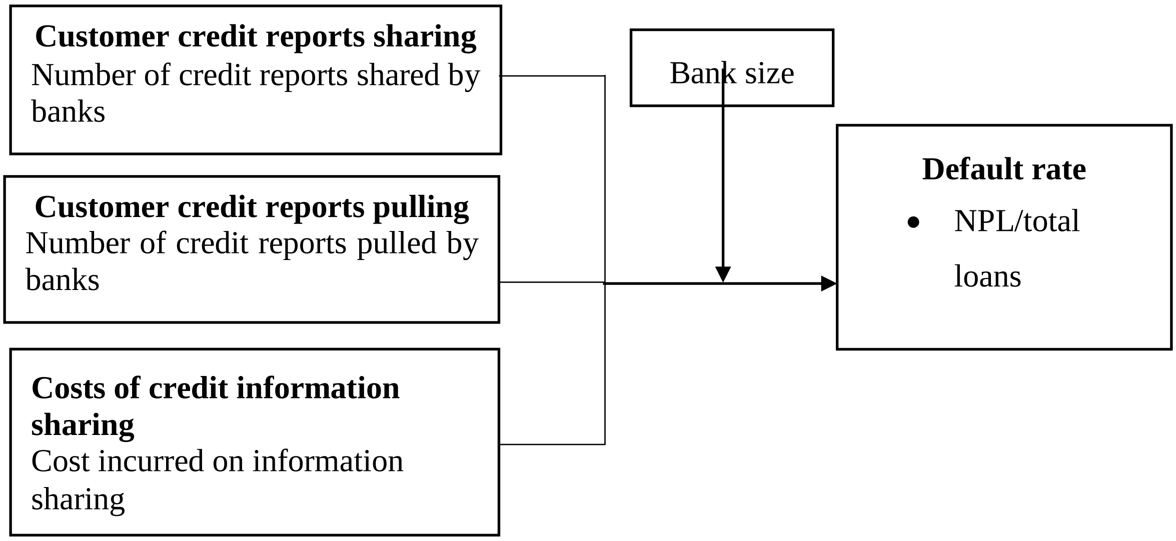

Figure 1: Conceptual framework

3.0 Research Methodology

Explanatory and descriptive research designs were used for the study. The study undertook a census by studying all 11 commercial banks listed at NSE. 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. 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 β_1, β_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 β_1, β_2, β_3 and β_4 are insignificant, no moderation effect exists and M becomes just another independent variable (MacKinnon, 2011).

4.0 Data Analysis and Interpretation

4.1 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 2 for results.

Table 2: 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

Table 2 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. Resulst in addition showed that the average number of client credit pulled 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.

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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.

4.2 Correlation Analysis

Table 3 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 3: 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 reduce information asymmetry.

4.3 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. 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. 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.

Table 4: 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

The outcome in Table 4 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).

Results in Table 4 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.

Further, the panel model in Table 4 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.

4.4 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 5 shows model the fitness for a regression model after moderation.

Table 5: 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 5 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) 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 effect of bank size on credit information sharing and default rates of loans issued by listed commercial banks in Kenya was rejected. 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.

5.0 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 concludes 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.

6.0 Recommendations

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.

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.

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