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CREDIT RISK COMPLIANCE LEVELS AND TECHNICAL EFFICIENCY OF COMMERCIAL BANKS IN KENYA: A DATA ENVELOPMENT ANALYSIS (DEA) MODEL APPROACH

Stephen Kisuli[1]*, Tabitha Nasieku[2], Gordon Opuodho[3], Kimanzi Kalundu[4]
[1.2.3.4]Jomo Kenyatta University of Agriculture and Technology, Kenya
*Corresponding Author:
stephenkisuli98@gmail.com

Abstract

This paper investigates how level of compliance with credit risk regulatory guidelines issued by the central bank of Kenya impacts on technical efficiency whilst considering bank size as a moderating variable. The study adopts a quantitative research design, where a panel data of ten years of a sample of all the licensed commercial banks in Kenya is applied. The technical efficiency scores are estimated with the help of Data Envelopment Analysis (DEA) and the correlation between compliance with credit risk and technical efficiency is estimated with the help of the two-limit Tobit regression model estimated by the means of the Maximum Likelihood Estimation (MLE) method. The study findings established that there is a negative and statistically significant correlation between credit risk and technical efficiency meaning that an increase in credit risk correlates with decreased technical efficiency among commercial banks. Bank size was found to be statistically significant in determining the impact of technical efficiency, which points to the role of scale-related variables in efficiency performance. The study suggests commercial banks to improve their credit risk management and the level of compliance with prudential credit risk guidelines to minimize excessive credit risk exposure and to promote technical efficiency. Moreover, regulators and policymakers are advised to take into account bank size in designing and implementing credit risk regulatory frameworks. The paper also recommends that future research should generalize the study to other financial institutions, including microfinance institutions and cooperative banks, and use longer time horizons to reflect changing regulatory and efficiency dynamics of the financial sector.

Keywords: Credit Risk, Technical Efficiency, Bank Size, Commercial Banks

1. Introduction

The banking sector's technical efficiency is a vital factor for the success of financial intermediation focused on developing economies, where resources are scarce, and their optimal utilisation is a priority (Korneev et al., 2023). Within commercial banking, technical efficiency is defined as a bank's capability to maximise the generation of loans and other earning assets vis-à-vis the different factors of production (Waweru et al, 2021). Greater technical efficiency translates to operational waste and productivity improvements, and performance upwards shocks, further bolstering the aim of prudential regulation.

On the back of multiple rounds of financial sector reforms and the imposition of regulatory strictures, the Central Bank of Kenya (CBK) has, of late, focused on prudential measures aimed at bolstering banks' internal management of risk, particularly with respect to credit risk (Wanjiru & Waweru, 2025). Credit risk regulation continues to be a focal point of banking practice, as the provision of commercial bank loans is the principal income-generating activity, while the provision of poor credit quality is the most constraining factor for banks to achieve the efficient transformation of inputs into outputs (Duho, 2020).

The Basel Accords set guidelines for determining credit risk to ensure the banks have adequate systems in place to manage the potential loss caused by debtors' failure to pay. These guidelines help in improving banks' asset quality and operational efficiency (Bayar et al., 2021). Emerging economies like Kenya have adapted these principles by implementing minimum credit risk regulations under the supervision of the CBK (Waweru et al., 2021). Nevertheless, little has been documented regarding the effect of compliance with credit risk management regulation on the technical efficiency of commercial banks in Kenya.

The presence of non-performing loans makes technical efficiency even more pertinent, as bad asset quality limits the ability of banks to efficiently produce outputs using given inputs (Margono et al., 2020). Banks with better compliance to the credit risk guidelines tend to have healthier loan portfolios, less credit losses, and better intermediation efficiency (Nyaga, 2022). On the other hand, poor compliance with the credit risk guidelines may contribute to inefficiencies by increasing the rate of loan defaults, worsening the allocation of available resources, and decreasing the overall productivity.

The effect of size on the relationship between technical efficiency and compliance with credit risk regulation can be understood in the context of the different characteristics of small and large banks (Siddique et al., 2024). Larger financial institutions may enjoy economies of scale, a more diversified credit portfolio, and more sophisticated credit risk management systems, allowing them to balance compliance with credit risk regulation and efficiency positively (Edunjobi & Odejide, 2024). Smaller financial institutions, on the other hand, may be constrained by their capacity and resources, resulting in a regulatory trade-off between compliance and efficiency (Ikape et al., 2023). Therefore, the size of a bank can be viewed as a moderating factor in the relationship between credit risk regulation compliance and technical efficiency.

The commercial banks in Kenya have been instrumental in providing support to credit provision and supporting economic activity; however, the intermediation process still exhibits disparities in the provision of technical efficiencies (Wanjagi et al., 2024). It still remains an empirical exercise to determine the effect of compliance on technical efficiency, especially with respect to the varying sizes of banks, since the reforms on credit risk regulation by the CBK have not focused on this issue. Therefore, this study aims to determine the relationship between the level of compliance with credit risk regulatory guidelines and the technical efficiency of commercial banks in Kenya, with particular emphasis on the size of the bank.

Despite substantial growth and regulatory reforms in the banking sector in Kenya, there are still concerns about the technical efficiency of commercial banks (Korneev et al., 2023). While banks operate in an increasingly competitive and technologically advanced environment, there is evidence that many commercial banks are not utilizing their resources optimally to generate maximum outputs (Margono et al., 2020. High operating costs, persistent cost-to-income ratios, and varying levels of non-performing loans suggest the existence of technical inefficiencies, where banks fail to convert inputs such as labor, capital, and deposits into optimal levels of loans and income (Addy, et al., 2024).

The issue of technical inefficiency is compounded by poor credit risk compliance practices and bank size disparities. Some banks still have high levels of non-performing loans despite the presence of regulatory guidelines issued by the Central Bank of Kenya, implying inefficiencies in the credit appraisal, monitoring, and recovery processes (Kirimi et al., 2023). These inefficiencies not only affect profitability but also limit the capacity of banks to expand credit to productive sectors of the economy. Smaller banks, in particular, may experience scale inefficiencies related to limited capital, outdated risk management systems, and high operational costs, while larger banks may experience managerial and bureaucratic inefficiencies that diminish operational effectiveness.

In the Kenyan context, episodes of bank distress, mergers, and regulatory interventions have raised questions about whether commercial banks are operating on or below the efficient frontier (Ikapel et al., 2023). Persistent differences in efficiency levels across banks indicate that technology adoption alone is not enough without effective credit risk compliance and optimal scaling of operations. However, existing empirical studies in Kenya have mainly focused on bank efficiency, credit risk, and bank size separately, resulting in limited understanding of the joint influence of credit risk compliance levels and bank size on the technical efficiency of commercial banks. This gap hampers policy and managerial insights needed to improve efficiency and secure the long-term stability of Kenya's banking sector.

2. Theoretical Background

This chapter reviewed theoretical and empirical literature relating to credit risk compliance levels, bank size, and technical efficiency of commercial banks in Kenya. Specifically, the chapter discussed theories that underpin credit risk management and bank efficiency, reviewed empirical studies on the relationship between credit risk compliance and technical efficiency, and examines literature on the influence of bank size on technical efficiency. The chapter also reviewed relevant regulatory and institutional frameworks governing credit risk management within the Kenyan banking sector. By synthesizing existing studies, this chapter identified gaps in the literature that justify the current study and informed the development of the study's conceptual framework and hypotheses.

2.1 Theoretical Review

The Credit Risk Theory, as developed by Saunders (1997), was formulated to explain that the inherent purpose of credit risk management in banks is to reduce losses caused by borrower defaults and non-performing loans (Hasnaoui & Hasnaoui, 2022). Initially, the theory was cantered on identifying and quantifying the risk of loan defaults and non-performing assets, highlighting that bank must manage credit exposures to ensure solvency and operational stability. In the 1980s and 1990s, researchers like Altman (1968) and Jorion (1997) extended the theory by introducing statistical models and risk assessment techniques, such as credit scoring, probability of default, and loan portfolio diversification, which offered systematic methods to quantify and manage credit risk. In the early 2000s, the theory was further refined to include regulatory frameworks, especially with the introduction of Basel II in 2004 and Basel III following the 2008 global financial crisis. These frameworks formalized risk-based capital requirements, mandatory loan classification, provisioning for non-performing loans, and stress testing, effectively integrating credit risk management into bank governance and regulatory compliance (Ogunmola et al., 2022).

Today, the theory not only guides banks in mitigating losses from borrower defaults but also underpins empirical research on the relationship between credit risk compliance and bank performance, including technical efficiency. Empirical studies have applied

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Credit Risk Theory widely in finance. For example, Berger and DeYoung (1997) analysed the impact of loan quality and credit risk management on bank performance in the United States, while Demirguc-Kunt and Detragiache (1998) analysed the impact of credit risk on bank fragility in emerging markets, emphasizing the relationship between non-performing loans and institutional stability.

The current study offers a conceptual explanation of the factors used in assessing the impact of credit risk regulatory compliance on the technical efficiency of commercial banks in Kenya. It is based on Credit Risk Theory, which states that the more credit risk principles are followed, the better banks can absorb internal and external credit-related shocks, thus increasing operational resilience and efficiency (Sitienei et al., 2023). This theoretical foundation is consistent with the study's objective of assessing the relationship between credit risk compliance and technical efficiency in the regulatory context of banking in Kenya.

2.2 Conceptual Framework

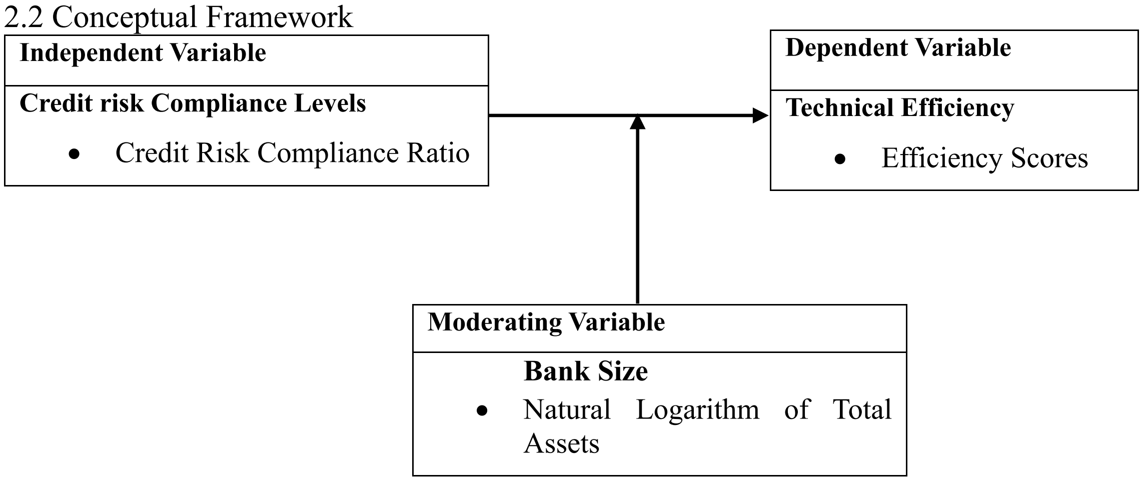

Figure 1: Conceptual Framework

2.3 Empirical Review

Altunbas et al. (2022) conducted a study in the European banking sector covering 2001–2009 to examine the impact of credit risk management on bank efficiency. The authors utilized a total of more than 800 commercial banks and applied Data Envelopment Analysis (DEA) to determine the technical efficiency, supplemented by panel regression models to determine the relationship between the efficiency and the measures of credit risk, non-performing loans (NPLs) and loan loss provisions (LLPs). Findings showed that banks that had lower NPL ratios and better provisioning coverage were more efficient technically. The research also established that bigger banks could handle credit risk and sustain efficiency more efficiently, and this proved the applicability of economies of scale in reducing risks. However, the research was limited to European economies and did not account for emerging market dynamics, leaving a knowledge gap in developing countries' contexts.

Jiménez et al. (2017) examined 1,200 banks in the United States from 2005 to 2015 to explore the effect of credit risk exposure on operational and technical efficiency. The study employed a stochastic frontier and panel regression models to establish that high NPLs levels caused a significant decrease in technical efficiency. Banks that engaged more rigorous credit risk management strategies such as more stringent lending standards and more loan provisioning further scored higher in efficiency scores. The research also emphasized that the effectiveness of credit risk mitigation was enhanced by the bank size and the idea that big banks were more effective at absorbing shocks. However, the study's focus on developed economies limits its generalizability to African banking environments, where regulatory enforcement and institutional capacity differ.

Obadire et al. (2021) reviewed 20 South African commercial banks over the period 2010-2018, to determine the relationship between credit risk management and bank efficiency and stability. The research utilized DEA to measure the technical efficiency scores and used a Tobit regression model to measure the impact of NPL ratio, provisioning, and credit concentration on efficiency. Results indicated that NPL ratios and technical efficiency were found to be negatively correlated and statistically significant. Larger banks whose credit risk management was more efficient retained their efficiency levels. The research, however, noted a gap in dealing with small banks, which do not have the resources to apply wholly to credit risk guidelines.

Mensah and Osei (2022) conducted a study across Ghanaian banks over the period 2012–2020 to investigate how loan portfolio quality affects bank performance and efficiency. The models employed in the study were the DEA and two-limit Tobit, which determined that NPLs, insider lending, and low collateral coverage had a negative effect on efficiency, whereas well-diversified portfolios and high-quality collateral positively influenced efficiency. The paper also observed that bigger bankers were more robust to credit shock, whereas smaller bankers showed constraints in their operations, showing a modulating effect of the scale of banks. However, the study failed to directly measure the level of compliance with regulations, which presents a gap that this paper fills by relating CBK credit risk compliance to technical efficiency.

Boamah et al. (2022) explored the relationship between credit risk and efficiency in 35 commercial banks in Kenya over the period 2013–2022. Using DEA to estimate technical efficiency and panel Tobit regression to model the effects of credit risk variables such as NPL ratios, provisioning coverage, and insider lending the study found that higher levels of NPLs and poor provisioning significantly reduced efficiency. Banks that were highly compliant in credit risk were in a position to sustain high levels of efficiency, which validated the Risk Absorption Theory. It has also been found that compliance was more effective with large banks and small banks had to grapple with the requirements of regulatory compliance at the expense of efficiency, which showed moderating effect of the bank size.

In Kenya, a similar study that explored the quality of loans and the influence on bank performance was done by Karanja and Wanjiru (2023) between 2014 and 2021. The research employed DEA to evaluate technical efficiency and maximum likelihood estimation (MLE) of panel regression analysis. Results showed that technical efficiency had a positive relationship with stricter management of credit risk, particularly, low NPL ratios and high levels of provisioning cover. The size of banks was found to be a crucial parameter, and big banks were more capable of absorbing credit shocks and remaining efficient. Nevertheless, the research indicated the need of further research on how regulatory compliance can influence beyond the simple credit risk metrics, which the present study addresses.

3. Methods

A quantitative research approach was adopted in this study, under which an explanatory research design was employed to examine how credit risk compliance levels affects technical efficiency of commercial banks in Kenya and also analyses whether bank size moderates the effect. The study was based on secondary panel data gathered on 37 licensed commercial banks in Kenya. The Central Bank of Kenya (CBK) and the Bank Supervision Annual Reports served as sources of data, dating back to 2013-2022.

3.1 DEA (First stage Analysis)

The current study employed Data Envelopment Analysis (DEA) that is a popular non-parametric method, developed by Charnes et al. (1978), to ascertain the efficiency of the commercial banks in Kenya. The bootstrap procedure was used to increase the precision and credibility of the DEA efficiency scores since it considers the effect of sampling and data noise (Wanke et al., 2019). In order to compute technical efficiency, the present study used efficiency perspective as applied by the DEA model.

Following the notation of Chen and Wang, 2022, consider a set of nDMUs: with each DMUj (j= 1, ..., n) using x_{ij} $(j = 1, \dots, m)$ and generating s outputs y_{rj} $(r = 1, \dots, s)$, the efficiency score of a DMU (e_0^*) can be computed as:

$$e_0^* = Max\left\{\theta = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{r=1}^{m} v_i x_{i0}}\right\}$$

Subject to

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{r=1}^{m} v_i x_{ij}} \leq 1; j = 1,2, \dots, n$$

Where;

v_i is a vector of input weights, $v_i \geq 0; i = 0; i = 1,2 \dots m$,

u_r is a vector of output weights, $u_r \geq 0; i = 0; r = 1,2, \dots s$,

x_{ij} = The amount of input i utilized by the jth DMU

y_{rj} = The amount of output r produced by the jth DMU

In case there is a total of nDMUs to be evaluated then each DMU consumes m types of inputs to produce s types of output. DMUj consumes amount x_{ij} of input i and produces amount of y_{rj} of output r. The ith type of input of DMUj is denoted as y_{rj}, y_{rj} ≥0 for s types of outputs (Cooper et al., 2011)

The ratio form yields an infinite number of solutions. The transformation of the ratio form for linear fractional programming selects a solution (u,v) for which $\sum_{i=1}^{m} v_i x_{i0} v = 1$.

The ratio form of the DEA is changed to a linear programming problem in the multiplier form (input orientation)

$$Max\ z = \sum_{r=1}^{s} \mu_r y_{ro}$$

Subject to;

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$$

$$\sum_{i=1}^{m} v_i x_{i0} v = 1$$

$$u_r,\ v_i \geq 0$$

The change of the variables from (u,v) to (μ, v) is a result of the Chames-Cooper transformation (Cooper et al., 2011).

After taking the dual of the equation, DEA is transformed to the envelopment form (Input orientation), as follows;

$$\theta * = Min\ \theta$$

Subject to;

$$\sum_{i=1}^{m} x_{ij} \lambda_j \leq \theta x_{i0} \qquad i = 1,2, \dots\dots\dots, m;$$

$$\sum_{j=1}^{n} y_{rj} \lambda_j \geq y_{r0} \qquad i = 1,2, \dots\dots\dots, s;$$

$$\lambda_j \geq 0 \qquad j = 1,2, \dots\dots\dots\dots, n$$

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In the envelopment form, the $\boldsymbol{\lambda}$ is a vector of intensity variables denoting the linear combination of DMUs. The objective function θ is a radial contraction factor that can be applied to DMUs inputs.

3.2 Second Stage Analysis: The Tobit Regression

These efficiency scores were considered a major dependent variable in the second stage to evaluate the influence of the degree of adherence to credit risk guidelines and bank size on technical efficiency. In this study, compliance level was included in the prudential measures instead of being regarded as a distinct goal. The corresponding ratio or measure was compared to the minimum requirement by the CBK and was rated as above Minimum, Meets Minimum or Below Minimum. The second step of the analysis involved the research undertaken by the current study on the effect of credit risk compliance on the efficiency scores of the commercial Banks in Kenya. The present study used the Tobit regression to cover the small range of efficiency scores within the 0-1 range (Li et al., 2022).

In particular, upper and lower censoring was specially modelled using the two-limit Tobit model in accordance with the specification of Rosett and Nelson (1975). Under upper and lower censoring, by the notations of (Antunes et al., 2022) the observed censored variable is. A measurement equation of subject i should follow.

$$y_i = \begin{cases} T_{L'} & \text{if } Y^*_i \leq T_{L'} \\ Y^*_i = x_i\beta + \boldsymbol{\varepsilon_{i,t}}\,, & \text{if } T_{L'} < Y^*_i < T_{U'} \\ T_{U'} & \text{if } \; Y^*_i \geq T_{U'} \end{cases}$$

y_i is the observed censored outcome variable for subject i; $T_{L'}$ and $T_{U'}$ are the lower and upper censoring values $T_L = 0$ and $T_U = 1$ for this study; Y^* is a latent variable that cannot be observed over its entire range. However, Y^* Is observed for outcome values between T_L and T_u, and is censored for outcome values less than or equal to T_L or outcome values greater than or equal to T_u

$y_i = x_i\beta + \boldsymbol{\varepsilon_{i,t}}$ is the structural equation for the Tobit model

The x's are factors observed for all cases and β's are regression coefficients

$\boldsymbol{\varepsilon_i} \sim \mathrm{N}\,(0, \sigma^2)$

3.3 Selection of Inputs and Outputs

Selection of the right input and output variables is very crucial in the use of DEA models. Two main definitions of the inputs and outputs are found in the literature on the efficiency of banking, namely, the production approach and the intermediation approach (Berger and Humphrey, 1997). The production strategy; perceives banks as service providers where deposits are the result and labour and capital are the inputs (Berger and Humphrey, 1997). Instead, the intermediation approach views banks as intermediaries between excess units (depositors) and deficit units (borrowers) by converting deposits and other inputs into investments and loans (Shrestha et al., 2025). In this method, deposits, labour, capital are viewed as inputs and investments and interest income are viewed as outputs (Sharma and Shen, 2025). The intermediation strategy was used since the focus of the research is the banking sector of Kenya and the study aims to explore the role of the banks in interconnecting the surplus and deficit units.

The issue concerning the inputs and outputs of the financial institutions as Benston (1972) and Clark (1984) mentioned did not have any consensus and the issue remains a subject of debate within the existing literature. The study employed the following inputs

(Operating Expenses, Total deposits, interest expenses) and outputs (interest income and investment income).

3.4 Economic Model Specification

The paper employed a two-limit Tobit regression model to be able to say the effect of credit risk compliance on the technical efficiency of commercial banks in Kenya and whether there is moderation of relationship between the two variables by bank size. The reason why the model was used was the censored behaviour of the dependent variable and it provided the estimates via the Maximum Likelihood Estimation (MLE). The model as it appeared on the baseline was:

$$Es_{i,t} = \beta_0 + +\beta_1 CRCL_{i,t} + \beta_2\, size_{i,t} + \varepsilon_{i,t}$$

To test for moderation, the interaction term between credit risk and bank size was introduced into the model. The modified model was expressed as follows:

$$ES_{i,t} = \beta_0 + \beta_1 CRCL_{i,t} + \beta_2\, size_{i,t} + \beta_3(CRCL_{i,t} \times size_{i,t}) + \varepsilon_{i,t}\,,\ \varepsilon_i \sim N(0,\sigma^2)$$

Where;

$CRCL_{i,t}$ = Refers to credit risk compliance level of bank i in time t which is measured using Credit risk compliance ratio computed using the formula; $CRCR_{i,t} = \frac{R}{CR_{i,t}}$; Where $CRCR_{i,t}$= Credit risk compliance ratio for bank i in time t. $CR_{i,t}$= observed prudential ratio for credit risk for bank i at time t. R= CBK prescribed regulatory threshold. NPL ratio should not exceed 5% for a bank to be considered to have acceptable credit risk. $CR_{i,t}$ is the regulatory variable for credit risk. Credit Risk is the risk that a borrower will not repay a loan or meet their obligations which can seriously threaten a bank's efficiency ratio of non-performing loans (NPLs) to total loans was used to assess the quality of a bank's credit portfolio and its credit risk management (Li et al., 2020). $CR_{i,t}$= Credit Risk Ratio; $CR_{i,t} = \frac{(NPL)_{i,t}}{(Total\ Gross\ Loans)_{i,t}}$

Since the CBK recommends that the NPL ratio of a bank should not fall below 5% of total gross loans (CBK Prudential Guidelines, 2024). In this context: $CR_{i,t} < 1$ indicates that the bank is non-compliant with the minimum regulatory threshold, signalling potential under-provisioning or misreporting of loan quality. $CR_{i,t} \geq 1$ indicates that the bank meets or exceeds regulatory expectations, reflecting adequate recognition of credit risk.

ES*i,t= Latent variable representing technical efficiency (DEA score)

$SIZE_{i,t}$ = Natural logarithm of Total Assets

$(CRCL_{i,t} \times size_{i,t})$ = Interaction term for moderating effect

β_0 = The intercept,

β1 = The coefficients for the independent variables.

β_2= The coefficient for the moderating variable (Bank Size),

β_3 = The moderating effect of bank size on the relationship between credit risk compliance levels and technical efficiency.

$\varepsilon_{i,t}$ = Error term

Subscript i = Commercial banks (Cross - section dimension) ranging from 1 to 37

Subscript t = Years (time - series dimension) ranging from 2013 to 2022.

4. Results and Discussion

In this section, the findings of the research about the compliance aspect of credit risk guidelines were discussed in connection with the technical efficiency of commercial banks in Kenya, which was moderated by the bank size. The results discussion put the results in the context of the study objectives and theoretical frameworks giving specificity to direction, magnitude and importance of the results.

4.1 Estimation of Efficiency Scores with DEA and Bootstrap Results.

The scores in technical efficiency of commercial banks in Kenya were derived by using a non-parametric method of Data Envelopment Analysis (DEA) since it is more suitable in determining the efficiency with which various commercial banks in Kenya use various inputs to generate higher outputs relative to a frontier or a best-practice point. The score of efficiency achieved using DEA is between zero and one, and a score of one means that the efficiency in resource use is high. Nonetheless, in order to decrease the biases of normal estimates of DEA due to sampling variability and random errors, bootstrap was employed to enhance the statistical validity of the estimates.

The bootstrap estimates indicate that, with adjustments to biases, the efficiency scores are less than those produced by normal DEA estimates, therefore, confirming the assertion that normal DEA models are more likely to overstate efficiency in the presence of uncertainties. The scoring of the efficiency with adjustment of the biases is very varied therefore it gives a more reliable estimate of the magnitude of the influence of prudential compliance and size on technical efficiency in commercial banks in Kenya.

Table 1. DEA and Bootstrap results of Efficiency Scores.

Year	Efficiency Score	Efficiency-Boot	Bias	Lower	Upper
2013	0.7842	0.7821	0.0021	0.6000	0.8900
2014	0.6754	0.6701	0.0053	0.5200	0.8000
2015	0.7609	0.7582	0.0027	0.5900	0.8700
2016	0.6589	0.6550	0.0039	0.4700	0.7600
2017	0.6569	0.6528	0.0041	0.4600	0.7800
2018	0.7432	0.7403	0.0029	0.5700	0.8500
2019	0.7100	0.7057	0.0043	0.5100	0.8300
2020	0.7807	0.7781	0.0026	0.6000	0.8900
2021	0.6589	0.6559	0.0030	0.4700	0.7700
2022	0.6781	0.6734	0.0047	0.4900	0.7900

Its efficiency score was between 0.6569 (2017) and 0.7842 (2013), which means that the financial sector has been relatively efficient throughout the years. The decrease in efficiency in 2016 and 2017 comes at a time when the interest rate capping rules in Kenya had an enormous effect in the banking industry by restricting lending margins and decreasing profitability. In 2019, the reinstatement of interest rate caps led banks to charge according to risk and enhance efficiency, potentially contributing to the 2019 and 2020 recoveries. The efficiency lags in 2016 and 2017 coincide with the years when the Kenyan government was implementing the Banking (Amendment) Act, 2016, which restricted the rate of interest banks could charge borrowers. This policy: Less credit, especially to small and medium enterprises (SMEs). This reduced the profitability of banks, resulting in cutting of costs and restructuring.

The rise in efficiency in 2018 and 2020 indicates that Kenyan banks have utilized mobile banking and fintech solutions. M-Pesa Mobile money services (including., M-Pesa) have been an international pioneer in Kenya and assisted in amplifying financial access and productivity. KCB and Co-operative Bank and Equity Bank have actively digitized their services and they have minimized operational expenses and increased their efficiency.

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4.2 Descriptive Statistics of Study Variables.

The descriptive statistics in this research gave a general understanding about the nature and characteristics of the key variables under study prior to econometric analysis. The descriptive statistics helped summarize the data on compliance with capital guidelines, bank size and technical efficiency in a way that aided in identifying the trends and the variation of the various commercial banks in Kenya. The descriptive statistics also helped in the identification of potential anomalies and data ranges, which is a notable factor in deciding whether the variables were suitable to be statistically analysed.

Table 2. Descriptive Variables of Study.

Variable	Type	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Efficiency Score	Overall	0.670	0.167	0.102	0.998	0.307	2.706
	Between		0.149	0.120	0.926		
	Within		0.112	0.254	0.445		
$CRCR_{i,t}$	Overall	0.330	0.063	0.060	0.396	0.823	3.112
	Between		0.044	0.025	0.350		
	Within		0.048	0.024	0.360		
Bank Size	Overall	24.733	1.614	20.60	29.014	0.421	2.499
	Between		1.593	22.09	28.362		
	Within		0.361	23.24	26.270		

The descriptive statistics reveal that the mean technical efficiency score of Kenyan commercial banks is 0.670, which implies that on average, the banks are operating at 67 percent of their potential efficiency in converting the inputs into outputs. Efficiency has a minimum score of 0.102 and a maximum of 0.998 with a slight positive skew (0.307), indicating that more banks have efficiency scores that are lower than the mean with a few banks operating near perfect efficiency. The difference across banks (0.149) is greater than the difference across banks over time (0.112), which means that bank-specific factors, including credit risk management and size, are the primary cause of differences in efficiency than seasonal changes.

The descriptive statistics for the credit risk compliance ratio show that Kenyan commercial banks generally operate below the prudential benchmark. The overall mean of 0.330 indicates that banks are substantially under-compliant, which corresponds to an industry average non-performing loan (NPL) ratio of about 16.5 percent. The relatively moderate standard deviation of 0.063 reflects some variation across banks and over time, although the maximum value of 0.396 suggests that even the best-performing observations did not meet full compliance. The minimum value of 0.060 highlights periods of severe credit risk exposure. Positive skewness of 0.823 indicates a clustering of banks at low levels of compliance, with few banks performing relatively better. The kurtosis of 3.112 suggests a leptokurtic distribution, implying occasional extreme deviations from average compliance. Overall, these results show that credit risk compliance is weak, uneven, and volatile across the sector. This highlights the need for strengthened credit risk management practices and enhanced regulatory oversight by the Central Bank of Kenya

The overall mean of bank size is 24.733 which indicates the scale of operations at the banks with a minimum of 20.60 and a maximum of 29.014. The skewness is positive but small (0.421) and it means that there are more banks of smaller size than the mean (the bank is huge). The differences in size are more among the banks (1.593) than between

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the banks at various times (0.361) and thus the bank size is predominantly stable year by year and appropriate to act as a buffer variable in the analysis.

4.3 Diagnostic Tests

The validity and reliability of the regression model were to be ensured by carrying out a set of diagnostic tests to investigate possible violations of any important assumptions.

4.3.1 Censoring Diagnostic Test

The Likelihood Ratio test was employed to test the hypothesis on whether the Tobit model, which fits the data with a censoring constraint on the dependent variable (efficiency score), has a better fit than the OLS regression model.

Table 3. Likelihood Ratio (LR) Test.

Censoring Type	Threshold	Number of Observations	Percentage of Total
Left-Censored	= 0.000	0	0.00%
Left-Near-Censored	≤ 0.500	2	5.71%
Uncensored	> 0.500 and < 0.950	35	94.59%
Right-Near-Censored	≥ 0.950	0	0.00%
Right-Censored	= 1.000	0	0.00%
Total Observations	-	37	100%

It was significant in the study due to the fact that the dependent variable (bank efficiency scores using the DEA model) falls within a particular range (0 to 1) that may imply censoring at the upper and/or lower levels

The summary of DEA efficiency scores shows that most of the data is uncensored. Of the 37 commercial banks, 35 banks (94.59) have efficiency scores that are above 0.500 and below 0.950. Because the vast majority of the data is not censored, the effects of credit risk compliance levels and bank size on technical efficiency can be estimated using the two-limit Tobit model with minimal effects of extreme values.

4.3.2 Generalized Residues Test

The second stage regression equation established the existence of endogeneity using the Generalized Residuals Test, which was conducted to correlate the three variables of prudential compliance with the bank size and the technical efficiency. This test can be used when the dependent variable is restricted in a model and when it tests the relationship of the residuals in the initial stage estimation to the error term in the equation.

Table 4: Generalized Residues Test.

N	Mean	Median	Min	Max	Std. Dev	JB p-value
37	0.003	0.001	-0.198	0.214	0.082	0.392

Table 4 provides the results of the generalized residuals test according to 37 observations. The residuals had the mean value of 0.003 with a median of 0.001 indicating that the residuals are centered about 0. The minimum and maximum observed values for the residuals were −0.198 and 0.214, respectively, suggesting no extreme points in the residual distribution. The residual standard deviation was 0.082, which indicated no variation around the mean value. A JB test produced a p-value of 0.392 indicating that the null hypothesis about normality could not be rejected and distribution is normal-like.

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4.3.3 Multicollinearity Test

Variance Inflation Factor (VIF) was used to confirm the existence of multicollinearity among the independent variables in the regression model. A VIF with a value above 10 is generally considered to have severe multicollinearity (Wooldridge, 2023).

Table 5. Results of Variance Inflation Factor (VIF).

Variable	VIF	1/VIF
$CRCL_{i,t}$	1.05	0.9523
Bank Size	1.38	0.7246
Mean VIF	1.215	-

Table 5 presents the VIF values of variables in the model, which are 1.05 and 1.38 with an average of 1.215. As these values are low, it implies that there is no strong correlation between the predictors. Because the values of the VIFs are low, this indicates that the model estimates are not highly influenced by multicollinearity and each of the independent variables contributes a unique value to the model.

4.3.4 Correlation Test

Pearson ccorrelation was employed to establish the strength and the quality of the linear relationship, which exists between the key variables, which include compliance with credit risk, bank size, and technical efficiency.

Table 6. Correlation Matrix

Variable	Technical Efficiency	$CRCL_{i,t}$	Bank size
Technical Efficiency	1.0000		
$CRCL_{i,t}$	-0.306	1.000	
Bank size	0.340	0.322	1.000

4.3.5 Normality Test

To test whether the Tobit regression equation satisfies the normality assumption of the residuals, the Jarque-Bera test was conducted and the outcomes are summarized in Table below.

Table 7. Jarque–Bera Test of Normality for Standardized Residuals

N	JB statistics	p value	Decision
370	0.72	0.7	Fail to reject H_0 - residuals approximately normal

Jarque-Bera statistic stands at 0.72 with the p value of .70, a value that is greater than the significance value of 0.05. Thus, reject the null hypothesis that the residuals follow a normal distribution. This implies that the error terms in the Tobit model are normally distributed, which is relatively correct and that the chance of valid inferences to model estimates is valid.

4.3.6 Heteroscedasticity Test

Heteroscedasticity is a variance of a residual that does not equal different values of the independent variables, which is not permitted by the classical linear regression model (Wooldridge, 2023). This violation could lead to inaccuracy of the parameter estimates and bias in the standard errors which could affect the reliability of testing a hypothesis. The Breusch-Pagan test was used to test the satisfaction of the homoscedasticity assumption as well as to test the need to have robust standard errors to accommodate any misaligned homoscedasticity.

Table 8. Breusch-Pagan Heteroscedasticity Test.

Test Statistic	p value	Conclusion
2.897	0.067	No heteroscedasticity ($p > 0.05$)

Table 8 indicates the outcome of the heteroscedasticity test by Breusch and Pagan. This test value is 2.897 and has a p-value of 0.067. Considering that the p-value is higher than the significance level of 0.05, the null hypothesis of homoscedasticity cannot be rejected. This means that the variance of the error terms is fixed. This gives a conclusion that there is no heteroscedasticity in the regression model. Thus, the outcomes of the standard error measurements may be regarded as valid.

4.3.7 Autocorrelation Test

Autocorrelation is a characteristic that indicates that the residuals of a panel data are either correlated over time or across units implying that the error terms are not independent (Shah *et al.*, 2023). When there is autocorrelation, it may cause biased and inefficient estimates of the coefficients that results in the wrong p-values and confidence intervals. To test autocorrelation, the Durbin-Watson (DW) statistic was employed, which is a typical test of the presence of first-order auto-correlation between regression residuals.

Table 9. Durbin-Watson Autocorrelation Test Results.

Test Statistic	Conclusion
1.81	No significant autocorrelation ($1.5 \leq DW \leq 2.5$)

Table 9 provides the Durbin Watson test statistics of the autocorrelation of the regression residuals. The test value was 1.81 and this lay within the acceptable range of 1.5 to 2.5. The outcome showed that there was no autocorrelation in the residual; this meant that the observations were not time-dependent. The lack of autocorrelation is used to explain that the results of regression analysis are valid.

4.3.8 Stationarity Test

To test the stationarity in this study and to ensure that the variables do not have any unit root to avoid spurious regression, the Levin-Lin-Chu (LLC) test was applied. LLC test is suitable with panel data since it takes into account cross-sectional information in establishing a common unit root in a sample of banks. The reason why the process was necessary is that efficiency scores and liquidity risk compliance levels are time series observations, and non-stationary observations can cause erroneous conclusions.

Table 10. Summarization of Stationarity Test Results.

Variable	Adjusted t-statistic	p value	Stationarity Status
$CRCL_{i,t}$	-3.1720	0.0000	Stationary
Bank Size	-3.1513	0.0010	Stationary
Technical Efficiency	-5.1275	0.0000	Stationary

Table 10 presents the results of the stationarity tests of credit risk compliance levels, and bank size and technical efficiency. The t-test of the variables (which have p-value 0.0000) is negative, which indicates that the variables are stationary, and they have constraints on the values of both the variance and the mean. The t-statistic of the variables with a p-value of 0.0010 is negative that indicates that the variables are not varying with time. The above results indicate that the variables satisfy the requirement of regression analysis of the model. The findings point to the lack of spurious regression findings depending on the variable's values.

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4.3.9 Hausman Specification Test

This test was adopted to determine whether individual effects are correlated with the model's explanatory variables. The null hypothesis (H_0): The observed variables are not related to the explanatory variables. This implies that the random effects estimator is efficient and consistent. Alternative hypothesis (H_1): Correlation exists between the non-observed effects and the explanatory variables, which means that fixed-effects estimators are consistent and preferable (Hausman, 1978).

Table 11. Results of Hausman Specification Test

Test	Chi-Square Statistic	p-value	Model Preferred
Hausman Specification Test	15.722	0.002	Fixed Effects

The test statistics of the Hausman Specification Test gave a Chi-square value of 15.722 and a p-value of 0.002. The results of the study indicated that p-value is less than 0.05 and therefore, it has been concluded that the null hypothesis, that the random effects model is consistent, has been rejected. The model of choice was the fixed effects model, i.e., the individual heterogeneity is related to the model variables. The fixed effects model was the best given that it could account to the time-invariant nature of banks that could affect credit risk compliance levels and technical efficiency.

4.4 Standard Tobit Regression Model

The reasons why the standard Tobit regression model is used in the research can be traced down to the nature of the dependent variable, derived technical efficiency estimates that are truncated within a given limited range hence breaking the conditions of the ordinary least square regression analysis methodology (Li *et al.,* 2022).

Table 12. Standard Tobit Regression Model Results.

Variable	Coefficient (β)	Std. Error	z-Statistic	p-value	Significance
Constant	-0.124	0.047	-2.638	0.008	Significant
$CRCL_{i,t}$	-0.132	0.040	-3.300	0.001	Significant
Bank Size ($size_{i,t}$)	0.063	0.022	2.864	0.004	Significant
Model diagnostics:					
Log Likelihood	-158.74				
LR Chi-square	72.18			0.000	Model Significant
Pseudo-R^2	0.208				
Sigma (σ)	0.361	0.019			
Number of Observations	370				

The Tobit regression findings reveal that technical efficiency of Kenyan commercial banks depends on credit risk and bank size to a greater extent. The constant term is negative (–0.124) and statistically significant at the 1% level ($p = 0.008$), suggesting that when both credit risk and bank size are zero, the baseline technical efficiency is below zero, which aligns with the censored nature of the DEA efficiency scores in the Tobit model.

Credit risk compliance level ($CRCL_{i,t}$) has a negative and statistically significant coefficient of –0.132 ($p = 0.001$), indicating that higher levels of non-performing loans relative to total gross loans reduce technical efficiency. This confirms the theoretical expectation that poor credit risk management diverts resources towards loan recovery, provisioning, and risk mitigation, thereby limiting the bank's capacity to efficiently convert inputs into outputs.

The coefficient of bank size is positive and significant (0.063) (p = 0.004), which means that bigger banks are more technically efficient. This contributes to the idea that larger banks enjoy economies of scale, diversification of resources and better risk management systems that place them in a position to conduct their business more effectively than smaller banks.

The model diagnostics indicate that the overall model is significant, with a Log Likelihood of –158.74 and an LR Chi-square of 72.18 (p = 0.000), demonstrating that the independent variables jointly explain variations in technical efficiency. The Pseudo-R^2 of 0.208 suggests that about 20.8% of the variation in technical efficiency is captured by credit risk and bank size, which is reasonable given the complexity of factors influencing bank efficiency. The sigma (σ = 0.361) reflects the standard deviation of the error term in the Tobit model, while the total number of observations (370) provides sufficient data to support the robustness of the results.

4.5 Standard Tobit Regression Estimates with Bank Size Moderator

In this study, the moderating effect of bank size was examined by including interaction terms in the standard Tobit regression model. Bank size was initially included as an independent variable, then interaction terms were created by multiplying bank size by the primary explanatory variable. These interaction terms were included in the regression to capture whether the relationship between the explanatory variable and the dependent variable changed with bank size. The statistical significance of the interaction coefficients was used to determine the existence of a moderating effect of bank size.

Table 13. Standard Tobit Regression Estimates: Moderating Effect of Bank Size.

Variable	Coefficient (β)	Std. Error	z-statistic	p-value	Significance
Constant	-0.118	0.129	-0.90	0.006	Significant
$CRCL_{i,t}$	-0.138	0.039	-3.385	0.001	Significant
Bank Size ($size_{i,t}$)	0.052	0.036	1.440	0.003	Significant
$CRCL_{i,t} \times size_{i,t}$	-0.030	0.009	-3.333	0.001	Significant
Model diagnostics:					
Log Likelihood	-142.60				
LR Chi-square	84.12			0.000	Model Significant
Pseudo-R^2	0.184				
Sigma (σ)	0.354	0.018			
Number of Observations	370				

The constant term is negative (–0.118) and significant (p = 0.006), reflecting the baseline level of technical efficiency when both credit risk and bank size are zero. Credit risk compliance level ($CRCL_{i,t}$) has a negative and statistically significant coefficient of –0.138 (p = 0.001), showing that higher non-performing loans relative to total gross loans reduce technical efficiency. This confirms that poor credit risk management limits a bank's ability to use resources efficiently, as more resources are diverted to mitigating loan losses.

The coefficient of 0.052 representing the positive and significant relationship between bank size and technical efficiency is 0.003 (p = 0.003). This is in favour of the opinion that larger banks enjoy economies of scale, diversified portfolios, and more effective risk management within the bank, contributing to greater operational efficiency. The interaction term between credit risk and bank size is negative and significant (–0.030, p = 0.001), suggesting that the effect of credit risk on technical efficiency is moderated by bank size. In particular, a bank tends to become more efficient, though credit risk has a more adverse effect on the efficiency of large banks as they increase in size. This shows that bank size does not fully protect the negative impact of high credit risk on institutions and responsibility in managing credit risk is of paramount importance even to large banks.

The model diagnostics indicate a good model fit: Log Likelihood = –142.60, LR Chi-square = 84.12 (p = 0.000), demonstrating that the independent variables jointly explain variations in technical efficiency. The Pseudo-R^2 = 0.184 suggests that 18.4% of the variation in technical efficiency is explained by credit risk, bank size, and their interaction, while sigma (σ = 0.354) reflects the standard deviation of the error term. Having 370 observations, the findings are strong and statistically valid.

4.6 Discussion

The negative and statistically significant coefficient of credit risk compliance levels in the current study suggests that higher levels of non-performing loans relative to total gross loans leads to lower technical efficiency, consistent with the theoretical expectation that poor credit risk management diverts resources into loan recovery, provisioning, and risk mitigation at the expense of productive intermediation. This result is in close agreement with a growing body of global empirical evidence indicating that high non-performing loans (NPLs) make banks less efficient (Akhtar et al., 2023).

Takahashi and Vasconcelos (2024) established that higher NPL ratios are negatively related to technical efficiency, as resources are tied up in managing distressed assets and unavailable for new lending or profitable operations, resulting in operational inefficiencies and weak performance frontiers. Similarly, an analysis of the Brazilian banking sector using DEA shows that high NPL volumes reduce technical efficiency, reinforcing that deteriorating asset quality constrains banks' ability to convert inputs into desirable outputs (Garcia & Meurer, 2022).

Onyango (2022) found that credit risk of Kenyan commercial banks has a significant and negative impact on intermediation efficiency, with higher levels of NPLs associated with lower efficiency scores, which is similar to the significant negative relationship identified in this study. However, not all empirical work in the Kenyan context or related financial sectors yields uniformly strong results. For example, Biwott and Macharia, (2018) study on technical efficiency of deposit-taking savings and credit societies (SACCOs) in Kenya found that NPLs did not significantly impact technical efficiency, despite the challenges they created for liquidity and operational performance. While SACCOs differ from commercial banks in structure and business model, this finding suggests that the impact of NPLs on technical efficiency may be context-dependent and dependent on institutional characteristics.

5. Conclusion

The findings demonstrate that lower levels of compliance with credit risk regulatory guidelines are associated with significantly reduced technical efficiency, while higher compliance levels enhance banks' ability to utilize resources efficiently. This indicates

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that adherence to prudential credit risk standards plays a critical role in minimizing inefficiencies arising from non-performing loans, excessive risk-taking, and misallocation of credit. Banks that consistently comply with regulatory thresholds tend to maintain healthier asset quality, lower impairment costs, and more stable earnings, thereby supporting higher efficiency levels.

The results further suggest that level of compliance with credit risk guidelines across banks matter, as partial or weak compliance undermines efficiency gains even among institutions with comparable resource endowments. This highlights that efficiency outcomes are not solely driven by input scale or market position, but also by the extent to which banks internalize and operationalize regulatory credit risk controls in their lending decisions.

In addition, the study confirms that bank size moderates the compliance–efficiency relationship. Larger banks generally exhibit higher efficiency due to economies of scale and advanced risk management frameworks; however, the efficiency benefits of size are significantly strengthened when accompanied by high levels of compliance with credit risk regulations. Where compliance is weak, size advantages are eroded by rising credit losses and regulatory costs. The study provides compelling evidence that the level of compliance with credit risk regulation is a fundamental driver of technical efficiency in the Kenyan banking sector. Effective compliance should therefore be viewed not merely as a regulatory obligation, but as a strategic tool for enhancing operational efficiency and financial sustainability.

It is recommended that commercial banks should keep a high degree of credit risk compliance since high level of compliance to credit risk regulatory guidelines is negatively linked to non-performing loans and positively linked to high degree of technical efficiency. Commercial banks are also encouraged to embrace practices that bring in the element of credit risk management in their operations and lending methods that make the objectives of risk mitigation and efficiency converge entirely.

It is also suggested that regulators and policymakers take into consideration bank size when making and enforcing credit risk regulations. The research noted that larger banks tended to be more successful in turning compliance into efficiencies, whereas smaller banks might need extra aid, like capacity-building interventions, technical assistance, or specific regulatory advice to make sure that compliance does not reduce efficiency. It is also suggested that a continuous monitoring and consecutive evaluation activity must be implemented to determine the effect of credit risk compliance on technical efficiency to be sure that regulatory goals correspond to an enhanced operational performance of banks of different sizes.

Future studies are suggested to examine more variables that can affect the association between credit risk compliance and technical efficiency like corporate governance, risk culture, technological adoption or managerial expertise. Further, it is suggested that researchers consider this relationship in other financial institutions, such as microfinance institutions and cooperative banks, and longer periods of time to reflect changing regulatory and operational dynamics.

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