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Liquidity Risk Compliance Levels and Technical Efficiency of Commercial Banks in Kenya: Application of Non-Parametric Data Envelopment Analysis Model

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Abstract: *This paper analyzed the relationship between liquidity risk compliance levels and technical efficiency of commercial banks in Kenya. The study adopted quantitative research design for a period of ten year ranging from 2013 to 2022. The population of the study was 37 licensed commercial banks, which produced a balanced panel of 370 firm-year observations. Data Envelopment Analysis (DEA) was used to estimate technical efficiency scores. The impact of liquidity risk compliance levels, bank size, and the relationship between liquidity risk compliance levels and bank size on technical efficiency was estimated using a two-limit Tobit regression model estimated with the Maximum Likelihood Estimation (MLE) technique. The study findings indicate that there is a positive and statistically significant correlation between liquidity risk compliance levels and technical efficiency, which implies that banks that are more compliant with liquidity risk prudential requirements are more efficient. This implies that effective liquidity management improves operational discipline, increases resource allocation, and promotes more efficient banking operations. Bank size positively and statistically significantly influence the technical efficiency, which means that bigger banks have economies of scale and are more capable of absorbing liquidity shocks. Moreover, the interaction effect of liquidity risk compliance levels and bank size is positive and significant, which proves that bank size mediates the relationship between liquidity risk compliance levels and technical efficiency. In particular, bigger banks can more easily utilize liquidity buffers without efficiency loss. The study recommends that commercial banks in Kenya should intensify liquidity risk management procedures and ensure compliance to prudential liquidity standards as a way of improving technical efficiency. Regulators and policymakers are urged to implement proportionate liquidity risk frameworks to consider differences in bank sizes to facilitate effective and efficiency-enhancing supervision. It is suggested that future studies should build on the analysis by including other institutional variables like risk culture, corporate governance, and technological adoption to elaborate on the differences in technical efficiency among commercial banks in Kenya.*

Keywords: Liquidity risk, Technical efficiency, Bank size, Commercial banks

1.0 Introduction

The banking sector liquidity risk compliance is essential in ensuring that financial institutions are able to fulfill their short-term commitments and remain operational efficiency, particularly in developing economies that are susceptible to macroeconomic shocks (Korneev *et al.,* 2023). After periods of financial strain, the Central Bank of Kenya (CBK) has focused on prudential liquidity risk provisions to protect the sustainability of individual banks (Wanjiru & Waweru, 2025). One of the most important regulatory instruments used to prevent institutional failures and stability in the banking sector is compliance with liquidity risk requirements, including having sufficient high-quality liquid assets in relation to short-term liabilities (Kirimi *et al.,* 2023).

In line with the Basel Accords, these requirements including the Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) seek to ensure that banks hold sufficient liquid assets to withstand short-term and structural liquidity shocks (Bayar *et al.,* 2021). In Kenya, these international standards have been localized by setting specific liquidity risk compliance levels under the watch of the CBK (Waweru *et al.,* 2021). CBK still underlines the importance of liquidity risk compliance as a tool to improve risk management and safeguard depositors (Liu & Xie, 2024). Regardless of these regulatory efforts, there is little empirical evidence that connects liquidity risk compliance to the technical efficiency of Kenyan commercial banks. This is a crucial gap considering that banks in Kenya experience special liquidity strains due to deposits, loan demand, and market volatility (Yahaya *et al.,*2022)

Technical efficiency, which reflects a bank's ability to maximize outputs using available inputs, is an essential measure of operational performance and regulatory compliance (Waweru *et al.,* 2021). Banks that effectively deal with liquidity risks are able to maximize the use of resources, minimize the cost of operations, and become resilient during financial stress. Conversely, inefficiencies can undermine banks' ability to translate liquidity risk compliance into enhanced performance, as mismanagement of liquid assets can negate the benefits of regulatory adherence (Nyaga, 2022). Thus, it is important to know how liquidity risk compliance and technical efficiency interact, especially when the size of the bank can moderate this interaction. Bigger banks can usually take advantage of economies of scale, diversify sources of funding, and put more robust internal mechanisms in place to sustain regulatory liquidity levels and remain efficient (Zhao *et al.,* 2024). Smaller banks, in turn, might not be able to fulfill these requirements without limiting operations or becoming riskier (Ben Lahouel *et al.,* 2024).

The banking industry in Kenya is a key economic driver as it gathers funds, distributes credit, and makes payments (Wanjagi *et al.,* 2024). However, the industry is still vulnerable to operational inefficiencies, which underscores the significance of efficient liquidity risk compliance in reducing the risks (Pasha, 2024). Despite the fact that CBK liquidity rules have been modified over the years, empirical evidence on whether compliance with these rules has led to a better technical efficiency among banks of different sizes remains limited (Ikapel *et al.,* 2023).

1.1 Statement of the Problem

Despite sustained regulatory reforms and increased adoption of financial technologies, commercial banks in Kenya continue to exhibit persistent technical inefficiencies, raising serious concerns about the effectiveness with which banking resources are transformed into financial services (Waweru *et al.,* 2021). Technical efficiency is fundamental to financial intermediation because inefficient banks use too many inputs, such as labour, capital, and operating expenses, to generate a given level of output, which raises the cost of credit and hampers economic growth (Wanjagi *et al.,* 2024). In Kenya, this issue is especially acute given the banking sector's dominance in financing households, small and medium-sized enterprises (SMEs), and government activities (Kirimi *et al.,* 2023). The persistence of technical inefficiency is reflected in rising operating costs, widening interest rate spreads, repeated bank distress and closures, and declining productivity indicators, despite compliance with Central Bank of Kenya (CBK) prudential regulations. This contradiction implies that compliance with prudential standards does not necessarily equate to technical efficiency. Instead, banks may be allocating significant resources to meeting regulatory requirements in a way that increases compliance costs without enhancing internal efficiency, particularly for smaller and medium-sized banks that lack economies of scale. Consequently, inefficient resource utilization continues to undermine competitiveness and sustainability within the sector.

Furthermore, Kenyan commercial banks operate in an increasingly constrained environment, marked by increased liquidity risk, liquidity pressures, and technological disruption (Ikapel *et al.,* 2023). These challenges mean that banks must operate at or near the efficiency frontier to stay viable. However, evidence suggests that many banks do not optimally allocate inputs, leading to excess capacity, redundant branch networks, suboptimal use of digital platforms, and weak cost control mechanisms. Such inefficiencies lower the capacity of banks to absorb shocks, making them more vulnerable to financial instability and systemic risk.

From a policy perspective, the absence of robust, efficiency-focused evidence presents a critical gap. While many studies in Kenya focus on profitability, liquidity, or financial stability, there has been little empirical attention to technical efficiency, which is a more direct measure of managerial and operational performance (Kinini *et al.,* 2024). Moreover, existing studies rarely integrate prudential regulatory compliance and bank size within an efficiency framework, leaving regulators and bank managers without clear guidance on whether current prudential policies enhance or constrain productive efficiency.

Despite the Central Bank of Kenya’s (CBK) stringent liquidity risk regulations, many commercial banks in Kenya continue to face periods of liquidity stress, which can negatively impact their technical efficiency (Kinini *et al.,* 2024). Failure to comply with liquidity risk requirements may compel banks to channel resources to meet the short-term commitments instead of maximizing the utilization of inputs to maximize outputs, thus lowering technical efficiency. Although previous research has been conducted on liquidity risk and banking stability, there is scant empirical research on the specific impact of liquidity risk compliance levels on technical efficiency in the Kenyan banking industry.

1.2 Research Objectives

i. To examine the influence of liquidity risk compliance levels on technical efficiency of commercial banks in Kenya.
ii. To determine the moderating influence of bank size on the relationship between liquidity risk compliance levels and technical efficiency of commercial banks in Kenya.

2.0 Literature Review

This chapter reviewed relevant theoretical, conceptual and empirical literature related to liquidity risk compliance level, bank size and technical efficiency of commercial banks in Kenya using the Data Envelopment Analysis (DEA) model. It reviewed the theories behind liquidity risk management, bank size, and efficiency in the banking sector, followed by conceptual discussion of the key study variables and their measurement. The chapter further analysed empirical studies from both global and local contexts, with emphasis on research that applied DEA in assessing bank efficiency. Through this review, gaps in existing literature were identified to justify the focus and methodological approach of the study, and the chapter concluded with a summary of the reviewed literature

2.1 Theoretical Review

Liquidity Preference Theory was formulated by John Maynard Keynes in 1936 in The General Theory of Employment, Interest and Money, and it challenged classical views by positing that interest rates are not solely determined by savings, but by the public's demand for liquidity and the money supply. Keynes believed that individuals and institutions hold money for transaction, precautionary, and speculative reasons, with expectations about future interest rates affecting liquidity demand. The theory was later formalized in the IS-LM framework by Hicks (1937) and extended by Baumol (1952) and Tobin (1956, 1958) to include inventory and portfolio selection approaches, emphasizing the trade-off between liquidity and return. In recent empirical finance research, scholars have applied Liquidity Preference Theory to banking liquidity and risk management, such as in studies that examine banks' liquidity buffers and compliance with regulatory liquidity requirements, demonstrating that precautionary liquidity motives influence banks' asset portfolios and risk behaviour. Berger and Bouwman (2009) applied liquidity preference concepts to examine the impact of liquidity creation on bank performance, while Vodova (2011) and follow-up studies in emerging markets linked liquidity holdings to risk exposure and performance outcomes. Post-2008 regulatory research has also used the theory to justify the Basel III liquidity standards, demonstrating the role of liquidity preference in explaining bank responses to stringent Liquidity Coverage Ratios and Net Stable Funding Ratios, including empirical work in African banking sectors that highlights the relationship between liquidity compliance, risk management, and efficiency (Bayar *et al.,* 2021).

In this research, the Liquidity Preference Theory offers a conceptual framework to study the effects of liquidity risk compliance on the technical efficiency of commercial banks in Kenya. It confirms the hypothesis that banks that comply with liquidity requirements can allocate resources more effectively, optimize input-output ratios, and have higher levels of technical efficiency even in times of financial stress.

2.2 Conceptual Framework

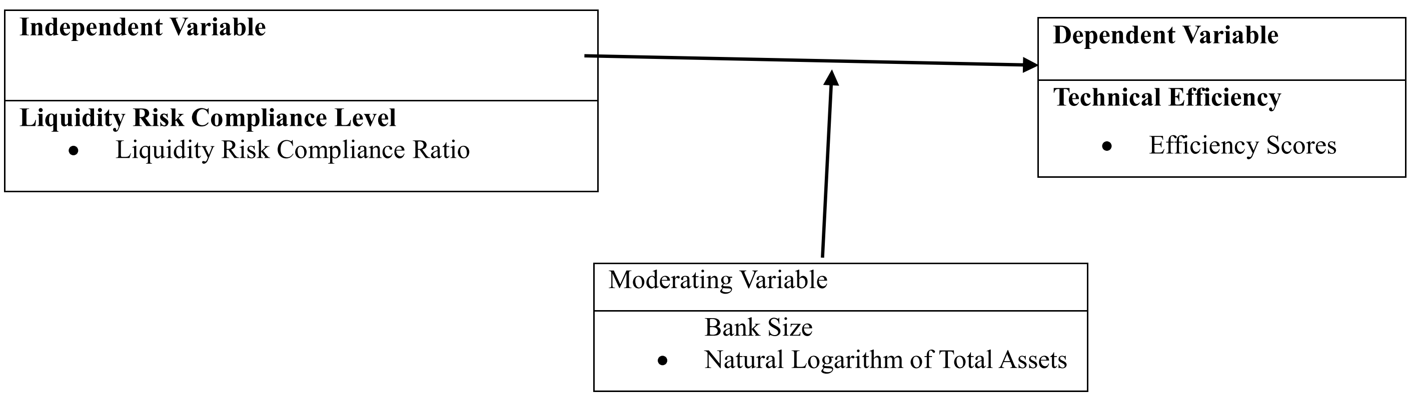

Figure 1: Conceptual Framework.

2.6 Empirical Review

Samad and Armstrong (2022) carried out a study in the United States and Europe in 2000-2010 with a sample of more than 1,000 commercial banks. They used dynamic panel regression models and used profitability, liquidity ratios and efficiency scores based on DEA to measure bank performance. They found that the banks that were better placed in terms of liquidity, as indicated by high liquidity coverage ratios and adequate liquid assets, were more efficient in terms of technical efficiency and resilience, especially in times of financial stress. The research also established that bigger banks were in a better position to convert liquidity compliance into efficiency benefits, which supports the idea that the size of banks amplifies the operational advantages of meeting liquidity requirements. These findings are consistent with the Liquidity Preference Theory and the Economies of Scale Theory, which states that sufficient liquidity is necessary to ensure efficient use of resources.

Obadire *et al.* (2022) studied 24 South African commercial banks between 2010 and 2018 to determine the correlation between compliance with liquidity risk and bank performance. The study estimated liquidity compliance using the Generalized Method of Moments (GMM) estimation by measuring ratios of liquid assets to short-term liabilities. The results showed that there was a strong positive relationship between liquidity compliance and technical efficiency, whereby banks that had sufficient liquid assets exhibited high efficiency in their operations and management of resources. The paper also identified a size effect as larger banks were better positioned to sustain liquidity demands without sacrificing efficiency whereas smaller banks experienced resource constraints that constrained their performance.

Boamah *et al.* (2023) examined the moderating role of bank size in the relationship between liquidity risk compliance and technical efficiency in 37 commercial banks between 2013 and 2022 in the Kenyan context. The study employed interaction term models in a panel regression framework and found that compliance with liquidity risk guidelines had a positive impact on technical efficiency, although the impact was significantly stronger in large banks. Smaller banks had a hard time keeping regulatory liquidity ratios without adversely affecting operational performance. The study found that regulatory frameworks must consider the size of banks in the enforcement of liquidity risk compliance to make sure that regulatory compliance is effectively translated into enhanced technical efficiency in banks of all sizes.

3.0 Methodology

A quantitative research approach was adopted in this study, under which an explanatory research design was employed. The explanatory design was adopted to investigate the influence of liquidity risk compliance levels on the technical efficiency of commercial banks in Kenya and to ascertain the moderating role of bank size in this relationship. The study is based on secondary panel data from 37 licensed commercial banks in Kenya. The data were sourced from the Central Bank of Kenya (CBK) and Bank Supervision Annual Reports from 2013 to 2022. This approach is suitable because it allows for the objective measurement of variables, hypothesis testing, and the determination of cause-and-effect relationships through statistical analysis across banks and over time.

3.1 DEA (First stage Analysis)

In an attempt to ascertain the efficiency of the commercial banks in Kenya, the research employed Data envelopment Analysis (DEA), which is a paramount non-parametric method, suggested by Charnes *et al*. (1978). The bootstrap procedure was used to increase the accuracy and reliability of the DEA efficiency scores since it considers effects of sampling and data noise (Konar *et al.,* 2025). In order to derive technical efficiency, this study embraced the efficiency viewpoint which relied on the DEA model.

Following the notation of Cook and Seiford (2009), consider a set of nDMUs: with each DMU_j (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

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

Subject to

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

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 j^{th} DMU
y_{rj} = The amount of output r produced by the j^{th} 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.,* 2014)
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, ν) 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;

$$\sum_{i=1}^{m} x_{ij}\lambda_j \leq \theta x_{i0} \qquad i = 1,2, \dots\dots, m;$$
$$\sum_{j=1}^{n} y_{rj}\lambda_j \geq y_{r0} \qquad i = 1,2, \dots\dots, s;$$
$$\lambda_j \geq 0 \qquad j = 1,2, \dots\dots\dots\dots, n$$

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 Analysis: Tobit Regression

In the second stage, these efficiency scores were used as a key dependent variable to measure the impact of level of compliance with liquidity risk guidelines and bank size on technical efficiency. For the purposes of this study, compliance level was incorporated as part of the prudential measures rather than considered as a separate objective. For every bank, the respective ratio or measure was compared to the minimum requirement by the CBK and evaluated based on whether it is above minimum meets minimum or below minimum.

In the second step of the analysis the current study examined the impact of liquidity risk compliance levels on the efficiency scores of the commercial Banks in Kenya. This study employed the Tobit regression to address the limited spectrum of efficiency scores that lie in the 0 to 1 range (Wang & Wang, 2022). Specifically, upper and lower censoring was accommodated with the two-limit Tobit model based on the specification of Rosett and Nelson (1975).

With upper and lower censoring, according to the notations of Wu *et al.* (2022) the observed censored variable is y_i. The following should be a measurement equation for subject i

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

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

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

3.3 Selection of Inputs and Outputs

Appropriate input and output variables are of great importance when using the DEA models. Two main definitions of the inputs and outputs in the research on the efficiency of banking are found in the literature, namely the production approach and the intermediation approach (Berger and Humphrey, 1997). The approach to production; considers banks as service providers where deposit is the result and labour and capital are the inputs (Berger and Humphrey, 1997). The intermediation approach conversely views banks as intermediaries that connect the excess units (depositors) with the deficit units (borrowers) by converting the deposits and other inputs into investments and loans (Shre*stha et* al., 2025). In this approach, deposits, labour, capital are considered as inputs and investments, and interest income as outputs (Smętek *et al.,* 2022).

The intermediation method was used since the object of the study is the banking industry in Kenya and the research aims to investigate how the banks connect the surplus and deficit units. Istaiteyeh *et al.* (2024) noted that there is no consensus on what is the input and output of the financial institutions and that the issue remains debatable in the present literature (Shah *et al.,* 2023). The following inputs were used (Operating Expenses, Total deposits, interest expenses) and outputs (interest income and investment income).

3.4 Specification of Economic Model.

In the study, two limit Tobit regression model was used to identify the effect of liquidity risk compliance on technical efficiency of commercial banks in Kenya and to establish that the relationship between the two variables is moderated by bank size. The model was used because of the censored behaviour of the dependent variable and provided the estimates with the help of the Maximum Likelihood Estimation (MLE). The initial model was def*i*ned as:

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

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

$$\boldsymbol{ES_{i,t} = \beta_0 + \beta_1 LRCL_{i,t} + \beta_2 size_{i,t} + \beta_{11}(LRCL_{i,t} \times size_{i,t}) + \varepsilon_{i,t}, \ \varepsilon_i \sim \text{N}(0, \sigma^2)}$$

Where:

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

$\boldsymbol{LRCL_{i,t}}$ = *R*epresent Liquidity risk compliance level which is measured using the liquidity risk compliance ratio

$(\boldsymbol{LRCL_{i,t} \times size_{i,t}})$= Interaction term for moderating effect $\boldsymbol{LRCR_{i,t}} = \frac{\boldsymbol{Liq_{i,t}}}{\boldsymbol{R}}$ where; $\boldsymbol{LRCR_{i,t}}$ = Liquidity risk compliance ratio for bank i at time t. $\boldsymbol{R}$ = CBK prescribed regulatory threshold. $\boldsymbol{Liq_{i,t}} = \frac{(\boldsymbol{Liquid\ Assets})_{i,t}}{(\boldsymbol{Total\ Customer\ deposits})_{i,t}}$. Liquid assets consist of cash on hand, balances with the CBK, short-term placements, and government securities with maturities not exceeding 91 days. This paper developed a liquidity risk compliance ratio according to the Central Bank of Kenya (CBK) Prudential Guidelines, which stipulates that the minimum liquidity ratio of commercial banks should be not less than 20 percent. Rather than relying on the raw liquidity ratio alone, the study adopts a regulatory-adjusted measure that captures the extent to which a bank's observed liquidity position

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complies with the prescribed regulatory benchmark. $LRCR_{i,t} < 1$ signifies that a bank is not in compliance with the CBK liquidity requirement, which reflect a high liquidity risk, and impaired ability to fulfill the short-term obligations. This non-compliance can put banks at the risk of liquidity stress, compelled asset liquidation, or the heightened reliance on expensive short-term funding. On the other hand, $LRCR_{i,t} \geq 1$ indicates that a bank has surpassed or satisfied the regulatory liquidity requirement, which can be read as a well-managed liquidity risk and an adequate liquidity cushion to absorb shock funding in the short-term.

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

$\boldsymbol{\beta}_0$ = The intercept,

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

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

$\boldsymbol{\beta_3}$ = The moderating effect of bank size on the relationship between liquidity risk compliance levels and technical efficiency.

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

Subscript $\boldsymbol{i}$ = Commercial banks (Cross - section dimension) ranging from 1 to 37

Subscript $\boldsymbol{t}$ = Years (time - series dimension) ranging from 2013 to 2022.

4.0 Findings and Discussion

This section addressed the research findings on the compliance element of liquidity risk requirement in the context of commercial banks technical efficiency in Kenya, which was moderated by the bank size.

4.1 Efficiency Scores Estimation with Bootstrap Results and DEA

The scores of technical efficiencies of commercial banks in Kenya were derived using a non-parametric method, which is Data Envelopment Analysis (DEA) due to its suitability in gauging the efficiency to which various commercial banks in Kenya make use of various inputs to generate more outputs relative to a frontier or best-practice standard. The scores obtained in DEA are between 0 and 1, where high scores mean that there is high efficiency in resource utilization. Nevertheless, to minimize biases related to normal DEA estimations due to sampling variability and random errors, bootstrap method was employed to enhance their statistical validity. The bootstrap estimates indicate that efficiency scores without the bias are lower than normal DEA estimates, which confirms the argument that normal DEA models often overestimate efficiency when encountered with uncertainties. The post-bias efficiency scores are highly varied, so they give a more plausible estimation to determine the role of prudential compliance and size on commercial bank technical efficiency in Kenya.

Table 1: The estimation of the efficiency scores using DEA and Bootstrap.

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 efficiency scores fell between 0.6569 (2017) and 0.7842 (2013), which shows that the financial sector has been fairly or less efficient over the years. The loss of efficiency in 2016 and 2017 comes at a period when interest rate capping policies in Kenya impacted significantly on the banking industry by reducing the lending margins and diminishing profitability. In 2019, interest rate caps were repealed, letting banks charge loans according to risk and enhancing efficiency, possibly driving the 2019 and 2020 recovery. The decline in efficiency in 2016 and 2017 coincides with the time when the Kenyan government revised the Banking (Amendment) Act, 2016, which restricted the amount of interest that banks could impose on borrowers. This policy: Decreased access to credit, especially to small and medium enterprises (SMEs). It lowered the profitability of the banks hence cost cutting and restructuring.

The efficiency increases in 2018 and 2020 indicates that Kenyan banks have utilized mobile banking and fintech solutions. Money In Kenya Finance Mobile money services (including., M-Pesa) have been a global leader and were used to enhance financial access and efficiency. KCB and Co-operative Bank, as well as Equity Bank, have digitized their services aggressively and they have lowered their operation costs and enhanced efficiency.

4.2 Descriptive Study Variables.

Descriptive statistics were applied in this research to give a simple understanding of the nature and characteristics of the important variables of interest before econometric analysis was applied.

Table 2: Descriptive statistics of the 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		
$LRCR_{i,t}$	Overall	1.623	0.700	0.882	3.201	1.021	3.735
	Between		0.634	1.000	3.000		
	Within		0.391	0.882	3.201		
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 technical efficiency, compliance- adjusted liquidity risk, and size of banks have significant variance between commercial banks in Kenya. The average technical efficiency level of 0.670 indicates that the commercial banks were operating at average 67 percent of the efficient frontier, which implies that there was efficiency gain through efficient use of inputs. The measures of efficiency were between 0.102 and 0.998, showing that there was a significant difference in operational performance among banks. The standard deviation is relatively low (0.167), which indicates average dispersion around the mean.

The liquidity risk compliance ratio had a total mean of 1.623, which implied that on average, the liquidity levels of the commercial banks had been well ahead of the CBK minimum level requirement. This means that there is usually a high liquidity stance in the sector. Nevertheless, the broad span of 0.882 to 3.201 indicates that there were banks that were below the regulatory standard at some time of the year whereas others had much higher levels of liquidity reserves. The liquidity compliance dispersion is high with a standard deviation of 0.700. The difference between variance (0.634) was higher than that of the within variance (0.391), which indicated that the differences in liquidity compliance were primarily due to structural differences among banks and not short-term variations across time. The positive skewness (1.021) and kurtosis (3.735) are high, showing a skewed distribution to the right with some banks having very high liquidity buffers which may indicate a conservative approach to liquidity, or aversion to risk.

Considering the rank of the banks, the total mean of 24.733 suggests a moderate bank size in the sample, where the mean varies between 20.60 to 29.014, which shows heterogeneity in asset bases of the commercial banks. The mean deviation of 1.614 indicates moderate variance of size. The between-bank change (1.593) was also much greater than the within-bank change (0.361); the implication was that bank size was relatively constant over time, but varied greatly across banks. The skew value (-0.421) and the kurtosis value (2.499) show that the distribution is skewed slightly to the right with no sign of extreme size outliers.

4.3 Diagnostic Test

In order to verify the validity and reliability of the regression model, a set of diagnostic tests were performed to test possible breaches of some major assumptions.

4.3.1 Censoring Diagnostic Test

Likelihood Ratio test was employed to determine whether the data would be better fitted by Tobit model with censoring on the dependent variable (efficiency score) as compared to 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%

The test played a crucial role in the research since the dependent variable (bank efficiency scores based on the DEA model) is not beyond a finite range (0 to 1) that might imply censoring at one or both ends (Wooldridge, 2023). The outline of the DEA efficiency scores is that most of the data is uncensored. Out of the 37 commercial banks, 35 banks (94.59%) have a score of efficiency of above 0.500 and below 0.950. The two-limit Tobit model was thus employed to determine accurately the impact of liquidity risk compliance levels and bank size on technical efficiency, as the majority of the data is uncensored, and with minimal effects of extreme values (Greene, 2018).

4.3.2 Generalized Residues Test

The second stage regression equation that related prudential compliance variable to bank size and technical efficiency tested whether or not endogeneity existed. This was done using the Generalized Residuals Test. This test can be used in models where the dependent variable is restricted and the test tests the relationship of the residuals in the first stage estimation with 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 demonstrates the results of the generalized residuals test with 37 observations. The mean of residuals was 0.003 with a median of 0.001 indicating that the residuals cluster around zero. 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 values had a standard deviation of 0.082, and there was no divergence in value as compared to the actual point. The outcome of a JB test was a p-value of 0.392, which indicates that the null hypothesis of normality could not be rejected, and distributions are more or less normal.

4.3.3 Multicollinearity Test

A test of multicollinearity is the Variance Inflation Factor (VIF). The presence of multicollinearity between the independent variables in the regression model is confirmed by the calculation of the Variance Inflation Factor (VIF). VIF exceeding 10 is usually a serious indicator of multicollinearity (Wooldridge, 2023).

Table 5: Results for Variance Inflation Factor (VIF)

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

Table 5 presented VIF values of 1.05 and 1.38 with a mean value of VIF of 1.215. These values are low; hence the predictors are not very correlated. The low values of the VIFs imply that the estimates of the model are not significantly influenced by multicollinearity, and each independent variable contributes its unique value to the model (Baltagi, 2021)

4.3.4 Correlation Test

The strength and the nature of the linear relationship existing between the key variables, which include compliance with liquidity risk compliance levels, bank size, and technical efficiency, were determined using Pearson Correlation. Pearson Correlation was chosen because using continuous data is suitable to get a measure that defines the extent to which two variables travel.

Table 6: Correlation Matrix

Variable	Technical Efficiency	$LRCL_{i,t}$	Bank size
Technical Efficiency	1.0000		
$LRCL_{i,t}$	0.412	1.000	
Bank Size	0.320	0.392	1.000

The results of the correlation suggest that there are significant relationships between technical efficiency, compliance-adjusted liquidity risk, and bank size of commercial banks in Kenya. Liquidity risk compliance is positively related to technical efficiency, and the correlation coefficient is 0.412, which indicates a moderate positive relationship between the variables. This implies that banks with stronger liquidity risk compliance, those maintaining liquidity levels at or above the CBK regulatory threshold, tend to exhibit higher levels of technical efficiency. Adequate liquidity positions facilitate banks to fulfill short-term liabilities without any hitch, without stress funding, and better resource allocation, which facilitate efficient operations.

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 7.

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

N	JB statistics	p value	Decision
370	0.72	0.70	Fail to reject H_0 - residuals approximately normal

Jarque-Bera statistic equals 0.72 and the p-value of 0.70 exceeds the significance level of 0.05. So, reject the alternative hypothesis that the residuals are normally distributed. This indicates that the assumption of the normal distribution of the error terms in the Tobit model is met at a reasonable level, and the model estimates would be valid in making inferences.

4.3.6 Heteroscedasticity Test

Heteroscedasticity is a situation whereby the variance of the residual changes at varying values of the independent variables, which is not permitted under the classical linear regression model (Wooldridge, 2023). The estimates of parameters may be inaccurate, and the standard errors may be biased due to this violation that may affect the reliability of testing a hypothesess (Chen & Wang, 2022). The Breusch Pagan test was used to test the assumption of homoscedasticity and test the existence of any heteroscedasticity that had to be captured by robust standard errors.

Table 8: Breusch-Pagan Heteroscedasticity Test

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

The heteroscedasticity test by Breusch and Pagan is found in Table 8. The test statistic is 2.897 and the p-value is 0.067. Since the p-value is higher than the significance level of 0.05, the null hypothesis of non-homoscedasticity cannot be rejected. This means that the variance of the error terms is fixed. This leads to interpretation that heteroscedasticity does not occur in the regression model. Hence, the outcome of the standard error measurements could be viewed as being valid.

4.3.7 Autocorrelation Test

The autocorrelation implies that the residuals of panel data are correlated across units or over time implying that the error terms are not independent (Shah et *al., 2*023). In case of autocorrelation, this may result in a biased and inefficient estimate of the coefficients resulting in erroneous p-values and confidence intervals. The test of autocorrelation was conducted using the Durbin-Watson (DW) statistic, which is a well-known test of first-order autocorrelation of 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 presents the Durbin-Watson test statistics of the autocorrelation of the regression residuals. The test value was 1.81, which was within the acceptable level of 1.5 to 2.5. This outcome showed no autocorrelation in the residuals; it showed that observations were not time-dependent. This lack of autocorrelation contributes to the interpretation of results of regression analysis being valid.

4.3.8 Stationarity Test

To ensure that there is no spurious regression in this study, the Levin-Lin-Chu (LLC) test was conducted to verify the absence of stationarity in the variables and to verify the non-existence of any unit root in the variables.

Table 10: Stationarity Test Results.

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

In Table 10, the stationarity tests of liquidity risk compliance levels, bank size and technical efficiency are presented. Negative t-test of variables having a p-value of 0.0000 show that the variables are stationary and constrained on the values of the variance and mean. The t-test value of the variables with p-value of 0.0010 is negative, indicating that there is no change in the variables over time.

The above results indicate that the variables satisfy the conditions required in the regression analysis of the model. The findings demonstrate that there are no spurious regressions outcomes depending on the values of the variables.

4.3.9 Hausman Specification Test

Was conducted to determine whether individual effects are correlated with the model's explanatory variables. The null hypothesis (H0): The observed variables are not correlated to the explanatory variables. 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).

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Table 11: Hausman Specification Test.

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

The Hausman Specification Test statistics gave a Chi-square of 15.722 with a p-value of 0.002. As the p-value is less than 0.05, the research has made a conclusion that the null hypothesis of the consistency of the random effects model is rejected. The preferred model is the fixed effects model, that is, individual heterogeneity correlates with the variables in the model.

4.4 Standard Tobit Regression Model

The rationale behind the application of the conventional Tobit regression model to the study could be associated with the fact that the dependent variable, the technical efficiency estimates, obtained through the Data Envelopment Analysis and truncated within a particular finite scope, thus breaking the premises of the ordinary least squares' regression analysis technique (Cheng *et al.,*2023).

Table 12: 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
$LRCL_{i,t}$	0.276	0.051	5.412	0.000	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-R²	0.208				
Sigma (σ)	0.361	0.019			
Number of Observations	370				

The regression findings show that the compliance to liquidity risk and the size of the banks play a statistically significant role in determining the technical efficiency of commercial banks in Kenya. The constant term is negative and statistically significant ($\beta = -0.124$, $p = 0.008$), suggesting that in the absence of liquidity risk compliance and bank size effects, baseline technical efficiency would be low.

The coefficient for liquidity risk compliance level is positive and highly significant ($\beta = 0.276$, $p < 0.001$), indicating that higher levels of liquidity risk compliance are associated with increased technical efficiency. This means that the banks that hold their liquidity levels beyond the minimum set by the CBK can use their funds more effectively. There is sufficient liquidity, which lessens funding stress, limits dependence on expensive short-term borrowing, and facilitates easier operations, thus increasing technical efficiency.

Bank size also exhibits a positive and statistically significant relationship with technical efficiency ($\beta = 0.063$, $p = 0.004$), indicating that larger banks tend to be more technically efficient than smaller banks. This observation aligns with the Economies of Scale Theory that suggests that larger institutions enjoy economies of scale in terms of cost efficiencies, diversification of funding sources, and superior operation and risk management systems. Consequently, bigger banks are better placed to make liquidity compliance a source of efficiency.

4.5 Standard Tobit Regression Estimates including Moderating effect of bank size

The findings of Standard Tobit Regression Estimates involving the moderating influence of bank Size were further analysed with the aim of not only of analysing the direct influence of liquidity risk compliance levels on technical efficiency but in modelling the effect of this influence by the moderating factor of bank size.

Table 13: Standard Tobit Regression Estimates with Bank Size as a Moderating effect.

Variable	Coefficient (β)	Std. Error	z-statistic	p-value	Significance
Constant	-0.128	0.129	-0.90	0.006	Significant
$LRCL_{i,t}$	0.276	0.050	5.520	0.000	Significant
Bank Size ($size_{i,t}$)	0.052	0.036	1.440	0.003	Significant
$LRCL_{i,t} \times size_{i,t}$	0.034	0.041	2.170	0.002	Significant
Model diagnostics:					
Log Likelihood	-142.6				
LR Chi-square	84.12			0.000	Model Significant
Pseudo-R²	0.184				
Sigma (σ)	0.354	0.018			
Number of Observations	370				

The findings of the interaction model show that liquidity risk compliance levels, the size of banks and their interaction have a joint impact on the technical efficiency of commercial banks in Kenya. The constant term is negative and statistically significant ($\beta = -0.128$, $p = 0.006$), suggesting that in the absence of liquidity risk compliance and size effects, baseline technical efficiency would be relatively low. This highlights the role of regulatory compliance and structural bank features in the explanation of efficiency results.

The coefficient for liquidity risk compliance levels is positive and highly significant ($\beta = 0.276$, $p < 0.001$), indicating that higher levels of liquidity risk compliance are associated with higher technical efficiency. This means that banks with a liquidity buffer exceeding the CBK regulatory minimum are in a better position to fulfill their short-term commitments without a premature delay of operations and this enhances the efficiency at which the inputs are converted to outputs.

Bank size also exhibits a positive and statistically significant effect on technical efficiency ($\beta = 0.052$, $p = 0.003$), suggesting that larger banks tend to operate more efficiently than smaller banks. The observation is in line with the Economies of Scale Theory, which argues that bigger banks have the advantage in terms of costs and diversified sources of funds and superior operational systems that improve efficiency.

Importantly, the interaction term between liquidity risk compliance levels and bank size is positive and statistically significant ($\beta = 0.034$, $p = 0.002$), indicating that bank size strengthens the positive relationship between liquidity risk compliance levels and technical efficiency. This finding suggests that bigger banks can more easily convert liquidity compliance into efficiency gains than smaller banks can. The efficiency benefits of having sufficient liquidity buffers are improved by the capacity of larger banks to exploit scale economies, better liquidity management structures, and wider access to the funding markets.

The general model is statistically significant as showed by the likelihood ratio chi-square of 84.12 ($p < 0.001$) that the explanatory variables collectively explain the variations in technical efficiency. The pseudo-R^2 value of 0.184 indicates that approximately 18.4 percent of the variation in technical efficiency is explained by liquidity risk compliance, bank size, and their interaction. The estimated sigma ($\sigma = 0.354$) reflects moderate variability in efficiency scores across banks. With 370 observations, the findings are robust and provide strong empirical support for the moderating role of bank size in the liquidity risk–technical efficiency relationship.

4.6 Discussion

The results of the present study showed that liquidity risk compliance levels, bank size, and their interaction had a joint and significant impact on the technical efficiency of commercial banks in Kenya. In particular, the positive and highly significant coefficient of liquidity risk compliance levels suggested that higher adherence to liquidity regulations was associated with improved technical efficiency. These findings were compared with previous empirical studies at the international, regional and local levels.

The findings were consistent with those of Ball (2023) in the United States, who found that banks with higher liquidity buffers were more efficient because of lower operational and funding risks. Similarly, (Boamah *et al.,* 2023) in China found that banks that complied effectively with liquidity regulations had higher technical efficiency scores, as liquidity management allowed for better resource allocation and minimized inefficiencies. In India, Sidhu *et al. (*2022) reported that banks with strong liquidity positions were better able to optimize their input-output combinations, confirming the positive role of liquidity compliance. However, contrasting results were found in Germany (Bechtel *et al.,* 2023) and Spain (Mariscal-Cáceres *et al.,* 2024), where stringent liquidity requirements were linked to lower efficiency. The studies suggested that higher compliance costs and lower lending flexibility may offset potential efficiency gains in some market contexts.

Within Sub-Saharan Africa, the results were similar to Ogundele and Nzama (2025) in Nigeria, who found that banks with adequate liquidity levels had higher efficiency scores because of better operational stability. Similarly, Marimira and Gumel (2025) in Ghana found a positive relationship between liquidity compliance and bank efficiency, emphasizing the role of risk management in resource optimization. The current study also highlighted the interaction between bank size and liquidity risk compliance, showing that larger banks translated liquidity compliance into greater efficiency gains. This was supported by Ally *et al*. (2025) in Tanzania, who reported that larger banks could leverage economies of scale, diversified funding sources, and advanced risk management systems to comply with liquidity regulations more effectively than smaller banks. In contrast, Okello (2018) in Uganda and Chikweche (2017) in Zambia found that smaller banks experienced higher relative costs of compliance, which constrained efficiency gains, resulting in insignificant or negative effects.

Within the Kenyan context, the findings were largely consistent with studies that emphasized the importance of liquidity management in improving bank efficiency. For example, Musiega *et al.* (2017) found that compliance with Central Bank of Kenya liquidity regulations had a positive impact on bank performance and stability. Similarly, Muriithi and Waweru (2017) noted that banks with higher liquidity ratios had better efficiency outcomes. The current study extended these findings by showing that bank size moderates the relationship, with larger Kenyan banks benefiting more from liquidity compliance than smaller ones. However, studies Mwaura *et al.* (2025) have found mixed results, indicating that variations in methodology, study periods, and approaches to measuring efficiency may account for the differences in findings.

5.0 Conclusion and Recommendations

This paper has investigated how liquidity risk compliance levels impacts the technical efficiency of commercial banks in Kenya and it has particularly focused on the mediating role of bank size. The study estimates technical efficiency using Data Envelopment Analysis (DEA) and the maximum likelihood estimation of a two-limit Tobit model to identify the empirical evidence of the relationship between compliance with CBK prudential liquidity requirements and bank technical efficiency.

The results established that liquidity risk compliance levels positively and statistically significantly impact technical efficiency, meaning that those banks that ensure that their liquidity levels do not fall below the regulatory mark are in a better position to turn their inputs into outputs. Maintaining adequate liquidity positions can alleviate funding stress, enhance regular operation procedures and reduce expensive emergency borrowing which lead to better technical efficiency. These findings highlight the significance of regulatory liquidity compliance not only as a measure to mitigate risks but also to augment working performance in the banking sector.

The study also develops that bank size is a positive factor that affects technical efficiency, indicating that bigger banks have economies of scale, diversified sources of funds and more sophisticated liquidity management and operational systems. Notably, the interaction analysis shows that the positive correlation between liquidity risk compliance and technical efficiency increases with the bank size, which suggests that bigger banks are in a better position to translate regulatory compliance into efficiency gains than smaller banks.

It is recommended that commercial banks should always ensure that they have a high level of compliance with CBK prudential liquidity requirements because high degree of compliance with liquidity risk is positively correlated with greater technical efficiency. Liquidity risk compliance should be incorporated in the overall operational and strategic planning platforms of banks to make sure that liquidity buffers are deployed in assisting to efficiently utilize resources instead of limiting productive activities. Proper liquidity planning must report a balance between regulation and best assets allocation to prevent inefficiencies caused by overabundant idle liquid resources.

The paper also suggests that regulators and policymakers should take into account bank size in the design and implementation of liquidity risk regulations. The results suggest that bigger banks can more easily convert liquidity compliance into efficiency, whereas smaller banks might have to struggle more to comply with regulatory requirements without efficiency losses. In this regard, it might need specialized regulatory advice, proportional oversight, or capacity-building programs to help smaller banks comply effectively.

Furthermore, it is recommended that the Central Bank of Kenya should strengthen continuous monitoring and evaluation processes in order to determine the impact of liquidity risk compliance on the technical efficiency of banks of various sizes. This would assist in ensuring that prudential liquidity guidelines meet the purposes they intend without causing unnecessary efficiency expenses on some parts of the banking sector.

Finally, it is recommended that future research explore additional factors that may influence the liquidity risk–technical efficiency relationship, such as corporate governance structures, technological adoption, funding structure, or risk culture. The analysis could also be extended to other financial institutions such as microfinance institutions and cooperative banks or use longer time horizons to reflect changing regulatory, macroeconomic and operation dynamics in the Kenyan financial system.

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