# “Can Financial Technology Transform Credit Risk Management? Evidence from Kenyan Commercial Banks”

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**Abstract**

The main aim of this study was to examine the extent to which financial technology adoption transforms credit risk management in Kenyan commercial banks. The study was anchored on the Theory of Financial Innovation. The study adopted a correlational research design. The study targeted a population of 37registered commercial banks in Kenya using a census sampling technique to gather all the necessary data from the entire population. A balanced panel of secondary data from the published audited financial statements for the period 2018 to 2023 was used. The collected data was subjected to a diagnostic test before applying regression analysis. The 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 technology explains 82.58% (adj $R^2$=0.8258, p=0.000) of variance in credit risk performance. The regression coefficient revealed (β= -0.002521, P=0.7068), showing that a unit increase in financial technology would lead to a 0.2521% insignificant decrease in credit risk performance. Therefore, the null hypothesis failed to be rejected. The study finally concluded that financial technology is found to have an insignificant relationship with credit risk performance in Kenyan commercial Banks. The study recommended that commercial banks’ management should be deliberate in accelerating a complete digital infrastructure that supports the banking process from start to end and should reduce partial implementations. Commercial bank managers should also set up technological adoption policies that align with the sector regulatory framework to avoid investing in a technological environment that has no impact on credit risk management. The study also recommended that the Central Bank of Kenya set up a digital infrastructure standardization policy to support technological adoption that can produce an impactful credit risk assessment.

**Keywords:** Financial Technology, Credit Risk Management, Kenyan Commercial Banks

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## 1. Introduction

The banking sector worldwide has been recognized as a significant contributor to the ongoing financial distress, with many commercial banks experiencing a loss of confidence in their systems. Credit risk is identified as a primary factor in this issue (International Monetary Fund, 2023). Historically, major economies have faced credit risk crises stemming from events such as the Asian financial crisis, the Argentine financial crisis, and the subprime mortgage crisis in the United States. These crises have also contributed to the ongoing European credit crisis, which resulted in the collapse of several regional banks (Yang & Masron, 2023). Currently, the poor performance of commercial banks is largely driven by challenges in credit risk management, with the Kenyan banking sector being no exception. This has led to the implementation of additional regulations aimed at addressing these challenges, including prudential policy guidelines for commercial banks. Recent surveys indicate an increase in loan losses, highlighting the significant burden of credit risk faced by these institutions (Central Bank of Kenya, 2022). The Credit Officer Survey report (2023) from the Central Bank of Kenya highlights credit risk as a significant challenge impacting the efficiency of commercial banks. In the past five years, there has been a notable increase in gross loans, reaching KES 3.9 trillion in 2023, driven by heightened demand for credit across various sectors. However, 66% of commercial banks view credit risk as a potential threat, primarily due to uncertainties regarding customers' income and rising unemployment. Additionally, financial technology has gained traction in the global financial market, enhancing customer experience and driving adoption through innovations such as mobile payments, digital lending, and money remittances. This growth has been supported by financial innovation theories that encourage banks to leverage technology to improve service delivery and develop products that enhance credit management. The success of financial technology in Kenya is closely linked to the significant increase in mobile phone penetration, which began in 2000, allowing mobile subscribers to access financial services without needing an internet connection.by telecommunications company Safaricom in 2007. This positioned Kenya for a digital transformation in the banking sector, further boosted by the launch of Equitel by Equity Bank, a platform that integrated more banking services (Chitari, Cohen & Hagist, 2021).

The Global Fin Index database shows that mobile banking adoption in Kenya is more widespread compared to other countries, with Kenya at 69%, followed by Thailand at 60%, Argentina at 35%, Russia at 33%, Singapore at 31%, and Brazil at 27%. Financial technology provides a strategic advantage by enabling consumers to have alternative credit scores based on traditional data and transaction history, thereby increasing their creditworthiness (Leong, 2017). Digital platforms in financial technology can also increase debt traps, leading to greater credit risk exposure among small and medium enterprises (Elizabeth, 2020). It enhances the chances of accessing finance by allowing commercial banks to offer credit to customers (Sheng, 2020). Likewise, financial technology improves the performance of commercial banks by encouraging more credit uptake. Therefore, banks should adopt a financial technology strategy to better support customers' access to credit (Mohammed, 2019). Implementing innovative financial technologies like mobile banking significantly enhances the competitive advantage of commercial banks by improving access, and banks should adopt mobile banking to expand their overall reach (Odhiambo & Mang'ana, 2022). Financial technology has also made a significant contribution to the banking sector in developing countries (Quattara & Hounsou, 2021) Additionally, financial technology can promote financial inclusion and help SMEs access finance quickly (Shofawati, 2019).

Financial technology, often referred to as fintech, significantly enhances access to financial services by enabling commercial banks to extend credit more efficiently to a broader range of customers (Sheng, 2020). These advanced technological services not only bolster the stability of commercial banks but also play a crucial role in mitigating credit risk, leading to a notable decline in non-performing loans (Banna & Alam, 2021). While a majority of bank customers utilize fintech services primarily for everyday transactions such as depositing and withdrawing funds, a smaller segment actively leverages these platforms to obtain loans (Hasan, Le & Hoque, 2021). Furthermore, innovative fintech solutions equip banks with sophisticated methods for conducting biological screenings, allowing them to accurately identify customers and prevent fraudulent activities. This enhanced security protects the integrity of banks' online products and ultimately contributes to a reduction in credit risk (Chen & Yang, 2019). Financial innovation theory has established a robust framework for the integration of financial technology within the banking sector. This theory posits that a primary driver for adopting innovative financial techniques is to foster growth and improve performance among commercial banks, ultimately leading to a sustainable competitive advantage. As financial institutions embrace technological advancements, they can systematically eliminate constraints that have historically limited their financial services. Through the adoption of various financial technology applications—ranging from automated credit scoring systems to advanced data analytics—banks can enhance their credit management processes.

These innovations not only streamline operations but also empower banks to meet rising credit demands effectively, adapting to customer needs in real-time (Sheng, 2021). Moreover, the strategic incorporation of financial technology allows commercial banks to optimize their risk assessment and decision-making processes, ensuring more efficient allocation of resources. This evolution illustrates how financial technology is not merely an addition to existing banking practices but a transformative force that reshapes the entire credit management landscape, significantly contributing to the overall business development and sustainability of commercial banks.

Research indicates that commercial banks in Kenya have increasingly embraced financial technology to enhance their banking services. Notably, statistics reveal that the credit sector has emerged as the most digitalized area within the banking industry. However, there has been limited focus in existing studies on the correlation between the adoption of financial technology and credit risk in these banks. This oversight has created a knowledge gap regarding how financial technology adoption impacts credit risk management in Kenyan commercial banks. This study aims to address and bridge this important knowledge gap.

### 1.1 Statement of The Problem

Credit risk has been on the rise in commercial banks in Kenya, leading to increased vulnerability within the financial sector compared to other economic sectors. This trend has resulted in a credit risk crisis that has diminished shareholders' wealth and attracted the attention of regulators, specifically the Central Bank of Kenya. As of 2023, Kenya's credit risk rating stands at 15.3%, an increase from 11.66% in 2018, placing the country eighth globally and above the global average of 10.9% in 2022. This high rating persists despite various interventions from the Central Bank of Kenya, which has implemented regulatory measures, policies, and guidelines aimed at curbing credit risk. These interventions include Credit Risk Management Guidelines, Non-Performing Loans

Guidelines, Credit Information Sharing Requirements, Interest Rate Policies, COVID-19 Response Measures, and the recently introduced Digital Lending Regulations. In response to these challenges, commercial banks have increasingly invested in technology to innovate and enhance their banking services. Currently, 81% of account holders are using mobile banking services. According to financial innovation theory, innovation can help improve efficiency and lower credit costs. While much of the existing literature has primarily focused on financial technology's role in improving access to banking services, there is a lack of studies examining its impact on credit risk. This study aims to bridge that gap by investigating the effect of financial technology adoption in commercial banks in Kenya.

**2. 1 Theoretical Literature Review**

The study was guided by financial innovation theory proposed by Silber (1983) based on the belief that the benefit expansion of money– related foundations is one of the essential reasons for financial innovation (Li & Zeng, 2010). He suggested that the critical reason behind financial innovation in financial services is to enhance growth and improve the performance of financial institutions (Blach, 2011). However, institutions always face some constraints in improving performance, including external pressure from the policy requirements and internal pressure such as management requirements and operational costs. These constraints promise management stability, but they also reduce the competitive advantage of the financial institutions. Therefore, the theory suggests that financial institutions will always strive to remove the constraints through financial innovation (Ndwiga & Maina, 2018). Financial innovation is an avenue on how commercials can design and adopt financial technology to explore effective credit risk management strategies. (Odhiambo 2022). Silber (1983) argues that institutional limitations, such as leadership style and management approaches, can interfere with bank performance, and the constraints can be eliminated through financial innovation technology. However, the theory discusses financial technology from the microeconomic viewpoint and eventually fails to demonstrate the financial technology from the increasing trend of behavioral finance (Junguna, 2013). The theory explains how commercial banks innovate new products, services and procedures that help to address the sector's inefficiencies as well as establish a competitive advantage. The theory provides a perspective to examine how financial technology adoption by commercial banks in Kenya is impacting the basic aspects of credit risk management and monitoring

**2.2 Empirical Review**

Banna & Alam (2021) investigated the impact of financial technology services on banking stability in Association of Southern Asian Nations (ASEAN) countries. The study used secondary unbalanced panel data from a random sample of 213 banks. The data was analyzed using principal component analysis, ordinary least squares, two-step dynamic systems generalized methods, and panel corrected standards error technique. The findings revealed that financial technology services accelerate bank stability by decreasing the level of default risk and eventually reducing the number of non-performing loans. Their study focused on the bank's stability using default risk and narrowed down on the role of mobile banking on credit risk management which was extensively examined in this study. Sheng (2020) examined the impact of financial technology on the ability of banks to offer credit to small and medium enterprises (SMEs) in China. Using secondary data from Chinese banks from 2011 to 2018, the study demonstrated that financial technology has a positive significant relationship with SMEs' credit access by facilitating the banking sector to supply credit facilities to SMEs. This study focused on using financial technology to enhance the capacity of banks to offer credits. The study failed to provide how such adoption will affect credit risk in commercial banks which remained to be an area that this study addressed.

Mohammed (2019) investigated the effect of financial technology, measured by mobile banking, on the financial performance of commercial banks in Kenya; the study employed a descriptive research design targeting a population of 43 commercial banks licensed by the Central Bank of Kenya. Using a random sampling technique, a sample of 305 employees was sampled, and primary data was collected by administering a structured questionnaire. In contrast, secondary data was analyzed from the Central Bank of Kenya publications, Communication Authority, and Kenya Bankers Association reports. The study found that financial technology has a significant relationship with financial performance, as measured by the uptake of digital credit. Therefore, banks should adopt a digital finance strategy to support their customers' credit access. Even though this study focused on financial performance, it did not provide a clear position on how credit risk impacts this performance when commercial banks employ financial technology in their operation; this study proposes to elaborate on how such adoption of technology will affect credit risk management in commercial banks.

Odhiambo and Mang'ana (2022) conducted a study to establish the relationship between the strategic adoption of technological innovations and competitive advantage in commercial banks in Kenya. Specifically, the study was to establish how the adoption of mobile banking affects competitive advantage. Their study adopted descriptive research design targeting a population of 43 commercial banks operating in Kenya; they utilized primary data that was collected using a semi-structured questionnaire that contained both closed and open-ended questions; the data was collected from the branch manager, head of the customer service, head of information technology and relationship officers comprising of 215 respondents. Using inferential analysis and descriptive statistics to analyze the data, they found that the adoption of mobile banking has a significant favorable influence on competitive advantage in commercial banks in Kenya, and banks should consider adopting mobile banking innovation technology to increase the overall reach of banking services. The study focused on adopting technology and how it impacts competitive advantage within the banking sector, as lending is one of the bank's core businesses. The study did not consider how such adoption would relate to credit risk in commercial banks, a gap that this study proposes to bridge. Chen et al. (2022) examined the potential financial technology risk to commercial banks in China; they collected secondary data from 19 systemically essential banks from 2011 to 2020. They used Z–score and non-performing loan ratio as a creation variable; they found out that financial technologies have a significant and positive influence on the deposit, loan business, and payment services, which increases competition pressure on commercial banks, leading to riskier behavior, which leads to an increase in financial risk. The study focused on how commercial banks respond to market pressure to define competition behavior that determines financial decisions made by the bank. At the same time, they did not consider how financial technology relates to credit risk, a topic worth exploring, which this study proposes to consider.

On the other hand, Leong (2017) examined the nurturing of the Financial technology ecosystem using a case of a youth microloan start-up in China, targeting a population of 300,000 college students, using primary data collected through in-depth semi-structured interviews from a sample of 16 staff and secondary data from the observation of financial information trend from the company archive, the study findings indicated that financial technology offers strategic capacity to enable consumers have alternative credit scores based on traditional data and transaction history of the user hence increases the credit worthiness of the user. This study focused on how adopting financial technology would enhance the repayment capacity of loans by examining the entire ecosystem within the financial technology in the education sector, and was not specific to mobile banking, which gave more weight among the commercial banks in Kenya. Despite the considerable emphasis on enhancing accessibility and expanding business opportunities, there remains a notable gap in the existing literature concerning the connection between financial technology adoption and credit risk. This lack of exploration is particularly significant, considering that credit risk is a fundamental challenge within the financial services sector. It has critical implications for institutional stability and the overall health of the economy.

## 3. Methodology and Results

This study adopted a longitudinal correlational research design. This design is concerned 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 37 commercial banks registered by the Central Bank of Kenya as of December 31, 2023. The study used secondary data from annually 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 and the 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-sectional dimensions, which necessitated a 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. The results are presented in the form of tables, and the analytical explanation has been attached to each table.

### 3.1 Research Model

Correlation analysis was used to test the variables to eliminate multicollinearity. 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 means and variances, which can indicate future trends. The logarithm was used to transform and normalize the data distribution in order to reduce the effects of outliers.

$$Y_{it} = \beta_0 + \beta_1 FNT_{it} + \beta_2 LNS_{it} + \beta_3 TCAR_{it} + \beta_4 LIQ_{it} + \beta_5 BZS_{it} + \beta_6 DEPFN_{it} + \epsilon_{it}$$

Where:

**$Y_{it}$** = Credit risk (dependent variable); measured by ratio of non-performing loans to gross loans

**FNT** = Financial Technology adoption (independent variable); measured by total number of mobile banking 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

$\epsilon$ = 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 technology is a product or service delivered through mobile phones, computers, the internet, or cards that are connected to a reliable digital payment system (Ozili, 2018). A transaction-based approach was used since it provides quantifiable dimensions that capture the true image of economic activity and involvement with financial services (Gupte, 2012). In addition, the number of mobile banking transactions also considers users' active participation in the banking services, and this corresponds to the World Bank'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* |
| Financial technology (FNT) | -10.0183 | 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 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 the normality assumption is required to conduct single or joint hypothesis tests about the model parameters. Findings of a study can only be generalized when residuals are assumed to be normally distributed (Gujarati, 2013). The most applied test for normality is the Jarque-Bera (JB) test. The results of the normality test are shown in Figure 3.2

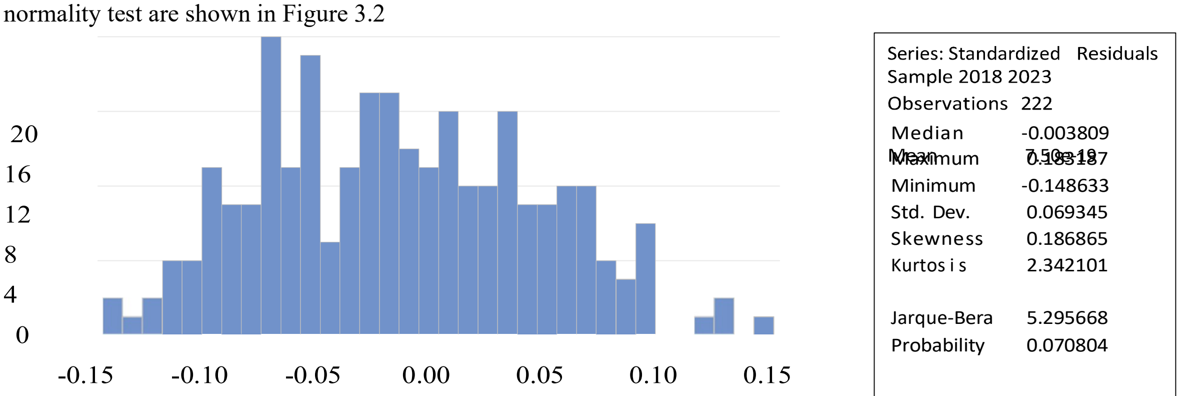


Figure 3.2: Results on the Test of Normality

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 0.070804, 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

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 | | 15.127458 | 6 | 0.0344 |
| Variable | Fixed | Random | Var (Diff.) | Prob. |
| FNT1 | -0.015739 | -0.015050 | 0.000022 | 0.8839 |
| LNS | -0.037170 | -0.072037 | 0.001839 | 0.4162 |
| TCAR | -0.009296 | -0.009966 | 0.000005 | 0.7587 |
| LIQ | -0.136718 | -0.216949 | 0.003368 | 0.1668 |
| BSZ | -0.032601 | -0.035049 | 0.000827 | 0.9322 |
| DEPFN | -0.631601 | -0.582494 | 0.008256 | 0.5889 |

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

**Source: Field Data, 2025**

In Table 3.2, the Hausman test results show a chi-square 11.127458 with a significant p value of 0.0344 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** | **Uncentered VIF** | **Centered VIF** |
|---|---|---|---|
| C | 0.08204 | 23772.69 | NA |
| LNS | 0.00325 | 296.2184 | 1.547500 |
| TCAR | 9.74006 | 1.152476 | 1.070828 |
| LIQ | 0.00157 | 45.52918 | 2.153425 |
| BSZ | 0.00011 | 20966.20 | 1.354502 |
| DEPFN | 0.00642 | 1040.253 | 1.550419 |
| FNT1 | 4.48005 | 1.118439 | 1.118356 |

**Source: Field Data, 2025**

As shown in Table 3.4, the centered VIF values for the regression equations in the model is much lower than 10, with the highest being 2.153425. 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 a heteroskedasticity 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). The 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**

| | |
|---|---|
| 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 three models are less than 1% which shows statistically significant results; therefore, the null hypothesis was strongly rejected and the alternative hypothesis accepted. This confirms the existence of heteroskedasticity, which paved the way for the adoption of GLS.

### 3.2.6 Autocorrelation Test

An autocorrelation test was conducted to establish whether residuals are correlated across time. The Regression analysis assumption requires that residuals should not be correlated across time; hence, the Durbin-Watson 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 | FNT | LNS | TCAR | LIQ | BSZ | DEPFN |
|---|---|---|---|---|---|---|---|
| Mean | 0.186666 | 17.74588 | 0.559176 | 0.170078 | 0.308399 | 24.76309 | 0.746825 |
| Median | 0.144118 | 17.79662 | 0.584246 | 0.143154 | 0.261836 | 24.49397 | 0.761774 |
| Maximum | 0.761985 | 18.31455 | 1.419064 | 8.491481 | 1.305179 | 27.98545 | 0.981979 |
| Minimum | 0.003752 | 16.85786 | 0.160912 | -0.567858 | -0.475568 | 21.78181 | 0.165981 |
| Std. Dev. | 0.148525 | 0.327677 | 0.205644 | 0.568538 | 0.214565 | 1.371786 | 0.110791 |
| Skewness | 1.908317 | -0.748020 | 0.675096 | 14.20192 | 1.271858 | 0.303839 | -2.128691 |
| Kurtosis | 6.878078 | 2.993805 | 5.097111 | 208.6266 | 7.692124 | 2.172190 | 10.47308 |
| Jarque-Bera | 273.8572 | 20.70312 | 57.54325 | 398574.0 | 263.5003 | 9.754501 | 684.2436 |
| Probability | 0.000000 | 0.000032 | 0.000000 | 0.000000 | 0.000000 | 0.007618 | 0.000000 |
| Sum | 41.43990 | 3939.585 | 124.1370 | 37.75728 | 68.46457 | 5497.407 | 165.7952 |
| Sum Sq. Dev. | 4.875179 | 23.72931 | 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 show that, across the banks and over the years, credit risk is concentrated at 0.18667, with individual ratios varying from the mean by 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 for technology (fintech) adoption, measured by number of mobile transactions (FNT), has a mean of 17.74588, a maximum of 18.31455, and a minimum of 16.85786, with a moderate skewness of -0.748020. This also indicates the potential for more mobile banking transactions in commercial banks.

**Table 4.1 Trend Analysis on Credit Risk**

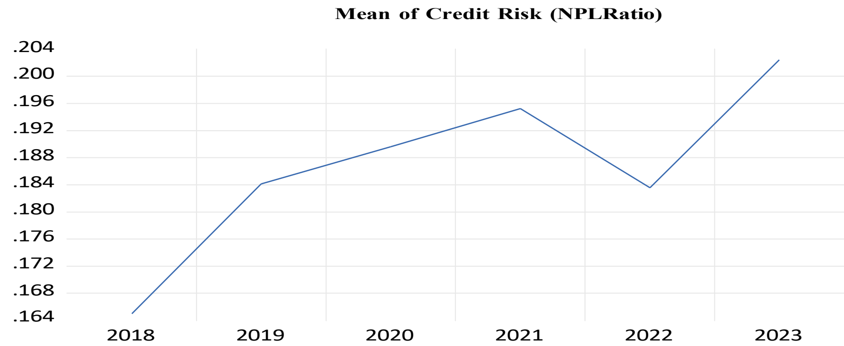


**Figure 4.1: Trend of Credit Risk**
**Source: Field Data, 2025**

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 of Financial Technology (FinTech) Adoption

The trend of the independent Variable Fintech adoption was presented in Figure 4.3 below

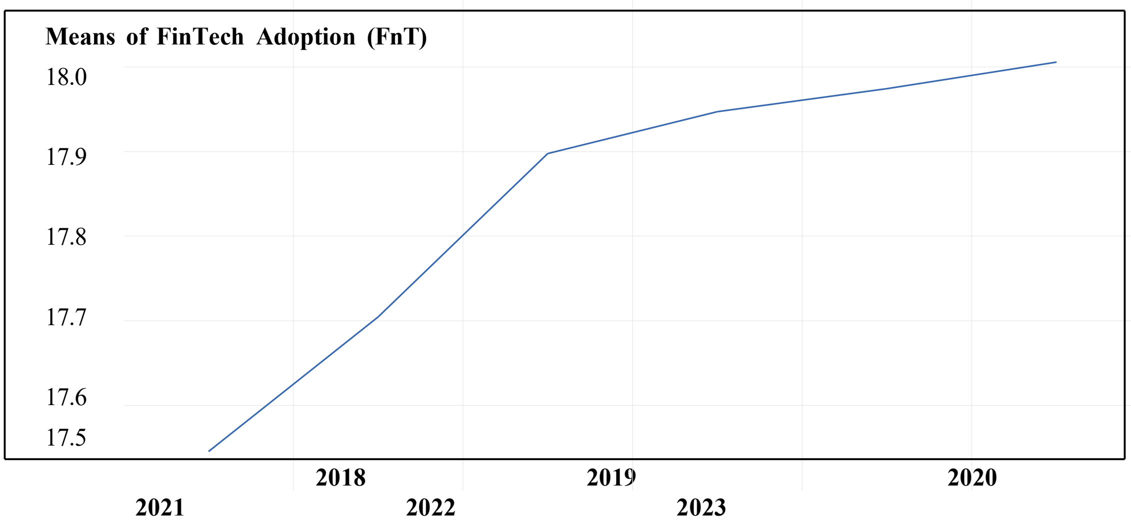


**Figure 4.2: Trend of Financial Technology**

**Source: Field Data, 2025**

Figure 4.2 indicates that the mean of Fintech adoption has been on an increasing trajectory during the period of the study, with a steep gradient of increase from 2018 to early 2020, which pictures the early stages of Fintech adoption in commercial banks. that could be interpreted to reflect different interventions employed by commercial banks during the period of the COVID-19 pandemic, during which there were sustained investments in digital financial services as the pandemic restricted traditional banking services. Thereafter, Fintech adoption continued to increase in 2021 to 2023, which suggests that digital transformation has continued to be a priority across the banking sector and that it was not just a short-term measure for the COVID-19 response, a trend that is consistent with the global banking trends on digitalization transformation and adoption

**4.2 Inferential Statistics**

The inferential statistics were from the multiple regression conducted to test the research hypothesis on the study objective**,** which aimed to establish the relationship between financial technology adoption and credit risk. The null hypothesis**, Ho,** was formulated that there was no statistically significant relationship between financial technology adoption 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 variables (Financial Technology adoption, FNT 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.

**Regression Results on the relationship between Financial Technology Adoption and Credit Risk**

**Tables 4.2: Relationship between financial technology adoption and credit risk**

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.642564 | 0.286437 | 2.243297 | 0.0261 |
| FNT1 | -0.002521 | 0.006692 | -0.376804 | 0.7068 |
| LNS | -0.047736 | 0.057031 | -0.837011 | 0.4037 |
| TCAR | -0.004940 | 0.003121 | -1.582620 | 0.1153 |
| LIQ | -0.020312 | 0.039674 | -0.511979 | 0.6093 |
| BSZ | -0.009894 | 0.010863 | -0.910801 | 0.3636 |
| DEPFN | -0.237177 | 0.080171 | -2.958396 | 0.0035 |
| R-squared | 0.859695 | | | |
| Adjusted R-squared | 0.825801 | | | |
| S.E. of regression | 0.077268 | | | |
| F-statistic | 25.36431 | | | |
| Prob(F-statistic) | 0.000000 | | | |
| Durbin-Watson | 1.404898 | | | |

***Represent significance at the 0.05 level**

**Source: Field Data, 2025**

Table 4.2 The results from Table 4.3 show that there is an insignificant negative relationship between adoption of financial technology and credit risk ($\beta = -0.002521$, $p = 0.7068$). This signifies that a one-unit increase in adoption of financial technology leads to an insignificant 0.2521% decrease in credit risk. Low credit risk implies reduced non-performing loans. One possible explanation for why the direct relationship between adoption of financial technology and credit risk performance is negative and insignificant could be due to incomplete digital transformation, since different commercial banks have different technological capabilities and approaches to technology integration in their banking services. This viewpoint was addressed in the theoretical assumption of the technology adoption lifecycle theory (Rogers,2003). Depending on how commercial banks adopt technology, each commercial bank has different risk management processes with different risk offsetting dynamics (Philippon, 2016).

The possible reasons as to why the direct relationship between adoption of financial technology and credit risk is negative could also be due to regulatory challenges of fintech adoption in the banking sector, which has been an ongoing discussion ever since the launch of the mobile money platform M-Pesa, which has dominated the local money transfer for some time. This resonates so well with a report by Didenko (2017) a review of the regulatory challenges underlying fintech in Kenya, this reports posed a clear indication to have mobile money separated from the communication authority be established under the banking act and it has remained an outstanding a challenge to locate mobile money business withing the existing regulatory framework and this has also been driven by rapid growth of technology that challenges Central bank of Kenya to respond to the change in a timely manner and there exist no clear way on the existence of a pro-active approach to Fintech adoption. This regulatory position was supported by the study by Gong (2023) that found out that despite commercial banks paying more attention to fintech adoption, banks need to establish a stable regulatory framework to guide fintech in the banking sector.

## 5. Conclusion and Recommendation

Based on the findings of the study, it is recommended that commercial banks take deliberate and strategic steps to accelerate the development of a comprehensive digital infrastructure that facilitates the banking process from initiation to completion. This means moving away from partial implementations that create administrative inefficiencies, such as segmented systems that fail to communicate effectively with one another, leading to potential delays and errors in service delivery. Moreover, commercial banks should establish robust technological adoption policies that align closely with existing regulatory frameworks. This alignment is crucial to ensure that investments in technology are not only financially sound but also enhance the bank's ability to manage credit risk effectively. Adopting technologies without a clear understanding of their impact on credit risk management could expose banks to unforeseen vulnerabilities. In addition, the Central Bank of Kenya should take proactive measures to develop a regulatory framework that standardizes digital banking infrastructure. Such a framework would provide essential guidelines and standards that support the adoption of financial technologies, thereby promoting consistency and reliability across the banking sector. By creating an environment that fosters impactful operational efficiency in credit risk assessment, the Central Bank can help ensure that financial institutions can adequately assess and manage their risk exposure in an increasingly digital landscape. This coordinated effort will ultimately contribute to the stability and resilience of the banking sector as it embraces technological advancements.

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