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Abstract

This study examines the impact of level of compliance with insider lending guidelines on the technical efficiency of commercial banks in Kenya while exploring the role of bank size as a moderator. The study employed a quantitative, explanatory research design and a longitudinal panel dataset from 37 commercial banks in Kenya over the period 2013-2022. It used secondary data from publicly available sources, such as annual reports, audited financial statements, and the Central Bank of Kenya's regulatory publications. The Data Envelopment Analysis (DEA) model was employed to compute bank efficiency scores. Due to the censored nature of the dependent variable, the Two-limit Tobit model is used in the regression analysis, with parameter estimation conducted using Maximum Likelihood Estimation (MLE). Findings from this study establish considerable variability in compliance levels for banks, and those meeting or exceeding thresholds have relatively high technical efficiency compared with those not in compliance. Notably, this study establishes that bank size moderates the impact of compliance on technical efficiency; in this matter, large banks have better capacity to absorb the associated cost involved in insider lending controls. Therefore, this study recommends improved means for compliance in addition to ensuring improved bank controls from management.

Keywords: *Insider Lending, Technical efficiency, Bank size, Commercial banks*

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1.0 Introduction

Insider lending has for years been identified to be one of the essential risks to the efficiency of the banking sector, more specifically to the governance risks faced by economies in the early stages of development (Goetz *et al.,* 2025). In the event that insider lending is inadequately regulated, the process may culminate in inefficient allocation of credit. As such, regulators have implemented insider lending prudence to mitigate the risk associated with excessive insider exposure (Girotti & Salvadè, 2022).

In Kenya, the regulation and enforcement of insider lending have significantly gained ground due to sustained incidents of bank distress due to governance risks (Safari, 2023). The efficiency of the insider lending regulation's enforcement highlights the importance of the regulations beyond the efficiency of the banking sector. Despite this cruciality, the empirical perspective concerning the impact of the degree of insider regulation compliance and technical efficiency is constrained. Furthermore, the efficiency of insider lending regulation is moderated by the size of the bank due to the superior monitoring abilities associated with more extensive banks. It is against this critical background that the need to explore the relationship between the degree of insider lending regulation and the efficiency of the technical aspect of the Kenya bank arises (Mwai *et al.,* 2023)

Globally, insider lending has been identified as a crucial factor in banking crises, especially in economies with underdeveloped regulatory institutions or concentrated ownership structures. According to an IMF working paper, insider lending is often characterized by misallocation of assets, increased credit risk, and substantial losses in times of economic downturn, particularly when internal controls and disclosure mechanisms are weak (Natufe & Evbayiro-Osagie, 2023)

Studies from South Asia, Latin America, and Eastern Europe have shown that banks with high levels of insider trading tend to underperform in terms of asset quality and capital adequacy, and are more likely to experience liquidity shortages (Barth *et al.,* 2023. In many of these jurisdictions, insider lending was found to be positively linked to loan defaults, especially when directors or executives had too much influence over credit approval processes. These findings highlight the broader concern that without stringent regulation, insider lending can undermine not just individual banks, but the stability of entire financial systems (Gonzalez *et al*., 2022).

In Kenya, insider lending has had a demonstrable impact on bank failures. The cases of Imperial Bank and Chase Bank, both put under receivership due to massive volumes of undisclosed or non-performing insider loans, show the risks of poor governance and regulatory blind spots (Abor *et al.,* 2022). These episodes have heightened scrutiny of insider dealings and led to regulatory reforms, including increased disclosure requirements and more severe penalties. Nevertheless, supervisory reports continue to identify connected party exposures as a persistent risk, particularly among small and medium-sized banks with limited capacity to manage risk (Mwai *et al*., 2023). Many banks fail to report insider loans accurately or bypass exposure limits through indirect lending structures (Mutuku & Wanjiku, 2023). The resulting opacity not only undermines the soundness of individual institutions but threatens the credibility of the broader banking sector (Njeri, 2022).

1.1 Statement of the Problem

Despite the presence of prudent insider lending regulation guidelines, insider credit risks continue to pose a challenge to the viability and efficiency of commercial banks, particularly in developing countries (Aduda & Obondy, 2021). In Kenya, there have been several instances of distress in the banking sector that have been partly informed by poor governance structures, high insider loan exposure, and poor regulatory compliance. While the Central Bank has continued to improve regulatory oversight to mitigate insider risk evasion attempts, there is evidence to suggest that the degree of regulatory compliance varies amongst the different commercial banks to some degree below, within, or perhaps above the insider loan limit regulation threshold. However, the relationship of such variation to the technical efficiency of the respective banks largely remains unknown.

The literature has largely focused on the empirical validity of the insider loan risk impact to the banks' profitability, credit risk, and financial instability Khan *et al.,* 2023). In particular, the literature has mainly considered the regulatory compliance variable for insider loan risks essentially binary while essentially discontinuous. There have been few attempts to specifically consider the mediating or moderating influence of bank sizes despite the fact that the literature articulates superior monitoring powers or governance structures amongst the large banks that essentially have distinct implications for the technical efficiency level.

1.2 Research Objectives

i. To examine the influence of level of compliance with insider lending guidelines on efficiency of commercial banks in Kenya.
ii. To evaluate the moderating influence of bank size on the relationship between level of compliance with insider lending guidelines and technical efficiency of commercial banks in Kenya.

2.0 Literature Review

The Agency Theory, first articulated by Jensen and Meckling (1976), describes the conflicts of interest between principals (shareholders) and agents (managers or insiders) in corporate governance. In the context of banking, the moral hazard theory emphasizes that insiders, such as directors, executives, or significant shareholders, may act in their self-interest rather than in the best interest of depositors or the financial system at large. Insider lending often becomes a manifestation of this conflict, where insiders use their privileged positions to access credit on favourable terms, bypassing standard risk assessment procedures. This can result in misallocated resources, increased default risk, and ultimately jeopardize the technical efficiency of the institution (Yao *et al.,* 2023). In this research, Agency Theory underpins the examination of insider lending practices and their implications for technical efficiency in Kenyan commercial banks. It establishes a theoretical basis for exploring the question of whether self-dealing behaviour among insiders contributes to systemic risk and whether appropriate controls and governance structures can mitigate this effect (Nguyen & Phan, 2022).

The Too-Big-To-Fail Theory asserts that big financial institutions are more likely to receive government or regulatory support in times of distress because of their size, interconnectedness, and perceived systemic importance (Stern & Feldman, 2004). This implicit guarantee can lead to risk-taking behaviour, as large banks may operate under the assumption that they will be bailed out in the event of failure. However, TBTF institutions also tend to benefit from economies of scale, diversified income streams, and more robust internal controls, which can increase resilience against financial shocks (Andersen & Jensen, 2022). In this study, the Too-Big-To-Fail Theory serves as the conceptual foundation for exploring the moderating effect of bank size on the link between insider lending and financial stability. It suggests that sizeable banks may be better equipped to absorb the adverse effects of insider lending due to higher capital buffers and stronger risk management frameworks, affecting the overall impact on technical efficiency (Kamau & Otieno, 2023).

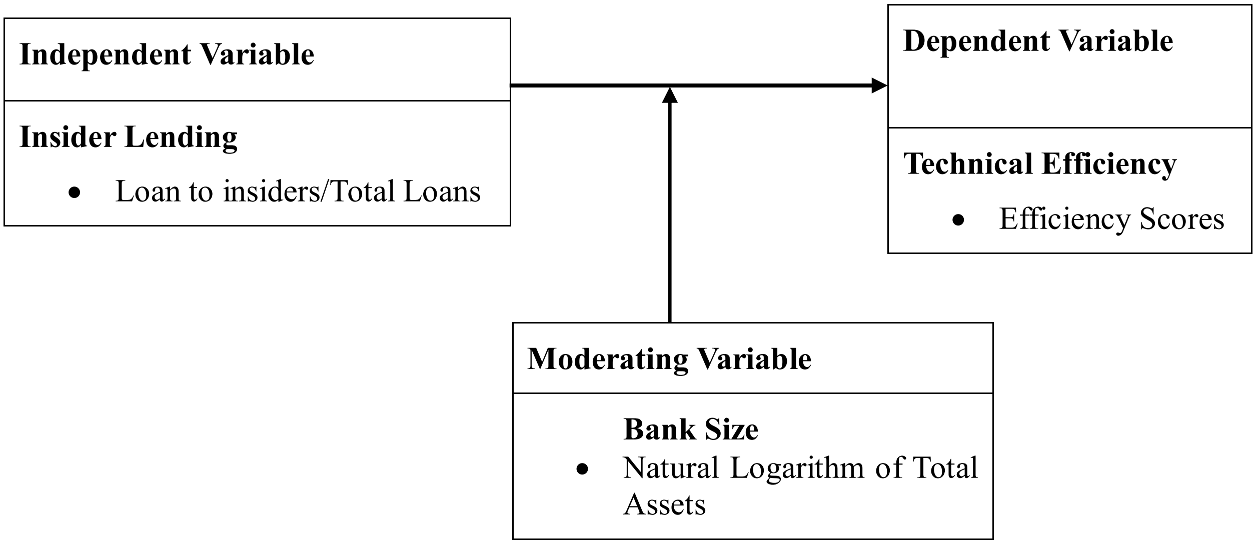

Figure 1: Conceptual Framework

2.1 Empirical Review

From a global perspective, Cull and Martinez Peria (2021) analysed the effects of insider lending on the financial soundness of commercial banks in Latin America and Eastern Europe. The research sought to examine whether transactions involving insiders and related parties affect the soundness of institutions and how the relationship is mediated by regulatory oversight. Using panel data for 124 banks spanning 2009 to 2018, the researchers applied a fixed effects panel regression to control for time-invariant heterogeneity among institutions. Results showed that higher levels of insider lending were significantly related to lower asset quality, higher loan default rates, and lower z-scores, indicating low financial stability. Furthermore, banks operating in jurisdictions with poor governance and weak enforcement mechanisms were more vulnerable to the destabilizing effects of insider dealings. These findings indicate that insider lending poses a material risk to financial stability, particularly in emerging and transitioning economies.

In an African context, Mensah and Kusi (2022) examined the impact of insider lending practices on the performance and stability of banks in Ghana and Nigeria. Drawing from a panel dataset of 28 commercial banks spanning 2012 to 2020, the research adopted the System Generalized Method of Moments (GMM) technique to address endogeneity issues. The analysis found that insider loans negatively impacted financial stability, proxied by z-scores and non-performing loan ratios. However, the magnitude of the effect was not uniform across institutional sizes. Larger banks had more capacity to absorb the risk posed by insider lending because of stronger capital buffers and more sophisticated risk management systems. In contrast, small and mid-sized banks were exposed to increased risk when insider lending was not properly regulated or disclosed, underscoring the importance of tailored supervisory approaches that take into account bank-specific characteristics.

In the Kenyan context, Ndegwa and Kamau (2022) examined the impact of insider lending on the quality of credit portfolios among commercial banks, using non-performing loans (NPLs) as the dependent variable rather than financial stability. The study used data from 30 commercial banks from 2014 to 2020, employing a panel fixed-effects regression model. Insider lending was

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calculated as a ratio between loans to related parties and gross loans. The results indicated a positive and statistically significant relationship between insider lending and NPL ratios (beta = 0.162, $p < .05$), indicating that insider loans are more likely to go bad. The study further noted that the impact was more pronounced in smaller banks, which often lack strong internal controls and governance oversight. While financial stability was not directly measured, the results suggest the extent to which insider lending undermines asset quality and credit risk, contributing indirectly to bank instability and long-term fragility. The study recommended better transparency in insider credit approvals and increased regulatory oversight by the Central Bank of Kenya to mitigate this risk.

3.0 Methodology

This study employed a quantitative explanatory research design to evaluate the level of compliance with insider lending on the technical efficiency of commercial banks in Kenya while assessing the moderating role of bank size. An explanatory design is ideal for this investigation, as it allows for hypothesis testing and analysis of potential causal relationships between insider lending practices, institutional size, and financial outcomes. The study used secondary data obtained from publicly available sources, mainly Central Bank of Kenya (CBK) Bank supervision reports, audited bank financial statements, and other regulatory publications for the period 2013 to 2022. The dataset consists of 37 fully licensed commercial banks that have consistently operated throughout the study period, which provides consistent and complete financial data. The use of panel data adds to the robustness of the study, taking into account both temporal and cross-sectional dynamics, which enhances the reliability of the findings.

3.1 DEA (First stage Analysis)

In the first analytical stage, DEA is used to calculate efficiency scores (dependent variable) representing financial stability. The study adopts an input-oriented DEA model under variable returns to scale (VRS), recognizing the structural and operational differences among Kenyan commercial banks. The input-oriented approach assumes that banks seek to minimize resource usage without compromising output levels

The inputs for the study included; Operating expenses, Total customer deposits, Interest expenses. These inputs represent the fundamental resources used in banking operations. The outputs are: Interest income, Total loans, Investments, Other non-interest income. These outputs represent the main income-generating activities of the bank. Efficiency scores are calculated yearly for each bank between 2013 and 2022. Banks with scores closer to 1 are considered more efficient.

To calculate technical efficiency, this study adopted the efficiency perspective based on the DEA model. Following the notation from Cook and Seiford (2009), consider a set of nDMUs: with each DMU$_j$ (j= 1, ..., n) using x_{ij} $(j = 1, \ldots, m)$ and generating s outputs y_{rj} $(r = 1, \ldots, s)$,

the efficiency score of a DMU (e_0^*) can be computed as

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

Subject to

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

Where;

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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. DMU_j consumes amount x_{ij} of input *i* and produces amount of y_{rj} of output r. The i^{th} type of input of DMU_j 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)

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

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;

$$\theta^* = \text{Min } \theta$$

Subject to;

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

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

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

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 DMU_o's inputs.

3.2 Second Stage: Tobit Regression Analysis

Given the censored nature of the efficiency scores (bounded between 0 and 1), the study uses a two-limit Tobit regression model estimated under Maximum Likelihood Estimation (MLE). In particular, the two-limit Tobit model as proposed by Rosett and Nelson (1975) is adopted to allow for upper and lower censoring of the dependent variable. Following the formulation by Long (1997), the observed censored variable y_i is defined as:

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$$y_i = \begin{cases} 0, & if\ Y^*_i \leq 0 \\ Y^*_i\ , & if\ 0 < Y^*_i < 1 \\ 1, & if\ Y^*_i \geq 1 \end{cases}$$

Y^*_i is the unobserved latent variable reflecting the true level of technical efficiency and y_i is the observed DEA efficiency score bounded between 0 and 1. The model is estimated using the Maximum Likelihood Estimation (MLE) technique, which ensures consistent and unbiased coefficient estimates. The insider lending guideline issued by CBK limits insider exposure to a maximum of 20% of a bank's core capital. To assess the level of compliance, a compliance adjustment formula was used, given as:

$$Compliance\ Adjustment = \frac{20}{Insider\ Lending\ Ratio}$$

Higher values for compliance adjustment signify better governance compliance, and values below one indicates excessive insider lending. This requirement for compliance adjustment has been applied to the data to reveal that most banks have values for adjustment at or higher than one.

The baseline model, used to test the direct effects of level of compliance with insider lending regulation and bank size on technical efficiency, is specified as:

$$\boldsymbol{ES^*_{i,t} = \beta_0 + \beta_1 LED_{i,t} + \beta_2 SIZE_{i,t} + \varepsilon_{i,t}\ ,\ \varepsilon_i \sim N\,(0, \sigma^2)}$$

To test for moderation, the modified model is expressed as follows:

$$\boldsymbol{ES^*_{i,t} = \beta_0 + \beta_1 LED_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 (LED_{i,t} \times SIZE_{i,t}) + \varepsilon_{i,t}\ ,\ \varepsilon_i \sim N\,(0, \sigma^2)}$$

Where:

$\boldsymbol{ES^*_{i,t}}$ = Latent variable representing technical efficiency (DEA score)

$\boldsymbol{LED_{i,t}}$ = Loan to insiders divide by Total Loans

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

$\boldsymbol{LED \times SIZE}$ = Interaction term for moderating effect

$\boldsymbol{\beta_0}$ = The intercept,

$\boldsymbol{\beta_1}$ = The coefficients for the independent variable.

$\boldsymbol{\beta_2}$ = The coefficient for the moderating variable (Bank Size),

$\boldsymbol{\beta_3}$ = The moderating effect of bank size on the relationship between level of compliance with insider lending guidelines and technical efficiency

$\boldsymbol{\varepsilon_{i,t}}$ = Normally distributed error term

DEA scores are observed in the interval (0, 1)

Subscript ***i*** = Commercial banks (Cross - section dimension) ranging from 1 to 37
Subscript ***t*** = Years (time - series dimension) ranging from 2013 to 2022

4.0 Findings and Discussion

This chapter discussed and interpreted the findings of the study on the level of compliance with insider lending guidelines, and the moderating role of bank size. The findings were interpreted in

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relation to the Central Bank of Kenya's prudential requirements. The analysis examined the extent of compliance and intensity of compliance of commercial banks in Kenya. The analysis employed the use of both description and diagnostics statistics which provide insights into the data's central tendencies, variability, and suitability for regression analysis.

4.1 Compliance Level with Insider Lending Guideline

The analysis of the adherence level of the insider lending guideline reveals a considerable disparity in the extent to which the commercial banks in Kenya adhere to the set regulatory guidelines on prudential lending. The guideline on insider lending was intended to limit excessive loans to connected parties, limit potential conflicts of interests, and limit potential losses to depositors. The results of the descriptive analysis show that the commercial banks are dispersed into three groups, below, within, and above the regulatory requirement.

Table 1: Compliance Level with Insider Lending Guideline

CBK Prudential Guideline	Below CBK Min/Max (%)	Meeting CBK Min/Max (%)	Above CBK Min/Max (%)
Insider Lending (≤20%)	10	55	35

From the analysis of insider lending compliance, it has been observed that there are significant disparities in relation to the extent to which commercial banks in Kenya have complied with the prudential ratio of 20 percent. The insider lending guideline is a means of moderating overexposure of banks to related parties that could hamper governance and bank performance. The dispersion of banks by compliance levels reflects a moderate level of compliance. In particular, 35 percent of the banks were operating above the regulatory requirement, which means that the insider lending ratio is well within the regulatory limit, as well as having a prudential buffer that safeguards against risks emanating from insiders. A higher number of the banks, 55 percent, met the regulatory requirement, which means that they were following the guideline very well but had very low levels of safeguards. On the other hand, 10 percent of the banks were operating below the regulatory requirement, which means there is a high risk emanating from excessive insider lending.

4.2 Construction of Compliance-Adjusted Insider Lending

The insider lending guideline issued by CBK limits insider exposure to a maximum of 20% of a bank's core capital. To assess the level of compliance, a compliance adjustment formula identified in chapter 3 employed. Higher values for compliance adjustment signify better governance compliance, and values below one indicates excessive insider lending. This requirement for compliance adjustment has been applied to the data to reveal that most banks have values for adjustment at or higher than one.

Table 2: Construction of Compliance-Adjusted Insider Lending

Prudential Indicator	CBK Regulatory Threshold	Raw Prudential Measure	Compliance Adjustment Formula	Interpretation
Insider Lending	≤ 20%	Insider Lending Ratio (%)	20 ÷ Insider Lending Ratio	Higher values indicate stronger governance compliance

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4.3 Efficiency Scores estimation using DEA and Bootstrap Results

The computation of efficiency scores through Data Envelopment Analysis (DEA) with a focus on the use of bootstrap estimates represents a key component of this research as it provides a definitive means of determining the efficiency of commercial banks in processing their inputs of capital, labour, and deposits to produce outputs such as loans and financial services. By effectively establishing the relative efficiency of banks through DEA, a broad evaluation of their performance can be realized. The use of the bootstrap estimates adds to the validity of the computed efficiencies by considering the possibility of sample bias in DEA. The efficiencies form the basis of the study as the dependent variable in the assessment of the role of insider loans compliance and bank size.

Table 3: Efficiency Scores estimation using DEA and Bootstrap Results

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

The bootstrap efficiency scores reported for the period 2013-2022 indicate fairly low bias values across all years, which signifies that the original Data Envelopment Analysis (DEA) efficiency scores are stable and reliable. The bias-corrected (Bootstrap) efficiency scores are slightly lower than the original scores, reflecting a necessary correction for potential sampling variability. For example, in 2014, the original efficiency score was 0.6754, while the bias-corrected score was 0.6701, and the bias was 0.0053.

This pattern is consistent across all years, with bias values ranging from 0.0021 to 0.0053, which fall within acceptable limits (Simar & Wilson, 2007). The use of bootstrapping helps increase the robustness of the DEA estimates, accounting for statistical noise and providing a better measure of efficiency.

These results suggest that financial stability, proxied by efficiency, was moderately robust throughout the study period, showing the highest performance during 2013 (bootstrapped efficiency score = 0.7821) and lowest in 2017 (bootstrapped efficiency score = 0.6528).

4.4 Descriptive Statistics for Study Variables

The use of descriptive statistics enabled the extraction of the key features of the variables under study. The variables under study included insider lending compliance, the size of the commercial banks, and the technical efficiency scores obtained using the DEA method.

Table 4: Descriptive Statistics for Study Variables

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		
Insider Lending	Overall	1.081	0.048	0.998	1.218	0.678	3.220
	Between		0.038	1.010	1.210		
	Within		0.033	0.998	1.218		
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 results showed that the efficiency scores, as estimated by Data Envelopment Analysis (DEA), had a mean of 0.670, suggesting an average performance of 67% of the maximum efficient frontier. A standard deviation of 0.167 was shown to have a degree of variability in efficiency levels. However, the minimum to maximum distribution (0.102 to 0.998) suggested considerable variability in efficiency differences between less efficient and more efficient banks. The skewness of 0.307 was slightly positive, suggesting a concentration of banks on lower efficiency levels, while the kurtosis of 2.706 suggested a distributional pattern which was tending to normal but was of medium peak. The between-group and within-group statistics suggested variability in efficiency in both inter-group (banks) variations (0.149) as well as in variations in efficiency levels over a period of time (0.112).

With respect to the insider lending compliance adjustment, the overall mean was 1.081, suggesting that the average bank was operating at a slighter lower number than the required 20%, in relation to insider lending. The low standard deviation of 0.048 suggested little variation in compliance. The range (0.998 to 1.218) demonstrated that the majority of the banks operated at the required threshold. Positive skewness of 0.678 indicated a modest number of banks with stronger compliance (higher values), and the kurtosis of 3.220 suggested a distribution slightly more peaked than normal, implying most banks clustered around the mean compliance level. Both the between (0.038) and the within (0.033) components are small in this case.

The overall mean of 24.733 for the bank size variable, which is in logarithmic form, revealed wide variation in the sizes of the banks. The standard deviation of 1.614 showed a moderate variation, while the minimum and maximum values of 20.60 and 29.014, respectively, established a wide variation in the sizes of the banks in Kenya. The positive skewness of 0.421 established a slight tendency for the smaller bank sizes to concentrate, while the kurtosis of 2.499 revealed that the distribution of the variable is nearly normal. The variation in the bank size between the banks is very high compared to the variation in the size among the groups. The ratio is 1.593 for the variation among, while the value for the variation within is 0.361.

4.5 Diagnostic Tests

Before the regression tests were performed, diagnostic tests were done to ensure that the observations were free from the assumptions necessary for the validity and reliability of the results.

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These tests were done to check for the validity of the assumptions related to the normality of the observations, multicollinearity, heteroscedasticity, and model specification.

4.6 Censoring Diagnostic Tests

These tests helped identify the applicability of censored regression techniques like the Tobit model relative to traditional linear models like the OLS model which assumes the dependent variable is continuous and unbounded.

Table 5: 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%

The results from the LR test show that most of the financial stability observations, as measured by efficiency scores, were uncensored, with 94.59% or 35 out of 37 banks falling within the middle range (greater than 0.500, but less than 0.950). This indicates that most banks operated within a moderate range of efficiency, neither at the low nor the high end of the efficiency scale.

A very small proportion (5.71% or 2 banks) were classified as left-near-censored (scores <= 0.500), meaning that a few banks exhibited low efficiency levels that approached the lower bound of the efficiency range. Importantly, no observations were fully left-censored (at 0) or fully right-censored (at 1.000), and no banks had scores close to the upper limit (0.950 or higher). These findings suggest there was limited censoring in the dataset, justifying the use of the Tobit model, which accommodates situations where the dependent variable is censored.

4.7 Generalized Residues Test

For testing if the residuals in the Tobit model are properly specified to follow a normal distribution, the Generalized Residual Test was used. For censored, or limiting, dependent variable analysis like in the Tobit model, it is possible for regular residuals to deviate from normality (Cunillera, 2024). This is because of the censoring mechanism in those observations. Generalized residuals provide a useful tool to determine if a model is appropriate, as well as to determine if assumptions in Tobit analysis are satisfied.

It calculates the generalized residuals for the Tobit model and proceeds to check for normality using descriptive statistics and the Jarque-Bera test statistic. The JB test statistic provides a p-value to check for normality in residuals. Decision rule is Null Hypothesis (H_0): The generalized residuals have a normal distribution. This means that the model is specified correctly. Alternative hypothesis (H_1): The generalized residuals are not normally distributed.If the JB p-value is greater than 0.05, it means that the null hypothesis is not rejected; hence, the model is correctly specified. If JB p-value ≤ 0.05, then the null hypothesis is rejected, implying misspecification and/or non-normal residuals.

Table 6: 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 6 shows the test results for the Generalized Residuals Test performed on the Tobit regression model. The number of observations was N = 37, reflecting the number of banks that were incorporated into this study. The residuals had a mean value and a median value close to zero, at 0.003 and 0.001 respectively, suggesting that there is no systematic over- or under-estimation associated with these residuals. The minimum and maximum residuals that were observed are -0.198 and 0.214, respectively. These show the spread of the residuals in terms of deviations, and a standard deviation of 0.082 indicates a small dispersion. This indicates that predictions made by the Tobit model were relatively accurate.

The p-value for Jarque-Bera is 0.392, which is above the significance level of 0.05. Therefore, based on the decision rule, we fail to reject the null hypothesis that the residuals follow a normal distribution. It is inferred, therefore, that this model is correctly specified, and all assumptions required for obtaining robust estimates for the Tobit model are satisfied.

4.8 Multicollinearity Test

Multicollinearity tests are used to assess if there is high correlation among two or more independent variables within a regression analysis. High multicollinearity compromises the stability of estimates and makes it difficult to analyse uniquely the separate effect of variables on the dependent variable (Biswas *et al.,* 2024). In this analysis, multicollinearity tests were used to justify that insider lending compliance adjustment and bank size are independent variables that uniquely explain changes in technical efficiency.

In this study, variance inflation factor (VIF) and tolerance statistics were employed to determine levels of multicollinearity. The variance inflation factor is a measure of the degree to which a regression coefficient is inflated in a set of correlated variables, while tolerance is the reciprocal of VIF. It measures the proportion of variance not explained by other predictors.

VIF values higher than 10 denote that there is a higher degree of multicollinearity, and the variable is highly correlated with other variables. A tolerance value lower than 0.1 indicates possible multicollinearity issues. Variables for which VIF ≤ 10 and Tolerance ≥ 0.1 are considered to be free of collinearity issues and can be included in the regression analysis.

Table 7: Variance Inflation Factor (VIF) Results

Variable	VIF	1/VIF	Interpretation
Insider Lending	1.42	0.7042	No multicollinearity (VIF < 10
Bank Size	1.38	0.7246	No multicollinearity (VIF < 10
Mean VIF	1.40	—	

Table 7 shows that all the values of the variance inflation factor were less than 10, and all the values of tolerance were greater than 0.1. This therefore suggests the absence of the problem of

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multicollinearity. This further means that the model would be able to determine the individual impact of the compliance level with insider lending and the size of banks on the efficiency of banks.

4.9 Correlation Test

The correlation analysis was used to determine the strength of the linear relationships between the variables of concern in the study, which were insider lending compliance adjustment, size of the banks, and technical efficiency (Gurung & Gurung, 2022). The Pearson correlation coefficient (r) was used to measure the extent to which there was a linear relationship between the pairs of variables.

A value of 0 for no linear relationship. Correlation coefficient values close to ±1 illustrate high correlation, while values close to 0 indicate poor correlation. The statistical significance of the correlation is determined using the p-value. $p < 0.05$ indicates statistical significance, while $p > 0.05$ indicates non-significance.

Table 8: Correlation Matrix

Variable	Technical Efficiency	Insider Lending	Bank size
Technical Efficiency	1.0000		
Insider Lending	0.426	1.000	
Bank Size	0.351	0.286	1.000

The correlation coefficient between the two variables, namely, technical efficiency and the adjustment for insider lending, is 0.426, which is an indication of a positive moderate correlation between the two variables. This result is an indication that banks that have higher levels of compliance with the guidelines for insider lending, as those with exposures within safe limits relative to the regulatory ceilings, are also banks that have high levels of efficiency.

Technical efficiency has a positive correlation with the size of the banks ($r = 0.351$), which means that larger banks tend to display greater technical efficiency. This might result due to economies of scale, better control mechanisms, as well as diverse activities of large banks.

The relationship between the insider lending compliance adjustment and bank size is less strong and positively related ($r = 0.286$), implying the fact that although large banks demonstrate improved insider lending governance, the relationship is not very strong. Therefore, the result indicates that bank size and insider lending are independent variables that reduce the problem of multicollinearity in the regression test.

4.10 Normality Test

The normality test was performed to check for the normality of the regression line residuals. The assumption of normality of the regression line or Tobit model results is of paramount importance to ensure that the regression estimates are unbiased (Gurung & Gurung, 2022). The study used this test to check for the validity of the assumption that the residuals for the dependent variable of technical efficiency were normally distributed. The Jarque-Bera test was used to test normality based on the skewness and kurtosis of the residuals to determine how different their distribution is from that of normality.

Decision Rule is Null Hypothesis (H_0): The residuals are normally distributed. Alternative Hypothesis (H_1): The residuals are not normally distributed. Decision rule is that; if JB P-value > 0.05, then H_0 is not rejected. This implies normality. If JB P-value ≤ 0.05, then H_0 is rejected. This implies non-normality.

Table 9: 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

Table 9 summarizes the result of a Normality Test performed on the residuals of the regression equation using the Jarque-Bera Statistic. The sample size was N = 370. The value of the Jarque-Bera Statistic was found to be 0.72 with a corresponding probability value of 0.70. This value surpassed the critical value of 0.05.

Since the p-value is well above 0.05, we fail to reject the null hypothesis (H_0). This implies that there is no statistically significant evidence of non-normal residuals. Hence, the tested hypothesis confirms the correctness of the model specification of the Tobit regression model. On this basis, the results imply that the estimated coefficients are to be considered reliable.

4.11 Heteroscedasticity Test

To investigate the validity of the Tobit model assumptions, the Breusch-Pagan test was performed to check for the presence of heteroscedasticity in the residuals. The results are summarized in the table below:

Table 10: Breusch-Pagan Test

Chi-square Statistic	Degrees of Freedom	p value	Conclusion
2.582	2	0.158	No heteroscedasticity detected

Since the p-value = 0.158 is greater than the 0.05 level of significance, we fail to reject the null hypothesis of homoscedasticity. This implies that the variance of the residuals is constant, and thus, there is no evidence of heteroskedasticity in the Tobit model. The result provides evidence for the robustness of the estimated model and demonstrates the reliability of the standard error estimates (Gujarati & Porter, 2020).

4.12 Autocorrelation Test

To test for the autocorrelation of the residuals in the regression model to ensure that independence is maintained, the autocorrelation test was used. Autocorrelation occurs when there is a correlation of the residuals (Kumar, 2023). The test conducted in this study ensured that the residuals for the Tobit regression model of insider lending compliance and insider lending as it related to size and technical efficiency had no correlation.

Durbin-Watson test was employed to determine whether there was first-order autocorrelation. The DW statistic takes a value between 0 and 4, with the following guidelines: A value of 2 denotes no autocorrelation while a value less than 2 implies the presence of positive autocorrelation. If the value is above 2, it shows negative autocorrelation. Decision rule is that: Null Hypothesis(H_0):

There is no autocorrelation in the residuals. Alternative hypothesis (H_1): There is autocorrelation in the residuals.

In other words, if DW is about 2, then we do not have enough evidence to reject H_0, which means lack of autocorrelation. On the other hand, if DW is substantially different from 2 in either direction, then we have enough evidence to reject H_0, which shows either positive autocorrelation or negative autocorrelation.

Table 11: Durbin-Watson Autocorrelation Test Results

Test Statistic	Conclusion
2.01	No autocorrelation

The outcome from the autocorrelation test on the regression model is provided in table above. The Durbin-Watson test measure indicates the autocorrelation level. The measure used here is given by the DW test value of 2.01, close to the critical value of 2. This indicates that the residuals in the regression model lack autocorrelation. Therefore, the results obtained regarding the impact of insider lending compliance and the size of banks on the aspect of technical efficiency can be relied upon.

4.13 Stationarity Test

The test was conducted in order to find out whether the variables in the study are stationarity in nature. The existence of stationarity is very important in analyzing the data using panel data analysis (Eje, 2022). Stations in a data can cause spurious results in regression analysis. The test utilized in determining the stationarity in the data is the Levin-Lin-Chu test. The Levin, Lin, and Chu test, known as the LLC test, is used to test whether or not panel data contains a unit root. The test assumes that there is one common unit root process in the cross-sections.

The LLC test also accounts for both serial correlation and time trends. Decision rule is; Null Hypothesis (H_0): The variable has a unit root (non-stationary). Alternate hypothesis (H_1): The variable is stationary. If the value of the LLC test statistic is significant (p-value ≤ 0.05), it leads to the rejection of the null hypothesis, suggesting that the variable is stationary. If the calculated p-value is greater than 0.05, it implies that the null hypothesis is not rejected

Table 12: Levin-Lin-Chu (LLC) Test Results

Variable	LLC Test Statistics	p-value	Conclusion at 5% Significance
Insider Lending	-2.986	0.001	Stationary at levels
Bank Size	-3.902	0.000	Stationary at levels
Technical Efficiency	-4.018	0.000	Stationary at levels

The Levin-Lin-Chu (LLC) Panel Unit Root Test results were further employed to check for the stationarity of the variables used in the study. Through the LLC Panel Unit Root Test results, the results obtained made it clear that the variables were all stationary at 5% Significance. For insider

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lending, the LLC statistic obtained was -2.986 at a p-value of 0.001. On the other hand, the LLC statistic for bank size was -3.902 at p-value 0.000.

Finally, for technical efficiency variables, the LLC statistic obtained at the p-value of 0.000 results was -4.018. Based on the results obtained for the p-value at 0.05 level of significance for the LLC statistic tests for all variables, the results clearly made it evident that the results for all variables were rejection of the null hypothesis at 0.05 significance level. That is to say that the results made it clear that the mean, variance, and autocovariance of the variables were constant over time.

4.14 Hausman Specification Test

The Hausman specification test was used to determine the right panel data analysis method between the Fixed Effects model and the Random Effects model. This test determines if there is a correlation between the individual-specific effects and the regressors. It is important to identify the right model to use because specifying the wrong estimator may result in biased estimates **(**Hausman, 1978**)**. If the p-value of the Hausman test is ≤ 0.05, then reject H_0 and prefer the fixed-effects model. If p-value > 0.05, then non-rejection of H_0 and the random effects model are preferred.

Table 13: Hausman Specification Test Results

Test Statistic (χ^2)	Degree of Freedom	p-value	Model Preferred
12.638	2	0.007	Fixed Effects

The Hausman specification test was used to determine the appropriate technique for estimating the model using panel data, fixed or random effects. The chi-square value obtained is 12.638 with 2 degrees of freedom, and its significance probability is 0.007. Since this is less than 0.05, it leads to rejection of the null hypothesis concerning the suitability of the random effects model. Therefore, the fixed effects model is preferred because it provides consistent and unbiased estimations for testing insider lending compliance and bank size in technical efficiency in Kenyan commercial banks.

4.15 Standard Tobit Regression Model Estimates

This section discusses the results of the standard Tobit regression model estimation undertaken to explore the interplay between insider lending compliance, the size of the banks, and the technical efficiency of commercial banks in Kenya. The application of the standard Tobit regression model to the research was justified by the fact that the dependent variable, technical efficiency, has a censored range of (0, 1) In this case, the application of the Ordinary Least Squares (OLS) regression model would not only produce biased results due to the censored nature of the dependent variable but would also result in the inconsistency of the parameter estimates due to the same reason.

In the context of the research, the technical efficiency scores obtained from the Data Envelopment Analysis (DEA) method are inherently bounded variables with the possibility of the banks being at the lower boundary of inefficiency and the frontier of the technical efficiency of the banks. In this scenario, the application of the OLS regression model would produce biased results due to the oversight of the model regarding the bounded nature of the dependent variable. In this regard, the standard Tobit regression model provides more reliable and consistent results regarding the impact

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of insider lending compliance and the size of the banks on the technical efficiency of the commercial banks in Kenya and therefore provides increased robustness to the results of the research and the validity of the policy and regulatory inferences of the research results.

Table 14: Standard Tobit Regression Model Estimates

Variable	Coefficient (β)	Std. Error	z-Statistic	p-value	Significance
Constant	-0.124	0.047	-2.638	0.008	Significant
Insider Lending ($Led_{i,t}$)	-0.113	0.039	-2.897	0.004	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	0.168				
Sigma (σ)	0.361	0.019			
Number of Observations	370				

The results in Table 14 indicate that the model was significant since the likelihood ratio chi-square of 72.18 with an associated p-value of 0.000 was observed. This implies that the variables used in the model significantly explained the variations in the variable technical efficiency. Even with the measurement issues inherent in the dependent variable being censored, the model explains the variations in technical efficiency with a pseudo- R^2 of 16.8 percent.

Insider Lending Compliance (β = –0.113, ρ = 0.004) has a negative and significant association at the 5 percent significance level, which indicates that lower compliance with the insider lending guideline is related to lower technical efficiency among commercial banks. This result suggests that banks with lower levels of compliance with the insider lending guideline are unable to manage risks effectively, leading to lower resource efficiency. Banks with higher levels of compliance with the insider lending guideline are able to manage risks effectively, hence improving efficiency.

On the other hand, size has a positive influence on technical efficiency. That means bigger banks have a greater degree of technical efficiency. This might be due to economies of scale or better access to technology. The result shows that size has a statistically significant influence on technical efficiency (β = 0.063, ρ = 0.004). The result verifies the scale efficiency hypothesis. The hypothesis states that bigger banks are better equipped to cover fixed expenses.

The constant term is negative and significant (β = -0.124, p = 0.008), indicating efficiency base values while the other variables are held constant. The sigma estimate (σ = 0.361) shows there is some variation in the efficiency variable, further supporting the model specification because of the censored efficiency scores.

4.16 Standard Tobit Regression Estimates with Moderating Effect of Bank Size

This section presented the findings of the standard Tobit regression model, which encompassed the moderating variable, bank size, and its interaction with the variable, insider lending compliance, to determine its effect on the technical efficiency of commercial banks in Kenya.

Table 15: Standard Tobit Regression Estimates with Moderating Effect of Bank Size

Variable	Coefficient (β)	Std. Error	z-statistic	p-value	Significance
Constant	-0.134	0.045	-2.756	0.006	Significant
Insider Lending ($Led_{i,t}$)	-0.126	0.038	-2.974	0.003	Significant
Bank Size ($size_{i,t}$)	0.043	0.021	3.000	0.003	Significant
$Led_{i,t} \times size_{i,t}$	-0.020	0.008	-2.500	0.012	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				

Findings from the standard Tobit Regression model, which accounts for the moderating role of bank size, highlight the significance of compliance with the insider lending guideline and its impact on the technical efficiency of commercial banks in Kenya. The findings from the standard Tobit Regression model for 370 observations presented a significant result, which is supported by the chi-square value of 84.12 ($p = 0.000$) for the LR chi-square, and the pseudo-R square of 0.184 indicates significant differences in the variable explaining efficiencies.

The coefficient on the compliance level regarding the insider lending rule was negative and significant (β = -0.126, $p = 0.003$). This finding means that lower levels of compliance, indicating high levels of lending to insiders beyond the regulatory threshold, are negatively related to technical efficiency. On the other hand, high levels of compliance are indicative of improved efficiency, suggesting better effectiveness of input use due to strict compliance with the insider lending rule. This finding highlights the significance of sound discipline and good governance practices in ensuring a cap on insider exposures which may otherwise affect credit and efficiency performance.

The size of the bank had a positive and significant effect on technical efficiency (β = 0.043, $p = 0.003$), which indicates that bigger banks tend to be more efficient than smaller ones. This can be explained by the scale economies, more sophisticated monitoring systems, or the institutional capability to enforce prudential rules.

The moderating effect of the level of compliance with the insider lending guideline on the relationship between compliance and efficiency was negative and statistically significant (β= -0.020, p-value= 0.012), and this showed that compliance with efficiency is moderated by bank size.

5.0 Conclusion

This research investigated the effects of compliance with insider lending prudential guidelines, size, and technical efficiency for commercial banks in Kenya. The research classified commercial banks based on their level of compliance below, at, or above the Central Bank of Kenya (CBK) inner lending guidelines. The findings of the research show that commercial banks that meet or exceed the CBK prudential guidelines on the level of compliance with insider lending activities exhibit high technical efficiency. On the other hand, commercial banks that perform below the stipulated guidelines on the level of compliance with insider lending show lower technical efficiency. The findings of the research confirm that poor compliance with the insider lending guidelines affects the technical efficiency of the commercial banks.

Further analysis shows that banks that exceed minimum compliance requirements are likely to achieve better efficiency results compared to those that complied with the rules. The implication here is that exceeding minimum requirements enhances internal control and risk management, which correspondingly improves efficiency. Empirical evidence supports the assertion that prudential regulation policy is efficient if banks incorporate compliance into their corporate culture rather than just seeing it as a regulatory requirement.

Both developed and emerging-market countries have presented findings that showed inefficient lending between the bank's insider groups led to poor credit discipline and increased levels of inefficiency arising from insider lending-related conflict of interest issues. The findings from the study are consistent with findings from African banking sectors that showed poor enforcement of insider lending rules can lead to increased inefficiency levels within bank performance.

6.0 Recommendations

The study recommends commercial banks to enhance their level of compliance with insider lending guidelines, with a view to not only meeting minimum requirement thresholds set within the guidelines by the Central Bank of Kenya (CBK) but to exceed them considerably. It is evident from the results of this study that those banks whose levels of insider lending compliance exceed the guidelines' requirements reach a higher level of technical efficiency compared to those whose levels still fall short of the guidelines' thresholds. Therefore, insider lending-related issues within the bank would need to benefit from strong internal controls and better insider-related transaction processes within the bank and strict monitoring and disclosure requirements, and hereby, become part and parcel of corporate risk management within the institution and not just a mere regulatory or procedural requirement.

In regulatory and policy terms, it is recommended that the CBK strengthen the oversight and enforcement approach aimed at the issue of insider loans, especially among the banks that are perennially below the threshold of prudent compliance. The approach to risk-supervision methodology needs to prioritize the level of compliance, rather than the absolute level of the insider loans, which are more reflective of the relative level of effectiveness. Moreover, incentives for supervisory recognition, such as relaxed intensity for monitoring, for banks that are normally above the threshold of prudent compliance on the issue of insider loans, could promote a culture that emphasizes positive compliance, which is more efficient.

For future research, it is recommended that the findings of this research be expanded by examining the dynamic effects of insider lending compliance. Additionally, other research may be conducted that investigates other countries that have similar rules and regulations. These researches can yield further knowledge and understanding of the effects of institutional differences on the efficiency effects of insider lending compliance.

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