REVIEWED JOURNAL of INTERNATIONAL Financial Management [ISSN 2663-127X]

Vol. 7, Iss. 1 (2026), pp. 151 - 163, July 14, 2026. www.reviewedjournals.com, ©Reviewed Journals

CREDIT RISK AND OPERATIONAL PERFORMANCE OF COMMERCIAL BANKS LISTED AT THE NAIROBI SECURITIES EXCHANGE IN KENYA

[1] Nyandege, J. O., [2] Kimani, E. M. & [3] Teimet, P. R.

Student, MSc in Finance, Jomo Kenyatta University of Agriculture and Technology, Kenya
Senior Lecturer, Jomo Kenyatta University of Agriculture and Technology, Kenya
CIA - Jomo Kenyatta University of Agriculture and Technology, Kenya

Accepted: June 30, 2026

ABSTRACT

This study sought to investigate how credit risk affects the operational performance of commercial banks listed on the Nairobi Securities Exchange (NSE) of Kenya between the years 2015 and 2024. This research was prompted by the consistent high levels of Cost to Income Ratio (CIR) that have been recorded in the banking industry of Kenya above the global standards of 40-55% while also recording high levels of non-performing loans above 14%. Based on the Credit Rationing theory, the research used a descriptive research methodology using the census approach targeting all 11 commercial banks listed on NSE. Panel secondary data were collected from the audited annual financial statements and analysed using the Statistical Package for Social Sciences (SPSS 25.0). Descriptive statistics indicated that the average proportion of expenses from operations was 53.9% of the operating income, while the average value of credit risk was 11.4% with minimal variations throughout the analysed period. Trend analysis results show a non-linear trend in both studied variables including the presence of the disruptions associated with the period of the COVID-19 pandemic. The results of correlation analysis reveal a statistically significant relationship between credit risk and CIR ($r = 0.388$, $p < 0.001$). The results of panel regression analysis prove that the credit risk significantly affects CIR positively ($\beta = 0.4358$, $t = 4.350$, $p = 0.000$) and accounts for 15.05% of the operational efficiency variation ($R^2 = 0.1505$), whereas the whole model proves its significance ($F = 19.124$, $p = 0.000$). These results demonstrate that growing NPLs negatively impact operational efficiency of banks via the "double penalty" effect through increasing the cost of provisions and reducing interest income.

Keywords: *Credit Risk, Operational Performance, Cost-To-Income Ratio, Non-Performing Loans, Commercial Banks, Nairobi Securities Exchange*

CITATION: Nyandege, J. O., Kimani, E. M. & Teimet, P. R. (2026). Credit risk and operational performance of commercial banks listed at the Nairobi Securities Exchange in Kenya. *Reviewed Journal International of Financial Management*, 7 (1), 151 – 163.

BACKGROUND OF THE STUDY

According to Greuning and Iqbal (2007) operational performance is a significant factor in the sustainability and competitiveness of banks, especially during periods of fluctuating interest rates, unpredictable equity prices, and levels of credit and liquidity constraints. Declining operational performance may be attributed to exposures to credit risk. In contrast, a bank with relatively good performance presents as having achieved effective risk management, sound lending practice, or making best use of its assets. Because of the regulatory pressures on listed banks, as well as market scrutiny from investors, operational performance is additionally important because it not only influences investor confidence but also relates to the overall stability of the financial system (Allen & Gu, 2018).

Operational performance indicates a bank's capacity to manage its available resources to maximize income generation while limiting its operating costs (Lotto, 2018). operational performance is represented using the Cost to Income Ratio (CIR) in this study, which is a widely recognized efficiency indicator for banks. The CIR ratio is determined by the ratio of a bank's operational activities to its operating income, which shows how much it costs a bank to earn income from its activities. The lower the CIR ratio the better as this means that the bank can earn more in income for each shilling of cost (Odunga, 2016). By focusing on the Cost to Income Ratio as the metric, the study aimed to examine how credit risk might affect operational performance of a bank.

Credit risk describes the situation where a borrower or counterparty does not meet its obligations in accordance with agreed terms and, as a result, causes a loss for the bank (Witzany, 2017). Credit risk remains an important risk within the financial services industry, as lending is a primary function of the commercial banking business and can be an inherent risk factor. Defaults on the repayment of loans produces non-performing loans (NPLs) in the bank’s loan book, which could increase credit risk and may not only compromise the financial performance of the bank but also jeopardise the operational performance of the bank (Putra et al., 2024). Credit risk can be associated with poor credit appraisal from an underwriter, inadequate collateral, changes in the economic climate, weakness in internal controls (Naili & Lahrichi, 2022). Credit risk is expected to demonstrate a negative relationship with operational performance.

Statement of the Problem

A properly functioning banking system demonstrates operational strength through efficiency metrics like Cost-to-Income Ratio (CIR). Effective banks around the world achieve CIR levels of between 40-55%, the highest-performing banks are operating CIRs of below 45% (European Banking Authority, 2024). With a low CIR ratio, banks are able to generate income at less than their operational costs, which is an indicator of efficiency, profitability, and long-term stability (Burger & Moormann, 2008). Being towards the threshold of a global benchmark enhances bank competitiveness while contributing to sustainable economic growth through a consistent supply of credit and increased confidence among investors. Commercial banks listed on the NSE have exhibited a distinct inefficiency and volatility in operational performance (Muriithi & Muigai, 2017). Recently released data from the industry indicates that the CIR for the entire banking sector also continues to remain significantly above global levels, as evidenced by the Kenya Bankers Association reporting a CIR of 56.7% for 2022, an increase to 64.2% for 2023, and a slight decline to 61.0% for 2024. This elevated status in the CIR that the banking sector faces indicates that Kenyan banks now face increased operational costs, greater variability in net interest margins (Kenya averaging 7–8% versus 3–4% globally), high non-performing loans (over 14% for the recent years), as well as liquidity mismatches. These aforementioned factors collectively present a challenging scenario for increased efficiency, reduced profitability, and increased exposure from financial shocks. A high CIR also continuously undermines shareholder value and decreases the available supply of credit in a country that ultimately reduces investment and capital growth (Gupta & Mer, 2023). Across these observations, a number of research gaps have been identified. There is a conceptual gap in that previous literature on profitability and return ratios has not fully incorporated the efficiency dimensions of digital innovation and customer responsiveness into the conception of CIR. There is a contextual gap as the vast majority of the studies were conducted in developed economies and provide little specificity to Kenya considering Kenya's diverse regulation and market conditions. A methodological gap has been identified, as most local studies have relied on either descriptive designs or qualitative designs as opposed to rigorous quantitative modelling. An empirical gap has been identified in newer studies assessing CIR in listed Kenyan banks in the current regulatory environment and in the wake of fintech's transformative effect. Finally, a theoretical gap remains in that much of the research has not been grounded in robust financial theories. This study aims to address these gaps quantitatively by examining factors associated with CIR in Kenyan banks using the credit rationing theory

Objective of the Study

The objective of the study was to examine the effect of credit risk on the operational performance of commercial banks listed at the Nairobi Securities Exchange, Kenya.

LITERATURE REVIEW

Theoretical Review

The study was underpinned by the credit rationing theory.

Credit Rationing Theory

Credit rationing theory, created by Stiglitz and Weiss in 1981. The theory argues that a bank cannot simply increase interest rates to establish the equilibrium in demand and supply of credit since higher rates will attract riskier borrowers (adverse selection) and will probably influence borrowers to engage in risky activities (moral hazard). Therefore, banks will typically ration credit or cap the loan amount or deny some applications, before establishing defaults to mitigate the consequences on their loan portfolio. The theory posits that poor rationing exposes banks to high-risk borrowers which can result in increased NPLs levels (Stiglitz & Weiss, 1981).

The theoretical assumptions especially the presence of information asymmetries and that interest rates cannot alone correct credit imbalances fit into the Kenyan banking sector quite well (Muli, 2017). Borrowers upon receipt of funds are often better informants of their financial state of affairs and projects than lenders. Therefore, banks risk adverse selection if rationing of credit is not appropriately applied. Were and Wambua (2014) state that the Kenyan market environment is constantly under pressure from fluctuating interest rates, currency depreciation and inflationary price pressures, thus increasing the likelihood of loan defaults and making credit rationing more of a relevant risk management tool.

The theory provides a powerful lens to think about the relationship between operational performance and commercial banks' credit risk. The theory establishes that a bank's quality management of credit allocation will directly have an impact on a bank's loan portfolio quality (Ssekiziyivu et al., 2017). In Kenya, this theory is still very applicable because it illustrates how banks continually search for the right balance to lend based on risk constraints and asymmetric information. However, it must also be recognized that the banking landscape is evolving with bank operations utilizing alternative means of lending. Credit Rationing Theory explains that increased credit risk from information asymmetry and poor loan quality reduces bank performance by raising the cost-to-income ratio (Odhiambo, & Ndede, 2019).

While the theory is powerful, it has limitations in the contemporary banking context. Brighi and Mussoni (2025) critique on the theory as it assumes the only means of controlling credit risk is through interest rate adjustment and rationing. It assumes a rudimentary model and does not allow for the use of modern tools such as credit scoring systems, collateral-based lending, and the regulatory requirements imposed on banks by the central banks prudential guidelines and Basel two and three standards. In addition, the incorporation of technological innovations in banking now allows customers to access information and reduce the impact of information asymmetry. Furthermore, competition among NSE-listed banks may create incentives to not ration as much to take up market share or develop a broader customer base.

Empirical Review

Isanzu (2017) studied credit risk influence on financial performance of five big Chinese commercial banks in the period from 2008 to 2014. Using secondary data and balanced panel regression analysis. Return on assets served as the indicator of financial performance. Credit risk was represented through non-performing loans, capital adequacy ratio, loan impairment reserve, and loan impairment expense. The analysis indicated that there was a significant correlation between non-performing loans and capital adequacy ratio and financial performance. The growing number of non-performing loans linked to poor ROA performance indicated the negative influence of credit risk ore profit and the need for adequate capital. Nevertheless, the investigation was limited with a small scale of samples and range of risk factors considered.

Muriithi et al., (2016) investigated the relationship between credit risk and financial performance of 43 banks operating in Kenya between 2005 and 2014. The study utilized secondary data obtained from the financial statements of the banks. credit risk was calculated according to the capital versus risk-weighted assets ratios. The study employed the techniques of panel data analysis, such as estimation through fixed effects and the Generalized Method of Moments (GMM). The pairwise correlation coefficients, F-statistics and coefficient of determination were computed as part of the evidence for the validity of the model. The results showed that credit risk greatly impacted the profitability of banks as there were many non-performing loans and poor quality of assets. The study did not take consideration on macroeconomic and qualitative risks.

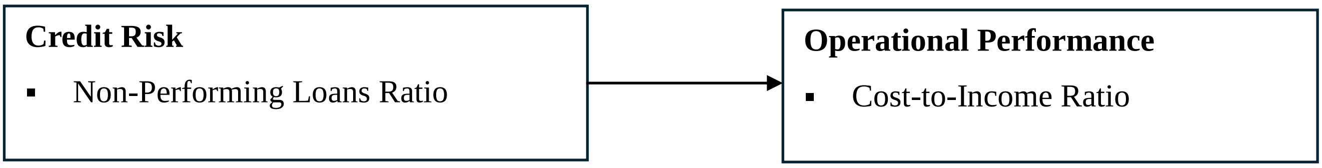
Ekinci & Poyraz (2019) investigated the effect of credit risk on financial performance of twenty-six commercial banks functioning in Turkey within the period of 2005-2017. Statistical reports of the Banks Association of Turkey were utilized to collect secondary data. The selected banks were divided into three categories of banks depending on their ownership: State-owned, Private and Foreign. The study applied panel data analysis method. Financial performance was measured with the use of ROA and ROE, whereas NPLs were used to measure credit risk. The results obtained showed the existence of the statistically and economically significant negative relationship with ROA and ROE, which means that high levels of NPLs negatively impact the bank performance. Although the study directly connects NPLs with profitability and stresses the importance of proper credit risk management, it does not provide any insight into the possible influence of other factors and differences among the banks.

Mwangi (2012) researched on the effect of credit risk management on financial performance of 26 commercial banks in Kenya. The study covering the years 2007 through 2011. The study follows a descriptive research design and analyses secondary data by using regression method. The results demonstrate that the relationship between risk management and profitability holds substantial relevance, with the ratio of non-performing loans negatively affecting return on equity more than capital adequacy ratio. Nevertheless, due to the narrow scope of metrics that have been researched by the scholar and short timeframe of five years, the impact of broader macroeconomic factors cannot be assessed.

Otieno et al. (2017) assessed the influence of credit risk management on financial performance in microfinance banks (MFBs) in Kenya, from the period 2011-2015. This study used a longitudinal research design using the panel data of 6 purposively selected microfinance banks from a population of 12 licensed microfinance banks. The study utilised both secondary and primary data. The secondary data was analysed using descriptive statistics and Pearson correlation while the primary data analysed using multiple regression analysis. The research observed a significant inverse connection between a portfolio that has some exposure to potentially defaulted loans (Portfolio at Risk) and the amount of reserve set aside (loan losses) as well as the resulting average financial results through Return on Average Assets and Return on Average Equity. By lacking control for external economic factors that may affect performance and a utilizing a small sample size and a short time frame the study is limited.

Conceptual Framework

The conceptual framework illustrates the relationship between credit risk and operational performance of commercial banks listed on the NSE.



Independent Variable **Dependent Variable**

Figure 1: Conceptual Framework

METHODOLOGY

This section provides the methodological framework adopted to examine the effect of credit risk on operational performance of commercial banks listed on NSE, Kenya.

Research Design

The research employed descriptive research design. Descriptive design fit this study as it enabled the employment of quantitative data to investigate the relationship between credit risk factors and operational performance.

Population of the Study

The study comprised all the 11 commercial banks listed at the NSE and operational from 2015 to 2024. The population was appropriate since it faced credit risk and is required by law to provide audited financial reports which ensure the data is analysed, available and was therefore deemed reliable for the study. The rationale for selected listed commercial banks was that they operate in a tightly regulated financial environment, they are subject to credit risk, and their operational performance can be objectively determined via published financial reporting (CBK, 2023).

Census Study

In this study, the census consisted of all the 11 banks listed under the banking sector of the NSE as of December 2024.

Data Collection Instruments

The research utilized a secondary data collection sheet. The data was collected from banks' financial available from their published financial reports, which were publicly available via their official websites and annual reports. These reports included the information necessary to calculate the financial ratios that indicated credit risk and operational performance. The use of secondary data method relates to cost, time, prior to the study, and as a secondary data methodology (Taherdoost, 2021). The secondary data collection ensured consistency, reliability, credibility, and quality since the data comes from audited, expected, and verified external sources.

Data Collection Procedure

The researcher first obtained a letter of introduction from Jomo Kenyatta University of Science and Technology before proceeding to the data collection stage. The researcher created a comprehensive list of all the commercial banks listed on the Nairobi Securities Exchange during 2015–2024. Data was obtained from the annual financial statements of each of these banks via either the individual banks' official websites, CBK or the NSE database.

Data Processing and Analysis

Data processing entailed cleaning, sorting, coding, transforming, and organizing raw data to conform to research requirements, whereas data analysis comprised finding patterns in the data analysed. Secondary data gathered from the audited financial statements and investment reports of the eleven listed banks were screened for their reliability, validity, and integrity before being coded and inputted into SPSS 25.0 for further analysis. The descriptive statistics technique was used to analyse and describe the data through measures such as mean, frequency, standard deviation, and variance. The inferential statistical test was then conducted to find correlations and relationships between variables and make generalizations about the data. Correlation analysis was used to investigate the relationship between variables, whereas panel regression analysis was conducted to investigate the influence of credit risks on operational performance. The findings from panel regression were presented in tabular form. The panel regression was modelled as:

$$\mathbf{Y = \beta_0 + \beta_1 X_{1it} + \varepsilon_{it}} \text{ …………………. } \textbf{Equation 1}$$

FINDINGS AND DISCUSSION

This chapter presents the empirical findings, statistical analysis, interpretation, and discussion of data collected.

Descriptive Statistics

Descriptive analysis was performed in order to determine the measures of central tendency and dispersion of the variables being investigated. The statistics are presented in Table 1.

Table 1: Descriptive Statistics

	N	Min	Max	Mean	Std. Deviation	Variance
Operational Performance	110	.3360	.9142	.5391	.0994	.010
Credit Risk	110	.0586	.1856	.1144	.0280	.001

Table 1 shows the descriptive statistics for the variables used in the study based on a balanced panel data set consisting of 110 observations. The descriptive statistics provide information about the distributional properties of the variables using measures of central tendency and dispersion. Operational Performance had its minimum and maximum values as 0.336 and 0.914 respectively. From the minimum value, it can be noted that there were operations where the listed commercial banks incurred lower operational costs compared to their generated income, while from the maximum value, there were operations where banks incurred much higher operating costs than their incomes. On average, the listed commercial banks invested 53.9% of their operating income on operational activities since its mean value was 0.539. Relatively low standard deviation value of 0.099 shows little dispersion from the mean, hence showing that despite being different, there was little variation in performance of operations by listed commercial banks.

Credit Risk had a minimum of 0.059 while a maximum of 0.186 was observed signifying variation in the quality of the loan portfolio of different commercial banks. With an average value of 0.114, it is clear that the credit risk level stayed within manageable limits for the entire period of analysis. A standard deviation of 0.028 implies low degree of variation around the average value. It is also evident from the variance value of 0.001 that there were no significant fluctuations in credit risk over time.

Trend Analysis

To examine the movement and directional behaviour of the variables over the study period trend analysis was conducted.

Trend Analysis for Operational Performance

The study established the trend analysis for operational performance. The result is shown in Figure 2.

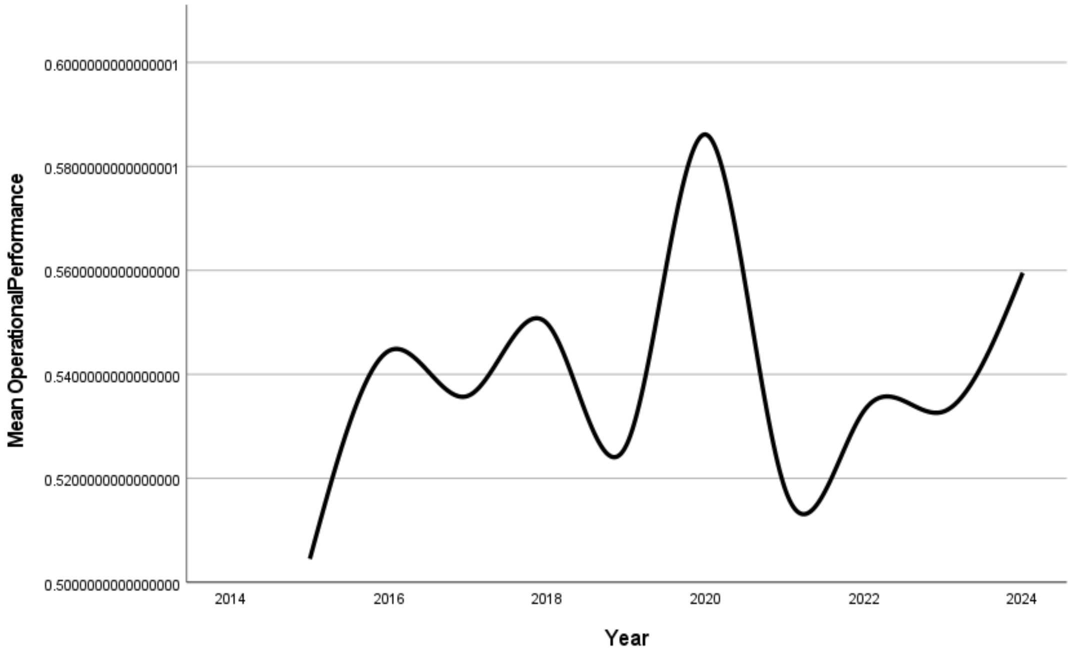


Figure 2: Trend analysis for operational performance.

The trend in the operational performance (CIR) for the studied period is illustrated in Figure 4.1, and it reveals a non-linear trend. CIR begins at a relatively low and favourable value in 2015 and increases steadily, meaning that the company experiences the decline in operational efficiency up to 2020 when it reaches its peak and the least favourable value. After 2021, CIR decreases steadily until 2024, reflecting the continuous improvement in operational efficiency. Such a decline before 2020 could be explained by the structural disturbances in the banking industry due to the emergence of the COVID-19 pandemic; namely, as a result of digitalization and operational transformations, commercial banks faced certain shifts in their cost structure and were unable to generate revenues due to the disruptions caused by the pandemic.

Trend Analysis for Credit Risk

The study established trend analysis for credit risk. The result is shown in Figure 3.

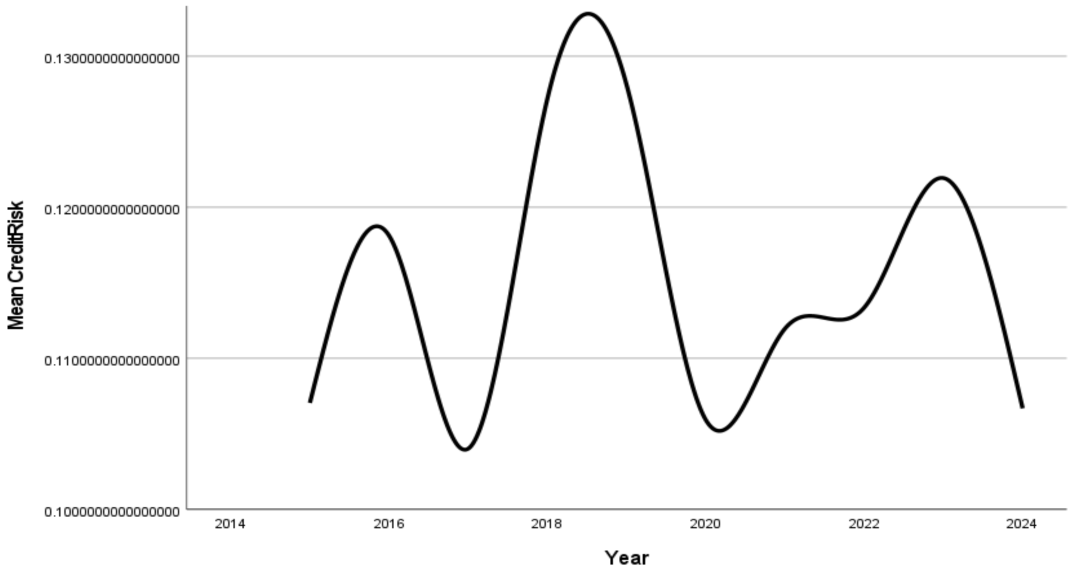


Figure 3: Trend analysis for credit risk

The pattern of credit risk reflects a growing trend since 2017 as shown in Figure 3, but with higher levels of credit risk around 2018 and 2019, while dropping in 2020. Since then, there have been fluctuations with a slow but steady upward trend till 2023 and another drop in 2024. The growing trend in the years prior to 2020 may be linked with poor quality of assets as well as the high rate of non-performing loans within the banks. The drop in 2020 is in line with the impact of certain policies that were adopted during the COVID-19 period. These included loan restructuring, payment suspension, and temporary regulatory forbearance. This helped control the rise in credit risk.

Inferential Statistics

Inferential statistics involved carrying out correlation analysis, regression analysis, ANOVA, coefficients of determination, and hypothesis testing.

Correlation Analysis

To determine the strength and direction of the relationship between the independent variable and the dependent variable correlation analysis was conducted as presented in Table 2.

Table 2: Pearson Correlation Matrix

Variables	Operational Performance	Credit Risk
Operational Performance	1.000 (0.000)	
Credit Risk	0.388*** (0.000028)	1.000 (0.000)

**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Table 2 shows the direction and degree of the linear association between operational performance and credit risk. These findings serve as initial insights into the nature of the association between changes in credit risk and operational performance of the listed commercial banks.

There exists a positive and statistically significant relationship between Credit Risk and Operational Performance as evidenced by CIR ($r = 0.388$, $p = 0.000028$). In this case, a low CIR represents high operational efficiency. This means that a positive relationship between Credit Risk and CIR implies that increasing credit risk results in decreasing rather than improving operational efficiency. These results support the hypothesis of this study and the Credit Rationing Theory. In this regard, declining loan portfolio quality due to asymmetric information and poor credit evaluation leads to high cost compared to income. This weak relationship ($r = 0.388$) will be explored further using panel regression in the next section.

Panel Regression for Credit Risk and Operational Performance

Regression analysis was performed to determine the effect of the credit risk on operational performance. The findings are illustrated in Table 3.

Table 3: Panel Regression Results

Variable	Coefficient (β)	Standard Error	t-Statistic	p-Value
Constant (Intercept)	0.5142	0.0245	20.988	0.000
Credit Risk	0.4358	0.1002	4.350	0.000
Model Fit & Diagnostic Statistics				
R-squared	0.1505			
Adjusted R-squared	0.1426			
F-Statistic	19.124			
Prob (F-Statistic)	0.0000			
Number of Observations (N)	110			

Table 3 shows the structural impact of the credit risk degeneration on the operating efficiency of commercial banks quoted on the Nairobi Stock Exchange (NSE) was estimated through an unadjusted bivariate panel regression model aimed at establishing the baseline transmission effect of asset quality on the bank's Cost-to-Income Ratio (CIR). According to the empirical findings of this panel regression analysis, the coefficient of Credit Risk is positive and statistically very significant at the 1% level of confidence (β=0.4358, t=4.350, p=0.000). In particular, this coefficient shows that any 1% increase in the NPL ratio results in a 0.4358% increase in the Cost-to-Income Ratio of the bank. Since the increasing CIR represents a structural decrease in profit efficiency, this positive coefficient shows a structural adverse relation in which the rising credit risk leads to poor performance. Moreover, the structural intercept is established at 0.5142 and is statistically highly significant (t=20.988, p=0.000), showing that in case the commercial firms quoted achieve absolute credit optimization or have a zero NPL ratio, then the Cost-to-Income Ratio would be fixed at 51.42%.

Assessing the global measures of fit, we can conclude that the model produces a Coefficient of Determination (R^2) equal to 0.1505 and hence indicates that the variable Credit Risk taken into consideration as a standalone independent factor contributes up to 15.05% of all variances in the performance of the studied banks. The slight adjustment in the value of Adjusted R^2 to 0.1426 compensates for the loss of the degree of freedom in the panel setting and also suggests that the single regression model remains reliable in its forecasting potential over all 110 observations. Lastly, the explanatory power of the model is confirmed through the value of the global F-statistic equal to 19.124 in combination with the vector of the exact probability being 0.0000. Since this global probability value is considerably lower than the conventional 1%, the model rejects the global null hypothesis (H_0: β_1=0), thereby indicating that the model configuration is theoretically sound and that Credit Risk has some predictive impact on the efficiency of the banks over the analysed 2015–2024 period.

One thing to note is that, even though Credit Risk is statistically significant, it only explains 15.05% of the variation in CIR across the panel. In effect, 85% of the operational performance differences between the banks listed on the NSE are due to other determinants which fall outside the purview of the above bivariate analysis, like interest risk, equity risk, liquidity risk, size of bank, efficiency of management, and economic conditions. This is true of the study's specific scope to consider credit risk as a separate predictor variable, and the need for multivariate modelling.

Analysis of Variance (ANOVA)

The Analysis of Variance (ANOVA) was executed to test the global significance of the isolated linear specification, checking whether the variation explained by the Credit Risk parameters is significantly greater than the unexplained residual variation. The results are shown in table 4.

Table 4: ANOVA Results

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Square (MS)	F-Statistic	Sign. (p-value)
Regression (Explained)	0.2538	1	0.2538	19.124	0.0000***
Residual (Unexplained)	1.4332	108	0.0132		
Total	1.6870	109			

The total variability in the panel data is split into the explained part, which is denoted as the Regression Sum of Squares (0.2538), and the unexplained part, denoted as the Residual Sum of Squares (1.4332), with 108 residual degrees of freedom (N-k-1). The corresponding global empirical F-statistic equals to 19.124, while its exact p-value is 0.0000. Since this p-value is significantly less than the critical value at the 1% significance level ($p < 0.01$), the global null hypothesis regarding the slope being equal to zero (H0: β1 = 0) is rejected. Thus, from a purely mathematical point of view, the stability of the structural equation is confirmed and, therefore, Credit Risk is found to be a predictor for the performance criteria of the chosen financial firms within 2015-2024.

Regression Coefficient Results

The specific localized parameters generated by the panel regression estimation determine the directional velocity and statistical weight of Credit Risk on the structural operational costs of listed banks. The results are shown in table 5.

Table 5: Panel Regression Coefficients Matrix

Variable	Coefficient (β)	Std. Error	t-Statistic	p-Value	95% CI Lower	95% CI Upper
Constant	0.5142	0.0245	20.988	0.000	0.4656	0.5628
Credit Risk	0.4358	0.1002	4.350	0.000	0.2372	0.6344

Operational Performance (CIR)=0.5142+0.4358(Credit Risk) +εit …. Equation 2

The estimated slope coefficient for Credit Risk equals 0.4358. It means that every increase of 1 percent in the level of NPL ratio results in an increase of 0.4358 percentage in the Cost-to-Income Ratio (CIR) of the bank. The coefficient is statistically highly significant ($t = 4.350$; $p = 0.000$).

The structural intercept (α) is 0.5142 and is statistically highly significant ($t = 20.988$; $p = 0.000$). It means that if the commercial institutions were able to eliminate the default risk completely (Credit Risk = 0%) by implementing absolute credit optimization strategy, the structural baseline Cost-to-Income Ratio would be equal to 51.42%.

Hypothesis Test Result

Since the empirical p-value of the Credit Risk coefficient is 0.000 ($p<0.01$), the Null Hypothesis (H_0) is therefore rejected at a 5% and more conservative 1% level of significance. As such credit risk has a structurally significant impact on the performance operations of commercial banks quoted on the Nairobi Securities Exchange. On an academic front, the positive coefficient of 0.4358 captures the operational cost incurred as a result of default by customers on loan repayment. Loan portfolio deterioration and non-performing assets re-classification as delinquent assets according to CBK prudential requirements implies that there is a double penalty that increases the Cost to Income Ratio (CIR). In line with the IFRS 9, banks incur additional cost related to loan losses and consequently, increase operational cost (numerator in CIR). Secondly, the delinquent loans become non-accrual loans and stop earning any interest income; hence the reduction of revenue margin (denominator in CIR). This is how the CIR is increased implying that operational inefficiency has been increased.

CONCLUSIONS AND RECOMMENDATIONS

This section provides a comprehensive synthesis of the research study, detailing the summary of key findings, the conclusions drawn from the empirical data, and subsequent policy and managerial recommendations. Credit risk configuration presented statistically reliable and mathematically solid properties, supported by the F-statistic and the accompanying p-value. Credit risk explains the majority of the total variation of the operational performance across time and between sampled institutions. In particular, the slope parameter of the credit risk measure is positively and very significantly related to the Cost-Income Ratio (CIR), or inversely related to efficiency, since an increase in CIR implies a decrease in efficiency. The slope parameter means that, for every unit increase in the NPL ratio, there would be a unit increase in the Cost-to-Income Ratio. That means that increasing defaults in credit would increase the structural cost relative to the income. Similarly, the structural baseline intercept has been estimated with extremely significant statistical property, which mathematically means that the Cost-to-Income Ratio will remain anchored at some positive constant value when there are no defaults in assets credit.

Through empirical findings, the study proves that credit risk is one of the major and significant determinants of inefficiency in operations in commercial banks listed on the NSE. By rejecting the null hypothesis of research, it becomes empirically evident that poor quality of the bank's assets contributes to reduced profitability. Specifically, the study shows the transmission channel to be the "double penalty" structural framework within the bank efficiency model, where non-performing loans make the bank spend significantly more on loan-loss provisioning under the requirement of the IFRS 9, increasing operating expenses and expanding the numerator of the Cost-to-Income Ratio (CIR). At the same time, non-performing loans become non-accrued, reducing interest income generation and decreasing the CIR denominator.

The current analysis confirms that Credit Rationing Theory remains a valid tool for the explanation of variations in the operations of listed banks on the Nairobi Stock Exchange. High statistical significance of the parameter related to credit risk is further evidence that information asymmetry is still creating real difficulties within the operations process. The decline in asset quality brings about a "double penalty," whereby not only do the provisioning costs under IFRS 9 rise but also the sources of income from interest become limited, which leads to an increase in the Cost-to-Income Ratio.

Based on the empirical evidence from the analysis of data, this study has developed a number of key recommendations for optimizing bank performance. Bank managers should enhance credit underwriting and loan portfolio evaluation through use of modern predictive data analytics, machine learning credit scoring models, and thorough pre-approval screening in order to determine the borrowers' creditworthiness and avoid defaults before transaction completion. Banks should also develop proactive surveillance mechanisms that would allow them to monitor their borrowers' financial condition and, accordingly, restructure distressed credits to prevent the occurrence of adverse delinquency migration and unnecessary IFRS 9 provisions. For the banks to cope with growing overhead costs of recovery, listed banks should engage in digitalization and automation of debt collections, legal proceedings, and collateral supervision to lower the cost of manual recovery units and thus stabilize the cost-income ratio. To conclude, CBK should continue exercising macroprudential regulation and enforce capital adequacy requirements to ensure that listed banks possess sufficient capital reserves that would be able to absorb any unexpected credit losses without affecting operational efficiency.

Recommendations for Further Research

Although this research presents straightforward and unbiased findings on the credit risk on bank operational performance, there are a number of limitations which could point to future econometric research areas. While the standalone Credit Risk model explains just part of the operational variation, further studies ought to address the problem by developing a multivariate panel model where Credit Risk would be considered together with other risk channels, such as interest rate risk, equity price risk and Basel III liquidity risk indicators. Since the analysis is concerned with commercial banks quoted on the NSE, future studies should extend the sample to other commercial banks (tier-2 and tier-3 banks), which are not listed, and to deposit taking microfinance institutions in order to see whether the current results apply to the entire Kenyan banking sector.

REFERENCES

Allen, F., & Gu, X. (2018). The Interplay Between Regulations and Financial Stability. *Journal of Financial Services Research, 53*(2), 233-248.

Brighi, P., & Mussoni, M. (2025). Credit Rationing and Financial Constraints. In *The Bank-Business Relationship: Information Asymmetries, Relationship Lending, and Regulation*. Cham: Springer Nature Switzerland.

Burger, A., & Moormann, J. (2008). Productivity in Banks: Myths & Truths of the Cost Income Ratio. *Banks & Bank Systems, 3*(4), 85-94.

Central Bank of Kenya. (2023). *Bank Supervision Annual Report 2023*. Nairobi: Central Bank of Kenya.

Ekinci, R., & Poyraz, G. (2019). The Effect of Credit Risk on Financial Performance of Deposit Banks in Turkey. *Procedia Computer Science, 158*, 979-987.

European Banking Authority. (2024). *Annual Report 2023*. Paris: European Banking Authority.

Greuning, H. V., & Iqbal, Z. (2007). Banking and the Risk Environment. In S. Archer & R. A. A. Karim (Eds.), *Islamic finance: The regulatory challenge*. Singapore: John Wiley & Sons (Asia) Pte Ltd.

Gupta, N., & Mer, P. (2023). Dividend Dynamics and Shareholders' Wealth: An Empirical Investigation Based on NSE100 Companies. *Asian Journal of Management and Commerce*, *4*(2), 280–286.

Isanzu, J. S. (2017). The impact of credit risk on financial performance of Chinese banks. *Journal of international business research and marketing*, *2*(3).

Lotto, J. (2018). The Empirical Analysis of the Impact of Bank Capital Regulations on Operating Efficiency. *International Journal of Financial Studies, 6*(2), 34.

Muli, E. N. (2017). *Effect of Information Asymmetry on Cost of Borrowing Among Micro-Finance Clients in Kenya* (Master's thesis, KCA University). Nairobi, Kenya: KCA University.

Muriithi, J. G., Waweru, K. M., & Muturi, W. M. (2016). Effect of Credit Risk on Financial Performance of Commercial Banks Kenya. *International Journal of Research in Commerce, Economics & Management, 6*(8), 1-13.

Muriithi, J., & Muigai, R. (2017). Quantitative Analysis of Operational Risk and Profitability of Kenyan Commercial Banks Using Cost Income Ratio. *IOSR Journal of Economics and Finance, 8*(3), 76-83.

Mwangi, G. N. (2012). *The Effect of Credit Risk Management on the Financial Performance of Commercial Banks in Kenya* (Master's thesis, University of Nairobi). Nairobi, Kenya: University of Nairobi.

Naili, M., & Lahrichi, Y. (2022). The Determinants of Banks' Credit Risk: Review of the Literature and Future Research Agenda. *International Journal of Finance & Economics*, *27*(1), 334-360.

Odhiambo, F. O., & Ndede, F. W. (2019). Credit Information Sharing Practices and Financial Performance of Commercial Banks in Kenya. *International Journal of Current Aspects*, *3*(6), 67-82.

Odunga, R. M. (2016). Specific Performance Indicators, Market Share and Operating Efficiency for Commercial Banks in Kenya. *International Journal of Finance and Accounting, 5*(3), 135-145.

Otieno, S., Nyagol, M., & Onditi, A. (2016). Relationship Between Credit Risk Management and Financial Performance: Empirical Evidence from Microfinance Banks in Kenya. *Research Journal of Finance and Accounting, 7*(6), 62-73.

Putra, C. I. W., Manurung, A. H., & Machdar, N. M. (2024). Effect of Capital Adequacy Ratio, Credit Policy, Liquidity Risk and Non-Performing Loan on Financial Distress. *Greenation International Journal of Economics and Accounting*, *2*(4), 309-322.

Ssekiziyivu, B., Mwesigwa, R., Joseph, M., & Nkote Nabeta, I. (2017). Credit Allocation, Risk Management and Loan Portfolio Performance of MFIs—A Case of Ugandan Firms. *Cogent Business & Management*, *4*(1), 1374921.

Stiglitz, J. E., & Weiss, A. (1981). Credit Rationing in Markets with Imperfect Information. *The American Economic Review, 71*(3), 393–410.

Taherdoost, H. (2021). Data Collection Methods and Tools for Research; a Step-by-Step Guide to Choose Data Collection Technique for Academic and Business Research Projects. *International Journal of Academic Research in Management (IJARM)*, *10*(1), 10-38.

Were, M., & Wambua, J. (2014). What Factors Drive Interest Rate Spread of Commercial Banks? Empirical evidence from Kenya. *Review of Development Finance, 4*(2), 73–82.

Witzany, J. (2017). Credit Risk Management. In *Credit Risk Management: Pricing, Measurement, and Modeling* (pp. 25–54). Cham, Switzerland: Springer.