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Influence of Financial Inclusion on Credit Risk Performance in Kenyan Commercial Banks

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Abstract

The main aim of this study was to establish the influence of financial inclusion on credit risk performance in Kenyan commercial banks. The study was anchored on asymmetric information Theory. The study adopted a longitudinal correlational research design. The study target population consisted of 37 commercial banks in Kenya. The study employed a census sampling technique to gather all the required necessary data from the existing population. A balanced panel of secondary data from the published audited financial statements for the period 2018 to 2023. The collected data was subjected to a diagnostic test before applying regression analysis. The collected data was analyzed using EViews-12 Statistical Package and descriptive statistics were computed to determine data characteristics and multiple regression was used to test and report hypotheses. From the regression results, financial inclusion explains 82.43% (adj R^2=0.8243, p=0.000) of variance in credit risk performance. The regression coefficient revealed (β=0.027624, P=0.0303) showing that a unit increase in financial inclusion would lead to 2.7624% significant change in credit risk performance. Therefore, the null hypothesis was rejected. The study finally concluded that financial inclusion is found to increase credit risk performance in Kenyan commercial Banks. The study recommended that commercial banks' management should be very sensitive in advancing financial inclusion programs which if not well undertaken can lead to an increase in credit risk and eventually affect the sustainability of commercial banks. One issue noted is that commercial banks should develop stringent credit risk scoring models that have the capacity to capture the different unique risk profiles of the new customers to reduce information asymmetry. Additionally, Central Bank of Kenya should consider policies that can arrest transitional risk associated with increased financial inclusion that can reveal the credit history of formerly excluded population to ensure enhanced credit risk assessment.

Keywords: Financial Inclusion, Credit Risk Performance, Kenyan Commercial Banks.

1. INTRODUCTION

Globally, credit risk management is considered as one of the most significant and enduring risks commercial banks face and it continues to remain a major concern for commercial banks today. The pressure arising from credit risk has put commercial banks under regulators' scrutiny and leading to financial distress. The latest global financial stability survey has identified the banking sector as the focal point of recent financial distress with many banks experiencing a potential loss of confidence in their systems which has prompted regulatory authorities and governments to implement mitigation measures (Otanga, 2018). Major economies have continued to report credit risk crisis both in African and within East Africa community (International Monetary Fund, 2023). In Kenya, commercial banks are heavily regulated, with credit risk being a primary challenge, The Central Bank of Kenya has established regulations to address this challenge (Central Bank of Kenya, 2022).

However, Kenya's banking credit risk performance has progressively increased from 11.66% in 2018, to 15.3% in 2023, this has positioned Kenya position eight globally, position four regionally and the worst in East Africa (CBK, 2024). This performance happened a alongside Central Bank of Kenya interventions and measures through policies and guidelines that are met to regulate credit risk performance. The prudential policy guidelines requirement on commercial banks through latest survey reported increased loss in loans a clear depiction of significant burden of credit risk among commercial banks. Theoretical perspective suggests that borrowers may have more information on their risk exposure than commercial banks, this might lead to difficulty in assessing credit worthiness, the banks therefore need to gather sufficient information about their customers in order to effectively manage credit risk (Tupangiu, 2017).

Financial inclusion has emerged as a key policy demand of most governments with most of the economies and financial institutions globally employing aggressive programs to reach the unreached population with banking services (Department of International Development, 2012).

Theoretical argument suggests that financial inclusion initiatives involve the entry of new customers into the banking sector which creates information asymmetry. This can eventually lead to moral hazards at the point of credit application (Richard, 2011). Financial inclusion strategies are pushed with the assumption that it is one of the key stimuli for economic growth (Sulaeman, 2020). There has been widespread commitment by financial institutions in Kenya that has pushed financial inclusion from 23% of adults' able to access banking services as compared to 84% in 2023 (World Bank, 2023). Kenyan banking sector fit the best context to study this relationship on the backdrop of the sector being the pioneer of financial inclusion through mobile money technology, the M-pesa which contributed to the increased inclusion. This transformation in the financial inclusion implementation happens alongside increased credit risk in the banking sector evidenced by increased non-performing loans.

However, the empirical evidence on the relationship between financial inclusion and credit risk performance in Kenyan commercial banks remain contentious, the existing literature presents a mix finding which. While some studies indicate that financial inclusion heightens credit risk for banks, others suggest that it diminishes it, presenting an area that requires further exploration. It is worth noting that statistics indicate a growing trend of commercial banks increasing their investments in financial inclusion. Therefore, against these escalating investments in Kenya, this study aimed to delve deeper into the correlation between financial inclusion and credit risk.

1.1 Statement of The Problem

Credit risk in commercial banks in Kenya has been on an increasing trend. It has exposed the financial sector compared to other economic sectors, eventually leading to a credit risk crisis. This crisis has reduced shareholders' wealth, putting commercial banks in the spotlight with the regulator, The Central Bank of Kenya. Kenya's credit risk rating stands at 15.3% (2023) from 11.66% (2018), positioning Kenya at position eight globally, way above the global average rate of 10.9% (2022), alongside increasing demand for credit. This rating is still high despite the Central Bank of Kenya's intervention through regulatory measures, policies and guidelines that includes Credit Risk management guidelines, non-performing loans guidelines, credit information sharing requirement, interest Rate policies, COVID-19 response measures and the latest Digital Lending regulations. Commercial banks have continued to broaden financial inclusion strategies leading to 84% of the adult population accessing financial services in 2023 as compared to 73% in 2018. As commercial banks have continued to reach the unreached population and expanding customer base and the additional regulations commercial banks continue to report credit risk as a major challenge. Existing literature has linked financial inclusion to credit risk, though the relationship has not been conclusively established, and it remains an open research area within the sector, this study aimed to bridge the gap by establishing the relationship between financial inclusion and Credit Risk in commercial banks in Kenya.

2. LITERATURE REVIEW

2.1 Theoretical Literature Review

This study was guided by Financial Asymmetric Information Theory. That stipulates that the borrower has more information on investment to be undertaken by the borrowed funds than the lender, this asymmetric nature of information presents two major problems of adverse selection and moral hazards (Tupangiu, 2027). Adverse selection happens when the bank cannot differentiate between borrowers of different risks, and this leads to borrowers repaying loans when they have the means to do it which eventually can lead to default (Boffondi & Gobbi, 2013). Moral hazard occurs when customers tend to provide misleading information about their credit capacity due to lack of proper information to conduct in-depth screening of the borrower at the point of credit application (Richard, 2011). Incomplete information about the financial state of the borrower occurs because of non- disclosure or delay of true state of financial information caused by new entry of customers in the financial markets, it occurs where the non-disclosure or delay is distributed within a time frame and such will lead to an increase in credit risk (Lindset, 2014).

The credit market faces serious effect of imperfections due to the presence of asymmetric information since lenders may lack the required information to set the prices for the loans therefore the lender is set in a position where it is difficult to determine the borrower's risk, leading to probability of default. This might lead to the introduction of loan monitoring cost for the new customers, introducing adverse selection problem in credit management due to lack of sufficient information on borrower's risk rating status. This will affect the capacity of repayment of loans forcing unworthy credit borrowers with low capacity of repayment taking high priced loans and credit worthy borrowers withdraw due to the introduced borrowing condition hence the probability of granting loans to borrowers of poor repayment which eventually exposes lenders to credit risk. In addition, Moral hazard effect arises since the lender cannot monitor the action of the borrower leading to uptake of risky credits by the borrower that is not approved which when it fails eventually lead to default (Okuyan, 2014). Therefore, this theory is essential in explaining the role financial inclusion plays in credit risk management.

2.2 Empirical Studies

Artavanis & Karra (2020) analyzed the effect of financial inclusion from the dimension of financial literacy on debt management among college students in public university in Massachusetts. The study adopted research survey design using a sample of 1000 students drawn from a large grant, primary data was collected using questionnaires. The study found out the unreached population of students with high level of financial illiteracy are likely to underestimate their future loan repayment and eventually risk defaulting into their loans while students that are reached with financial information and poses high financial literacy level can easily estimate their future repayment of loan. In their study they considered financial inclusion in the dimension of access while this study will consider usage as a measure of financial inclusion in respect to credit risk. In addition, the researchers collected primary data through interviews while this study utilized panel time series data for the observations.

Similarly, analytical review of empirical articles by Kamal *et, al.* (2021) on the impact of financial inclusion on banks financial stability in commercial banks, reviewing 100 round articles from the globe for the period 2000 to 2020. The articles were selected from different research engines including Google scholar, science direct, emerald and springs link. Findings from their review revealed that financial inclusion has a negative influence on financial stability since financial inclusion increases non-performing loans. While their study review focused on the role of financial inclusion on banks stability which also had other dimensions of profitability using secondary data, this study focused majorly on the relationship of financial inclusion on credit risk.

On the other hand, several studies have contradicted the finding of indirect relationship between financial inclusion and credit risk. A study by Mohamed (2020) that aimed at testing the relationship between the financial inclusion indicators and bank credit risk in the Middle East North Africa (MENA) targeting banks licensed in MENA in a sample of 19 counties, the study adopted a descriptive research design using secondary data from the Global Findex compiled by the world bank for the period 2011 to 2017 and Fitch IBCA bank scope database. Using the Least Square Dummy variables to estimate the non-linear model, the study found that banks' credit risk stability is accomplished by expanding financial services to households and small to medium-sized enterprises (SMEs). The study by Mohamed measured financial inclusion in the accessibility and usage of credit and debit cards; the study did not consider financial inclusion from the dimension of adoption of mobile banking. At the same time, he considered the ratio of loan losses to provision, while this study used nonperforming loans to gross loans to measure credit risk.

Mehrotra & Yetma (2015) reviewed various literature on financial inclusion issues for central banks, focusing on the level of financial inclusion and policy actions intended to support access to financial services; they concluded that increased financial inclusion facilitates smoothing and makes it easier for households to access the instruments of borrowing. The literature by the researchers focused on how financial inclusion facilitates access to borrowing, but their findings did not provide a conclusive policy position on how banks can leverage financial inclusion to manage credit risk an area that remained a specific focus for this study.

Shidadeh *et al.* (2019) examined global evidence on the effect of financial inclusion on bank performance and credit risk. They sampled 701 banks from 189 countries and measured financial inclusion in the number of branches, savings, loans, credit cards, debit cards, and formal bank accounts, while non-performing loans measured bank risk. They found that increased financial inclusion activities increase credit risk. In summary, the studies reviewed have demonstrated mixed results that financial inclusion can either increase or reduce credit risk though non of the studies addressed the endogeneity factors within the relationship this unveiled a gap. This study examined the effect of financial inclusion on credit risk in commercial banks in Kenya by addressing the endogeneity factors by controlling other variables within the banking sector.

3. METHODOLOGY AND RESULTS

This study adopted a longitudinal correlational research design. This design concerns with finding the relationship between variables without control or manipulation (Bhandari, 2021). In addition, the used design also includes procedures in quantitative research in which researchers measure the degree of association between two or more variables using the statistical procedure of correlation analysis; the degree of association is presented in numbers to show whether the variable is related or not (Otanga, 2021). This study was conducted in Kenya and targeted the commercial banking sector. These are banking institutions that receive deposits from customers and utilize the deposits to issue loans and advances and provide savings accounts. They are critical in Kenya's financial systems and spread throughout its major towns (Bebbora,2019). The target population for this study was 37 commercial banks in Kenya registered from 2018 to 2023 by the Central Bank of Kenya. CBK (2023) reports indicate that commercial banks are categorized as large, medium, or minor using the weighted index, which comprises assets, customer deposits, capital and reserves, and the number of deposit and loan accounts. Commercial banks were considered for this study since their core business is directly involved with credit risk management, which fits the primary goal of this study.

The study adopted a census sampling technique by considering all the 37 commercial banks registered by the Central Bank of Kenya as of 31st Dec 2023. The study used secondary data from annual published financial reports of the 37 commercial banks from 2018 to 2023, constituting 222 data points. The data was sourced from financial information from commercial banks, financial information from Central Bank of Kenya (CBK) reports accessed through their respective websites over the research period. The collected data had both time-series elements as well as cross section dimensions which provided a need for hierarchical panel data analysis technique using the EViews-12 Statistical Package. Descriptive statistics were computed to determine data characteristics such as means, frequencies and standard deviations. Multiple regression was used to test and report research hypotheses. This study incorporated control variables to provide a comprehensive analysis of the financial health and structural characteristics of commercial banks in Kenya. The multiple regression analysis was based on the panel fixed effects, as supported by the Hausman Test, mitigating bias from time invariant omitted factors. and the results presented in the form of tables and the analytical explanation have been attached to each table.

3.1 Research Model

Correlation analysis was used to test the variables to eliminate the multi-collinearity effect, The data used includes both time series and cross-sectional data. This was summarized into a panel data set and estimated using panel data regression. The data set was tested for stationarity at all levels to get meaningful sample mean and variance, which can indicate future trends. The logarithm was used to transform and normalize the data distribution in order to reduce the effects of outliers.

$$Y_{it} = \beta_0 + \beta_1 FI_{it} + \beta_2 LNS_{it} + \beta_3 TCAR_{it} + \beta_4 LIQ_{it} + \beta_5 BZS_{it} + \beta_6 DEPFN_{it} + \epsilon_{it} \text{ .... Equation 3.1}$$

Where:

Y_{it} = Credit risk (dependent variable); measured by ratio of non-performing loans to gross loans
FI = Financial inclusion (independent variable); measured by natural log of number of total transactions
LNS = Lending (control variable); measured by ratio of gross loans to total assets
TCAR = Capital Adequacy Ratio (control variable) measured by ratio of total capital to total assets
LIQ = Liquidity Ratio (Control variable); measured by ratio of equity capital to gross loans
BZS = Bank Size (Control Variable); measured by natural log of bank assets
DEPFN = Deposit Financing (Control variable); measured by ratio of deposits to total assets
ϵ = Error term

$\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$, = Regression coefficients

i = Cross section, representing the number of commercial banks in the study
t = time series, representing quarterly data per commercial bank in the study

Financial inclusion is considered in different dimensions that include access, usage, quality and affordability, Usage focuses on the actual utilization of the financial services which includes frequency of use as well as duration (World Bank, 2015). Transactional based was used to since it provides quantifiable dimensions that capture the true image of the economic activity and involvement with financial services (Gupte, 2012). In addition, number of transactions also considers users active participation in the banking services, and this corresponds to the World Banks's Findex strategy that is currently deriving new dimensions of measuring financial (Klapper, 2012).

3.2 Diagnostic Tests

Diagnostic tests were conducted before applying the collected data to regression analysis. The researcher performed various diagnostic tests, including a model specification test using the Hausman test, a unit root test using Levin, Lin, and Chu (LLC), a test of normality utilizing the JB test, an autocorrelation test using the Durbin-Watson test, and a multicollinearity assessment using the Variance Inflation Factor (VIF). This process ensured that the classical linear regression model (CLRM) assumptions were upheld.

3.2.1 Unit Root Test

Before conducting empirical estimates, the datasets were subjected to a unit root test to establish their stationarity condition using the Levin–Lin-Chu unit test (LLC). This was conducted to check the stability of the data and to avoid obtaining spurious regression results by using non-stationary series. The null hypothesis in the unit root test indicates that the time series used in the study has a unit root; therefore, it is non-stationary. The alternative hypothesis posits that the time series is stationary. The results of using the Levin-Lin-Chu (LLC) test for the unit root are summarized in Table 3.1.

Table 3.1: Summary of the Levin, Lin, Chu (LLC) Common Root Test Results on the Study Variables

Study Variable	Statistic	Prob.
Credit Risk (NPLRATIO)	-7.65948	0.0000*
Financial inclusion (FI)	-14.4302	0.0000*
Lending (LNS)	-8.72198	0.0000*
Capital Adequacy Ratio (TCAR)	-140.507	0.0000*
Liquidity Ratio (LIQ)	-25.6559	0.0000*
Bank size (BSZ)	-2.67276	0.0038*
Deposit Financing (DEPFN)	-11.4396	0.0000*

**** Represent significance at the 0.05 level.***

Source: Field Data, 2025

The results in Table 3.1 show that all the variables were stationary at levels. All the variables of the study had a probability level below 0.05, suggesting the null hypothesis was rejected and the alternative hypothesis accepted. The implication was that the data for all the variables across the time period of the study were established to be stationary; therefore, there was no fear of spurious regression

3.2.2 Test for Normality

Brooks (2008) stated that normality assumption is required to conduct single or joint hypothesis tests about the model parameters. Findings of a study can only be generalized only when residual are assumed to be normally distributed (Gujarati, 2013). The most applied test for normality is the Jarque-Bera (JB) test. The results of normality test are shown in Figure 3.2.

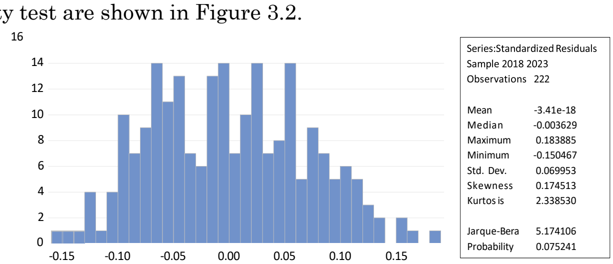

Figure 3.2: Results on the Test of Normality

The results in Table 3.2 show that the residual from the regression model was normally distributed, with the reported probability that the Jarque-Bera statistics exceed in absolute terms the observed value, the lowest being 0.075241, which is greater than the 0.05 level of significance. This implies that the assumption of regression analysis regarding normality is met since the JB tests are insignificant at the 5% level, and the study failed to reject the null hypothesis.

3.2.3 Hauman Model Specification Test

In order to choose between fixed and random effect model for the regression model, Hausman test was conducted as a confirmatory test and the result is as presented in Table 3.3. The null hypothesis under this test is that errors are not correlated with the regressors Where the null hypothesis is supported, the random effect model is adapted, otherwise, the fixed effect model is accepted

Table 3.3: Hausman Test Results for Model 3.1

Test Summary		Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random		11.663441	6	0.0399
Variable	Fixed	Random	Var (Diff.)	Prob.
FI1	0.036753	0.028897	0.000032	0.1646
LNS	-0.033399	-0.067495	0.001780	0.4190
TCAR	-0.008985	-0.009691	0.000004	0.7378
LIQ	-0.129895	-0.210511	0.003211	0.1549
BSZ	-0.032537	-0.035285	0.000819	0.9235
DEPFN	-0.628710	-0.585379	0.007988	0.6278

*****Represent significance at level 5%***

Source: Field Data, 2025

In Table 3.2, the Hausman test results show a chi-square 11.66 with a significant p value of 0.0399 implying that at 5% level, the null hypothesis was rejected, and the alternative hypothesis was accepted hence the Fixed Effect model was used to analyze the model.

3.2.4 Multicollinearity Test

In testing for multicollinearity, Variance Inflation Factor (VIF) was used, and the study adopted the rule of thumb for VIF Value of 10 as the threshold and the test result as shown in Table 3.4 below.

Variable	Coefficient Variance	Centered VIF
C	0.070026	NA
FI1	0.000160	1.048997
LNS	0.002976	1.416295
TCAR	9.55E-06	1.068288
LIQ	0.001517	2.011841
BSZ	9.98E-05	1.310302
DEPFN	0.006458	1.496585

Source: Field Data, 2025

As shown in Table 3.4, the centered VIF values for all the regression equations in the models are much lower than 10, with the highest being 2.388599. Gujarati (1995) asserts that multicollinearity will only be a problem if and only if one of the VIF values is greater than 10, which was not the case with the presented results on the VIFs.

3.2.5 Heteroskedasticity Test

The study conducted hereskedasticity test to test the assumption that the residual has a constant variance. General Least Square (GLS) with cross-section weights and the white cross-section coefficient covariance method was preferred to Ordinary Least Square (OLS). Likelihood Ratio Test was used. The test provides an assessment as to whether the residual from the research regression model is characterized with homoskedasticity. The test results are summarized in Table 3.5 below.

Table 3.5: Summary of Likelihood Ratio (LR) Test

	Model 3.1
LR – Test	267.3578
df	37
p - Values	0.0000

Source: Field Data, 2025

From the results in Table 3.5, the p - values in all the three models are less than 1% which shows statistically significant therefore the null hypothesis was strongly rejected and the alternative hypothesis accepted, therefore this confirmed existence of heteroskedasticity that paved way for the adoption of GLS.

3.2.6 Autocorrelation Test

Autocorrelation test was conducted to establish whether residuals are correlated across time, Regression analyses assumption requires that residuals should not be correlated across time hence Durbin Witsons Test was used to test correlation. The test directly examines the structure of the error in the study model which is critical when modelling credit risk (Moyo, 2022). The summary of the DW-Test is summarized in Table 3.6 below.

Table 3.8: Summary of Durbin – Watsons Test

	Model
DW - Test	1.420164

Source: Field Data, 2025

4. RESULT AND DISCUSSION

4.1 Descriptive Analysis

Table 4.1 presents the descriptive statistics for the study variables, Credit risk and financial inclusion and the control variables

	NPLRATIO	FI	LNS	TCAR	LIQ	BSZ	DEPFN
Mean	0.186666	18.56224	0.559176	0.170078	0.308399	24.76309	0.746825
Median	0.144118	18.56801	0.584246	0.143154	0.261836	24.49397	0.761774
Maximum	0.761985	18.94823	1.419064	8.491481	1.305179	27.98545	0.981979
Minimum	0.003752	17.99288	0.160912	-0.567858	-0.475568	21.78181	0.165981
Std. Dev.	0.148525	0.232102	0.205644	0.568538	0.214565	1.371786	0.110791
Skewness	1.908317	-0.292624	0.675096	14.20192	1.271858	0.303839	-2.128691
Kurtosis	6.878078	2.287104	5.097111	208.6266	7.692124	2.172190	10.47308
Jarque-Bera	273.8572	7.869295	57.54325	398574.0	263.5003	9.754501	684.2436
Probability	0.000000	0.019553	0.000000	0.000000	0.000000	0.007618	0.000000
Sum	41.43990	4120.818	124.1370	37.75728	68.46457	5497.407	165.7952
Sum Sq. Dev.	4.875179	11.90556	9.346014	71.43493	10.17444	415.8771	2.712680
Observations	222	222	222	222	222	222	222

Source: Field Data, 2025

From Table 4.1, the minimum credit risk in commercial banks in Kenya measured by non-performing loans to gross loans (NPLRATIO) is 0.003752, while the highest number is 0.761985. The average credit risk is 0.186667. The means of credit risk shows that, across the banks and over the years, credit risk concentrated at 0.18667 with individual ratios varying from the mean with a percentage of 14.853%. This indicates that with a positive skewness of 1.908317, which implies that some banks are exposed to significantly higher credit risk than others. Additionally, the mean of

Financial Inclusion measured by the natural log of total transactions (FI) was 18.56224 with a maximum of 18.94823 and a minimum of 17.99288 with a moderate negative skewness of – 0.292624, which indicates a tendency towards more transaction volumes in commercial banks.

Table 4.1 Trend Analysis on Credit Risk

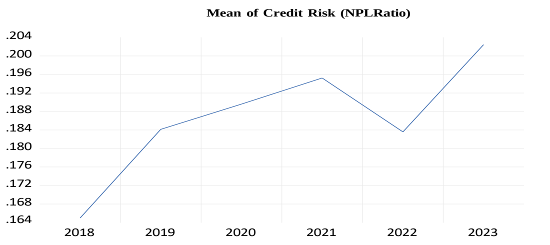

Figure 4.1: Trend of Credit Risk
Source: Field Data, 2025

Credit risk performance gradually increases and steady between 2018 t0 2019 with a sharp trajectory in 2020 which could be associated with the economic impact of COVID-19. The performance later drop depicting economic recovery in 201 t0 2022 which later picked upward in 2023 demonstrating an existing challenge in addressing credit risk management among commercial banks.

Table 4.2 Trend Analysis on Financial Inclusion

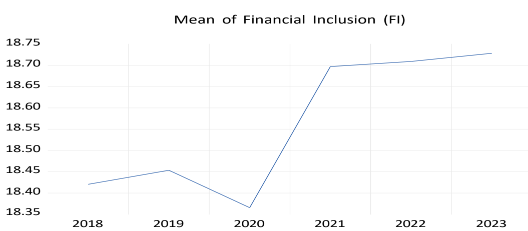

Figure 4.2: Trend of Financial Inclusion
Source: Field Data, 2025

Figure 4.2 indicates that financial inclusion performance measured by total number of transactions continued to increase in perion 2028 to 2019 which could be associated to progress made before the COVID-19 which later followed by drop in performance that could be linked to reduced banking activities in 2020 that affected banking through early 2021. This performance picked up later in 2021 which could be associated to successfully implementation of Central Bank of Kenya COVID-19 responses. The performance has continued to increase in subsequent period of 2023 which matches the global performance.

4.2 Inferential Statistics

The inferential statistics were from the multiple regression conducted to test the research hypothesis on the study objective that aimed to establish the relationship between financial inclusion and credit risk. The null hypothesis H_o was formulated that there was no statistically significant relationship between Financial Inclusion and credit risk among commercial banks in Kenya. Fixed effect simple regression analysis was conducted on the study variables in the model of the study which included the interaction of independent variable (Financial Inclusion, FI and the control variables (Lending Ratio, Capital adequacy ratio, Liquidity Ratio, Bank Size and Deposit Financing) as measured against dependent variable, Credit Risk and the results were presented in Table 4.2

4.2 Regression Results on the relationship between Financial Inclusion and Credit Risk

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.723458	0.264624	2.733911	0.0069
FI1	0.027624	0.012654	2.183042	0.0303
LNS	-0.052531	0.054555	-0.962908	0.3369
TCAR	-0.004910	0.003091	-1.588515	0.1139
LIQ	-0.024067	0.038953	-0.617831	0.5375
BSZ	-0.012950	0.009991	-1.296198	0.1966
DEPFN	-0.239031	0.080359	-2.974533	0.0033
R-squared	0.857758			
Adjusted R-squared	0.824383			
S.E. of regression	0.077728			
F-statistic	25.70042			
Prob(F-statistic)	0.000000			
Durbin-Watson	1.420164			

***Represent significance at the 0.05 level**

Table 4.2 shows the regression results from testing the relationship between the study variables in the primary model 3.1. It reveals that Financial Inclusion and Credit Risk have a weak but statistically significant positive relationship (ß = 0.027624, p = 0.0303), this result suggests that as financial inclusion increases, it leads to a corresponding 2.8% increase in credit risk. The study findings are consistent with those in Musau *et al* (2019) who reported a direct relationship between financial inclusion and credit risk among commercial banks in Kenya and advocated that financial inclusion through increase mobile accounts increases credit risk performances indicators through increased deposit mobilization. The result supports the findings in Ghasama *et al* (2020) who conducted similar study using similar variables among commercial banks in Indonesia, their findings revealed significant and positive relationship between financial inclusion and credit risk in commercial banks. The findings are also in line with a study from (Ahamed & Mallick 2019) which explains that increased financial inclusion due to entry of new unfamiliar customers increases credit risk in banks. It further justifies the findings of Ozili (2021) who reported that financial inclusion has positive relationship with credit risk suggesting that increased account ownership increases non-performing loans. This further justifies the findings in Shidah *et al* (2019) and Kamal et al (2021) that concluded that financial inclusion has positive significant relationship with credit risk. The results resonate well with the asymmetric information theory by Akerlof (1970) assumptions of incomplete information, that allows adverse selection and moral hazard to sets in as was expanded in Chepkwony (2018) and Tupangiu (2017) as well as Boffondi *et al* (2013) their theoretical review findings agreed that entry of new customers in accessing banking services exposes banks to information asymmetry and banks are not able to identify borrowers of low or high credit risk and this exposes banks to credit risk. The results also contradict the findings in the other past studies; Mohamed (2020), Jung et, al. (2023), Van et, al. (2021) and Shidah (2020) who found out that financial inclusion has significant negative relationship with credit risk.

5. CONCLUSION AND RECOMMENDATION

Based on the findings that growth in credit risk due to the increased effort to reach an unreached population with banking services commercial banks' management should be very sensitive in advancing financial inclusion programs, if care is not well undertaken can lead to an increase in credit risk and can eventually affect the sustainability of banks. This calls for commercial banks managers to develop stringent credit risk scoring models that have the capacity to capture the different unique risk profiles of the new customers to reduce information asymmetry. It will be very important for The Central bank of Kenya the regulator to consider regulations and policies that takes care of the transitional risk associated with increased financial inclusion. This can include adoption of responsible lending strategies through well-defined data infrastructures that can reveal the credit history of formerly excluded population such as adoption of additional data sources such M-Pesa transactions history to enhance credit risk assessment as well as other available data sources such as utility bills payment history. The findings confirm the applicability of Asymmetric Information Theory to the modern context of rapid digital financial inclusion in the emerging financial markets with is a valuable extension of the classic theory.

REFERENCES

1. Ahamed, M. M., & Mallick, S. K. (2019). Is financial inclusion good for bank stability? International evidence. *Journal of Economic Behavior & Organization*, 157, 403-427. https://doi.org/10.1016/j.jebo.2017.07.027
2. Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3), 488-500. https://doi.org/10.2307/1879431
3. Artavanis, N., & Karra, E. (2020). Financial literacy and student debt management: Evidence from Massachusetts. *Journal of Consumer Affairs*, 54(2), 624-649. https://doi.org/10.1111/joca.12289
4. Bebbora, P. (2019). *Banking sector development in Kenya: A comprehensive analysis*. Kenya Banking Association.
5. Bhandari, P. (2021). *Research design and methodology: A comprehensive guide*. Academic Press.
6. Boffindi, M., & Gobbi, G. (2013). *Information asymmetries and bank lending decisions* (Working Paper No. 951). Bank of Italy.
7. Brooks, C. (2008). *Introductory econometrics for finance* (2nd ed.). Cambridge University Press.
8. Central Bank of Kenya. (2022). *Bank supervision annual report 2022*. CBK Publications.
9. Central Bank of Kenya. (2023). *Bank supervision annual report 2023*. CBK Publications.
10. Central Bank of Kenya. (2024). *Quarterly economic review: Fourth quarter 2023*. CBK Publications.
11. Chepkwony, J. (2018). Information asymmetry and credit risk management in Kenyan commercial banks. *East African Journal of Banking and Finance*, 3(2), 45-62.
12. Department for International Development. (2012). *Financial inclusion: Reaching the unbanked*. DFID Publications.
13. Ghasama, A., Hidayat, R., & Nugroho, L. (2020). Financial inclusion and credit risk: Evidence from Indonesian commercial banks. *Asian Economic and Financial Review*, 10(6), 726-738. https://doi.org/10.18488/journal.aefr.2020.106.726.738
14. Gujarati, D. N. (1995). *Basic econometrics* (3rd ed.). McGraw-Hill.
15. Gujarati, D. N. (2013). *Basic econometrics* (5th ed.). McGraw-Hill Education.
16. International Monetary Fund. (2023). *Global financial stability report: Safeguarding financial stability amid high inflation and geopolitical risks*. IMF Publications.

17. Jung, H., Park, K., & Lim, S. (2023). Financial inclusion and bank risk-taking behavior: Cross-country evidence. *Journal of Banking & Finance*, 147, 106-124. https://doi.org/10.1016/j.jbankfin.2022.106124
18. Kamal, M., Usman, M., & Rahman, A. (2021). Financial inclusion and bank stability: A systematic literature review. *International Journal of Banking and Finance*, 16(1), 89-112. https://doi.org/10.32890/ijbf2021.16.1.4
19. Klapper, L. (2012). Measuring Financial Inclusion: The Global Findex Database. Brookings Papers on Economic Activity.
20. Lindset, S. (2014). Information asymmetry and credit risk assessment in emerging markets. *Emerging Markets Finance and Trade*, 50(3), 78-95. https://doi.org/10.2753/REE1540-496X500305
21. Mehrotra, A., & Yetman, J. (2015). Financial inclusion issues for central banks. *BIS Quarterly Review*, March, 83-96.
22. Mohamed, A. H. (2020). Financial inclusion and bank credit risk: Evidence from MENA countries. *Journal of Financial Services Research*, 58(2), 195-218. https://doi.org/10.1007/s10693-019-00318-4
23. Moyo, B. (2022). *Panel data econometrics in banking research*. Palgrave Macmillan.
24. Musau, S., Muathe, S., & Mwangi, L. (2019). Financial inclusion and credit risk performance of commercial banks in Kenya. *International Journal of Economics and Finance*, 11(4), 86-98. https://doi.org/10.5539/ijef.v11n4p86
25. Okuyan, H. A. (2014). Moral hazard problem in banking sector: A literature review. *International Journal of Economics and Finance*, 6(6), 120-129. https://doi.org/10.5539/ijef.v6n6p120
26. Otanga, D. (2018). Credit risk management and financial performance of commercial banks in Kenya. *African Journal of Business Management*, 12(8), 230-241. https://doi.org/10.5897/AJBM2018.8524
27. Otanga, D. (2021). *Correlational research design in banking studies: Applications and implications*. East African Publishers.
28. Ozili, P. K. (2021). Financial inclusion and bank profits. *Journal of Financial Inclusion*, 5(1), 78-95. https://doi.org/10.1108/JFI-03-2021-0023
29. Richard, E. (2011). Factors of non-performing credit and their effect on banking performance in Tanzania commercial banks. *Advances in Management and Applied Economics*, 1(2), 87-99.
30. Shidadeh, M., Hao, L., & Ahmad, W. (2019). Global evidence on the effect of financial inclusion on bank performance and risk: Does bank origin matter? *Quarterly Review of Economics and Finance*, 74, 176-190. https://doi.org/10.1016/j.qref.2019.04.004
31. Shidah, M. (2020). Financial inclusion and credit risk management in emerging economies. *International Review of Financial Analysis*, 71, 101-115. https://doi.org/10.1016/j.irfa.2020.101115
32. Sulaeman, A. (2020). Financial inclusion as a driver of economic growth: Evidence from developing countries. *Journal of Development Economics*, 142, 102-118. https://doi.org/10.1016/j.jdeveco.2019.102118
33. Tupangiu, G. (2017). *Information asymmetry in credit markets: Theory and practice*. Financial Publications Ltd.
34. Van, L. T., Vo, A. T., Nguyen, N. T., & Vo, D. H. (2021). Financial inclusion and economic growth: An international evidence. *Emerging Markets Finance and Trade*, 57(1), 239-263. https://doi.org/10.1080/1540496X.2019.1697672
35. World Bank (2015). How to Measure Financial Inclusion. World Bank Group
36. World Bank. (2023). *Global Findex Database 2023: Financial inclusion, digital payments, and resilience in the age of COVID19*. World Bank Publications.