Addis Ababa University

College of Business and Economics

Department of Accounting and Finance

Efficiency-Risk Interplay in Banking: Theoretical Insights and Empirical Evidence from Ethiopia

By: Daniel Tolesa Agama

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Doctor of Philosophy (PhD) in Accounting and Finance (Specialization in Accounting)

August 2025

Addis Ababa, Ethiopia

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APPROVAL SHEET

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STATEMENT OF THE AUTHOR

I, Daniel Tolesa Agama, hereby declare that this dissertation is my original work. All sources of materials used in this research have been duly acknowledged. This dissertation has been submitted in fulfillment of the requirements for the Doctor of Philosophy (PhD) Degree in Accounting and Finance (Specialization in Accounting) at Addis Ababa University, College of Business and Economics, and is deposited in the University Library, where it will be accessible to borrowers under library regulations.

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LIST OF ABBREVIATIONS AND ACRONYMS

Abbreviation	Meaning
BCBS	BCBS: Basel Committee on Banking Supervision
BCC	Banker, Charnes, and Cooper Model (DEA)
BIS	Bank for International Settlements
CADQ	Capital Adequacy Ratio
CBE	Commercial Bank of Ethiopia
CCR	Charnes, Cooper, and Rhodes Model (DEA)
CI	Confidence Interval
CPI	Consumer Price Index
CRR	Credit Risk of Ethiopian Banks
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DGMM	Difference Generalized Method of Moments
DMU	Decision-Making Unit
DRS	Decreasing Returns to Scale
e.g.	For example,
ECONGR	Economic Growth
FEM	Fixed Effects Model
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
IRR	Interest Rate Risk
IRS	Increasing Returns to Scale
LQR	Liquidity Risk of Ethiopian Banks
MKT_SHARE_LAA	Market Share in Loans and Advances
NBE	National Bank of Ethiopia

Abbreviation	Meaning
POLS	Pooled Ordinary Least Squares
PTEBC	Pure Technical Efficiency of Banks in Ethiopia
REM	Random Effects Model
ROAA	Return on Average Assets
SEBC	Scale Efficiency of Banks in Ethiopia
SEM	Systematic Equation Models
SYS-GMM	System Generalized Method of Moments
TEBC	Technical Efficiency of Banks in Ethiopia
VAR	Vector Autoregressive
VIF	Variance Inflation Factor
VRS	Variable Returns to Scale

DEDICATION

This dissertation is dedicated to my family, who endured the sacrifices, the sleepless nights, and the countless challenges that came with this journey. Your patience, love, and unwavering support have been my greatest strength.

To my wife, Rahel Taye, whose resilience and encouragement carried me through the toughest years—when my time was scarce, and responsibilities pulled me away—you remained my greatest source of support. "Sora-Konjo", as I lovingly call you, your sacrifices and unwavering belief in me made this accomplishment possible.

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TABLE OF CONTENTS

TABLE OF CONTENT (Continued)

TABLE OF CONTENT (Continued)

TABLE OF CONTENT (Continued)

TABLE OF CONTENT (Continued)

LIST OF TABLES

LIST OF TABLES (Continued)

LIST OF FIGURES

ABSTRACT

Efficiency-Risk Interplay in Banking: Theoretical Insights and Empirical Evidence from Ethiopia

Daniel Tolesa Agama

PhD Dissertation

Addis Ababa University (2025)

This study examines the interplay between technical efficiency and risk in 17 Ethiopian commercial banks over 2014–2022. Technical efficiency is measured using bias-corrected Data Envelopment Analysis under the Charnes–Cooper–Rhodes (CCR) constant returns to scale and Banker–Charnes–Cooper (BCC) variable returns to scale specifications. Efficiency differences by ownership and size are compared via Mann–Whitney U tests. Dynamic panel estimations—Difference Generalized Method of Moments and fixed-effects models—assess (a) the effects of credit risk and liquidity risk on efficiency, and (b) the effects of efficiency on subsequent credit and liquidity risks. Profitability (return on average assets), capital adequacy ratio, and bank size are included as additional efficiency determinants. Findings indicate that higher credit and liquidity risks significantly increase technical efficiency, while greater efficiency leads to elevated subsequent credit and liquidity risks. Profitability positively affects efficiency; capital adequacy has no significant effect; and larger banks exhibit slightly lower efficiency. Public banks underperform private peers in overall and scale efficiency yet exceed them in pure technical efficiency. These results support Financial Intermediation Theory and the Skimping and Moral Hazard hypotheses and reject the Bad Management hypothesis for public banks. Banks should integrate robust risk controls with efficiency initiatives, and regulators should consider these interplay effects when formulating policies.

Keywords: bias-corrected DEA; technical efficiency; credit risk; liquidity risk; Mann–Whitney U; Difference GMM; fixed-effects; Ethiopian commercial banks

CHAPTER ONE: INTRODUCTION

1.1. Background of the Study

The banking sector has been largely identified as a key propeller of economic growth mainly through its financial intermediation, credit provision, and resource allocation roles (Jiménez-Hernández et al., 2019; Neves et al., 2020). In economies around the world, banks facilitate capital mobilization and investment financing, thereby acting as critical instruments for economic stabilization and financial inclusion (Bessis, 2015; Mishkin, 2021). At the center of a bank's performance lies the delicate relationship between operational efficiency and risk management. Agency theory, as formulated by Jensen & Meckling (1976), has offered the basis for understanding how managerial incentives can generate riskier behavior in the interests of efficiency. Empirical studies have also demonstrated that efficiency gains are associated with higher credit and liquidity risk (Akdeniz et al., 2023; Berger & Bouwman, 2013; Ghenimi et al., 2017; Ilmiani & Meliza, 2022).

The Ethiopian banking sector, however, has a special institutional setting that reinforces these dynamics. The market is dominated by state-owned banks notably the commercial bank of Ethiopia (CBE), which, for example, controls approximately 59 percent of total banking assets and 60 percent of deposits as of 2022 (CEPHEUS, 2023; NBE, 2024). In contrast, the newly emerging private banking industry—opened up in 1994[1]—is still in its nascent phase (NBE, 2024; World Bank, 2019). Historical prohibitions on foreign entry coupled with the lack of a fully developed capital market limit competitive pressures as well as diversification opportunities. Moreover, Ethiopian banks are required to implement Basel I standards—a regulatory framework that is considerably outdated relative to the risk-based actions reflected in Basel II and III (Basel Committee, 2013; World Bank,

[1] The first private bank in Ethiopia was Awash Bank (established in 1994), followed by Dashen Bank (1995) and Bank of Abyssinia (1996). During the study period from 2014 to 2022, only 17 commercial banks published an annual report; the remaining private banks were licensed and commenced operations after 2021, and were therefore not considered in this study.

2019). These structural and regulatory idiosyncrasies imply that the conventional efficiency–risk trade-offs of developed economies may not apply in Ethiopian context.

Beyond these institutional characteristics, the Ethiopian banking system plays a particularly vital role in its economy. In the absence of a developed security market that supports equity financing, Ethiopian commercial banks serve as the major instruments for resource allocation, investment financing, and liquidity stabilization (CEPHEUS, 2023; National Bank of Ethiopia, 2022).

However, the sector has also been traditionally characterized by structural inefficiencies, regulatory asymmetries, and pronounced market concentration (NBE, 2024). These conditions, in conjunction with the dominance of state-owned banks and strict regulatory frameworks, have influenced key outcomes such as liquidity management, loan pricing, and the overall extension of financial services.

During the period from 2014 to 2022, the sector was further challenged by macroeconomic instability. Persistent inflationary pressures—peaking at 33.8% in 2022—foreign exchange shortages, and liquidity constraints have adversely affected both operational efficiency and risk exposures within the banking system (IMF, 2024; World Bank, 2019). Under such conditions, the ability of banks to maintain stable lending portfolios and manage financial risks effectively is considerably compromised.

Given these structural facts and macroeconomic constraints, a comprehensive assessment of the efficiency–risk nexus in the Ethiopian banking sector is warranted. Such an investigation is essential not only for identifying sectoral vulnerabilities but also for informing policy recommendations aimed at enhancing financial stability. As reforms such as monetary policy adjustments and gradual financial liberalization are anticipated in the post-2024 landscape, understanding the dynamics of efficiency and risk in the pre-reform era (2014–2022) becomes critical for both academic inquiry and practical policymaking.

1.2. Statement of the Problem

Notwithstanding an extensive body of international literature exploring the association between risk management and bank efficiency—evidenced in works such as Altunbaş et al. (2007), Fiordelisi et al. (2011), Muhammed et al. (2023), and Tan & Floros (2013, 2019)—little is known about how these dynamics unfold within the Ethiopian banking environment. Banks that achieve higher operating efficiency may simultaneously shift onto riskier assets: Hughes et al. (1995) demonstrate that competitive pressures and lax oversight drive managers toward elevated credit and liquidity risk, a tendency further explained by the Skimping hypothesis (Williams, 2004) and the Moral Hazard framework (Jeitschko & Jeung, 2005).

Ethiopia's commercial banking sector exhibits institutional characteristics likely to modify these standard trade-offs. State-owned banks dominate market share, private-sector entry dates back only to 1994, foreign banks remain excluded, and an underdeveloped capital market limits diversification opportunities (CEPHEUS, 2023; NBE, 2024; World Bank, 2019). Moreover, the industry still operates under the Basel I regulatory framework—outdated relative to the risk-sensitive regimes prevailing elsewhere—undermining the adoption of advanced, market-based prudential tools (World Bank, 2019, p. 12).

International theoretical and empirical research offers competing explanations of the efficiency–risk nexus. The Poor Management hypothesis argues that weak governance and aggressive cost-cutting yield spurious efficiency gains at the expense of robust credit and liquidity controls (Berger & DeYoung, 1997; Fiordelisi et al., 2011; Podpiera & Weill, 2008). In contrast, the Bad Luck hypothesis attributes dips in bank performance to exogenous shocks—economic downturns, regulatory shifts—irrespective of managerial competence (Podpiera & Weill, 2008). Empirical findings are equally mixed: some studies find that elevated credit and liquidity risk erode technical efficiency, while others document that strategic risk-taking can bolster bank performance, or that high efficiency itself alters institutions' risk profiles in divergent ways (Jiménez-Hernández et al., 2019; Q. M. Le, 2018; Tan & Floros, 2018; Yitayaw et al., 2023).

Despite a rich global literature exploring the interplay between bank risk and technical efficiency, several critical gaps endure—especially within Ethiopia's distinctive institutional environment. First, no empirical study has yet examined how Ethiopia's legacy of state-dominated market leadership, delayed private sector entry, restricted foreign competition and adherence to Basel I regulations collectively shape the trade-off between operating efficiency and credit or liquidity risk. Without such localized analysis, it remains unclear whether international findings—often derived from liberalized or foreign-exposed banking systems—hold under Ethiopia's protected, capital-constrained regime.

Second, extant research tends to treat the efficiency–risk nexus unidirectionally, focusing either on how credit and liquidity risk erode or enhance technical efficiency, or conversely, on how banks' efficiency levels influence their subsequent risk exposures. This bifurcated framing overlooks the possibility of simultaneous, bidirectional interactions: efficient banks might pursue riskier assets in search of higher returns, while sound risk management practices may themselves drive efficiency gains. The absence of studies designed to capture this two-way dynamic leaves fundamental questions about causality unresolved.

Third, the predominant reliance on long-panel dynamic estimation techniques—such as vector autoregression (VAR) and structural equation modeling (SEM)—poses a methodological barrier in settings characterized by short time spans of available data. Ethiopia's banking sector, with its relatively brief data horizon, cannot support the time-series depth these techniques require. Consequently, there is an urgent need for alternative static or semi-parametric models that credibly identify efficiency–risk interdependencies within a limited temporal framework.

Finally, the moderating roles of bank ownership and size, together with the joint consideration of credit and liquidity risk as both determinants and outcomes of efficiency, remain unexplored. Public and private institutions may face divergent regulatory incentives and resource constraints, while smaller banks often exhibit different risk-return profiles than their larger counterparts. Investigating how these organizational characteristics condition the efficiency–risk relationship will provide nuanced insights essential for policymakers and bank managers in emerging markets like Ethiopia.

Without rigorous evidence addressing these gaps, regulators and bank managers in Ethiopia lack the insights necessary to balance performance objectives with sound risk governance. This study therefore undertakes a comprehensive, two-way empirical investigation: it measures technical efficiency of Ethiopian commercial banks using Data

Envelopment Analysis (DEA)—disaggregated by ownership and size—and then (a) models the effect of credit-risk and liquidity-risk ratios on DEA-derived efficiency scores and (b) assesses how those efficiency scores predict subsequent credit and liquidity risk exposures, using static panel regressions tailored to Ethiopia's data constraints.

1.3. Research Questions

To achieve the general objective of examining the efficiency–risk trade-off in the Ethiopian banking industry, the study is guided by the following research questions:

1. What are the technical efficiency levels of Ethiopian commercial banks?
2. What risk-related and bank-specific factors determine technical efficiency in Ethiopian commercial banks?
3. What is the effect of technical efficiency on credit and liquidity risk exposures in the Ethiopian banking sector?

1.4. Objectives of the Study

The general objective of this dissertation is to present a stringent examination of the efficiency–risk trade-off in the Ethiopian banking industry. Given the limitations of short panel data, the study adopts a unidirectional analytical approach to explore how risk factors influence bank efficiency and how efficiency, in turn, affects risk exposures. These specific objectives target the core components of the research question, ensuring a comprehensive and structured exploration of both technical efficiency and the associated risk exposures. Accordingly, the specific objectives are to:

1. estimate and comparatively analyze the technical efficiency scores of Ethiopian commercial banks, with particular attention to variations across ownership and size.

2. identify the key determinants of technical efficiency in Ethiopian banks, with a primary focus on credit and liquidity risk, while also examining the roles of capitalization, profitability, and bank size.

3. examine the effect of technical efficiency on credit and liquidity risk exposures, recognizing the limitations in modeling bidirectional causality due to data constraints.

1.5. Research Hypotheses

Based on the theoretical framework and prior empirical literature, the study tests nine specific hypotheses that reflect the efficiency–risk interplay in Ethiopian commercial banks. These hypotheses are formulated to align with the study's specific objectives and are grounded in established theoretical propositions and empirical findings. While they are briefly outlined here for structural clarity, a detailed justification for each hypothesis—supported by relevant literature—is provided in Chapter Two section 2.5: Theoretical framework and hypotheses development.

1. H1: There is a statistically significant difference in technical efficiency scores between public and private banks in Ethiopia.
2. H2: Among private banks, large banks exhibit significantly higher technical efficiency scores than small banks, reflecting structural advantages in resource allocation and operational scale.
3. H3: Credit risk (CRR) has a statistically significant negative effect on technical efficiency in Ethiopian commercial banks.
4. H4: Liquidity risk (LQR) negatively affects technical efficiency in Ethiopian commercial banks.
5. H5: Return on average assets (ROAA) positively influences technical efficiency, suggesting that higher profitability enables efficiency improvements.
6. H6: Capital adequacy ratio (CADQ) positively affects technical efficiency in Ethiopian commercial banks, as stronger capital buffers enhance operational stability.
7. H7: Bank size negatively affects technical efficiency, reflecting potential diseconomies of scale in larger banking institutions.
8. H8: Technical efficiency positively influences credit risk (CRR) in Ethiopian commercial banks.

9. H9: Technical efficiency positively influences liquidity risk (LQR) in Ethiopian commercial banks.

1.6. Significance of the Study

This dissertation makes a number of useful contributions to academic and practice in Ethiopian—and broader emerging-market—banking literature. First, from an academic standpoint, it takes classic efficiency–risk approaches a step further by extending beyond cost-based measures to derive the first full set of DEA-based operating-efficiency benchmarks (overall, pure, scale) for all Ethiopian commercial banks during 2014–2022. By estimating two competing models—a model that connects credit/liquidity risk to technical efficiency and the causality in the opposite direction—this paper clarifies the relationship between the variables in the setting of a highly regulated Basel I environment. In this, the paper addresses a significant gap in empirical studies using short-panel data and regulated banking systems and thereby provides a methodological template for comparable investigations in comparable data-scarce, emerging-market contexts.

Second, methodologically, the two-stage GMM/FEM approach under short-panel conditions provides a replicable blueprint for unraveling risk-to-efficiency and efficiency-to-risk relationships where joint system estimation is not possible. This contribution demonstrates how researchers can take advantage of limited time series (N = 17, T = 9) to produce robust direction-specific results, rather than relying exclusively on long-panel SEM or accepting endogeneity biases.

Third, the results provide policymakers and bank managers with actual, domestically-derived information to inform regulatory reform and risk management strategy. The officials of the National Bank of Ethiopia can use the DEA benchmarks to establish more refined capital and liquidity requirements, and commercial banking institutions can contrast their functional ratios with those of their counterparts in order to recognize inefficiencies attributable to credit or liquidity risks.

Finally, by contrasting our findings against Ethiopia's unique regulatory setting—Basel I capital minimums, forex-surrender precepts and agricultural-lending quotas—this study discerns the absolute need for locally attuned policy. While such structural regulations were not explicitly captured in our empirical specifications, situating our DEA benchmarks and risk–efficiency trade-offs in that setting underscores how future studies need to quantify such mandates in context-dependent regulatory design.

1.7. Delimitations/Scope of the Study

1.7.1. Geographic Delimitation

This study focuses exclusively on Ethiopian commercial banks. It includes the 17 deposit-taking commercial banks that were under the supervision of the National Bank of Ethiopia during the study period. Other financial institutions—such as newly established banks, microfinance institutions, and development banks—are excluded to maintain consistency in institutional characteristics and reporting standards across the sample.

1.7.2. Temporal Delimitation

The period of analysis spans from 2014 to 2022. This timeframe was chosen to ensure a balanced panel dataset that covers all 17 commercial banks in the sample, as the most recently established among them issued its first financial report in 2014. Although the number of licensed commercial banks has grown to 31 in recent years, limiting the scope to banks with full data across the entire study period enhances comparability and avoids sample imbalance.

1.7.3. Thematic Delimitation

The study centers on the interplay between technical efficiency and risk exposure in the Ethiopian banking sector. Specifically, it examines how credit risk and liquidity risk relate to technical efficiency, as measured by Data Envelopment Analysis (DEA). These two risk types were selected due to their high significance in both operational performance and regulatory oversight. Other dimensions of risk—such as market risk or operational risk—are beyond the scope of this investigation.

While the thematic focus of this study is the relationship between technical efficiency and risk exposure—specifically credit and liquidity risks—additional variables such as ownership structure, bank size, profitability, and capital adequacy are included in the empirical model as control and contextual factors. These variables are not the primary focus of the investigation but are incorporated to account for institutional and financial heterogeneity across banks. Their inclusion enhances the robustness of the analysis by helping isolate the effects of risk variables on efficiency and vice versa, consistent with empirical practices in banking efficiency research.

1.7.4. Methodological Delimitation

Technical efficiency is estimated using DEA (including overall, pure, and scale efficiency scores). The efficiency–risk nexus is explored through two estimation procedures: (i) a dynamic panel model using Generalized Method of Moments (GMM), where risk variables explain efficiency, and (ii) a static Fixed Effects Model (FEM), where efficiency scores predict risk. Higher-order dynamic models such as Structural Equation Modeling (SEM) or Vector Auto-Regression (VAR) are not employed due to the short panel (N=17, T=9), which limits model reliability. To ensure robustness, winsorization is applied at the 1st and 99th percentiles, and subgroup analyses are conducted by ownership type and size, with special attention to the dominant state-owned bank (CBE).

1.8. Limitations of the Study

Despite the methodological rigor and contributions of this study, several limitations should be acknowledged, which may inform the interpretation of results and offer direction for future research.

1.8.1. Temporal and Data Limitations

The primary limitation lies in the relatively short panel structure of the dataset (17 banks over 9 years), which restricts the ability to model long-run dynamics and structural shifts in the efficiency–risk relationship. This limitation also precludes the use of more advanced time-series techniques such as Vector Auto-Regression (VAR) or cointegration-based approaches that require longer time horizons.

1.8.2. Methodological Constraints

Due to the data structure, the study employs two separate estimation techniques (GMM and FEM) to analyze the bi-directional relationship between risk and efficiency. However, these models are estimated independently rather than simultaneously, meaning the dynamic feedback effects between efficiency and risk are not captured in a single integrated framework. More sophisticated methods, such as Structural Equation Modeling (SEM) or system-based GMM estimators, were avoided to preserve model reliability, given the small sample size and limited time dimension.

1.8.3. Scope of Risk Dimensions

The study focuses solely on credit risk and liquidity risk due to their regulatory importance and data availability. However, other important risk dimensions—such as market risk, operational risk, and interest rate risk—are excluded. This thematic limitation narrows the generalizability of the efficiency–risk findings across all possible risk categories in banking.

1.8.4. Omission of Institution-Specific Variables

Although the study draws upon global empirical literature on the efficiency–risk relationship, it does not incorporate detailed institution-specific variables (e.g., corporate governance, management quality, or compliance practices) that could further explain variations in efficiency across banks. This omission is primarily due to the lack of publicly available granular data for Ethiopian banks.

1.8.5. Regulatory Environment and Policy Dynamics

While the regulatory framework, particularly Basel I compliance, is discussed contextually, its evolution is not modeled empirically. Thus, potential changes in regulation over time and their impact on efficiency or risk are not quantitatively captured, which may limit insights into the role of policy in shaping bank behavior.

1.9. Operational Definitions of Key Terms

Bank: A bank is a financial institution licensed to accept deposits, extend credit, and provide a range of financial services to individuals and businesses. In this study, the focus is on banks that operate under regulatory oversight in Ethiopia.

Basel Accord: The Basel Accords are a series of international regulatory frameworks developed by the Basel Committee on Banking Supervision. They establish minimum capital requirements, risk management standards, and supervisory guidelines for banks. In the context of this study, reference may be made to how historical Basel I requirements have influenced the regulatory framework within which Ethiopian banks have operated, particularly in relation to risk management practices.

Commercial Bank: A commercial bank is a type of bank that primarily offers services such as deposit taking, lending, and payment processing to retail and corporate customers. These institutions operate for profit and are distinct from specialized institutions like development banks or microfinance institutions. In Ethiopia, these banks form the backbone of the country’s financial system.

Credit Risk: Credit risk is the potential for losses due to a borrower's failure to meet the contractual obligations related to loans or other credit instruments. In the context of this study, credit risk is one of the primary risk factors examined as it relates to a bank's operational performance and efficiency.

Data Envelopment Analysis (DEA): DEA is a non-parametric linear programming technique used to measure the relative efficiency of decision-making units—in this case, banks. The method evaluates the conversion of multiple inputs into outputs without requiring a predefined functional form, making it well-suited for the heterogeneous banking data used in this study.

Difference GMM (Generalized Method of Moments): The difference GMM is a dynamic panel data estimation technique that addresses potential endogeneity by using lagged variables as instruments. This method is used as a primary analysis check for the determinants of technical efficiency.

Efficiency Score: Efficiency Score refers to a numerical value derived from DEA that indicates the relative operational performance of a bank compared to its peers, where a score of 1 (or 100%) denotes an efficient bank operating on the frontier.

Efficiency: Efficiency generally refers to the ability of an entity to maximize outputs while minimizing the use of inputs. In the banking sector, this concept is often operationalized as technical efficiency—measured as the extent to which banks convert resources into financial services. The study employs Data Envelopment Analysis (DEA) to estimate these efficiency scores.

Efficiency–Risk Trade-off: This term describes the relationship between a bank's technical efficiency and its exposure to financial risk. The trade-off concept suggests that efforts to maximize efficiency might be accompanied by increased risk-taking, or conversely, that higher efficiency could help moderate risk exposures. The study investigates this interplay within Ethiopian commercial banks.

Endogeneity: Endogeneity refers to a condition in which an independent variable is correlated with the error term in a regression model, potentially leading to biased estimates of the model's parameters.

Exogenous Shocks: Exogenous Shocks refers to unexpected events or external factors that impact the banking sector, such as economic crises or regulatory changes, which can influence both efficiency and risk parameters.

Financial Risk: Financial risk refers to the potential for monetary loss due to various uncertainties in financial markets and operations. In banking, this includes risks such as credit risk, market risk, liquidity risk, and operational risk. This study focuses on credit risk and liquidity risk as key dimensions of financial risk within the Ethiopian banking context.

Fixed Effects Model: Fixed effects model refers to a panel regression model that controls for time-invariant characteristics of the observational units, thus isolating the effect of variables that change over time.

Liquidity Risk: Liquidity risk refers to the risk that a bank might not be able to meet its short-term financial obligations due to an inability to convert assets into cash without significant loss. This study analyzes liquidity risk to understand its association with technical efficiency in the Ethiopian banking sector.

Outliers: Outliers are the d**ata** points that deviate significantly from the overall pattern of the dataset, which can potentially skew or distort statistical analyses if not properly addressed.

Panel Data: Panel data consists of observations on multiple entities (in this case, banks) across several time periods (2014–2022). This type of data enables the analysis of both cross-sectional and time series variations, which is crucial for investigating the contemporaneous relationships between efficiency and risk.

Random Effects Model: Random Effects Model is a panel regression approach that assumes individual-specific effects are uncorrelated with the independent variables, allowing for both within and between-entity analysis.

Robustness Checks: Robustness checks is an additional analyses or tests conducted to verify the stability and reliability of the main research findings, such as subsample analyses or alternative model specifications.

Static Panel Regression: A static panel regression is an econometric technique that analyzes the relationship among variables without explicitly incorporating dynamic (lagged) effects. The study employs fixed and random effects models under this framework to assess contemporaneous associations between efficiency and risk.

Structural Imbalances: Structural Imbalances is the differences or disparities within the banking sector, such as those observed between public and private banks or across banks of different sizes, which may influence efficiency outcomes and risk management.

Technical Efficiency: Technical efficiency is the specific measure of how well a bank turns its inputs into outputs, relative to best practice benchmarks. In this study, a bank achieving a score of 1 (or 100%) is considered technically efficient, operating on the production frontier as determined by DEA.

Winsorization: Winsorization is a data trimming process that caps extreme values (outliers) to specific percentiles (commonly the 1^{st} and 99^{th} percentiles). This technique helps mitigate the disproportionate influence of outliers on the study's results.

Ownership Structure: For the purposes of this study, ownership structure refers to the classification of banks based on the nature of their controlling interests. Banks are categorized as either state-owned (public) or private institutions. State-owned banks are those in which the government possesses a controlling stake, often influencing strategic and operational decisions. Private banks, on the other hand, are predominantly owned by non-governmental entities, which can include individuals, corporations, or private investors. This distinction is critical, as variations in ownership can affect governance mechanisms, risk management practices, and ultimately, the efficiency dynamics of the banking sector.

Bank Size: Bank size denotes the scale at which a bank operates and is typically determined by measurable criteria such as total assets, market share, or branch network. In this study, special emphasis is placed on distinguishing between small and large-sized private banks. This categorization is essential because bank size influences operational scope, resource availability, and economies of scale. Large banks may benefit from diversified revenue streams and scale efficiencies, while small banks might be more agile but could face higher relative costs. These size-related differences are expected to affect the technical efficiency dynamics and risk profiles observed in the analysis.

1.10. Structure of the Dissertation

This dissertation is organized into five chapters that guide the reader from the study's background and research framework to the empirical findings and conclusions. The core empirical analysis is presented in Chapter 4, which is subdivided into three independent sections corresponding to the three manuscripts that form the analytical heart of the study. The overall structure is as follows:

Chapter 1: Introduction. This chapter provides the research background, problem statement, and general and specific objectives. It outlines the research questions, scope, delimitations, and offers operational definitions of key terms. This groundwork sets the stage for a comprehensive explanation of the efficiency–risk trade-off in Ethiopian commercial banks.

Chapter 2: Literature Review. In this chapter, the previous literature on banking efficiency, risk management, and their interplay is critically reviewed. The theoretical framework is discussed, highlighting gaps in the literature—particularly in the context of emerging markets like Ethiopia—which the study aims to address.

Chapter 3: Research Methodology. This chapter elaborates on the empirical strategies and data collection methods used in the study. It describes the panel dataset of Ethiopian commercial banks (2014–2022), the application of Data Envelopment Analysis (DEA) for efficiency measurement, and the subsequent econometric modeling (static panel regressions and dynamic difference GMM) employed to examine the relationships between technical efficiency and risk exposures. Data treatment procedures, such as winsorization to mitigate outliers, and various robustness checks are also detailed.

Chapter 4: Data Presentation and Analysis This chapter is subdivided into three independent sections that correspond to the three manuscripts constituting the empirical analysis:

4.1 Analysis of Technical Efficiency: This section presents the estimation and comparative analysis of the technical efficiency scores of Ethiopian commercial banks using DEA. Banks are categorized by ownership structure (public versus private) and by size (large, medium, and small) to provide baseline measures of efficiency and to identify any structural imbalances in the industry.

4.2 Risk Factors and other factors affecting the Technical Efficiency: In this section, the study examines the association between risk factors—specifically credit and liquidity risks—and technical efficiency. Using dynamic GMM model, this part evaluates the determinants that influence banks' efficiency scores.

4.3 The Efficiency–Risk Nexus: This section explores the contemporaneous relationship between technical efficiency and risk exposures. It quantifies how variations in efficiency scores relate to observed credit and liquidity risks in the Ethiopian banking sector. The analysis also includes subsample evaluations (e.g., excluding the dominant state-owned bank) and robustness checks to validate the overall findings.

Chapter 5: Discussion, Implications, and Recommendations: The final chapter summarizes the key findings, discusses their implications for banking practice and policy, and suggests directions for future research.

CHAPTER 2: REVIEW OF RELATED LITERATURE

2.1. Introduction

This chapter provides a comprehensive review of the theoretical and empirical literature related to bank efficiency, risk, profitability, and regulatory influence, with a particular focus on the Ethiopian banking sector. The primary objective is to establish a solid conceptual and empirical foundation for understanding the multifaceted dimensions of bank performance. In doing so, the chapter examines how banks convert inputs into outputs efficiently and analyzes how this process interacts with risk-taking behaviors and profitability considerations under various regulatory regimes.

The review is structured around several core themes. First, it introduces foundational theories of bank efficiency, including the concepts of technical efficiency and the methodologies used to measure it, such as Data Envelopment Analysis (DEA). The discussion then shifts to the influence of risk factors and other control variables such as, bank ownership, size, profitability, and capital adequacy shape operational performance. The chapter also investigates the interplay between efficiency and risk measures, drawing on theoretical frameworks like the skimping hypothesis and moral hazard. Finally, the review assesses the influence of international regulatory frameworks—contrasting Basel I with more advanced regimes—and synthesizes these insights into a conceptual framework that underpins the formulation of the study's hypotheses.

By integrating these diverse strands of literature, the chapter not only clarifies existing debates but also identifies critical gaps that the current study seeks to address. Ultimately, this review lays the groundwork for the subsequent empirical analysis and contributes to a deeper understanding of how structural and contextual factors affect bank performance in an emerging market setting.

2.2 Institutional Background

Ethiopia's banking system has long served a central role in the country's socio-economic development by mobilizing domestic savings, financing key sectors, and facilitating broader economic diversification. However, its evolution has been characterized by an enduring tension between developmental objectives and the modern imperatives of operational efficiency and risk management. To understand the importance of our study on the efficiency–risk interplay, it is essential to examine both the historical trajectory of the banking sector and the influence of international regulatory standards, notably the Basel Accord.

2.2.1 A Brief History and Ongoing Challenges in the Ethiopian Banking Sector

The modern banking era in Ethiopia began with the establishment of the Bank of Abyssinia in 1905 under Emperor Menelik II, marking the country's formal entry into modern financial intermediation. Although this institution laid the groundwork for channeling financial resources, its design was inherently exclusionary. Reorganized as the State Bank of Ethiopia in 1931, it predominantly served the imperial court, foreign traders, and a narrow urban elite, leaving the vast majority of Ethiopians reliant on informal financial networks (Gebrehiwot & Wolday, 2006 cited in Lelissa & Fava, 2024). This early phase not only underscored the limited reach of banking services but also deprived the economy of vital resources needed for widespread financial development.

A dramatic shift occurred during the Derg socialist regime (1974–1991), when the nationalization of all financial institutions transformed Ethiopia into a monolithic, state-controlled banking system. Under Proclamation No. 76/1975, the Commercial Bank of Ethiopia (CBE) absorbed nearly all commercial banking activities. Despite the regime's intentions to align the sector with socialist development, the centralized approach led to severe inefficiencies. Directed lending policies forced banks to allocate over 70% of credit to public enterprises, resulting in non-performing loans that at times exceeded 40% of total portfolios (World Bank, 1992). In addition, the severe limitations in branch expansion meant that the banking network could not effectively mobilize domestic savings or support diversified economic development, leaving the sector with one of Africa's lowest branch-to-population ratios (IMF, 1991). These structural inefficiencies, combined with poor risk management practices, laid dormant challenges that would later impede sustainable growth.

Following the collapse of the Derg, the EPRDF era (1991–2018) introduced controlled liberalization into the banking sector with the 1994 Banking Proclamation (No. 84/1994). This reform allowed private banks to enter the market, leading to a significant increase in industry competition. Private banks such as Awash Bank (established in 1994) and Dashen Bank (established in 1995) soon emerged, operating with modern practices and exhibiting higher efficiency—indicated by lower cost-to-income ratios—compared to their state-controlled counterpart, the CBE. However, strict regulatory constraints, including mandatory Treasury bill purchases, branching restrictions, and a prohibition on foreign bank entry, resulted in the persistence of a dual system. State-owned banks retained a dominant market share (with the CBE still controlling about 58% of sector assets by 2018) even as private banks outperformed them in efficiency metrics. Moreover, these constraints amplified risk management issues; uniform capital reserve requirements, irrespective of borrower quality, and inadequate liquidity risk controls have contributed to elevated non-performing loan ratios and heightened vulnerabilities to operational disruptions (IMF, 2018; NBE, 2018).

The current Prosperity Party era (2018–present) marks the most dynamic phase of reform in Ethiopia's banking sector. Landmark developments during this period include the establishment of the Ethiopian Securities Exchange (ESX) in 2024, the introduction of a managed float exchange rate system in 2024, and the liberalization of interest rate policies. These reforms aim to modernize Ethiopia's financial system and reduce its heavy reliance on traditional bank intermediation, which continues to account for nearly 99% of financial assets (NBE, 2024). The growth in the number of commercial banks—from 18 to 32 between 2018 and 2024—and rapid digital transformation, evidenced by the Telebirr platform's 32 million users, signal promising advances. However, underlying problems persist. Although private banks now operate more efficiently, state-owned institutions like the CBE still hold disproportionate market share, and regulatory forbearance has created a predictable pattern of risk mismanagement. For instance, the imposition of uniform capital adequacy ratios and inadequate liquidity risk frameworks exposes banks to systemic vulnerabilities and heightens credit risk, thereby limiting the sector's capacity to support sustainable economic development.

It is within this context that examining the interplay of operational efficiency and risk management becomes critical. Efficiency, in its capacity to enhance productivity and cost-effectiveness, is vital for boosting the overall competitiveness of the banking sector. At the same time, robust risk management is essential to safeguard banks against external shocks and operational disruptions. Studying the efficiency–risk nexus is therefore not a mere academic exercise; it is integral to identifying how improvements in bank operations can translate into greater financial stability and, by extension, foster broader economic growth.

2.2.2 The Origins, Requirements, and Rationale Behind the Basel Accord

Alongside domestic reforms, the evolution of international regulatory frameworks has profoundly shaped modern banking practices. The Basel Accords represent a landmark series of global standards developed by the Basel Committee on Banking Supervision to address systemic vulnerabilities and ensure that banks maintain adequate capital and sound risk management practices.

Basel I, introduced in 1988, established the seminal concept of risk-weighted assets to standardize capital adequacy requirements across diverse banking systems (BCBS, 2006). This framework was a pioneering response to the cross-border banking crises of the 1980s, designed to mitigate systemic risk by ensuring that banks possessed sufficient capital buffers. However, its one-size-fits-all approach—for example, the zero risk weight assigned to government debt of OECD countries—proved to be overly simplistic and even counterproductive, as it encouraged undue sovereign exposure.

Responding to these criticisms, Basel II was formulated in 2004 around a three-pillar system: first, developing risk-sensitive capital calculations based on Internal Ratings-Based (IRB) approaches; second, enhancing supervisory review; and third, promoting greater transparency and market discipline (BCBS, 2006). The subsequent Basel III framework (2010–2017) further broadened the scope of regulation by emphasizing macroprudential measures aimed at ensuring systemic stability. Key innovations of Basel III include the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR), both of which were developed in response to the liquidity crises that exposed critical vulnerabilities during the global financial crisis (BIS, 2011).

In Ethiopia, although many African countries have progressed to adopting Basel II or Basel III standards, the domestic regulatory framework remains largely aligned with Basel I principles. The National Bank of Ethiopia (NBE) traditionally prioritizes developmental lending, often channeling over 40% of bank credit into sectors such as agriculture, manufacturing, and infrastructure through directive-based quotas (NBE, 2024). This approach underscores a significant regulatory divergence: while international best practices now emphasize risk-sensitive capital adequacy and liquidity management, Ethiopian banks are required to maintain a uniform Capital Adequacy Ratio of 8% regardless of the underlying risk profile of their loan portfolios. Consequently, risk management issues—including inefficient differentiation between low- and high-risk lending—persistently hamper the sector's efficiency, ultimately limiting its contribution to economic development. The ongoing challenge is to harmonize these domestic practices with modern, internationally recognized standards—a harmonization that is essential for strengthening the resilience and performance of Ethiopia's banking system.

2.3 Theoretical Review of Literature

This section synthesizes the foundational theoretical frameworks underpinning the analysis of banking institutions. It elaborates on the rationale for banks' existence, the multifaceted nature of efficiency in banking, the imperatives of risk management, and the complex tradeoffs between efficiency and risk. These interrelated perspectives provide the conceptual foundation necessary to understand both the operational practices of banks and the tensions inherent in pursuing operational efficiency while managing financial risk.

2.3.1 Financial Intermediation Theory`

Financial intermediation theory offers a fundamental explanation for the existence and role of banks. Grounded in seminal works by Gurley & Shaw (1960) and further refined by Diamond (1984), this framework posits that banks emerge as efficient solutions to pervasive market imperfections such as information asymmetry and high transaction costs. Banks perform delegated monitoring by pooling funds from numerous depositors and then lending to a diversified portfolio of borrowers. This process not only mitigates the high costs individual depositors would incur in assessing and monitoring creditworthiness, as outlined in Diamond's (1984) delegated monitoring model, but also improves liquidity by transforming short-term deposits into long-term loans (Bryant, 1980; Diamond & Dybvig, 1983). Additionally, banks reduce transaction costs by providing payment, settlement, and other essential financial services (Benston & Smith, 1976). By transforming and diversifying risk, banks also lower the overall risk borne by individual depositors (Saunders & Cornett, 2018). In essence, financial intermediation theory establishes that the existence of banks is a rational economic response to inherent market imperfections, resulting in more efficient capital allocation and enhanced financial stability.

2.3.2 Theories of Efficiency in Banking

Efficiency is a critical determinant of a bank’s competitive performance and financial health. Theoretical frameworks in this domain derive from industrial organization and microeconomic theory, and they are particularly tailored to capture the unique characteristics that differentiate financial institutions from other types of firms. In the banking context, efficiency is frequently decomposed into multiple dimensions, each reflecting distinct aspects of operational performance.

Cost Efficiency is primarily concerned with a bank's ability to produce a given set of outputs—such as loans, deposits, and payment services—at the minimum possible cost. This dimension encompasses both technical efficiency and allocative efficiency. Technical efficiency specifically examines how well a bank uses its inputs given its technological capabilities and existing operating conditions. In this regard, technical efficiency is often subdivided further into:

Overall Technical Efficiency (OTE): This measure assesses the bank's ability to maximize output from its combined input bundles, identifying how closely a bank's operations approach the best-practice frontier. OTE reflects both the operational decisions and the scale at which the bank operates, providing a holistic view of performance relative to its peers (Banker et al., 1984; Charnes et al., 1978).

Pure Technical Efficiency (PTE): Isolating the role of managerial performance, PTE controls for scale economies by evaluating how effectively managers allocate and utilize inputs independent of the scale of operations. It focuses squarely on process and managerial efficiency—that is, the ability of a bank to transform inputs into outputs when scale distortions are removed (Berger & Mester, 1997).

Scale Efficiency (SE): This measure quantifies the extent to which a bank operates at an optimal size. Scale efficiency is calculated as the ratio of overall technical efficiency to pure technical efficiency, thus capturing the performance gains or losses associated with scaling operations. A bank that is not operating at the optimal scale incurs inefficiencies either due to diseconomies (often resulting from excessive bureaucratic or coordination costs) or from economies not fully exploited in smaller operations (Berger et al., 1993; Mester, 1996).

Together, these technical efficiency measures (OTE, PTE, and SE) provide a nuanced picture of a bank's operational performance. While overall technical efficiency offers a comprehensive assessment, pure technical efficiency zeroes in on managerial capacity, and scale efficiency highlights potential cost advantages or disadvantages related to the bank's size. Such detailed analysis is particularly relevant for emerging markets, where banks often face additional burdens from structural inefficiencies and resource constraints.

Beyond cost efficiency, Profit Efficiency also plays a significant role in determining performance. This dimension delves into a bank's ability to generate maximum returns from its assets, integrating revenue generation alongside stringent cost controls, as discussed by Berger et al. (1993). Revenue Efficiency examines how effectively banks convert their inputs into revenue under prevailing market conditions, offering further insight into operational effectiveness.

Moreover, X-Efficiency, a concept introduced by Leibenstein (1966) and later applied in the banking context by Berger & Humphrey (1997), measures deviations from an internally set frontier of efficiency. X-efficiency captures the managerial discipline and organizational slack that may prevent banks from achieving their full productive potential.

Thus, the multifaceted approach to assessing efficiency in banking—including overall, pure, and scale efficiency—allows researchers to distinguish between the impacts of managerial practices, technological use, and operational scale. This detailed understanding is essential for tailoring strategic interventions that enhance efficiency, safeguard against risk, and ultimately strengthen financial performance. When integrated with empirical findings, these theoretical perspectives provide a robust framework for analyzing the challenges and opportunities within the banking sector, particularly in environments marked by diverse organizational sizes and emerging market dynamics.

Together, theories of efficiency in banking provide a comprehensive framework to assess how operations can be optimized—yet they also highlight that pursuit of efficiency can affect, and be affected by, other operational dimensions, including risk management.

2.3.3 Risk Management Theories in Banking

Banks inherently assume a range of risks as part of their financial intermediation activities (NBE, 2010; Saunders & Cornett, 2018). Risk management theories offer the conceptual tools for identifying, measuring, monitoring, and mitigating these risks to secure solvency, stability, and value creation over time. The literature on risk management underscores several core banking risks:

Credit Risk: Credit risk, which pertains to the risk of borrower default, is widely recognized as one of the most critical risks in banking (Bessis, 2015). To mitigate this risk, theoretical approaches emphasize diversification, drawing on the principles of Markowitz's portfolio theory when applied to loan portfolios; by diversifying their investments, banks can reduce unsystematic risk and smooth out the impact of individual defaults. In parallel, credit scoring models, such as those developed by Altman (1968) provide systematic frameworks to evaluate the creditworthiness of potential borrowers based on financial ratios and historical performance data. Complementing these statistical approaches, structural models pioneered by Merton (1974) conceptualize credit risk through an option pricing lens, linking the volatility of a firm's assets to its likelihood of default. Additionally, banks employ collateral requirements and contractual covenants as practical tools to safeguard their positions; these mechanisms serve to secure loans and provide legal remedies if the credit quality deteriorates. Continuous monitoring, as advocated by Diamond (1984), further reinforces the management of credit risk by ensuring that early warning signals are detected and remedial actions are promptly executed. This integrated suite of strategies—combining diversification, quantitative assessments, structural modeling, and robust protective measures—forms the cornerstone of effective credit risk management in modern banking practices.

Liquidity risk—Saunders & Cornett (2018) defined liquidity risk as the inability to meet financial obligations as they come due without incurring significant losses—is a fundamental challenge in bank risk management. This risk is conceptually anchored in the seminal model of Diamond & Dybvig (1983), which illustrates how banks' engagement in maturity transformation creates inherent fragility. In their model, banks accept short-term deposits and extend long-term loans, a practice that, while pivotal for stimulating economic activity, also renders them vulnerable to rapid liquidity outflows or bank runs if depositors lose confidence. This vulnerability emphasizes the critical importance of maintaining robust asset liquidity and funding stability. Banks mitigate liquidity risk by ensuring a balanced funding structure, relying on a mix of stable core deposits and more volatile wholesale funding, and by implementing comprehensive contingency funding strategies that prepare them for sudden liquidity shocks(Bessis, 2015; Diamond & Dybvig, 1983). Effective liquidity risk management is thus central not only to preserving the operational integrity of banks but also to safeguarding overall financial system stability.

Market Risk: Market risk arises from adverse fluctuations in the prices of key financial variables, including interest rates, exchange rates, equities, and commodity prices.

Grounded in the seminal work of Markowitz (1952) on portfolio theory, market risk is further contextualized through asset pricing models such as the Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory. These models help explain how changes in market conditions affect asset returns and risk exposures. To quantify market risk, practitioners employ quantitative measures such as Value-at-Risk (VaR) and Expected Shortfall (ES), which aggregate potential losses across a portfolio and provide essential metrics for both internal risk management and regulatory compliance (Jorion, 2007). This framework enables banks to systematically evaluate the sensitivity of their portfolios to market shocks and to design strategies that mitigate potential adverse outcomes.

Operational Risk: Operational risk pertains to losses arising from inadequate or failed internal processes, human error, system failures, or external disruptive events. Unlike market or credit risks, operational risk is often more diffuse and challenging to quantify due to its multifaceted nature. The academic and practitioner literature emphasizes the importance of establishing robust control frameworks as a means of mitigating operational risk. This involves implementing regular internal evaluations such as self-assessments and scenario analyses, which facilitate the early detection and remediation of vulnerabilities. In circumstances where risk cannot be entirely eliminated, transferring a portion of the risk through insurance is often advocated as part of an integrated risk management strategy. By adopting these measures, banks not only protect themselves against operational disruptions but also enhance their overall resilience and continuity in the face of unforeseen events.

Interest Rate Risk (IRR): Interest rate risk (IRR) is a particular subset of market risk that emerges from mismatches in the timing—or repricing characteristics—of a bank's assets and liabilities. Such discrepancies can lead to significant volatility in net interest income, thus impacting the institution's economic value. To manage IRR, banks employ a variety of analytical techniques, among which Gap analysis is used to evaluate the difference between interest-sensitive assets and liabilities. Duration analysis, originally developed by Macaulay (1938) and later refined by Fisher & Weil (1982), provides a measure of the weighted average maturity of a bank's cash flows, offering critical insight into the potential impact of interest rate movements. Additionally, banks commonly use simulation models to project how changes in interest rates might affect the balance sheet. These analytical tools are integral to a bank's risk management strategy, serving to mitigate the adverse effects of interest rate volatility while aiding in the preservation of profitability and stability.

2.3.4 Theoretical Frameworks for the Efficiency–Risk Nexus

2.3.4. 1 Interpreting the Efficiency–Risk Trade-off

The link between risk and banking efficiency is a key topic of contention in financial economics, where researchers examine the intricate tradeoffs that prevail between financial stability, cost minimization, and risk exposure. Efficiency, frequently conceptualized as the capacity of banks to maximize output at minimum cost, is a significant indicator of financial performance. Yet, the quest for efficiency without sound risk management practices might exacerbate financial instability in many aspects, including credit default, liquidity crises, and systemic weaknesses (Berger & DeYoung, 1997; Williams, 2004).

A number of competing and complementary theoretical paradigms try to explain the nexus between risk and efficiency. Some writers contend that risky banks are exposed to increased risk as a result of inadequate managerial control, while others view that institutions might deliberately assume risk in an effort to attain short-run efficiency gains. Other theories address the wider market problems, such as competition-induced risk-taking, liquidity exposures, systemic rescue operations, and portfolio strategy.

This sub-section discusses various theoretical views, drawing on the literature to synthesize a solid conceptual foundation for analyzing the efficiency-risk tradeoff in banking.

2.3.4.2 Theoretical Frameworks Explaining the Efficiency–Risk Trade-off

1. The Bad Management Hypothesis

The Bad Management Hypothesis, according to Berger & DeYoung (1997), contends that failures in banking operations result in higher exposure to financial risks. Banks characterized by inefficiency, according to this hypothesis, are marked by weak governance structures and hence are more susceptible to operational failure, including inefficient loan screening, inefficient borrower monitoring, and inefficient risk management procedures.

One of the primary arguments in this approach is that inefficiency comes before financial weakening, such that banks dealing with operational inefficiency are likely to suffer from credit losses and increasing default rates. Inefficient banks do not have well-established systems for timely identification of financial stress, such that risk exposures build up over a period, ultimately creating instability and possible systemic crises.

This hypothesis has been extensively used to clarify why financially unstable banks are less cost efficient, and thereby support the contention that inefficient management is a primary determinant of financial vulnerability.

2. The Skimping Hypothesis

The Skimping Hypothesis, which was also developed by Berger & DeYoung (1997) and subsequently refined by Williams (2004), gives a different explanation of the efficiency–risk tradeoff. Rather than attributing financial instability to inefficiency of management, this theory asserts that banks can deliberately underinvest in risk management controls with the aim of achieving higher efficiency.

In line with this model, financial institutions that slash costs frequently reduce investments in loan underwriting, credit analysis, and monitoring after lending, thereby improving operational efficiency but concurrently enhancing their long-term financial vulnerability. This approach enables banks to report high cost-cutting measures and profitability in the short run; however, in the long run, poor risk management results in high default rates, liquidity crises, and systemic instability overall.

A key aspect of this hypothesis is that the adverse consequences of skimping are typically lagged, so that banks that take on efficiency-driven risk may at first seem stable, but later suffer financial difficulties as loan defaults materialize.

3. The Moral Hazard Hypothesis

The Moral Hazard Hypothesis, formulated by Jeitschko & Jeung (2005), looks at the combined effects of competitive pressure and monetary incentives on bank risk-taking behavior. The hypothesis contends that banks operating in highly liberalized financial markets may engage in risky lending, speculative investment, and high-risk asset portfolios in order to attain profits at the cost of financial soundness.

A key assumption in this theory is that banks expecting regulatory bailouts or systemic protection can engage in riskier financial approaches, expecting that their viability will be underpinned by government intervention in times of crisis. The expectation lowers the incentive for prudent financial management, with banks favoring efficiency in terms of excessive risk-taking, building financial volatility.

The hypothesis emphasizes how competitive banking markets can promote efficiency-maximizing behavior that is, in the long run, destabilizing. It shows how some institutions might prefer short-run financial rewards to the detriment of long-run stability.

4. The Portfolio Optimization Trade-Off

The Portfolio Optimization Trade-Off, following Markowitz's Portfolio Theory (1952), examines the efficiency-risk relation through asset diversification policy. It argues that banks that are cost-efficient in their optimization have a tendency to concentrate investments in high-yielding assets with higher exposure to market risk and systemic volatility.

Although portfolio selections that emphasize efficiency improve financial outcomes, they concurrently heighten vulnerability to macroeconomic disturbances. This suggests that institutions that prioritize immediate returns via concentrated investments might face greater financial instability during periods of economic decline. This concept demonstrates that banking models aimed at cost efficiency necessitate well-balanced risk diversification strategies to ensure long-term stability.

5. The Bad Luck Hypothesis

Bad Luck Hypothesis, originally developed by Berger & DeYoung (1997), offers a strong theoretical description regarding the link between risk and efficiency in banking. The hypothesis presents a move away from efficiency-first paradigms, which hold the view that financial risk precedes inefficiency, as opposed to inefficiency being the cause of financial instability. That is, negative exogenous circumstances—be they economic recessions, financial crises, regulatory shocks, or geopolitical incidents—compel banks to incur extra expenses, shift managerial focus, and rebalance asset portfolios, thereby decreasing their organizational efficiency. As opposed to the Bad Management Hypothesis, which explains inefficiency as a consequence of poor management and internal problems, the Bad Luck Hypothesis suggests that bank inefficiency is not necessarily the immediate outcome of managerial decisions, but rather the consequence of unforeseen external risk determinants.

Essentially, the Bad Luck Hypothesis argues that an increase in financial risk—particularly through an increase in non-performing loans (NPLs) and deterioration in asset quality—compels banks to devote a disproportionate number of resources to damage control rather than improving operating efficiency. This shift in priority leads to higher operating costs, reduces aggregate efficiency, and places systemic constraints on financial institutions. The hypothesis contradicts conventional wisdom that only managerial discipline can alleviate efficiency losses, emphasizing instead the exogenous character of the financial risk pressures that confront banks.

The theoretical foundations and key assumptions of Bad Luck Hypothesis:

One of the fundamental postulates of the Bad Luck Hypothesis advances the argument that inefficiency in the activities of banking is not a product of intentional deficiencies but an outcome of unforeseen financial shocks necessitating immediate strategic reconfigurations. The aggravation of credit risk, shifts in market conditions, and general macroeconomic instability compel banks to shift their attention from cost-reduction drives to risk-mitigating strategies, thereby weakening their capacity to sustain best-in-class levels of performance. The hypothesis assumes efficiency to be inherently reactive, which means that times of high risk automatically reduce efficiency, even in well-managed financial institutions.

The hypothesis draws on several conceptual mechanisms through which external risk dynamics can precipitate efficiency deterioration. An increase in non-performing loans—stemming from factors beyond managerial control, such as macroeconomic recessions, inflationary pressures, or borrower-specific challenges—necessitates heightened provisioning, loan restructuring, and debt recovery measures, thereby diverting resources from efficiency-enhancing activities. Market volatility can cause liquidity shortages, compelling financial institutions to maintain higher liquidity reserves, which, in turn, constrains their capacity to pursue efficiency-driven investments. Regulatory dislocations, including unforeseen policy shifts, governmental interventions, or shifts in compliance requirements, impose costly operational adjustments that detract from efficiency. Furthermore, banks with substantial exposure to vulnerable sectors of the economy—such as agriculture, real estate, or industrial finance—are prone to greater inefficiencies during sector-specific downturns, thereby reinforcing risk-based efficiency losses.

The model theorizes that banking inefficiency must not necessarily be explained by either poor management decisions or institutional regulatory failure but rather as the result of unfavorable economic conditions that increase exposure to financial risks.

Application of the Bad Luck Hypothesis in Banking Markets

The Bad Luck Hypothesis is extremely relevant in various banking systems, particularly for financial markets that confront excessive external volatility, macroeconomic shocks, and sectoral shocks. Banks in emerging economies are often subject to larger efficiency losses owing to exogenous exposure to risk, which makes the hypothesis even more important in circumstances where there is frequent external financial shock.

One of the key uses of this hypothesis can be traced in credit-based banking systems, where high loan exposure enhances vulnerability to economic fluctuations. In such systems, financial crises, default by borrowers, and unexpected changes in regulations induce banks to undertake inefficiency-driven financial restructuring, thus compounding the impact of risk on performance results. Similarly, financial institutions faced with foreign exchange shortages, inflationary pressures, and liquidity constraints often find it difficult to maintain operational efficiency, hence confirming the theoretical postulations of the Bad Luck Hypothesis. Moreover, banking markets that have poor diversification opportunities—where institutions are strongly connected with a narrow set of prevailing economic sectors—show higher vulnerability to declines in efficiency provoked by risk. As large sectors such as agriculture, trade finance, or industrial development experience downturns, banks that serve such sectors experience declines in efficiency as exposure to financial risk rises (Berger & DeYoung, 1997).

How Efficiency and Risk Interact: Integrated Theoretical Insights

Taken together, these five theories illustrate that efficiency and risk are deeply interdependent, with their interaction shaped by institutional frameworks, financial market conditions, and external regulatory environments. The Bad Management Hypothesis and Skimping Hypothesis offer opposing perspectives on whether inefficiency is inherent or deliberate, while the Moral Hazard Hypothesis highlights the role of market competition in risk-taking behaviors. The Portfolio Optimization Trade-Off demonstrates how efficiency-driven asset selection can increase financial vulnerability, and the Bad Luck Hypothesis reverses the causal direction, arguing that risk accumulation disrupts efficiency rather than inefficiency leading to financial instability (Berger & DeYoung, 1997).

This synthesis underscores the complexity of efficiency–risk relationships, suggesting that financial institutions must strike a delicate balance between cost optimization and systemic risk mitigation. Understanding these theoretical lenses is essential for analyzing how banks adapt to financial uncertainty, providing insights into institutional resilience, risk-adjusted efficiency models, and regulatory oversight strategies.

In conclusion, the efficiency–risk nexus in banking operates within a multifaceted theoretical framework, with different models attributing causal priority to either efficiency or risk. While some theories argue that banking efficiency drives risk outcomes, others emphasize how risk escalation disrupts efficiency performance. The five theories discussed provide a comprehensive conceptual foundation for examining banking stability, market vulnerabilities, and long-term financial sustainability, reinforcing the importance of holistic risk-aware efficiency strategies.

2.4 Empirical Literature Review

The empirical literature offers a critical bridge between theoretical constructs and real-world banking practices, providing nuanced insights into how efficiency and risk management are measured and operationalized across different banking environments.

This section synthesizes the current state of empirical research on bank efficiency, risk management, and the interplay between these two essential dimensions. In doing so, it highlights methodological advancements, compares findings across international and emerging market contexts, and identifies key gaps that motivate the present study. The review starts with the relationship between efficiency and risks in banking industry which is followed by other factors controlled in the estimates.

2.4.1. The Relationship between Efficiency and Risk in Banking

The banking efficiency literature has commonly viewed the link between technical efficiency and bank risk as an interplay. While, on the one hand, a vast majority of empirical research has treated credit risk and liquidity risk as determinants—or independent variables—affecting technical efficiency, on the other hand, there exists an increasing number of studies that analyze the impact of technical efficiency on banks' risk profiles thereafter. This section integrates both the views to provide an overall picture of the efficiency–risk relationship.

2.4.1.1 Influence of Credit and Liquidity Risk on Technical Efficiency

A number of studies have examined to what degree exogenous risk factors, including credit risk and liquidity risk, influence the technical efficiency attainable by a financial institution. High levels of either credit or liquidity risk have been posited to impose added operating problems and expenses. Banks with higher credit risk, for instance, might have to hold larger loan loss reserves or embark on more conservative lending policies that restrict the capital available for enhancing operating efficiency. Likewise, liquidity risk—generated by the problem of matching alternative short-term deposits and long-term lending commitments—can hamper the operational flexibility of banks and interfere with their capacity to realize economies of scale or undertake process enhancements.

Empirical studies have provided support for competing perspectives on how bank risk influences operational efficiency. For instance, Jiménez-Hernández et al. (2019) and Le (2018) demonstrate that high credit risk levels are associated with inefficiencies, largely stemming from declining asset quality and subsequent financial instability. These studies suggest that elevated credit risk forces banks to incur higher operating costs—such as increased loan loss provisions—and limits their ability to invest in efficiency-enhancing initiatives. Similarly, research by (Tan & Floros (2013, 2018) and Yitayaw et al. (2023) lends support to the liquidity risk perspective. Their findings indicate that when banks face liquidity constraints, they tend to adopt overly conservative operating strategies, which in turn lower overall efficiency. In this view, both high credit and liquidity risks result in increased operational expenses and reduced performance efficiency.

Contrary to these findings, a number of more recent empirical studies report a strong positive relationship between risk and technical efficiency. For example, Ilmiani & Meliza (2022) alongside other research by Tan & Floros (2018) and Yitayaw et al. (2023), find that, under certain conditions, banks displaying higher levels of credit risk actually exhibit greater technical efficiency. This counterintuitive result suggests that some banks might be leveraging risk-taking—whether in lending practices or asset allocation—to achieve higher returns and streamline their operations. Moreover, on the liquidity risk front, studies by Ilmiani & Meliza (2022), Jiménez-Hernández et al. (2019), Le (2018), Lema (2017) and Ma & Soh (2021) document instances where increased liquidity risk is positively related to technical efficiency. Such findings imply that banks capable of optimizing their liquidity management—despite facing significant constraints—may be better positioned to use their resources efficiently.

In sum, while some empirical evidence indicates that high credit and liquidity risks can lead to increased costs and reduced operational performance, alternative studies reveal that, in specific contexts, elevated risk levels may coexist with—or even positively contribute to—technical efficiency. This duality highlights the complex, context-dependent nature of the efficiency–risk nexus, thereby underscoring the need for further research to identify the underlying conditions and institutional factors that determine whether risk impairs or, conversely, promotes bank efficiency.

2.4.1.2 Technical Efficiency's Influence on Credit and Liquidity Risk

On the other hand, literature also provides instances where technical efficiency determines the risk profile of a bank, pointing towards a feedback effect. The skimping hypothesis states that banks that strongly compete on becoming more efficient—through cost-cutting and streamlining operations—can potentially end up neglecting necessary investments in adequate risk management processes.

Such an absence of investment has the ability to lead to an accumulation of credit risk over time, with financial institutions putting in place more aggressive lending strategies or lowering underwriting standards to maintain their cost-efficiency. Empirical research, including that of Fiordelisi et al. (2011) and Yitayaw et al. (2023), corroborates this stance in demonstrating that banks with higher technical efficiency scores are exposed to higher credit risk due to the fact that they are more prone to risk-taking behavior.

The impact of technical efficiency on liquidity risk is equally complicated. Efficient banks are likely to enhance their cash management strategies, which will lead to a decrease in liquidity pressure and the accumulation of sufficient liquidity reserves (Benti & Biru, 2023; Ilmiani & Meliza, 2022).

A counterargument exists; banks with minimal operating flexibility—typical of some highly efficient banks—may lack adequate reserves to be immune to unforeseen liquidity shocks. Such an impact can be especially pronounced under the circumstances of turbulent markets, when even small alarms may trigger intense liquidity pressure. Research by Tan & Floros (2018) and Wudu & Veni (2019) has shown that, under some circumstances, the quest for higher efficiency can increase liquidity risk, as financial institutions are less adaptable to offset the abrupt changes in cash flow requirements.

Collectively, the two views reveal a complex and interrelated relationship between banking risk and technical efficiency. For one, excessive credit risk and liquidity risk can impose costs and operational restrictions that diminish technical efficiency. Conversely, efficiency seeking might induce banks to forego essential risk management practices, elevating credit and liquidity risks. The mixed and sometimes conflicting evidence present in the literature demands a context-based analysis, especially in emerging economies like Ethiopia where institutional and regulatory contexts may influence these relationships.

By explaining these complex interrelationships, this study aims to contribute to a better understanding of how financial institutions are able to achieve both high levels of performance and stability in a competitive, often turbulent environment.

2.4.2. Other Control Factors Affecting Technical Efficiency of Banking Institutions

This section covers a set of important determinants that influence technical efficiency, drawing on both theoretical frameworks and empirical findings. The determinants covered in this review are ownership structure, bank size, profitability, and capital adequacy—each of which has been controlled to estimate the effect of credit risk and liquidity risk on the operating efficiency of banking organizations.

2.4.2.1 Bank Ownership Structure

The literature that is available on the efficiency of banks has consistently indicated the preponderant influence of ownership structure on daily operations. Empirical research has established significant differences in the technical efficiency of public and private banks, but the direction of the relationship is controversial. For example, Rao & Lakew (2012) use a non-parametric model for the years 2000-2009, which estimates an average inefficiency rate of approximately 27%. However, they are unable to establish a statistically significant relationship between the type of ownership and the efficiency scores. In contrast, work by Lelissa & Kuhil (2016), analyzing 18 banks for the years 1995-2015, theorizes that government-owned banks are more efficient overall compared to private banks in both technical performance and managerial efficiency. In favor of this perception, Lelissa (2014) compares Ethiopian banks from 2008 to 2012 with an intermediary approach and concludes that public banking institutions tend to be nearer to the efficiency frontier than private ones. Additional confirmation is provided by Tanwar et al. (2020), Zhu et al. (2020) and Ijara & Sharma (2020). For example, Ijara & Sharma (2020), who, in their analysis of 17 commercial banks from 2014 to 2018, note that public banks tend to be more efficient, even as the inefficiency inherent in the sector as a whole dominates. Surprisingly, diverging results have also been documented in support of privately owned financial institutions record higher efficiency ratings (Alemu, 2016; Chaluvadi et al., 2018; Gupta et al., 2020; Lema, 2017). Such discrepancies in empirical results imply that, though public banks can gain from specific strengths in their operations, like focused resource allocation and stringent risk management approaches, context and managerial dimensions—in tandem with institutional designs—significantly shape efficiency results. Consequently, the ownership structure analysis suggests that the determination of efficiency does not lie exclusively with whether a bank is private or public but is rather a function of a combination of managerial practice, strategic conduct, as well as the overall operating environment.

2.4.2.2 Bank Size: Scale Advantages and Disadvantages

The influence of the size of banking organizations on technical efficiency is complex, being a dynamic trade-off between the advantages accruing to economies of scale and the dangers of over-expansion. On one hand, economies of scale allow big banks to amortize fixed costs over a vast asset base, negotiate more favorable terms in procurement or financing, and allocate resources in a manner that optimizes cost-reduction. On the other hand, over-expansion can lead to inefficiencies, diseconomies of scale, and operational rigidity. As banks grow larger, they may encounter bureaucratic inefficiencies, slower decision-making processes, and increased complexity in internal coordination. Additionally, excessive size can dilute accountability and create systemic risk, where failures in one segment of the bank may have widespread repercussions.

Empirical research has revealed that, to a certain limit, growth helps to decrease average expenditure and improve company efficiency (Czerwonka, 2019; Grmanová & Ivanová, 2018; Novickytė & Droždz, 2018; Weiwei et al., 2021). But as banks increase in size, evidence indicates that particularly large banks—especially those from emerging or transition economies like Ethiopia—tend to suffer from severe coordination-related problems, heightened administrative complexities, and delayed decision-making processes. These phenomena generate diseconomies of scale that ultimately minimize the initial efficiencies realized from expansion.

Moreover, conflicting positions in the academic literature argue that smaller banks can achieve higher efficiency by leveraging their operational flexibility and delivering more tailored products adapted for niche markets (I. C. Henriques et al., 2018). This flexibility allows smaller banks to act more quickly on changing trends in the market, thus avoiding the bureaucratic rigidity often plagued by larger banks with inflexible organizational structures. The large volume of literature exploring the nexus between bank size and efficiency presents a variety of opposing views. Some scholars maintain that larger financial institutions have increased efficiency due to economies of scale and advantages brought about by diversified financial operations (Jiménez-Hernández et al., 2019; T. Le, 2018; Ma & Soh, 2021; Maji & Saha, 2023; Yitayaw et al., 2023).

Conversely, other studies indicate that small banks generally possess greater efficiency scores, thus highlighting the value of flexibility along with streamlined organizational structures (Ikapel et al., 2023; Jelassi & Delhoumi, 2021; Lakshmanasamy, 2021; Ullah et al., 2023).

In contrast to these contesting arguments, the present research hypothesizes that the size of banks does not have a statistically significant impact on efficiency. This supposition acknowledges the nonlinearity of the relationship in the sense that though size will yield some benefits up to a certain extent, it is not always an absolute driver if other surrounding conditions—such as the quality of management, technological adoption, and the nature of the regulatory regime—are also considered.

2.4.2.3 Profitability as a Catalyst for Efficiency

Profitability, as conventionally expressed in terms of return on average assets (ROAA), is both an outcome and determinant of technical efficiency in banks. On the one hand, effective operating procedures—e.g., optimum use of resources, streamlined work flows, and judicious risk management—can lower costs and thereby improve profitability. On the other hand, high profitability creates the financial room and agility to invest in advanced technology, extensive employee training programs, and improved risk management systems.

These investments in turn result in better operational processes and continued efficiency gains, establishing a feedback loop of positivity in which profitability and efficiency build upon one another. The literature provides strong empirical evidence in support of this interrelation. Lakshmanasamy (2021) argues that profitability is an important driver in bringing about efficiency improvement since profitable banks have greater potential to invest their profit in innovation and system development. This perspective is also enlightened by Lema (2017), who argues that highly profitable banks are more likely to invest their profit in initiatives for enhancing business performance. Similarly, Maji & Saha (2023) illustrate that banks operating in contexts where resources are scarce and competition is high have a significant advantage in maximizing efficiency. Moreover, Ullah et al. (2023) add to this body of literature by showing that, especially in developing markets, profitability not only directly maximizes efficiency but also guards against the operational inefficiencies of underinvestment.

Collectively, these investigations highlight the fact that under the competitive and constrained regimes of emerging markets, profitable banks are more likely to improve their technical efficiency. The inter-dependent relationship that exists between efficiency and profitability is particularly important in developing economies such as Ethiopia, where financial institutions are confronted with both limited resources and also intense competitive pressures. In these contexts, the capability to attain greater technical efficiency can render a lasting competitive edge. Banks that are profitable have the capacity to capitalize on their financial strength to enhance infrastructures, institute more stringent risk management strategies, and enhance service delivery, resulting ultimately in additional efficiency improvements.

On the other hand, banks with signs of reduced profitability may experience difficulty in allocating resources to these key areas and thus sustain inefficiency trends. Thus, by the evidence from the above studies, this study assumes that highly profitable Ethiopian banks—reflected in high ROAA figures—are bound to perform well on technical efficiency examinations, thereby supporting the theory that financial strength is a main driver of operational enhancement.

2.4.2.4 Capital Adequacy and Efficiency

Capital adequacy ratios are, after all, meant to make financial institutions hold a sufficient reserve to cover unexpected loss and hence guarantee financial stability. Literature is, however, mixed on the extent to which increased capital buffers are drivers of improved technical efficiency. Especially in some research—especially studies targeting Basel I frameworks for emerging markets—the capital adequacy ratio seems to act as a buffer and not necessarily as a performance improvement tool. The contrast between capital requirements designed for protection and instruments that could potentially enhance operational performance constitutes a crucial aspect of this area of research. Despite these varied views, a large body of literature recognizes capital adequacy as an important determinant of technical efficiency. Various empirical research works confirm the premise that higher capital buffers can contribute to the stability of banking operations, thus imparting resistance to financial shocks and indirectly promoting improvements in efficiency.

For example, Jelassi & Delhoumi (2021) used a two-step Data Envelopment Analysis (DEA) on Tunisia's ten largest banks from 1995 to 2017 and found that better capital adequacy is positively correlated with higher efficiency scores. Such positive correlations have also been observed in research examining other emerging markets. Research on Indian banks by Lakshmanasamy (2021) and Maji & Saha (2023) corroborates the opinion that adequate capital not only induces stability but also enhances operational efficiency by enabling investments in technology and risk management practices. This observation is also reinforced by Ma & Soh's (2021) investigation of Malaysian commercial banks, where it is revealed that increased capital adequacy is linked to superior performance on operational efficiency measures.

Based on the cumulative evidence from these studies, this research hypothesizes that banks with high capital adequacy ratios will be more technically efficient. This relationship suggests that high capital buffers do not only protect organizations from exogenous shocks; indeed, they can also support more efficient allocation of resources, encourage investments in innovative practices, and consequently translate to better all-around performance.

In the settings of emerging markets, where financial constraints and volatility are more severe, having an optimal level of capitalization may be all the more critical for technical efficiency preservation.

2.4.2.5 The Role of other Control Variables affecting credit risk and liquidity risk

Another essential part of the literature highlights that the estimated relations between banking risk and technical efficiency are sensitive to the inclusion of control variables. When credit risk is the dependent variable, a number of studies have looked at how risk profiles are influenced by variables like profitability, capital adequacy, economic growth, and inflation. The evidence available is still inconclusive.

In Kosovo, Shkodra & Ismajli (2017) report that liquidity risk and profitability risk factors positively affect credit risk, i.e., even banks with good financial positions can experience high levels of credit risk when conducting their operations in circumstances of increased liquidity risk. Conversely, research carried out in Jordan (Kharabsheh, 2019) and India (Koju et al., 2018) also document an inverse link between credit risk and profitability. According to these studies, banks with high profitability practice more conservative lending, thus having lower exposure to credit risk. Likewise, existing research on capital adequacy reports mixed results. Kharabsheh (2019); and Radivojevic & Jovovic (2017) affirm a positive correlation—suggesting that banks with bigger capitals may take higher credit risk, possibly driven by higher risk-taking incentives—whereas Koju et al. (2018) discover banks with large capital exhibit less exposure to credit risk, perhaps due to assuming more conservative risk management approaches. In addition, the impact of macroeconomic variables further complicates the issue.

Ha (2020) and Radivojevic & Jovovic (2017) studies indicate economic growth decreases credit risk, by presumably making income more stable and improving asset quality; however, no statistically significant effect is found by Kharabsheh (2019) in Jordanian banks. Inflation has area-specific impacts; for instance, Morina (2020) demonstrates that inflation has adverse influences on credit risk in Kosovo. Other studies (e.g., Ha, 2020; Radivojevic & Jovovic, 2017), however, demonstrate inflation's positive influences in Vietnam and emerging markets, respectively. When liquidity risk is rendered the dependent variable, a similar change in control variables' impact can be observed. Abdelaziz et al. (2022) study financial institutions from the MENA region and find that a rise in return on average assets (ROAA)—a profitability measure—normally results in a decline in liquidity risk, suggesting an inverse relation.

In contrast, Al-Homaidi et al. (2019), targeting Indian banks, discover a positive link between liquidity risk and profitability, suggesting that increased profitability might stimulate banks to raise their risk exposure to capture growth opportunities. Regarding capital adequacy, empirical evidence tends to favor its contribution to reducing liquidity risk, as shown by El-Chaarani (2019) in the context of Middle Eastern banks. Al-Homaidi et al. (2019), however, have evidence that indicates increased capital buffers may encourage liquidity risk-taking behavior in some contexts, thus pointing to significant regional disparities.

The interaction between economic growth, inflation, and liquidity risk is complex and multidimensional. According to Bhati et al. (2019) and El-Chaarani (2019), there is a positive link between economic growth and liquidity risk, which implies that good economic conditions encourage banks to increase lending activities, thus leading to potential liquidity strains.

In contrast, Wudu & Veni (2019) report an absence of meaningful correlation between liquidity risk and economic growth in the case of Ethiopian banks, stating that regional economic conditions and the regulatory framework can change this relationship. Whereas Sopan & Abhijit (2018) find that inflation exacerbates liquidity risk, Wudu & Veni (2019) find inflation to have minimal influence on the liquidity weakness of Ethiopian banks.

Therefore, the absence of robust evidence for the contribution of profitability, capital adequacy, economic growth, and inflation in the efficiency–risk relation highlights the significance of incorporating these control variables into empirical specifications for understanding the efficiency–risk nexus. Based on these considerations, this research can more effectively determine the direct impact of technical efficiency on credit risk and liquidity risk.

2.5 Theoretical Framework and Hypotheses Development

Literature suggests bank efficiency is an outcome of a multifaceted interaction of numerous factors, including the ownership structure, bank size, profitability, capitalization, and risk factors like credit and liquidity risks. The conceptual framework (Figure 2.1) presumes that these factors directly influence technical efficiency and also have interrelated relationships.

Traditionally, risk determinants—liquidity risk and credit risk—are viewed as efficiency constraints, as higher risk raises the operating cost and diverts resources from efficiency-improving activities. Recent empirical findings demonstrate a reversed causal relationship in which banks that achieve higher efficiency may relax risk management controls, leading to higher exposure to credit and liquidity risk. The regulatory environment in this integrated framework serves as a moderator, affecting the way banks prioritize efficiency enhancement and prudent risk management practices.

This section presents the study's hypotheses, each grounded in the theoretical frameworks discussed above and supported by empirical literature. The hypotheses are grouped into three thematic categories aligned with the research objectives.

2.5.1. Efficiency Variations by Ownership and Size

2.5.1.1 Ownership Structure and Efficiency

The Agency Theory (Jensen & Meckling, 1976) and the Bad Management Hypothesis (Berger & DeYoung, 1997) suggest that private banks, driven by market discipline and profit motives, are more likely to adopt efficient operational practices than public banks, which may suffer from bureaucratic inertia and weaker accountability. However, empirical findings in the Ethiopian context present a mixed picture. While Rao & Lakew (2012) found no significant relationship between ownership and efficiency, Lelissa & Kuhil (2016) and Lelissa (2014) argue that public banks are more efficient, citing stronger managerial performance and proximity to the efficiency frontier. Similarly, Ijara & Sharma (2020) observed higher efficiency in public banks. In contrast, studies such as Alemu (2016), Lema (2017), and Gupta et al. (2020) support the superior efficiency of private banks. These conflicting findings underscore that ownership structure alone may not fully explain efficiency variations among banks. Instead, efficiency appears to be shaped by a complex interplay of managerial practices, institutional frameworks, and regulatory conditions. Nevertheless, the persistent debate in the literature—combined with the theoretical expectations of Agency Theory and the Bad Management Hypothesis—warrants further empirical investigation.

Accordingly, the first hypothesis of this study is formulated as follows:

H1: There is a statistically significant difference in technical efficiency scores between public and private banks in Ethiopia.

2.5.1.2 Bank Size and Efficiency

The Economies of Scale Theory posits that larger banks achieve cost advantages by spreading fixed costs over a greater volume of operations, thereby enhancing efficiency. In the banking sector, economies of scale refer to the cost advantages that institutions gain as their operational size increases. Specifically, larger banks are able to reduce their average cost per unit by distributing fixed costs—such as infrastructure, compliance, and technology—across a greater volume of transactions and assets. This phenomenon results in a lower cost per dollar of loans or assets as the scale of operations expands (Jacewitz et al., 2020). Empirical evidence further supports this relationship, particularly within community banks, where scale efficiencies have been shown to enhance competitiveness and financial performance. Complementary findings by Asongu & Odhiambo (2019) also highlight the role of size and efficiency in driving economies of scale across African banking institutions.

In addition to scale-related advantages, the Resource-Based View (RBV) offers a robust framework for analyzing bank performance through the lens of internal strategic assets. RBV posits that institutions can achieve sustained competitive advantage by leveraging resources that are valuable, rare, inimitable, and non-substitutable. In the banking sector, these often include advanced technological infrastructure, highly skilled personnel, and strong brand reputation—elements that contribute to superior operational and financial outcomes (Donnellan & Rutledge, 2019).

Moreover, Liu et al. (2010) provide a comprehensive review of empirical approaches to RBV in banking, identifying multiple methods for evaluating both resource endowments and performance outcomes. Their findings emphasize the importance of aligning internal capabilities with strategic planning, suggesting that RBV is not merely a theoretical construct but a practical tool for enhancing decision-making and long-term value creation. Together, these perspectives underscore how large banks may outperform competitors not solely due to scale, but because of their ability to mobilize and manage core competencies effectively.

Empirical studies, including Czerwonka (2019), Grmanová & Ivanová (2018), and Weiwei et al. (2021), also support the notion that bank size positively influences efficiency, though the effect may taper beyond a certain threshold. In the Ethiopian context, this hypothesis examines whether large private banks exhibit higher technical efficiency due to structural and operational advantages. Thus, the second hypothesis is formulated as follows:

H2: In the case of private banks, large banks show significantly higher technical efficiency scores compared to small banks in Ethiopia.

2.5.2. Hypotheses Development within the Efficiency–Risk Framework

This section develops hypotheses based on two broad categories of determinants: the test variables (credit risk and liquidity risk) and performance and structural control variables.

2.5.2.1. The Effect of Credit Risk on Efficiency

The Bad Luck Hypothesis (Berger & DeYoung, 1997) suggests that external shocks—such as deteriorating asset quality or macroeconomic instability—lead to increased credit risk, which in turn forces banks to allocate more resources to damage control, thereby reducing operational efficiency. Empirical studies such as Jiménez-Hernández et al. (2019) and Le (2018) support this view, showing that high credit risk levels are associated with inefficiencies due to increased provisioning and conservative lending. However, more recent findings (e.g., Ilmiani & Meliza, 2022) suggest that under certain conditions, banks with higher credit risk may also exhibit greater efficiency, possibly due to aggressive lending strategies that boost short-term performance. This duality highlights the need for context-specific analysis in emerging markets like Ethiopia. Based on this reasoning, the third hypothesis is stated as follows:

H3: Credit risk has a statistically significant negative effect on the technical efficiency of banks in Ethiopia.

2.5.2.2. Liquidity Risk as an Efficiency Determinant

The Bad Luck Hypothesis also applies to liquidity risk, suggesting that external financial pressures—such as mismatches between short-term liabilities and long-term assets—can constrain operational flexibility and reduce efficiency. Empirical studies by Tan & Floros (2013, 2018) and Yitayaw et al. (2023) confirm that liquidity-constrained banks often adopt conservative strategies that limit process optimization.

Conversely, other studies (e.g., Ilmiani & Meliza, 2022; Ma & Soh, 2021) show that banks facing liquidity risk may still achieve high efficiency through optimized cash management. These divergent findings highlight the intricate nature of the relationship between efficiency and liquidity risk within unstable contexts.

Accordingly, the fourth hypothesis is formulated as follows:
H4: Liquidity risk has a statistically significant negative effect on the technical efficiency of banks in Ethiopia.

2.5.2.3. Profitability and Efficiency

The Bad Management Hypothesis of Berger & DeYoung (1997) implies that inefficient banks often suffer from poor profitability due to weak governance and suboptimal resource use. Conversely, profitability can act as a catalyst for efficiency by enabling banks to invest in technology, staff development, and risk management systems. Empirical studies strongly support this interdependence. Lakshmanasamy (2021) and Lema (2017) argue that profitable banks are more likely to reinvest earnings into operational improvements. Maji & Saha (2023) and Ullah et al. (2023) further show that in resource-constrained environments like Ethiopia, profitability enhances efficiency by enabling strategic investments and shielding against underinvestment. This feedback loop between profitability and efficiency is particularly relevant in emerging markets, where financial agility is crucial for sustained performance.

Hence, the fifth hypothesis is proposed as follows:
H5: Profitability, measured by return on average assets (ROAA), has a statistically significant positive effect on the technical efficiency of Ethiopian banks.

2.5.2.4. Capital Adequacy and Efficiency

The Portfolio Optimization Trade-Off and the Moral Hazard Hypothesis offer contrasting perspectives on the role of capital adequacy in banking performance. The former views capital as a strategic buffer that enables banks to absorb shocks, optimize resource allocation, and enhance operational efficiency. In contrast, the latter suggests that insufficient capital may incentivize excessive risk-taking, potentially undermining efficiency and stability.

Although capital buffers are primarily designed to ensure resilience, they do not automatically guarantee performance gains. Nonetheless, empirical evidence from emerging markets consistently supports a positive relationship between capital adequacy and efficiency. Studies such as Jelassi & Delhoumi (2021), Lakshmanasamy (2021), Maji & Saha (2023), and Ma & Soh (2021) show that adequate capitalization enables investments in technology, risk management, and innovation—key drivers of operational efficiency.

In the Ethiopian banking context, characterized by volatility and structural constraints, capital adequacy plays a dual role: it protects against exogenous shocks and facilitates strategic resource allocation. This hypothesis examines whether well-capitalized banks in Ethiopia demonstrate superior technical efficiency.

Accordingly, the sixth hypothesis is stated as follows:

H6: Capital adequacy is positively and significantly associated with the technical efficiency of banks in Ethiopia.

2.5.2.5. Bank Size and Efficiency

While bank size is often associated with efficiency gains due to economies of scale, the relationship is not universally positive. The Bad Luck Hypothesis suggests that large banks may be more exposed to systemic risks, while internal frictions—such as coordination challenges and bureaucratic inertia—can offset scale advantages. These dynamics imply a non-linear relationship between bank size and efficiency, where benefits may taper or reverse beyond a certain threshold.

Unlike H2, which compares efficiency between large and small private banks, this hypothesis examines the continuous and non-linear effect of bank size, measured as the natural logarithm of total assets, on technical efficiency. It seeks to determine whether efficiency gains persist as banks grow, or whether very large banks face diminishing returns due to structural and operational constraints.

Empirical evidence on this relationship is mixed. Studies such as Abdulahi et al. (2023), Jiménez-Hernández et al. (2019), Le (2018), Maji & Saha (2024), and Ma & Soh (2021) report a positive association between bank size and efficiency, often attributing gains to better resource utilization and technological investment. However, other studies—Ikapel et al. (2023), Jelassi & Delhoumi (2021), Lakshmanasamy (2021), and Ullah et al. (2023)—find an inverse relationship, suggesting that beyond a certain size, banks may suffer from inefficiencies linked to complexity and misaligned incentives. In the Ethiopian context, where institutional and technological scalability may be limited, this hypothesis explores whether increasing bank size continues to enhance efficiency or introduces new constraints.

Thus, the seventh hypothesis of the study is stated as follows.
H7: Bank size has a statistically significant non-linear effect on technical efficiency in Ethiopian banks.

2.5.3. Effect of Efficiency on Credit and Liquidity Risks

2.5.3.1 The Function of Efficiency in Credit Risk

The Skimping Hypothesis (Berger & DeYoung, 1997; Williams, 2004) argues that banks pursuing cost efficiency may underinvest in credit risk controls, leading to increased exposure over time. Empirical evidence from Fiordelisi et al. (2011) and Yitayaw et al. (2023) supports this view, showing that highly efficient banks often face higher credit risk due to aggressive lending and reduced underwriting standards. In the Ethiopian context, where regulatory oversight and risk management practices vary, this trade-off is particularly relevant.

Accordingly, the eighth hypothesis is formulated as follows:
H8: Higher technical efficiency significantly increases credit risk among Ethiopian banks, consistent with the Skimping Hypothesis.

2.5.3.2 Efficiency's Effect on Liquidity Risk

The relationship between efficiency and liquidity risk is multifaceted. While efficient banks may improve liquidity management (as noted by Benti & Biru, 2023), they may also reduce precautionary liquidity buffers to optimize returns, increasing vulnerability to shocks. Studies by Tan & Floros (2018) and Wudu & Veni (2019) show that efficiency-driven banks may lack the flexibility to respond to unforeseen liquidity demands, especially in turbulent markets. This supports the view that efficiency-seeking behavior can elevate liquidity risk.

Thus, the ninth hypothesis is stated as follows:

H9: Technical efficiency has a statistically significant positive effect on liquidity risk in Ethiopian banks, as efficiency-oriented strategies reduce precautionary liquidity holdings.

2.6 Synthesis of Literature and Identification of Research Gaps

2.6.1. Synthesizing Theoretical and Empirical Perspectives on the Efficiency–Risk Nexus

The relationship between risk and efficiency in banking has been identified as an interplay, i.e., risk exposure can lead to inefficiencies, and efficiency improvement initiatives can also influence financial risk profiles. Theoretical frameworks, particularly financial intermediation theory (Diamond, 1984), highlight the intermediation role of banks in trying to maximize financial transactions through reducing transaction costs, allocating credits, and bridging information asymmetry. In addition to this, risk management frameworks elucidate the methods employed by banks to neutralize credit risk and liquidity shortages through financial instruments like diversification, collateral lending, and contingency funds (Bessis, 2015; Diamond & Dybvig, 1983).

The trade-off between risk and efficiency is usually described using competing theoretical frameworks, five of which—Bad Management Hypothesis, Skimping Hypothesis, Moral Hazard Hypothesis, Portfolio Optimization Trade-Off, and Bad Luck Hypothesis—give different interpretations of how banks trade off operational efficiency for financial risks. These theoretical models map well into empirical studies, which have had inconclusive outcomes on whether risk compromises efficiency or improves performance under certain conditions.

2.6.2. Empirical Evidence for the Impact of Risk on Efficiency

Empirical research investigating the influence of credit risk and liquidity risk on operating efficiency offers contradicting results for the direction of such a relationship. Some research suggests that high levels of credit risk are linked to inefficiencies as declining asset quality and financial instability compel banks to have increased operating expenses (Jiménez-Hernández et al., 2019; T. Le, 2018). These findings support the Bad Luck Hypothesis, which holds that risk precedes and constrains efficiency rather than inefficiency being responsible for instability (Berger & DeYoung, 1997).

Consequently, studies on liquidity risk dynamics have demonstrated that illiquidity lowers the flexibility of operations, limits economies of scale, and deters investments to enhance efficiency (Tan & Floros, 2013, 2018; Yitayaw et al., 2023). The evidence is in line with the portfolio optimization trade-off because liquidity problems compel banks to face more stringent capital management constraints, thereby aggravating systemic inefficiencies.

On the other hand, empirical research also presents instances where higher risk levels occur alongside greater efficiency, contradicting conventional expectations. Research by Ilmiani & Meliza (2022), Tan & Floros (2018), and Yitayaw et al. (2023) demonstrates that institutions that take strategic risks—such as through aggressive lending practices or focused asset allocation—can enhance their operational effectiveness, using risk exposure as a pathway to higher profitability. These results are partly in alignment with the Moral Hazard Hypothesis, which has posited that competitive pressures encourage efficient banks to adopt riskier but potentially more lucrative financial policies (Jeitschko & Jeung, 2005).

Also, empirical data from studies such as Jiménez-Hernández et al. (2019), Le (2018), and Ma & Soh (2021) shows that banks that optimize liquidity management can maintain efficiency despite risk constraints, in line with the arguments that liquidity risk does not necessarily compromise efficiency if properly managed. This reinforces the Portfolio Optimization Trade-Off, which states that efficiency-driven financial strategies must be offset with diversification to reduce exposure to economic volatility.

2.6.3. Empirical Evidence on the Effect of Efficiency on Risk

A growing body of research examines the impact of banking efficiency activity on financial risk, rather than risk constraining efficiency. The Skimping Hypothesis (Berger & DeYoung, 1997; Williams, 2004) foresees that banks that maximize efficiency by minimizing costs have a tendency to underinvest in risk management, thus credit risk accumulates over time. Empirical studies support this position, with empirical evidence indicating that banks with high efficiency tend to use aggressive lending policies, which involve leniency in underwriting standards for purposes of retaining cost-efficiency, thereby exposing them to higher default rates (Fiordelisi et al., 2011; Yitayaw et al., 2023).

Similarly, efficient banks usually increase their liquidity buffers, which in turn reduces liquidity pressures and strengthens financial activities (Benti & Biru, 2023; Ilmiani & Meliza, 2022).

Yet, empirical evidence demonstrates that efficiency-oriented institutions can have lower flexibility to liquidity shocks and hence be more susceptible during market downturns and crises (Tan & Floros, 2018; Wudu & Veni, 2019). The result is consistent with the Skimping Hypothesis that posits that banks with emphasis on short-term efficiency targets tend to neglect prudent financial buffers and become vulnerable to systemic liquidity risk.

The Moral Hazard Hypothesis illuminates the actions of efficient banks to engage in riskier behavior, particularly in competitive financial markets that encourage institutions to expand their lending portfolio and venture into speculative investment (Jeitschko & Jeung, 2005). Empirical observations provide cases of banks with high technical efficiency ratings taking on higher credit risk, confirming that market competition creates financial instability due to efficiency (Tan & Floros, 2018; Wudu & Veni, 2019).

Notwithstanding the extensive theoretical and empirical bank efficiency and risk literature, substantial gaps persist, especially in the Ethiopian commercial banking context. The gaps are particularly concerning methodological limitations, inconsistencies in empirical studies, and the need for systematic estimation techniques suitable for short-panel banking data. The correction of these gaps improves the conceptualization of the efficiency-risk relationships, thereby generating insights with implications for both scholarly development and policy practice.

1. Uncertainty About the Efficiency-Risk Trade-off

The literature has provided mixed evidence about the impact of excessive credit and liquidity risk on efficiency, some of which suggests that greater credit risk and liquidity constraints lower technical efficiency as they raise operating costs and undermine financial intermediation. Other studies argue that strategic risk-taking can improve efficiency as it fosters improved resource allocation and competitive optimization. This divergence warrants additional empirical investigation, especially in controlled banking environments such as Ethiopia, where policy intervention and capital constraints influence efficiency results.

2. Inconsistent Evidence Regarding Efficiency's Influence on Risk Exposure

Efficiency is usually a reflection of managerial and operational ability; however, research says that efficiency might have a direct influence on risk profiles too. Though the Skimping Hypothesis supposes that low-cost banks might skim on risk management efforts, thereby leaving themselves vulnerable to high default rates, other research says that efficient banks enhance their risk management simply by virtue of enhanced screening and resource allocation. The conflicting empirical findings necessitate rigorous testing to shed light on how efficiency levels influence credit and liquidity risk exposures within the Ethiopian financial environments.

3. Efficiency–Risk Estimation Techniques Adaptation for Short-Panel Data

Most of the efficiency–risk research utilizes long-panel datasets, which may not be tenable under circumstances where there is limited data availability. The Ethiopian banking industry has a comparatively short-panel structure, which reduces the possibilities of implementable simultaneous equation models (SEM) or dynamic models with highly persistence characteristics such as the vector auto-regression (VAR) model. The insignificance of lagged dependent variables in dynamic estimates justifies the abandonment of dynamic modeling methods (GMM) in favor of static modeling methods (FEM), citing an empirical limitation in the capacity of short-panel studies to investigate fully efficiency–risk dynamics.

By filling these basic gaps, this research provides empirical insight into efficiency–risk interdependencies, methodological improvement for banking research using short panels, and a foundation for subsequent studies on efficiency-risk trade-offs in emerging market economics.

2.7 Conceptual Framework Diagram

This conceptual framework organizes the study's hypotheses within the broader efficiency–risk paradigm and reflects the multidimensional nature of technical efficiency in Ethiopian banks. It distinguishes between two primary categories of determinants: risk-based factors, including credit risk and liquidity risk (H3 and H4), which form the core analytical focus of the study; and structural and performance-related factors, such as capital adequacy, profitability, and bank size (H5 to H7), which represent strategic and operational influences beyond direct risk exposure.

Although the theoretical framework acknowledges the potential bidirectional relationship between efficiency and risk—where technical efficiency may influence credit and liquidity risks (H8 and H9)—the empirical analysis does not test this direction due to data limitations. Specifically, the use of short panel data in the Ethiopian banking context precluded the application of advanced bidirectional estimation techniques such as Vector Autoregression (VAR) or Structural Equation Modeling (SEM). Thus, the study tests H8 and H9 using separate static estimation models by controlling seven bank specific and macroeconomic variables.

In addition to these factors, the framework incorporates group-level comparisons to explore differences in efficiency scores based on ownership structure (public vs private; H1) and size segmentation among private banks (large vs small; H2). Together, these elements provide a comprehensive structure for analyzing the efficiency-risk interplay and its implications within the Ethiopian banking sector.

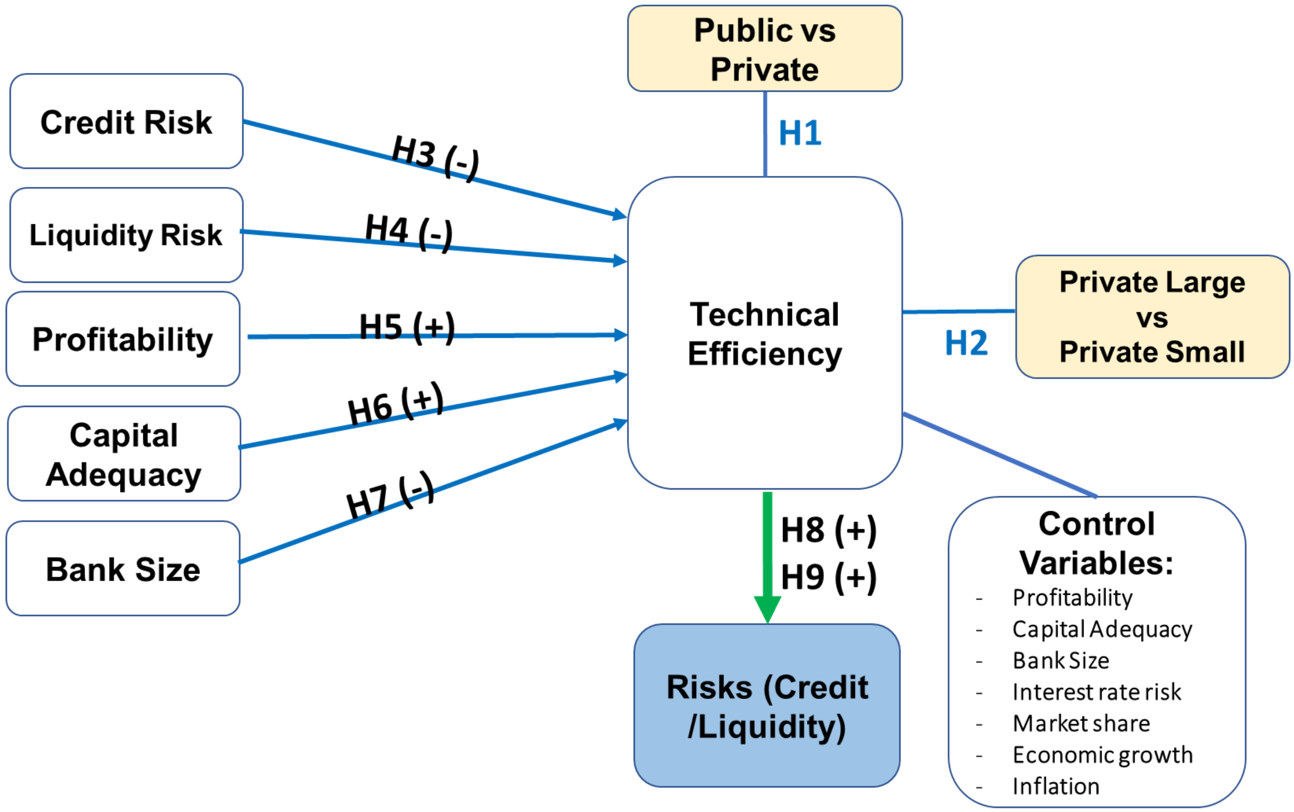

Figure 2.1: Integrated Conceptual Framework of the Efficiency–Risk Interplay in Ethiopian Commercial Banks

Source: Adapted from the literature reviewed in Chapter 2 (Author's synthesis).

CHAPTER 3: METHODOLOGY

3.1 Introduction

This chapter outlines the methodological framework adopted to examine the efficiency–risk trade-off in the Ethiopian commercial banking industry. The study employs explanatory research design and a quantitative research approach using panel data for the period 2014–2022. The empirical strategy unfolds in two stages. Technical efficiency scores are first estimated using Data Envelopment Analysis (DEA). The study then undertakes a two-pronged econometric investigation. The first part employs a dynamic panel estimation using the Difference Generalized Method of Moments (DGMM) to identify the determinants of technical efficiency, with a particular emphasis on credit and liquidity risk, while also accounting for the persistence of efficiency scores. The second part applies static panel regression models to examine the contemporaneous impact of technical efficiency on credit and liquidity risk. However, due to data limitations in the Ethiopian banking context—specifically the use of short panel data—the study does not empirically test the bidirectional relationship between efficiency and risk, as advanced estimation techniques such as Vector Autoregression (VAR) or Structural Equation Modeling (SEM) could not be applied. Data treatment procedures and robustness checks are also detailed.

3.2. Research Paradigm and Ontology

This study is firmly grounded in a positivist research paradigm, which asserts that reality exists independently of human perception and can be objectively measured and quantified. In alignment with this view, the investigation operates under the assumption that the relationships between technical efficiency and banking risk factors are governed by observable, external phenomena.

This paradigm justifies the use of rigorous, hypothesis-driven quantitative methods. It employs Difference GMM and static panel regressions. These methods test and validate causal linkages. They focus on efficiency measures[2] (OTEBC and PTEBC) and risk exposures (credit risk and liquidity risk). This approach yields empirical evidence that is replicable and generalizable. Consequently, the study contributes robust findings to academic discourse on banking efficiency and risk management.

Complementing the positivist stance, this research also adopts an objectivist (realist) ontology. This perspective contends that the constructs under investigation, including overall technical efficiency, pure technical efficiency, credit risk, and liquidity risk, are manifestations of an underlying reality that can be measured without bias. Under this ontological framework, the use of observable indicators derived from reliable secondary sources ensures that the inherent characteristics of banking operations and risk exposures are accurately captured. The commitment to an objectivist ontology reinforces the study's emphasis on data-driven analysis and supports the derivation of causal inferences based on statistically validated relationships. Overall, this combined epistemological and ontological orientation underscores the study's dedication to a transparent, systematic, and methodologically rigorous investigation into the dynamics of efficiency and risks in the Ethiopian banking sector.

3.3 Research Design and Data

This study is based on a panel dataset that captures both cross-sectional and temporal variations among Ethiopian commercial banks. The dataset, spanning from 2014 to 2022, includes detailed information on various aspects of bank characteristics—such as ownership structure, which classifies banks as state-owned or private, and bank size[3], categorized into large, medium, and small. In addition, the dataset encompasses financial

[2] All efficiency measures in this study were computed using the bias-corrected approach. For simplicity, the terms "overall technical efficiency," "pure technical efficiency," and "scale efficiency" are used to refer to their respective bias-corrected forms: OTEBC, PTEBC, and SEBC. In each abbreviation, the suffix "BC" indicates that bias correction has been applied.

[3] Bank size is classified according to the National Bank of Ethiopia's 2 percent asset-share threshold (NBE, 2024). Under this scheme, the Commercial Bank of Ethiopia (CBE) is designated the sole "largest and systemic" institution. Banks whose asset shares exceed 2 percent of total industry assets are deemed medium-sized, while those below this threshold are classified as small.

performance metrics essential for Data Envelopment Analysis (DEA), incorporating multiple input measures (e.g., deposits and non-interest expenses) and output measures (e.g., total loans, net interest income, and non-interest income) for estimating technical efficiency. Moreover, it includes quantitative indicators of risk, specifically credit risk and liquidity risk, to facilitate a comprehensive analysis of the efficiency–risk nexus. Data have been systematically collected from published financial reports of the 17 commercial banks, industry databases, and World Bank database, thereby ensuring the high reliability and validity of the dataset.

For the aim of this research, a sample of seventeen commercial banks was selected, comprising sixteen privately owned institutions and the state-owned Commercial Bank of Ethiopia (CBE). The choice was based on the availability of complete panel data from 2014 to 2022, obtained from the annual reports of the respective banks. The selected banks account for a total of 98.2% of total deposits, 97.7% of loans and advances, 97.9% of total assets, and 94.5% of customers in the Ethiopian banking industry (CEPHEUS, 2023; NBE, 2024). The sample is, therefore, considered representative of the commercial banking sector in Ethiopia, which offers a good ground for analysis.

Data Transformation and Normalization

Given the marked disparity in bank sizes—with one publicly owned bank being extremely large[4] relative to the sixteen private banks—the dataset is subject to significant skewness. This extreme variation might distort empirical results by allowing outliers to disproportionately influence the analysis. To mitigate this issue, a logarithmic transformation was applied to the input and output variables. This transformation compresses the range of the data, reduces skewness, and enhances the symmetry of the distribution, facilitating more reliable statistical inference while ensuring that the underlying model assumptions (e.g., normality of residuals) are met.

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[4]According to National bank report, CBE is the only systematic and large bank in the industry with roughly more than half total assets of the sector (NBE, 2024).

In addition to the log transformation, we conducted a robustness check by scaling the variables using a bank size measure (i.e., total assets) to directly control for size effects. Comparative analyses between the results obtained via the logarithmic approach and the size-scaled approach confirmed that the empirical findings remained consistent. These complementary normalization techniques ensure that our analysis is not unduly driven by the outlier effect inherent in the data. Detailed results, including the diagnostic t ests and sensitivity analyses for both methods, are provided in chapter 4 for reference.

3.4 Efficiency Measurement Using Data Envelopment Analysis

The study employs Data Envelopment Analysis (DEA) to estimate the technical efficiency of banks. DEA is a non-parametric method that offers several significant advantages. It avoids the need for a pre-specified functional form, which is particularly beneficial when the relationship between inputs and outputs is complex. Additionally, DEA is capable of handling multiple inputs and outputs, allowing for a comprehensive evaluation of bank performance. It also facilitates relative comparisons by scaling efficiency scores so that a score of 1 (or 100%) indicates that a bank is operating on the efficiency frontier. These DEA-derived efficiency scores serve as a central measure throughout the empirical analysis in this dissertation.

3.4.1. Theoretical Foundations of DEA

Data Envelopment Analysis (DEA) is a non-parametric linear programming methodology used to evaluate the relative efficiency of decision-making units (DMUs), such as banks in our case, that utilize multiple inputs to produce multiple outputs. Developed by Charnes et al. (1978) in their seminal paper "Measuring the Efficiency of Decision-Making Units," DEA constructs a piecewise linear production frontier based on observed data points, where efficient DMUs lie on the frontier and inefficient ones are enveloped by it. Unlike parametric methods (e.g., Stochastic Frontier Analysis), DEA does not require assumptions about the functional form of the production function, making it ideal for banking studies where the relationship between inputs and outputs is complex and context-dependent

(Cooper et al., 2007). We utilize both CCR (Charnes-Cooper-Rhodes) and BCC (Banker-Charnes-Cooper) models to measure technical efficiency of Ethiopian commercial banks[5].

3.4.1.1 The CCR Model (Charnes-Cooper-Rhodes, 1978)

The CCR model, named after its creators Charnes et al. (1978), represents the foundational form of Data Envelopment Analysis (DEA) and operates under the assumption of constant returns to scale (CRS). This model evaluates the overall technical efficiency of decision-making units (DMUs) by comparing their ability to transform multiple inputs into multiple outputs relative to the best-performing units in the sample (Ramanathan, 2003).

The CRS assumption implies that all banks, regardless of size, can proportionally scale their inputs and outputs without experiencing diminishing or increasing returns. This makes the CCR model particularly suitable for assessing efficiency in perfectly competitive markets where all firms operate at optimal scale.[6] By assuming constant returns to scale, the model attributes inefficiency solely to poor input-output conversion rather than scale-related factors.[7]

Mathematically, the CCR model solves a linear programming problem. The efficiency score is the ratio of weighted outputs to weighted inputs. A constraint ensures no DMU exceeds an efficiency score of 1. Section 3.4.3 discusses the model specification in detail.

The CCR model is widely used in banking studies to measure absolute efficiency, but its CRS assumption may not hold in real-world scenarios where banks operate at varying

[5] Alternative methods for efficiency analysis include Stochastic Frontier Analysis (SFA), which incorporates statistical noise and assumes a specific functional form for the production frontier; Free Disposal Hull (FDH), a non-parametric method similar to DEA but without convexity assumptions; and Thick Frontier Approach (TFA), which uses econometric techniques to estimate a range of possible frontiers. While these methods offer valuable insights, DEA was selected for its flexibility and suitability in handling multiple inputs and outputs without requiring distributional assumptions.

[6] Constant Returns to Scale (CRS) in DEA assume that output changes in exact proportion to input changes. The CCR model, introduced by Charnes, Cooper, and Rhodes (1978), is built on this assumption and is appropriate when all Decision-Making Units (DMUs) are presumed to operate at an optimal scale.

[7] Under the CRS assumption, any inefficiency detected by the CCR model is attributed to technical inefficiency rather than scale inefficiency. This allows for a clear assessment of how effectively inputs are converted into outputs, independent of size-related advantages or disadvantages.

scales. For example, due to various hurdles such as imperfect competition, government regulations, financial constraints, and innovations, DMUs might not operate at their optimal level (Banker et al., 1984). Moreover, larger banks like the Commercial Bank of Ethiopia (CBE) might benefit from economies of scale, while smaller private banks could face diseconomies. Consequently, the VRS of BCC has been employed with the assumption that a proportional increase/decrease in input level may cause a proportionally more or less increase/decrease in the level of output.

3.4.1.2 The BCC Model (Banker-Charnes-Cooper, 1984)

The BCC model, introduced by Banker, Charnes, and Cooper in 1984, extends the CCR model by incorporating variable returns to scale (VRS), thereby addressing scenarios where DMUs do not operate at optimal scale. The VRS assumption acknowledges that banks may experience increasing returns to scale (IRS) when expanding or decreasing returns to scale (DRS) when overextended, making the BCC model more flexible and realistic for heterogeneous banking sectors like Ethiopia's. For robustness check, we run both the CCR and BCC models though the later can provide more reliable information on DMU's efficiency than the former (Kamarudin et al., 2019; Nguyen & Pham, 2020). These models, when applied together, provide a comprehensive view of efficiency dynamics in Ethiopia's banking sector, informing policy and managerial decisions. However. the BCC model is particularly useful for analyzing sectors with significant size disparities, such as Ethiopia's banking industry, where CBE's dominance skews the efficiency distribution.

3.4.2. Input and Output Variable Specifications

3.4.2.1. Introduction

The selection of input and output variables depends on data availability and the research inquiry under consideration (Pastor et al., 1997). There are two approaches, namely, production and intermediation, identified in literature regarding the inputs and outputs measurement (Berger & Humphrey, 1997; Fethi & Pasiouras, 2010). The intermediation approach treats commercial banks as channels that relate savers and borrowers, playing a role in channeling funds from surplus units to deficit ones (Yue, 1992). Whereas, the production approach treats commercial banks as units that use labor and capital to produce deposits and loans (Ar & Kurtaran, 2013; Rao & Lakew, 2012). The intermediation approach is recommended to evaluate the banks' efficiency as a whole, unlike the production approach, which is used to evaluate efficiency at the bank branch level (Berger & Humphrey, 1997; Fethi & Pasiouras, 2010).

In Ethiopia’s tightly regulated banking environment, management exercises far greater control over inputs (staff levels, funding costs, operating expenses) than over outputs (loan demand, interest income) (Rao & Lakew, 2012). An input-oriented DEA model aligns with the intermediation framework. It focuses the efficiency analysis on how well banks minimize their controllable inputs. It also examines how banks reallocate those inputs. At the same time, it ensures that required outputs are delivered. This orientation reflects the reality of Ethiopian commercial banks. In these banks, market forces and supervisory directives largely dictate outputs. It also ensures that improvements in measured efficiency translate into actionable insights. Those insights center on cost management and resource deployment.

The study applies both constant returns to scale (CRS) and variable returns to scale (VRS) frontiers under this input-orientation to unpack where inefficiencies lie. The CRS assumption serves as a yardstick for overall technical efficiency, treating all banks as if they could scale inputs and outputs up or down proportionally without altering their productive technology. In contrast, the VRS assumption relaxes that proportionality, isolating pure technical efficiency—the effectiveness of managerial decisions in input use—from scale efficiency, which captures gains or losses from operating above or below optimal size. By decomposing overall technical efficiency into these two components, the study can diagnose whether banks’ shortfalls stem from suboptimal resource allocation (pure inefficiency) or from non-ideal scale (scale inefficiency). This dual-frontier, input-oriented strategy, grounded in the intermediation approach, thus furnishes a nuanced, actionable assessment of Ethiopian banks’ performance.

In sum, to measure the efficiency of Ethiopian commercial banks, this study employs the intermediation approach (Sealey & Lindley, 1977) input-oriented CRS and VRS assumptions. This method is supported by recent studies (Bhatia & Mahendru, 2019; Henriques et al., 2020; Wasiaturrahma et al., 2020).

3.4.2.2. Determination of the Number of Input and Output Variables

The choice of how many inputs (m) and outputs (s) to include in a DEA model depends on the number of decision-making units (n). Avkiran (2006, p. 27) recommends that n exceed the product of inputs and outputs ($n > s \times m$). Golany & Roll (1989) impose an even stricter rule, namely that n should be greater than twice the sum of inputs and outputs ($n > 2 \times [s + m]$). In our case, the number of DMUs (n) is 17 which is not only greater than the product of the number of outputs (3) and inputs (2), but also greater than twice the sum of output and inputs (i.e., $2\times (3+2) =10$).

Therefore, the input variables include total deposits, which capture the core liability base and funding capacity of the banks, as highlighted by Berger & Humphrey, (1997). Additionally, non-interest expenses are included to measure the operational costs excluding funding expenses, as suggested by Fethi & Pasiouras (2010). For the outputs, the study has chosen total loans and advances, which represent the primary earning asset and the intermediation function of the banks. Net interest income is selected to reflect the core profitability derived from the interest spread, while non-interest income is included to account for fee-based revenue, indicating service diversification. These variables provide a comprehensive and balanced view of the banks' performance, ensuring the robustness and validity of the DEA model. Table 3.1 provides details of the input and output variables.

Table 3.1: Input and Output Variables for Measuring Efficiency Scores of Ethiopian Commercial Banks

Variable name	Description and source (in millions of birr)
Input variables:	
Non-Interest expenses	Non-Interest expense of each commercial bank per year.
Deposits	Total deposits to each commercial bank per year
Output variables:	
Net-Interest income	Interest income net of interest expenses of each commercial bank per year.
Non-interest income	Non-Interest income of each commercial bank per year.
Loans and advances	Loans and advances of each commercial bank per year

3.4.3 Model Specification

Technical efficiency is defined as the ratio of outputs (y) to inputs (x). To maximize this ratio, one must either increase outputs or reduce inputs, which is the implicit assumption of the CCR model's CRS (Charnes et al., 1978). In scenarios where DMUs utilize multiple inputs and produce multiple outputs, the efficiency score is calculated as the linear weighted sum of outputs divided by the linear weighted sum of inputs (Avkiran, 2006; Ramanathan, 2003).

Mathematically, this can be expressed as:

$$\theta = \frac{\sum_{r=1}^{s} u_r y_r}{\sum_{=1}^{m} v_i x_i} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where:

θ = technical efficiency

s = number of outputs

u_r = weights assigned to output r

y_r = amount of output r produced by the DMU

m = number of inputs

v_i = weights assigned to input i

x_i = amount of input i used by the DMU

The weights u and v are determined through a specially formulated linear programming problem (Ramanathan, 2003). Thus, to compute the efficiency score (θ) of the target DMU (DMU_0), the following linear programming model is employed. First, the Input oriented CCR Model can be estimated by:

Input-Oriented CRS (CCR) Model

For a given decision-making unit (DMU_o), solve the following linear program:

Minimize θ ……………………………………………. (2)

Subject to:

1. $\sum_{j=1}^{n} \lambda_j \, x_{ij} \leq \theta x_{i0}$, for each input i = 1, …, m:
2. $\sum_{j=1}^{n} \lambda_j \, y_{rj} \geq y_{r0}$, for each output r = 1, …, s:
3. $\lambda_j \geq 0$, for all DMUs j = 1, …, n:

Where:

- **θ** is the input-oriented technical efficiency score of DMU_o.
- $\mathbf{x_{ij}}$ is the value of input i for DMU j.
- $\mathbf{y_{rj}}$ is the value of output r for DMU j.
- $\mathbf{x_{i0}}$ and $\mathbf{y_{r0}}$ are the input and output values for the DMU under evaluation.
- **n** is the number of DMUs.
- **m** is the number of inputs.
- **s** is the number of outputs.

Input-Oriented VRS (BCC) Model

The VRS version imposes an additional convexity constraint. For DMU_0, solve:

Minimize θ ……………………………………………. (3)

Subject to:

1. $\sum_{j=1}^{n} \lambda_j \, x_{ij} \leq \theta x_{i0}$, for each input i = 1, …, m:
2. $\sum_{j=1}^{n} \lambda_j \, y_{rj} \geq y_{r0}$, for each output r = 1, …, s:
3. $\lambda_j \geq 0$, for all DMUs j = 1, …, n:
4. Convexity constraint: $\sum_{j=1}^{n} \lambda_j = 1$

Where:

- **θ** is the input-oriented technical efficiency score of DMU_0.
- $\mathbf{x_{ij}}$ is the value of input i for DMU j.
- $\mathbf{y_{rj}}$ is the value of output r for DMU j.
- $\mathbf{x_{i0}}$ and $\mathbf{y_{r0}}$ are the input and output values for the DMU under evaluation.
- **n** is the number of DMUs.
- **m** is the number of inputs.
- **s** is the number of outputs.

The first two constraints ensure the data is enveloped within the lower and upper bounds, respectively. The third constraint allows for VRS, while the last constraint requires non-negativity for all inputs and outputs.

If the CRS and VRS efficiency scores differ, it indicates the presence of scale inefficiency. Scale efficiency (SE) measures how close a firm is to its optimal scale size (Avkiran, 2006, p. 28). Scale efficiency is, therefore, calculated as:

$$\mathrm{SE} = \frac{\mathrm{OTE}}{\mathrm{PTE}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{ (4)}$$

Where:

- OTE = technical efficiency under CRS (equation 2)
- PTE= pure technical efficiency under VRS (equation 3)

Thus, overall technical efficiency is the product of pure technical efficiency and scale efficiency. A DMU is scale inefficient if $\mathrm{SE}<1$, indicating it operates under either increasing or decreasing returns to scale (Ji & Lee, 2010). If $\mathrm{SE}=1$, the DMU is scale efficient and exhibits CRS, implying all DMUs operate at the same optimal scale size. If SE<1, the DMU exhibits decreasing returns to scale (DRS) or increasing returns to scale (IRS). DRS suggests the DMU is too large and should reduce its size, while IRS indicates the DMU should increase its size to achieve economies of scale (Avkiran, 2006; Ramanathan, 2003).

Under Decreasing Returns to Scale (DRS), a proportionate increase in inputs leads to an increase in outputs less than in proportion. The optimal size of the bank has now been passed. Overhead and coordination costs begin to overshadow scale economies. Supervisory levels rise and decision-making becomes slow. To return to the CRS frontier, the bank must shrink. Options include contracting branch networks, pruning product lines, or divesting noncore units. These operations restore balance so that each additional input can fully contribute to the output (Avkiran, 2006; Ramanathan, 2003).

Conversely, with Increasing Returns to Scale (IRS), the DMU is working below optimal size. Incremental increases in inputs yield more than proportional increases in output. Fixed expenses, for example, IT infrastructure and risk management systems, are not fully utilized. Therefore, the bank can achieve significant efficiency gains by growing thorough which it spreads fixed costs over a bigger base and reap economies of scale.

With this framework, the study assesses the technical efficiency of Ethiopian commercial banks using the classical CCR and BCC models. We also compare the efficiency scores by ownership (public and private) and bank size (large, medium, and small). Moreover, the study tests whether the efficiency score difference are statistically significant using the Non parametric Mann-Whitney U test. Given the non-normality of DEA-derived efficiency scores and the imbalance in group sizes (with only one public bank) compared to multiple private banks), the study employed the non-parametric Mann-Whitney U-test (also known as the Wilcoxon rank-sum test) to compare the distributions of efficiency scores between public and private banks, and large private and small private banks.

Mann Whitney U test is a nonparametric statistical test used to find the differences between two independent groups (Loboschefski, 2010). In contrast to parametric tests like the independent samples t-test, the Mann Whitney U test is not based on the assumptions of homogeneity of variances and normal distribution. The usefulness of this feature is enhanced when working with efficiency scores, particularly those obtained from Data Envelopment Analysis (DEA), that are typically bounded between 0 and 1 and tend to have skewed distributions with possible outliers. In this section of the study, where a comparison of commercial banks' efficiency scores is being made by ownership and bank size, the Mann Whitney U test provides an acceptable alternative by ranking the data instead of assuming a distributional form.

3.5. Estimating Risk and Structural Determinants of Technical Efficiency Using a Dynamic Panel Approach (DGMM)

3.5.1. Justification for Dynamic GMM

In this phase, the study employs the Generalized Method of Moments (GMM) to analyze mainly the effect risk factors and other structural control variables on technical efficiency in the Ethiopian commercial banking sector. With a structured focus on risk-based factors—namely credit and liquidity risk—and complementary structural and performance-related variables such as capitalization, profitability, and bank size, it addresses hypotheses 3 to 7. The GMM approach is particularly suitable for addressing potential endogeneity issues and capturing dynamic relationships in panel data (Arellano & Bond, 1991; Blundell & Bond, 1998).

A key justification for using the Difference GMM (DGMM) approach in the study is that it effectively addresses the dynamic nature of technical efficiency scores, which are expected to exhibit persistence over time. Given that past performance and efficiency levels likely influence current outcomes, it is important to include a lagged dependent variable in the model. However, incorporating such a variable introduces endogeneity concerns—ordinary estimation techniques can yield biased and inconsistent estimates due to the correlation between the lagged dependent variable and the error term. The dynamic DGMM estimator overcomes this problem by using appropriate lagged levels as instruments (Greene, 2019; Roodman, 2009, p. 105), thereby mitigating biases from omitted variable effects and reverse causality (Arellano & Bond, 1991; Blundell & Bond, 1998). This approach is well-supported in the literature, including the rule-of-thumb guidelines provided by Bond (2002), which have been widely adopted in similar empirical studies (Adeleye et al., 2017; Ejemeyovwi & Osabuohien, 2020).

Moreover, our panel dataset is characterized by a relatively large number of cross-sectional units (i.e., 17 Ethiopian commercial banks) with a moderate time dimension of 9 years. This "large N, small T" setting is particularly well-suited for the DGMM methodology, as it provides sufficient cross-sectional variation while keeping the instrument count manageable (Arellano & Bond, 1991). Overall, the use of DGMM enables to capture the persistence in efficiency and provides a robust framework for examining the determinants of technical efficiency in the presence of endogenous regressors.

To validate the suitability of the DGMM estimator for the analysis, diagnostic tests were conducted, including the Arellano–Bond test for second-order serial correlation in the first-differenced errors. According to Bond's (2002), rule-of-thumb, the absence of significant second-order serial correlation confirms that the instruments are valid and that the dynamic specification is appropriate. Although this section briefly highlights the justification and diagnostic results, a comprehensive presentation of these tests, along with further discussions on model validation, is provided in Chapter 4, section 4.2.1. This rigorous methodological framework ensures that our estimation of the determinants of technical efficiency in Ethiopian commercial banks is both robust and reliable.

3.5.2. Definitions of Model Variables used in the Dynamic DGMM

Based on the literature review and nature of the study we selected the dependent and explanatory variables described in Table 3.2.

Table 3.2: Definitions of Model Variables used in the Dynamic GMM

Variable (symbol)	Description	Expected sign
Efficiency Scores	OTEBC and PTEBC estimated by equation 2 and 3	NA
Credit risk (crr) %	Ratio of loan loss provision to total loan and advances.	+
Liquidity risk[8] (lqr) %	Ratio of total loans to total assets	+
Profitability (roaa)	Net income to average assets	+
Capital adequacy (cadq)	(Ratio of total equity to total assets)*100	+
Size (ln(ta))	Logarithm of total assets	-

Note: OTEBC = Bias Corrected Overall technical efficiency, PTEBC = Bias Corrected Pure technical efficiency

[8] The author alternatively computed liquidity risk as a ratio of total loans & advances to total deposits, and also total liquid assets to deposits ratio, the results are quantitatively similar to those reported here.

3.5.3. Model Equation

The dynamic panel model is specified as follows:

$$Y_{it} = \alpha Y_{it-1} + \beta x_{it} + \omega_t + \varepsilon_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where:

- Y_{it} represents the efficiency score of bank *i* at time t estimated using equation (2) and (3) for OTE and PTE, respectively.
- Y_{it-1} = is the lagged efficiency score
- α represents an autoregressive (persistence) parameter.
- x_{it} represents a vector of regressors which include credit risk, liquidity risk, profitability, size and capital adequacy (defined in Table 3.2)
- β represents a vector of parameters to be estimated.
- ω_t represents the year dummies used to control for time-specific effects
- ε_{it} represents the random error term.

3.5.4. Data and Sample

The dataset comprises annual observations from 17 commercial banks operating in Ethiopia, spanning the period from 2014 to 2022. The data is sourced from the annual reports of the respective banks. The selected banks represent a significant portion of the Ethiopian banking industry, providing a comprehensive basis for analysis. Section 3.3., in this chapter, details the target population, sample size, and sample selection criteria for the study.

3.6. Estimating the Effect of Technical Efficiency on Credit and Liquidity Risks

3.6.1. Introduction

The motivation for the study in this section stems from the findings related to the second objective of the study, which identified various risk factors as significant determinants of banking efficiency. Building on these insights, the current section shifts the focus to explore the reverse relationship: how efficiency scores influence risk factors within the Ethiopian commercial banking sector. By examining efficiency as a potential determinant of credit and liquidity risks, this section aims to provide a comprehensive understanding of the interplay between efficiency and risk management in banks.

Efficiency in banking operations is crucial for maintaining stability and profitability, and understanding its impact on risk factors is essential for effective risk management. This study employs a static panel analysis (the fixed effect model (FEM), random effect model (REM), and Pooled Ordinary Least square (POLS)) to investigate how technical efficiency affects credit and liquidity risks.

These models facilitate a detailed assessment of the contemporaneous effect of technical efficiency on credit and liquidity risk measures, offering insights into how operational performance is interlinked with risk dynamics in banks. The results of this analysis aim to inform both banking practitioners and policymakers, contributing to more balanced decisions regarding efficiency enhancements and risk management strategies.

3.6.2. Definitions and Measurements of Model Variables

The primary variables of interest are the overall technical efficiency (OTEBC) and pure technical efficiency (PTEBC) measures, computed using equations 2 and 3, in section 3.4.3, respectively.

Table 3.3: Definitions of Model Variables

Variable (symbol)	Description	Expected Sign
Dependent Variables:		
Credit risk (CRR)	Ratio of loan loss provision to total loans and advances	
Liquidity risk (LQR)	Ratio of total loans and advances to total assets	
Test Variables:		
Overall technical efficiency (OTE)	Estimated using DEA under constant return to scale assumption (Equation 2)	+
Pure technical efficiency (PTE)	Estimated using DEA under variable return to scale assumption (Equation 3)	+
Control Variables:		
Interest Rate Risk (IRR)	Ratio of interest rate sensitive assets to total assets	+/-
Profitability (ROAA)	Ratio of net income to average total assets	+
Capital Adequacy (CADQ)	Ratio of total equity to total assets	+
Market Share (MSLAA)	Percentage share of the bank in the total industry's loans and advances	+
Economic Growth (ECONGR)	Annual percentage growth rate of GDP	+
Inflation (CPI)	Annual percentage change in the consumer price index	+

3.6.3. Model Equation

To ensure the reliability and robustness of the econometric models, this study incorporates several diagnostic tests as an integral part of the methodology. Specifically, the Hausman specification test has been made to determine whether the fixed effects specification is preferable over the random effects model by testing for systematic differences in the estimators (Baltagi, 2021). Complementarily, the Breusch-Pagan Lagrange Multiplier (LM) tests to assess whether Random Effect (re) was preferred to Pooled OLS (Greene, 2019).The rationale behind these tests and their role in validating the econometric strategy are discussed here; however, the detailed test statistics and corresponding results will be presented later in Chapter 4, section 4.3.3.

The study applied fixed-effects regression models to examine the impact of banks' efficiency on their liquidity and credit risks. The choice of fixed-effects estimation for each dependent variable was based on the results of Hausman tests. The study opted for the static panel data model, specifically the fixed-effects model, for several reasons. Firstly, the static model is straightforward and effectively demonstrates the relationships between our test variables (overall technical efficiency and pure technical efficiency) and the control variables (profitability, capital adequacy, market share, economic growth, and inflation).

Below are the model equations for each of the four cases. In these equations, CRR_{it} and LQR_{it} represent the credit risk and liquidity risk for bank i at time t, respectively. The test variables are specified as either $OTEBC_{it}$ (overall technical efficiency) or $PTEBC_{it}$ (pure technical efficiency). Additionally, a series of k control variables X_{jit} (for j=1,2, …, k) are included in each equation representing bank i at time t. Unobserved bank-specific effects are captured by u_i, and $\varepsilon_{it,}$ represents the idiosyncratic error term.

Model 1: Credit Risk with OTEBC as Test Variable

$$CRR_{it} = \alpha_0 + \alpha_1 OTEBC_{it} + \sum_{j=1}^{K} \alpha_{j+1} X_{jit} + u_i + \varepsilon_{it,} \quad \text{i= 1, …, N; t=1, …, T. …. (1)}$$

Model 2: Credit Risk with PTEBC as Test Variable

$$CRR_{it} = \beta_0 + \beta_1 PTEBC_{it} + \sum_{j=1}^{K} \beta_{j+1} X_{jit} + u_i + \varepsilon_{it,} \quad \text{i= 1, …, N; t=1, …, T. …. (2)}$$

Model 3: Liquidity Risk with OTEBC as Test Variable

$$LQR_{it} = \gamma_0 + \gamma_1 OTEBC_{it} + \sum_{j=1}^{K} \gamma_{j+1} X_{jit} + u_i + \varepsilon_{it,} \quad \text{i= 1, …, N; t=1, …, T. …. (3)}$$

Model 4: Liquidity Risk with PTEBC as Test Variable

$$LQR_{it} = \delta_0 + \delta_1 PTEBC_{it} + \sum_{j=1}^{K} \delta_{j+1} X_{jit} + u_i + \varepsilon_{it,} \quad \text{i= 1, …, N; t=1, …, T. …... (4)}$$

Each model is run separately to avoid the multicollinearity issues observed when including both $OTEBC_{it}$ and $PTEBC_{it}$ in the same regression. The coefficients α_1, β_1, γ_1 and δ_1 captures the individual impacts of each efficiency measure on the respective risk outcomes. The control variables (X_{jit}) include: interest rate risk, profitability, capital adequacy, market share, economic growth, and inflation (refer to Table 3.3. for detail definition of each variable).

Each model was tested for multicollinearity and autocorrelation to ensure the robustness of the results. The analysis was conducted using Stata software, version 15.

In summary, this chapter has outlined the theoretical framework, methodology, and model specifications that underpin the analysis of technical efficiency, the effect of risk factors and others, and its effect on credit and liquidity risks. The detailed presentation of the dynamic and static models, along with the justification for choosing the Difference GMM and the diagnostic tests outlined herein, establishes a robust analytical foundation for this study.

With these methodological tools in place, the next chapter shifts focus to the empirical evidence. Chapter 4: Data Presentation and Analysis will present the descriptive statistics of the dataset, report the results from the diagnostic tests, and offer a comprehensive evaluation of the model estimates. This progression from theory to practice not only validates the chosen approach but also sets the stage for a deeper understanding of the interplay between efficiency and risk management in the Ethiopian banking sector.

CHAPTER 4: DATA PRESENTATION AND ANALYSIS

This chapter presents the empirical results of the research, classified into three different but chronologic sections, each with an important input toward an overall analysis of the risk and efficiency behaviors of Ethiopian commercial banks over the 2014–2022 period. Section 4.1 discusses the technical efficiency scores of Ethiopian banks, according to their evaluation by Data Envelopment Analysis (DEA), and presents descriptive statistics, comparison analysis by bank ownership and size, and statistical validation of differences in efficiencies between various institutional types. Section 4.2 examines the risk-based determinants of efficiency by controlling for structural factors effect on efficiency using Difference GMM estimation method. Lastly, Section 4.3 examines efficiency and financial risk nexus, evaluating how technical efficiency changes affect credit risk and liquidity risk in the Ethiopian banking industry using static panel econometric models.

4.1 Efficiency of Ethiopian Commercial Banks

This section presents the empirical assessment of the technical efficiency of Ethiopian commercial banks, estimated using DEA for the years 2014–2022. As financial intermediation plays a core role in commercial banks, the insights into efficiency scores provide valuable information on institution performance, resource allocation, and industry competition.

This section has been organized into four analytically separate subsections to facilitate systematic evaluation of bank efficiency in Ethiopia. The first provides descriptive statistics for the input and output variables used for determining efficiency scores and hence lays the empirical ground for the analysis. The next captures trends of efficiency for Ethiopian banks using tabular and graphical displays to show sectoral developments with time. The third undertakes comparative analysis of efficiency for ownership structure and size of banks with the hope of establishing structural differences between banking institutions. The last undertakes statistical tests for determining if observed differences between bank types on observed scores of efficiency are statistically significant. In order to ensure robustness and reliability of results, further tests are conducted following relevant data transformation with these results given before the conclusion of the section.

4.1.1 Descriptive Analysis of Input and Output Variables

Descriptive statistics of key input and output variables provide an initial overview of the financial size and operating diversity of Ethiopian banks. Table 4.1.1 summarizes these variables, in millions of Ethiopian Birr, for 17 commercial banks for the 2014–2022 period with observations, mean values, standard deviations, and minimum-to-maximum ranges.

The reported variables in the efficiency analyses are Net Interest Income, Non-Interest Income, and Loans & Advances. The Net Interest Income has a mean of 2,587.84 million Birr with a high standard deviation of 5,896.59, indicating high variation among the banks. The range of the variable is between 25.56 million Birr and 43,466.70 million Birr, indicating the variation in the capabilities of institutions to generate interest income. Non-Interest Income has high heterogeneity, with a mean of 1,302.34 million Birr and a standard deviation of 3,410.27 million Birr, which explains the variation in fee-based revenues and other income-generating sources of banks. Likewise, Loans & Advances—a major area of banking activities—has a mean of 27,107.29 million Birr, with a standard deviation of 51,282.93 million Birr, which illustrates diversified lending behavior of banks in Ethiopia.

Input variables influencing efficiency performance are Non-Interest Expenses and Deposits, which are driving factors for cost and liquidity. Non-Interest Expenses, representing operational and administrative expenses, present a mean value of 2,235.73 million Birr, with a standard deviation of 5,860.79 million Birr, suggesting cost structure differences between banks. Deposits, being a fundamental source of liquidity, present an average value of 48,236.38 million Birr; however, they also have a high standard deviation of 122,658.30 million Birr, suggesting high disparities in deposit mobilization by various institutions.

Together, these numbers offer a preliminary insight into financial trends across the industry, enabling further efficiency studies to identify performance drivers and trends within the industry.

Table 4.1.1. Descriptive Statistics of Input and Output Variables (Millions of Birr)

Category	Variable	Obs	Mean	Std. Dev.	Min	Max
Output Variables	Net Interest Income	153	2,587.84	5,896.59	25.56	43,466.70
	Non-Interest Income	153	1,302.34	3,410.27	24.23	35,816.80
	Loans & Advances	153	27,107.29	51,282.93	270.40	332,100.00
Input Variables	Non-Interest Expenses	153	2,235.73	5,860.79	47.31	57,462.80
	Deposits	153	48,236.38	122,658.30	500.23	889,442.00

Notes: All monetary values are in millions of Ethiopian Birr (1 USD =51.9938 ETB, June 30, 2022). Data covers 2014-2022 for 17 Ethiopian commercial banks.

Source: Author's calculations based on Banks' Annual Financial Reports

4.1.2. Relationship Between Input and Output Variables

To evaluate interrelationships among bank inputs and outputs, Table 4.1.2 reports Pearson correlation matrix as a measure of association between main financial measures of efficiency. The high interrelationships between measures of revenue and cost offer empirical proof of the existence of integrated production processes and hence the suitability of Data Envelopment Analysis (DEA) for estimating efficiency.

It is interesting to observe that Net Interest Income is highly correlated with Non-Interest Income ($r = 0.8928$, $p < 0.01$), indicating that banks with more interest income also earn high revenue from other sources of income, including service charges and transaction charges. Besides, Net Interest Income is almost perfectly positively correlated with both

Loans & Advances ($r = 0.9867$, $p < 0.01$) and Deposits ($r = 0.9940$, $p < 0.01$), indicating that volumes lent and core deposits are major determinants of bank profitability.

Accordingly, Non-Interest Expenses also show high correlations with revenue dimensions—showing close association with Net Interest Income ($r = 0.9533$) and Non-Interest Income ($r = 0.9674$)—reflecting the close association between cost structures and revenue generation mechanisms. These observations indicate that banks that have greater operating expenses also have greater income levels, confirming the industry's highly integrated banking model in which revenues and costs are aligned.

The observed relationships underscore the usefulness of multivariate efficiency measurement models because individual financial indicators cannot be examined in a vacuum. The correlation patterns validate the application of DEA, which can effectively capture the multi-input, multi-output nature of bank operations, yielding robust efficiency scores across Ethiopian commercial banks.

4.1.3. Efficiency of Ethiopian Commercial Banks

The performance of commercial banks is central to financial sector competitiveness and stability, and it determines how efficiently institutions are able to translate inputs into outputs. The paper uses Data Envelopment Analysis (DEA) to estimate the technical efficiency of 17 Ethiopian commercial banks from 2014 to 2022, producing three important efficiency measures. First Overall Technical Efficiency (OTEBC) which measures efficiency under the condition of constant returns to scale (CRS). Second, the Pure Technical Efficiency (PTEBC) which separates managerial effectiveness by removing scale effects. Third, the Scale Efficiency (SEBC) to determines if banks are producing at an optimal scale.

Table 4.1.2. Pearson Correlation Matrix of Input and Output Variables

Variable	(1)	(2)	(3)	(4)	(5)
(1) Net Interest Income	1.0000				
(2) Non-Interest Income	0.8928***	1.0000			
(3) Loans & Advances	0.9867***	0.8626***	1.0000		
(4) Non-Interest Expenses	0.9533***	0.9674***	0.9196***	1.0000	
(5) Deposits	0.9940***	0.8930***	0.9744***	0.9474***	1.0000

Notes: *** $p < 0.01$ (two-tailed tests). All coefficients significant at 1% level; Data covers 17 Ethiopian commercial banks from 2014 to 2022; N = 153

Source: Author's calculations based on Banks' Annual Financial Reports

Efficiency measures for various banks over time are presented in Tables 4.1.3, 4.1.4, and 4.1.5, and Figures 4.1.1 to 4.1.9 present yearly trends in efficiency along with categorical groupings. The subsequent sections synthesize the data and analyze visible trends, pointing out variations in efficiency by institutional size and ownership structure.

4.1.3.1. Overall Technical Efficiency (OTEBC)

Table 4.1.3 presents the 2014-2022 OTEBC scores of 17 Ethiopian commercial banks, providing a comprehensive view of the extent to which banks can transform inputs into outputs. The DEA estimate using constant returns to scale (CRS) allows us to make a sufficient analysis of the trend of the industry's efficiency.

The mean efficiency rate in the industry demonstrates an upward trend, increasing from 0.831 in 2014 to 0.939 in 2022, with a total mean of 0.856 spanning nine years. The consistent improvement in efficiency indicates that Ethiopian commercial banks have progressively enhanced their operational processes and resource utilization over time.

Table 4. 1.3: Overall Technical Efficiency of Ethiopian Commercial Banks

Banks*	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	Ave.
AIB	0.857	0.817	0.800	0.849	0.872	0.957	0.943	0.950	0.958	0.889
AbB	0.708	0.784	0.744	0.727	0.767	0.870	0.840	0.954	0.935	0.814
AdIB	1.000	0.963	0.942	0.867	0.831	0.833	0.894	0.916	0.973	0.913
BoA	0.720	0.675	0.702	0.770	0.807	0.833	0.849	0.922	1.000	0.809
BrB	0.727	0.764	0.931	0.897	0.805	0.791	0.912	0.871	0.899	0.844
BuB	0.813	0.832	0.799	0.792	0.832	0.980	0.952	0.975	1.000	0.886
CBE	1.000	0.989	0.739	0.682	0.708	0.661	0.654	0.605	0.643	0.742
CBO	0.882	1.000	1.000	1.000	1.000	1.000	0.875	0.953	1.000	0.963
DB	0.961	0.801	0.759	0.762	0.743	0.822	0.872	0.995	0.992	0.856
DGB	0.762	0.698	1.000	0.808	0.949	1.000	1.000	1.000	0.961	0.909
EB	0.780	0.860	0.853	0.838	0.834	0.878	0.867	0.915	0.978	0.867
HB	0.700	0.688	0.749	0.807	0.760	0.849	0.891	0.899	0.946	0.810
LIB	0.781	0.814	0.784	0.785	0.831	0.842	0.862	0.953	1.000	0.850
NIB	0.908	0.852	0.800	0.813	0.769	0.849	0.913	0.948	0.916	0.863
OIB	0.724	0.712	0.706	0.645	0.784	0.780	0.866	0.863	0.828	0.768
WB	0.796	0.782	0.799	0.823	0.864	0.790	0.845	0.915	0.926	0.838
ZB	1.000	0.880	0.905	0.913	0.802	0.965	0.966	0.945	1.000	0.931
Ave.	0.831	0.818	0.824	0.810	0.818	0.865	0.882	0.917	0.939	0.856
Min.	0.700	0.675	0.702	0.645	0.708	0.661	0.654	0.605	0.643	
Max.	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
SD	0.109	0.100	0.097	0.085	0.066	0.091	0.075	0.089	0.089	

Note: **Ave.**: Mean overall technical efficiency score; **Min.**: Minimum efficiency score; **Max.**: Maximum efficiency score; **SD**: Standard deviation of efficiency scores; *****Banks are listed alphabetically by abbreviated name.
Source: Author's calculations based on annual reports (2014–2022).

A closer examination of the efficiency scores shows considerable heterogeneity among financial institutions. Private banks AdIB, CBO, and ZB have consistently high levels of efficiency, as expressed through scores nearing the optimum value of 1.000. Specifically, AdIB records an appreciable mean overall efficiency of 0.913, whereas CBO records a higher mean efficiency of 0.963, reflecting the operational efficacy in the field of private banking institutions.

In contrast, state-owned Commercial Bank of Ethiopia (CBE) demonstrates a declining trend in efficiency, reflecting potential inefficiencies of large-scale public banking. While CBE initiated with a perfect efficiency score (1.000) in 2014, its efficiency decreased steadily to 0.643 in 2022, while the mean overall efficiency stands at 0.742. This disparity reflects structural and operational differences between private and public banks, and additional investigation is warranted for institutional governance, the efficiency of resource allocation, and regulatory constraints influencing public-sector banking performance. Besides bank-by-bank analysis, sector-wide efficiency dispersion shows a declining standard deviation from 0.109 in 2014 to 0.089 in 2022. The reduction in volatility is a sign of homogenization of the Ethiopian banks to a more comparable level of efficiency, and it reflects increasing sector-wide standardization in operations.

Yet, the trend in efficiency scores still points to significant institutional disparities, as the minimum efficiency scores decreased from 0.700 during the early years to as low as 0.643 in 2022, while the maximum values remained consistently at 1.000.
Figure 4.1.1 illustrates clear proof that the overall technical efficiency of the Ethiopian banking sector has increased over time; however, striking disparities between the various banks still exist.

Figure 4.1.1 illustrates the yearly trajectory of the mean bias-corrected overall technical efficiency (OTEBC) of Ethiopian commercial banks for the nine-year period from 2014 to 2022. Each point on the line marked represents the average OTEBC score estimated for all the banks in the sample for each respective year. According to the figure, the average OTEBC was 0.831 for 2014 and has increased steadily to 0.939 as of 2022. The steady increase indicates that, on average, the Ethiopian commercial banks have, over time, enhanced their capacity to convert inputs to outputs.

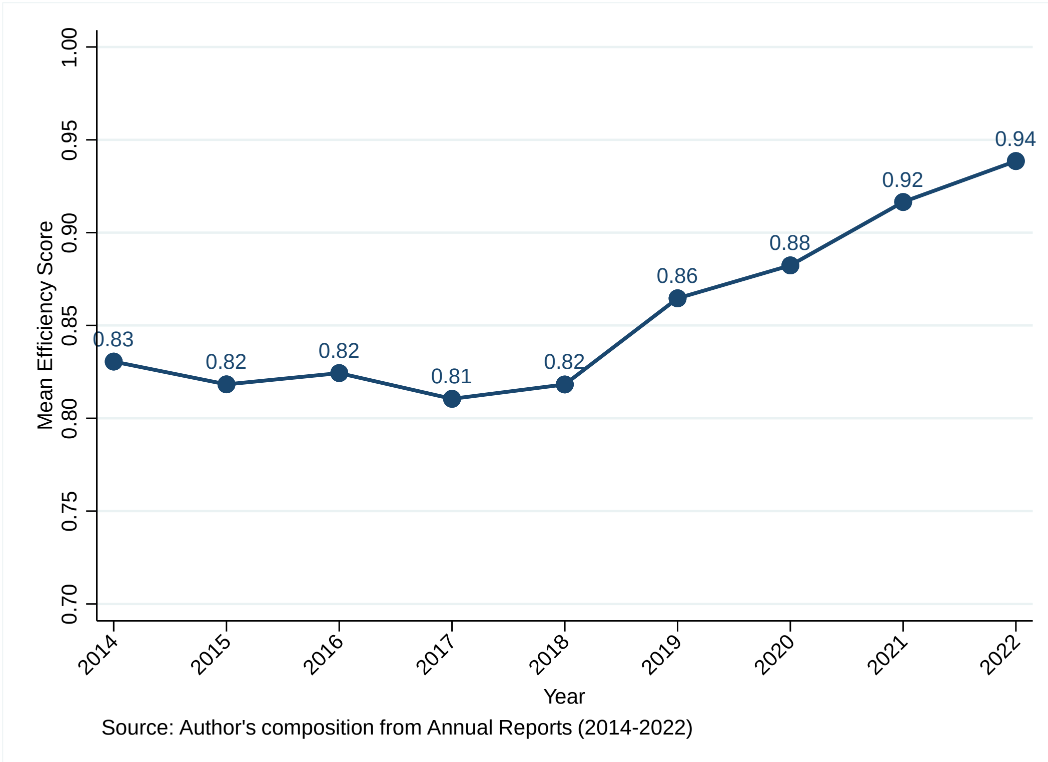


Figure 4.1.1: Mean of Overall Technical Efficiency Scores of Ethiopian Commercial Banks

4.1.3.2. Pure Technical Efficiency (PTE)

Table 4.1.4 presents the Pure Technical Efficiency (PTEBC) of Ethiopian commercial banks for the period 2014–2022, separating managerial performance through the elimination of scale effects. While OTEBC indicates overall operational efficiency, PTEBC measures the success of management decisions and internal bank operations.

Pure technical efficiency across the industry remains high, with a mean value of 0.902, indicating that the Ethiopian banks—apart from scale-related constraints—are primarily managerially efficient.

A closer examination reveals high PTEBC stability in most banks. Outstanding managerial performance is recorded by the state-owned CBE, which has a perfect PTEBC score of 1.000 for all years within the study period. While the public sector bank recorded aggregate

Table 4. 1.4: Pure Technical Efficiency of Ethiopian Commercial Banks

Bank*	2014	2015	2016	2017	2018	2019	2020	2021	2022	Ave.
AIB	0.989	0.995	0.998	0.994	0.951	0.957	0.943	0.978	0.958	0.974
AbB	0.947	0.988	0.963	0.978	0.999	0.993	0.996	1.000	0.997	0.985
AdIB	1.000	0.982	0.955	0.875	0.837	0.836	0.897	0.918	1.000	0.922
BOA	0.732	0.683	0.704	0.773	0.811	0.834	0.850	0.943	1.000	0.814
BrB	0.806	0.801	0.935	0.898	0.807	0.808	0.969	0.913	0.942	0.875
BuB	0.852	0.865	0.823	0.813	0.835	0.981	0.952	0.977	1.000	0.900
CBE	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
CBO	0.931	1.000	1.000	1.000	0.954	1.000	0.994	0.971	1.000	0.983
DB	1.000	0.850	0.810	0.784	0.751	0.822	0.874	1.000	1.000	0.877
DGB	1.000	0.806	1.000	0.813	0.965	1.000	1.000	1.000	0.962	0.950
EB	0.836	1.000	0.944	0.880	0.869	0.910	0.888	0.937	0.990	0.917
HB	0.702	0.694	0.754	0.816	0.761	0.850	0.891	0.901	0.976	0.816
LIB	0.794	0.816	0.785	0.790	0.833	0.851	0.863	0.953	1.000	0.854
NIB	0.923	0.862	0.802	0.816	0.771	0.861	0.936	1.000	0.944	0.879
OIB	0.731	0.727	0.713	0.646	0.824	0.812	0.885	0.871	0.848	0.784
WB	0.798	0.783	0.802	0.916	0.924	0.804	0.889	0.954	0.943	0.868
ZB	1.000	0.910	0.923	0.976	0.803	0.966	0.969	0.945	1.000	0.944
Ave.	0.885	0.868	0.877	0.869	0.864	0.899	0.929	0.957	0.974	0.8902
Min.	0.702	0.683	0.704	0.646	0.751	0.804	0.850	0.871	0.848	
Max.	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
SD	0.109	0.112	0.107	0.100	0.084	0.079	0.052	0.040	0.040	

Note: **Ave.**: Mean pure technical efficiency score; **Min.**: Minimum efficiency score; **Max.**: Maximum efficiency score; **SD**: Standard deviation of efficiency scores; ***Banks are listed alphabetically by abbreviated name.
Source: Author's calculations based on annual reports (2014–2022).

technical efficiency deterioration (as revealed by OTEBC findings), its pure technical efficiency remains at its optimum, suggesting that scale inefficiencies, not managerial inefficiencies, are to blame for its deteriorating operating performance.

Nevertheless, there are marginal differences in the managerial effectiveness of some private banking institutions. Whereas institutions such as ZB and CBO record nearly flawless PTEBC ratings throughout, others, such as HB and OIB, exhibit inconsistency over the years. For instance, HB recorded an efficiency rate of 0.702 in the year 2014, indicating poor managerial performance during its initial years, with a consistent improvement in efficiency in later years.

The difference in managerial efficiency has reduced over the years, as seen in a gradual drop in the standard deviation—from 0.109 in 2014 to only 0.040 for 2021 and 2022. The consistent decline shows a trend towards uniformity of best managerial practices, thereby enhancing standardization of operations across the industry. Ethiopian banks have progressively implemented optimum management structures, enhancing banking operations and internal decisions.

Figure 4.1.2 shows the annual PTEBC pathway with consistent improvement in efficiency. The initial mean efficiency of 0.87 in 2014 showed relative stability between 2015 and 2018 with minor fluctuations around 0.85. Starting from 2019, the efficiency trends indicate progressive rises to 0.89 in 2019, 0.92 in 2020, 0.95 in 2021, and 0.97 in 2022.

This consistent rising pattern reflects managerial betterment in Ethiopian bank operations, with increasing application of data-based decision frameworks, automation of internal processes, and improved governance structures. Since pure technical efficiency disentangles scale effects, such gains reflect gains in the execution of internal operations and not in external structural aspects.

Annual financial reports between 2014–2022 validate efficiency maximization, further supporting the fact that Ethiopian banks have consistently improved management practices over time. Figure 4.1.2 supports this trend of improvement, emphasizing the increased managerial effectiveness fueling sectoral efficiency enhancements.

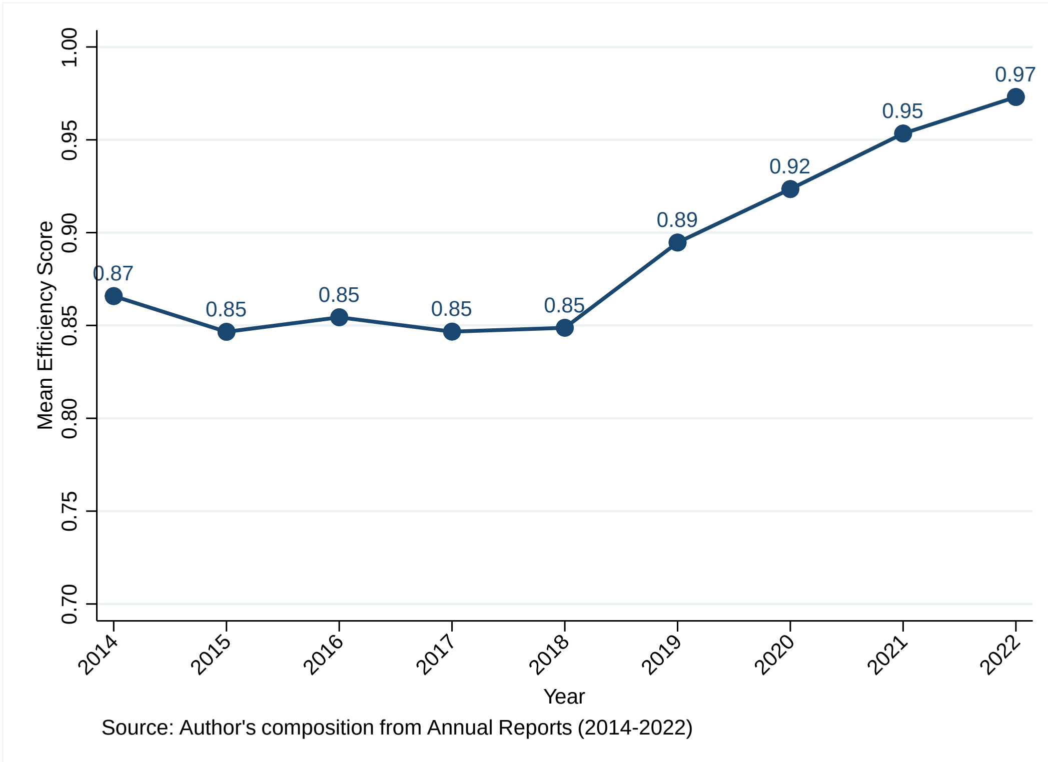


Figure 4.1.2: Mean of Pure Technical Efficiency Scores of Ethiopian Commercial Banks

In summary, the empirical results confirm efficiency improvements in Ethiopian commercial banks, yet the evidence also reveals institutional variation in performance trends. OTEBC trends confirm increasing overall efficiency, yet disparities between private and public banks suggest the potential for scale inefficiencies in large public institutions. Conversely, PTEBC results confirm high managerial efficiency, confirming that efficiency shortfalls are primarily a function of operating scale constraints rather than governance deficits.

These findings inform discussions on financial sector reform, institutional reconfiguration, and regulatory developments, with implications for environmentally sustainable banking efficiency enhancement in Ethiopia.

4.1.3.3 Scale Efficiency (SE)

Scale efficiency (SE) is described in terms of the ratio of overall technical efficiency (OTEBC) to pure technical efficiency (PTEBC) as a measure of the degree to which banks achieve their optimal scale to increase production output. Large values of scale efficiency show that banks are producing at an optimum level for their size and hence are reducing inefficiencies related to over-expansion as well as wasteful utilization of resources.

Table 4.1.5 presents 17 Ethiopian commercial banks' estimates of scale efficiency for the period 2014–2022 along with their yearly averages, minimum, maximum, and standard deviations. The findings indicate that the average scale efficiency of the banking industry is approximately 0.964. This implies that, on average, the majority of the banks are close to their optimal scale size. A very large number of Ethiopian banks show high scale efficiency scores with figures close to or equal to 1.000 across a series of years. This indicates that they are successful in leveraging size of the institution for improving operating performance. Banks like AdIB and BoA repeatedly record scale efficiency near unity, and therefore highlight their capability to produce at an optimal size with few inefficiencies from non-optimal production levels.

Yet, some banks record considerable reductions in scale efficiency over time, the most notable being the state-owned Commercial Bank of Ethiopia (CBE). In 2014, CBE recorded a perfect scale efficiency value of 1.000; yet, by 2022, it had decreased considerably to 0.643, considering an overall average scale efficiency of only 0.742.

The observed declining trend indicates that CBE is faced with inefficiency of large-scale operations, where size-related complexities and administrative inflexibility could militate against optimal performance. The results agree with the hypothesis that as companies grow in size, they may face coordination issues, bureaucratic constraints, and scale diseconomies that adversely affect efficiency of operations.

Table 4. 1.5: Scale Efficiency of Ethiopian Commercial Banks

Bank*	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**Ave.**
AIB	0.866	0.821	0.802	0.854	0.917	1.000	1.000	0.971	1.000	0.915
AbB	0.747	0.793	0.773	0.743	0.767	0.875	0.844	0.954	0.938	0.826
AdIB	1.000	0.981	0.986	0.991	0.993	0.995	0.997	0.998	0.973	0.990
BOA	0.984	0.988	0.997	0.997	0.995	0.999	0.999	0.977	1.000	0.993
BrB	0.901	0.954	0.995	0.999	0.997	0.979	0.941	0.955	0.954	0.964
BuB	0.954	0.962	0.971	0.974	0.996	0.999	1.000	0.998	1.000	0.984
CBE	1.000	0.989	0.739	0.682	0.708	0.661	0.654	0.605	0.643	0.742
CBO	0.948	1.000	1.000	1.000	1.000	1.000	0.881	0.981	1.000	0.979
DB	0.961	0.943	0.937	0.972	0.990	1.000	0.999	0.995	0.992	0.976
DGB	0.762	0.866	1.000	0.993	0.983	1.000	1.000	1.000	0.999	0.956
EB	0.933	0.860	0.904	0.952	0.960	0.965	0.977	0.977	0.988	0.946
HB	0.997	0.991	0.994	0.989	0.999	0.999	1.000	0.997	0.969	0.993
LIB	0.983	0.997	0.998	0.994	0.998	0.989	0.999	1.000	1.000	0.995
NIB	0.983	0.989	0.998	0.997	0.998	0.986	0.975	0.948	0.970	0.983
OIB	0.991	0.979	0.990	0.999	0.951	0.960	0.978	0.992	0.977	0.980
WB	0.997	1.000	0.996	0.898	0.935	0.983	0.950	0.959	0.982	0.967
ZB	1.000	0.967	0.980	0.936	0.998	0.999	0.997	1.000	1.000	0.986
Ave.	0.942	0.946	0.945	0.939	0.952	0.964	0.952	0.959	0.964	0.964
Min.	0.747	0.793	0.739	0.682	0.708	0.661	0.654	0.605	0.643	
Max.	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	
SD	0.080	0.067	0.087	0.095	0.085	0.084	0.089	0.093	0.085	

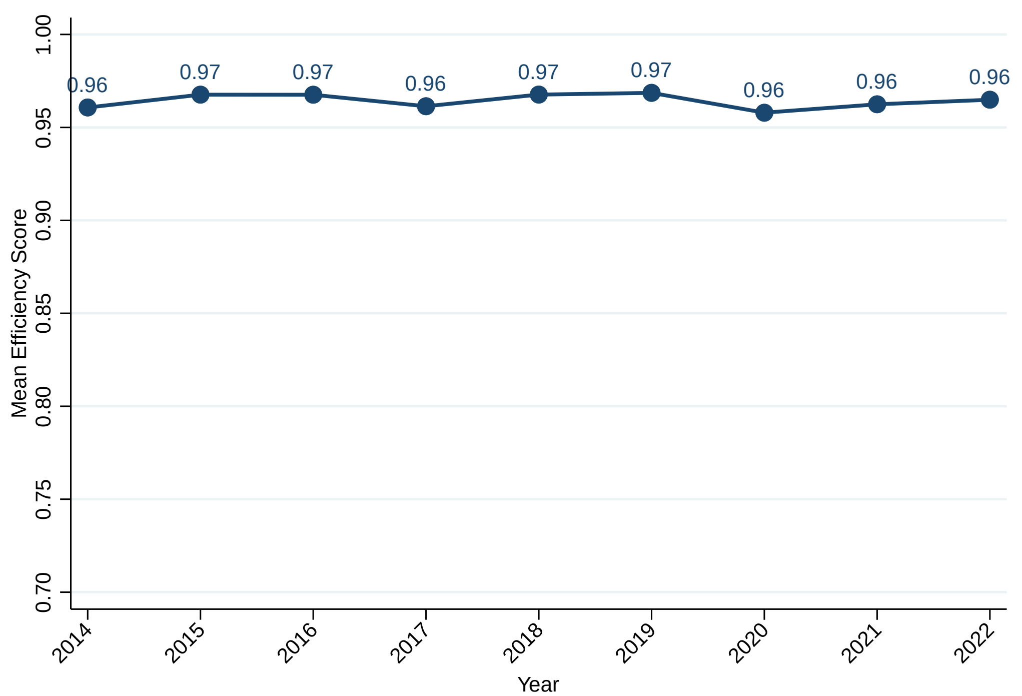
Note: **Ave.**: Mean scale efficiency score; **Min.**: Minimum efficiency score; **Max.**: Maximum efficiency score; **SD**: Standard deviation of efficiency scores; *Banks are listed alphabetically by abbreviated name.

Source: Author’s calculations based on annual reports (2014–2022).

Despite the presence of individual bank heterogeneity, the overall mean scale efficiency is consistently high, which aligns with the perception that banks in Ethiopia are mostly producing at a level near their optimum scale. Scale efficiency measures have a standard deviation of between 0.080 and 0.093 throughout the research period, indicating the presence of moderate scale efficiency variation between banking institutions.

However, the fact that the majority of financial institutions have scale efficiency scores close to 1.000 shows that scale-related inefficiencies are largely individual-institution specific and not industry-wide. This finding highlights the need for targeted managerial and structural reforms, particularly for larger banking institutions like CBE, to reduce scale-related obstacles and improve management at higher institutional levels.

Figure 4.1.3 is a line graph plotting Ethiopian commercial banks' average scale efficiency scores, differentiating yearly trends from 2014 to 2022. The vertical axis is utilized to present the average scale efficiency (ranging from 0.70 to 1.00), whereas the horizontal axis is employed to present the study years (2014–2022).



Source: Author's composition from Annual Reports (2014-2022)

Figure 4.1.3: Mean of Scale Efficiency Scores of Ethiopian Commercial Banks

The evidence in the figure reveals that scale efficiency scores have remained high and constant during the study period, in favor of sustaining the performance of the industry at almost optimum levels. The average scale efficiency ratio for 2014 was 0.96, which was followed by a marginal increase to 0.97 in 2015 and stability at 0.97 in 2016. The industry shrank modestly to 0.96 in 2017 prior to a comeback to 0.97 in 2018, which indicates nearly optimal scale efficiency levels. From the years 2019 to 2022, scale efficiency consistently remained within a narrow spectrum (0.96–0.97), demonstrating negligible variations.

The relatively stable trend of efficiencies among Ethiopian banks implies that, for the majority of these banks, strategies of scale utilization have continued to work during the period of the study. The fact that average performance measures have on average remained high implies that banks have managed their scale well, thereby conducting operations with optimum efficiency in terms of scale.

The sustained trend of scale efficiency—highlighted in Figure 4.1.3—provides valuable information on how banks utilize their institutional scale to optimize operating performance. Private banking institutions exhibit exemplary scale efficiency, thereby enhancing their capacity to effectively handle operational growth.

Large state-owned bank (CBE) experience efficiency loss with growth, with concern being expressed over bureaucratic rigidities and complexity of operations affecting performance.

Scale efficiency throughout the industry is always higher, suggesting that, on average, Ethiopian commercial banks operate close to the optimal level of efficiency, thus minimizing misallocation of resources.

In sum, the empirical evidence shows that Ethiopian commercial banks have, for the most part, maintained optimal scale efficiency over the study period, indicating their ability to well utilize institutional size in the practice of banking. However, some banks—particularly large public institutions—register a decline in scale efficiency, lending credence to the theory that expansion beyond a certain threshold can result in operational inefficiencies. These findings set the stage for the further comparative analysis between bank types by category, including ownership-based efficiency trends and institutional size differences, which are addressed in the sections that follow.

4.1.4. Efficiency scores comparison by Ownership and Size

4.1.4.1. Overall Technical Efficiency (OTEBC) by Ownership

Figure 4.14 displays trends in bias-corrected overall technical efficiency (OTEBC) of Ethiopian commercial banks from 2014 to 2022, by two categories of ownership: public banks, represented by the Commercial Bank of Ethiopia (CBE), and private banks.

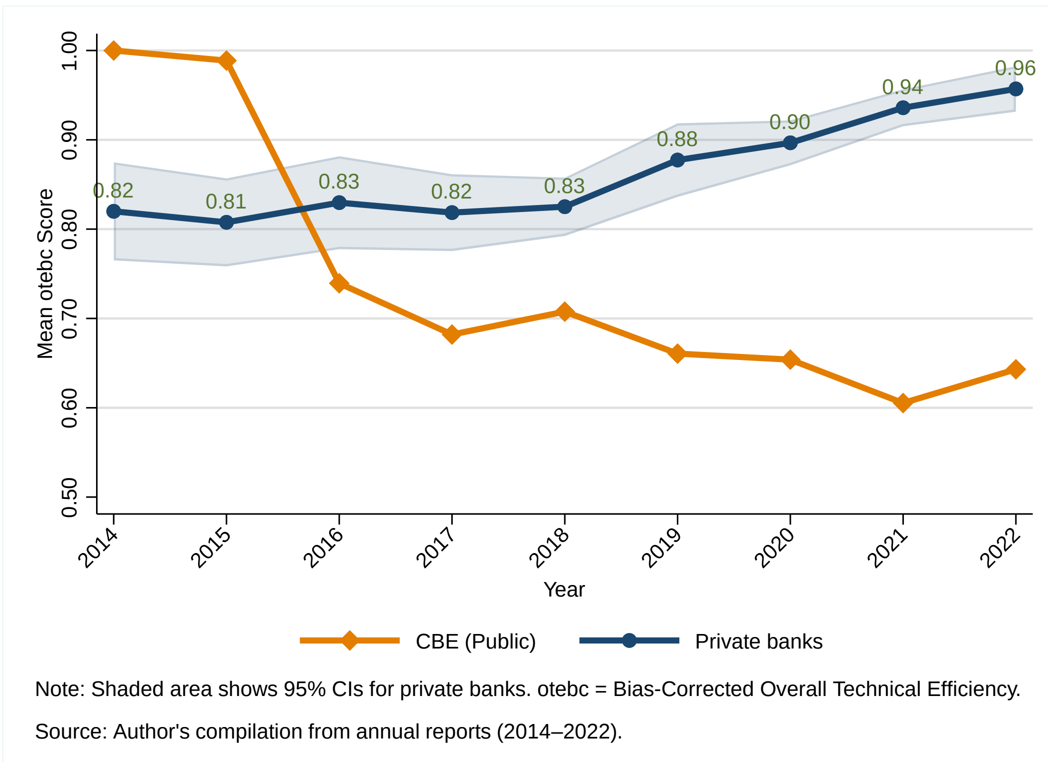


Figure 4.1.4: Overall Technical Efficiency Trends of Ethiopian Commercial Banks: Ownership

The graph reveals a stark difference in the performance of the two groups across the years. While in 2014 CBE had a perfect efficiency score of 1.00, private banks recorded a comparatively lower score of approximately 0.82. As the years passed, however, these initial scores changed in diverging directions. The CBE efficiency score had a continuous fall, falling consistently from the highest level of 2014 down to approximately 0.64 in the year 2022. Private banks, however, recorded an upward trend as their mean OTEBC rose consistently from approximately 0.81 in the year 2015 up to approximately 0.96 in the year 2022.

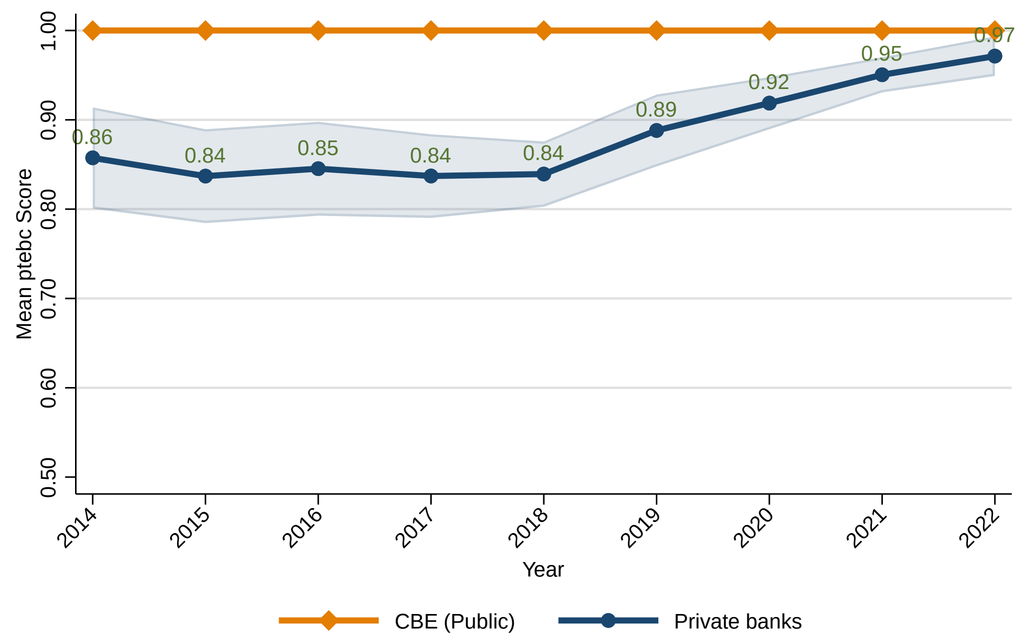
This comparison reveals two significant observations. First, although the general trend within the industry (as illustrated in Figure 4.1.1) is a shift forward to higher technical efficiency, this aggregate measure conceals considerable disparity when ownership is taken into account.

Second, the diverging trends indicate that the public bank, the CBE, has experienced declining efficiency over time, while the private banks have consistently enhanced their performance, reflecting possible differences in the managerial styles, operating policies, or regulatory frameworks of the two groups. The fact that the efficiency estimates for the private banks are highly precise—as indicated by the narrow 95% confidence intervals—also lends support to the reliability of this detected upward trend.

Cumulatively, these results emphasize that ownership structure is one of the main drivers of general technical efficiency in the banking sector in Ethiopia. The difference established between private and public banks gives a clear basis upon which to further investigate the factors behind these discrepancies, as will be tested statistically and elaborated in the next sections.

4.1.4.2. Pure Technical Efficiency (PTEBC) Analysis by Ownership

Figure 4.1.5 presents a graphical depiction that delineates the average pure technical efficiency (PTEBC) scores of commercial banks in Ethiopia, differentiating between public and private ownership, for the timeframe spanning from 2014 to 2022.



Note: Shaded area shows 95% CIs for private banks. ptebc = Bias-Corrected Pure Technical Efficiency.

Source: Author's compilation from annual reports (2014–2022).

Figure 4.1.5: Pure Technical Efficiency Trends of Ethiopian Commercial Banks: Ownership

Pure technical efficiency serves to evaluate managerial performance by excluding the influence of scale effects, thereby indicating the efficacy with which a bank manages its internal processes. Table 4.1.4 reveals that the public bank, which is typically represented by the Commercial Bank of Ethiopia (CBE), records a perfect PTEBC score of 1.000 throughout the entire period under investigation. Private banks, however, while showing relatively high pure technical efficiency, portray some extent of variation. That is, private banks' annual scores show moderate variability, usually within a high range, mostly fluctuating between around 0.84 and 0.97.

These differences are readily apparent in Figure 4.1.5, where the curve for the public bank is flat at the upper bound, and the curve for private banks has minimal deviation over time.

Figure 4.1.5 is employed to strengthen the general pattern in Figure 4.1.2, which illustrates the average pure technical efficiency scores for the entire sample, by demonstrating that the relatively higher performance of the public bank is not fully reflected in the private banking sector. The discrepancy that these plots point out suggests that although managerial efficiency is strong throughout the industry, there are considerable differences associated with the ownership aspect.

In particular, the public bank maintains a high internal efficiency rate consistently, while private banks, although efficient, exhibit somewhat lower average performance measures that have some fluctuation on a year-to-year basis. This segmented view of PTEBC by ownership provides a basis for further investigation, which will explore the underlying factors that could explain the observed differences.

4.1.4.3. Scale Efficiency (SEBC) Analysis by Ownership

Figure 4.1.6 presents a line graph depicting annual trends in the mean scale efficiency (SEBC) of Ethiopian commercial banks, by ownership, over the period 2014-2022. Scale efficiency is defined as the ratio of total technical efficiency to pure technical efficiency and reflects how efficiently a bank uses its size to generate outputs.

The data underlying Table 4.1.5 demonstrate that the industry's overall mean SEBC is quite high—at approximately 0.952—implying that banks on average are very near their optimal size.

The graph in Figure 4.1.6 indicates that although the public bank recorded a perfect scale efficiency value of 1.000 in the year 2014, its performance in subsequent years declined significantly, at times extending to much lower levels. In contrast, the private banks consistently record high and stable scale efficiency measures, having remained near 1.000 for the whole period under investigation. The display in Figure 4.1.6 clearly shows the time profile of the scale efficiency development when disaggregated by ownership type, pointing out that, despite the overall strength of the aggregate scale efficiency measure for the industry, there are severe imbalances between private and public institutions.

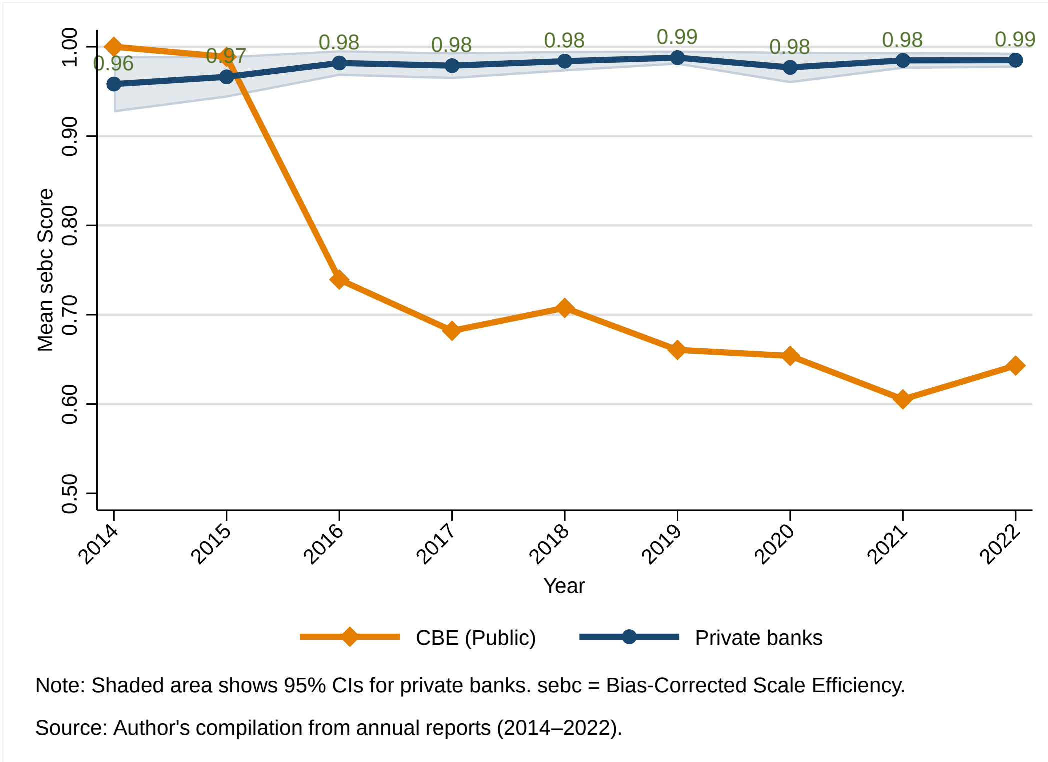
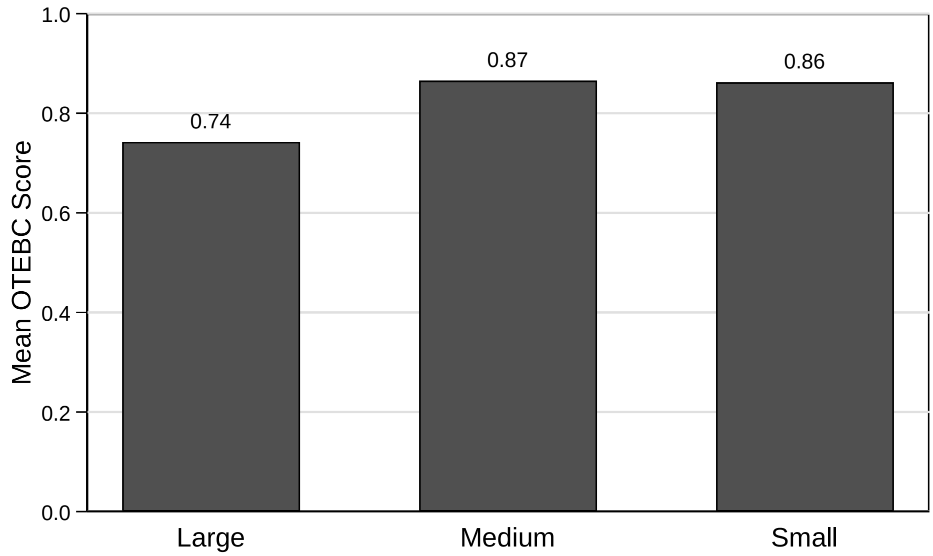


Figure 4.1.6: Scale Efficiency Trends of Ethiopian Commercial Banks: by Ownership

4.1.4.4. Bank Efficiencies and Size

Figure 4.1.7 shows the bias-corrected average overall technical efficiency (OTEBC) scores of Ethiopian commercial banks, grouped into three by asset size. The research distinguishes among three bank types: Large Banks, symbolized by the CBE, the market leader in the sector; Medium Banks, denoting five private banks with assets over 2% of the sector total; and Small Banks, signifying eleven private banks with assets constituting less than 2% of the sector total. The evidence illustrates that the large bank (CBE) shows a considerably lower mean efficiency score of about 0.74. Conversely, medium banks record a superior mean score of approximately 0.87, whereas small banks have an average efficiency of approximately 0.86.

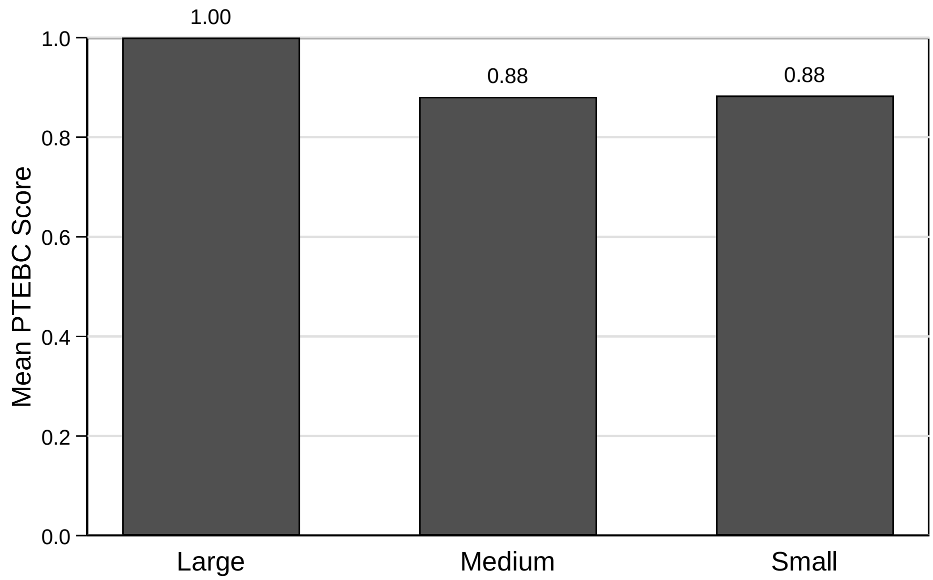


Notes: OTEBC = Bias-Corrected Overall Technical Efficiency (0 = lowest, 1 = highest).
Classification: Large (CBE as sole outlier); Medium (>2% total banking sector assets); Small (<2%).
Data source: Author's compilation from annual reports (2014–2022).

Figure 4.1.7: Mean Overall Technical Efficiency of Ethiopian Commercial Banks: by Size

The results indicate that the large predominant institution is expected to experience operational and managerial difficulties that limit its capacity for optimum efficiency, even with its large size. Medium-sized banks, however, seem to achieve greater balance between size of operations and efficiency, recording the highest average OTEBC among the various categories. Although the small banks are small in size, they have high operational efficiency, likely due to gains from greater flexibility and reduced bureaucratic impediments. This relative assessment suggests that economies of scale need not necessarily result in improved technical efficiency for all size groups uniformly. Instead, it highlights the complex relationship between the size of banking institutions and their efficiency of operation, providing a platform for further investigation into the underlying factors contributing to such differences in efficiency across different institutional sizes.

Similarly, Figure 4.1.8 graphs the mean PTEBC scores of Ethiopian commercial banks, divided into three size categories: Large, Medium, and Small based on their total asset size.

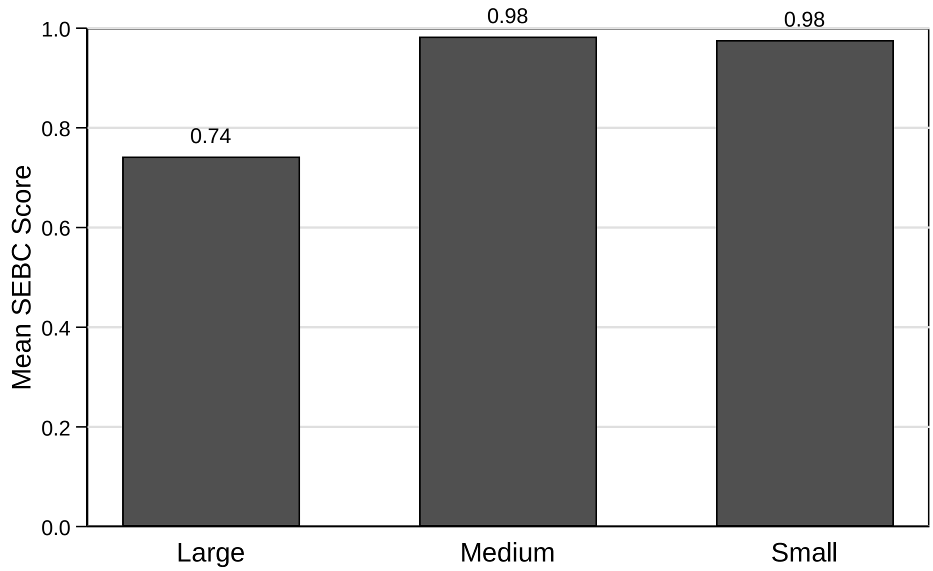


Notes: PTEBC = Bias-Corrected Pure Technical Efficiency (0 = lowest, 1 = highest).
Classification: Large (CBE as sole outlier); Medium (>2% total banking sector assets); Small (<2%).
Data source: Author's compilation from annual reports (2014–2022).

Figure 4.1.8: Mean Pure Technical Efficiency of Ethiopian Commercial Banks: by Size

The bar chart clearly shows that the large bank attains a maximum PTEBC score of 1.00, implying that its internal management is perfectly efficient. However, medium banks and small banks have an average PTEBC score of around 0.88. As technical efficiency in its purest sense decouples the impact of size from managerial performance, the findings indicate that although the leading large institution has higher internal efficiency, medium and small-sized private banks display similar managerial performance levels. The similarity across private banking institutions—in spite of the variation in asset size—suggests that factors such as managerial practices and organizational processes continue to be effective across institutions. Lastly, the results articulated in Figure 4.1.8 offer a foundation for extending research on the impact of internal mechanisms and operating structures on efficiency results for different sizes of banks.

Figure 4.1.9 presents Ethiopian commercial banks' mean bias-corrected scale efficiency (SEBC) scores, groupwise by size for the years 2014–2022.



Notes: SEBC = Bias-Corrected Scale Efficiency (0 = lowest, 1 = highest).
Classification: Large (CBE as sole outlier); Medium (>2% total banking sector assets); Small (<2%).
Data source: Author's compilation from annual reports (2014–2022).

Figure 4.1.9: Mean Scale Efficiency of Ethiopian Commercial Banks: by Size

As seen from the Figure 4.1.9, the large bank, CBE, has a low average SEBC score of about 0.74, which implies that, as much as it has a large asset base, it is less efficient to achieve optimal scale efficiency. However, the medium and small banks have high average SEBC scores, each of about 0.98, which implies that these banks are close to optimal scale. This stark differential suggests that whereas smaller private banks—whether classified as medium or small—have been able to effectively use their size for competitive advantage, the far larger institution seems to have operational or managerial issues that prevent it from being able to completely translate its size into optimum performance. The results indicate that economies of scale do not necessarily bring about improved efficiency, but instead, that the connection between bank size and operating performance is complex and probably affected by variables like organizational structure, managerial practices, and flexibility.

4.1.5 Comparative Analysis by Ownership and Bank Size

Integrating the information from the tables and figures, several points emerge. First, the overall temporal trends in OTEBC (Table 4.1.3 and Figure 4.1.4) point to a general improvement in efficiency among Ethiopian banks. However, the public bank (CBE) initially demonstrates near-perfect efficiency only to experience a subsequent decline, as further highlighted in Figure 4.1.7.

Second, when considering managerial performance, the high PTEBC scores (Table 4.1.4, Figure 4.1.5, and Figure 4.1.8) confirm that private banks have maintained strong operational control throughout the period. The public bank's consistent maximum PTEBC, while seemingly positive, indicates that the decline in its overall performance is not due to management shortcomings but rather is a matter of scale.

Third, the evaluation of scale efficiency in Table 4.1.5, Figure 4.1.6, and Figure 4.1.9 provides further differentiation. Private banks, regardless of whether they are medium or small, show near-optimal scale efficiency. The public bank's lower SEBC points to structural or operational complexities related to its large size.

These findings suggest that while managerial practices are robust across the sector, the challenges of scale—particularly for the public bank—are the primary drivers of observed inefficiencies. These differences will be examined further in the following sections, where we apply statistical tests to assess the significance of the differences by ownership and bank size.

4.1.5.1. Hypothesis Testing for Efficiency Differences by Ownership

Hypothesis H1 posits that there is a statistically significant difference in technical efficiency scores between public and private banks in Ethiopia.

Given the non-normality of DEA-derived efficiency scores and the imbalance in group sizes (with only one public bank compared to multiple private banks), we employed the non-parametric Mann-Whitney U-test (also known as the Wilcoxon rank-sum test) to compare the distributions of efficiency scores between public and private banks.

Mann-Whitney U-Test Results

Table 4.1.6 summarizes the test outputs for each efficiency measure. The test results are provided along with the number of observations, rank sums, test statistics (z-values), and two-tailed p-values.

Table 4.1.6: Mann-Whitney U-Test Results for Efficiency Measures by Ownership

Efficiency Measure	Group	Obs.	Observed Rank Sum	Expected Rank Sum	z-value	p-value
OTEBC	Private	144	11,448.5	11,088	2.797	0.0052
	Public	9	332.5	693		
PTEBC	Private	144	10,552.5	11,088	-4.175	<0.0001
	Public	9	1,228.5	693		
SEBC	Private	144	11,533.5	11,088	3.456	0.0005
	Public	9	247.5	693		

Note: "Obs." represents the number of observations in each group.

Source: Author's calculations based on annual reports (2014–2022).

The Mann Whitney U test was used to examine H1. For the OTEBC, the test yielded a z-value of 2.797 and a p-value of 0.0052. In this test, private banks have an observed rank sum that is higher than expected, while the public bank has a rank sum lower than expected. The statistically significant result ($p < 0.01$) indicates that the median OTEBC is significantly different between public and private banks, with public banks exhibiting significantly lower OTEBC scores. This suggests that the public bank (CBE) suffers from inefficiencies that diminish overall performance, despite other factors. This supports the higher mean efficiency by private banks than public banks graphed in Figure 4.1.4 and Figure 4.1.7.

For pure technical efficiency, the test produces a z-value of –4.175 with a p-value that is effectively zero (<0.0001). The negative z-value implies that the median PTEBC score for the public bank is significantly higher than that for private banks (also revealed in Figure

4.1.5 and Figure 4.1.8). In other words, when pure managerial performance is isolated from scale effects, the public bank's performance is outstanding—achieving a perfect or near-perfect PTEBC consistently—relative to the private banks. This confirms that internal management within the public bank is not the source of its overall lower efficiency.

The scale efficiency comparison results in a z-value of 3.456 and a p-value of 0.0005. Here, private banks have an observed rank sum significantly higher than expected, while the public bank's rank sum is substantially lower (see Figure 4.1.6 and Figure 4.1.9 for pictorial comparison). This statistically significant difference indicates that the ability to operate at an optimal scale is notably inferior in the public bank compared to private banks. Hence, the public bank's overall efficiency decrement is driven primarily by scale inefficiencies.

These hypothesis tests clearly link the descriptive statistics with our inferential analysis. The results support H1 by indicating significant differences in efficiency scores between public and private banks. In particular, the overall and scale efficiency measures are lower for the public bank, while pure technical efficiency remains strong.

4.1.5.2. Testing Hypothesis H2: Efficiency Differences by Bank Size

In this section, the study focuses on comparison of private banks[9], by further classifying them on their size based on their asset holdings. In the classification, banks with an asset share that exceeds the defined threshold of 2 percent are defined as large private banks, while those with smaller asset shares (less than 2 percent of the total assets of the sectors) are considered as small private banks.

Hypothesis H2 posits that, among private banks, large banks exhibit significantly higher technical efficiency scores than small banks. To examine this claim, the study employed

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[9] The author purposively excludes the CBE, the only public commercial bank, due to its incomparable size in the banking industry.

the Mann Whitney U test to compare three efficiency measures: overall technical efficiency (OTEBC), pure technical efficiency (PTEBC), and scale efficiency (SEBC).

Table 4.1.7 summarizes the test results, including the observed and expected rank sums, z values, and corresponding p values for each efficiency measure.

Table 4.1.7: Mann-Whitney U-Test Results for Efficiency Measures by Bank Size

Efficiency Measure	Group	Obs.	Observed Rank Sum	Expected Rank Sum	z-value	p-value
OTEBC	Large	45	3,333	3,262.5	0.304	0.7611
	Small	99	7,107	7,177.5		
PTEBC	Large	45	3,315	3,262.5	0.227	0.8205
	Small	99	7,125	7,177.5		
SEBC	Large	45	3,548	3,262.5	1.231	0.2182
	Small	99	6,892	7,177.5		

Note: “Obs.” denotes the number of banks in each group.

Source: Author’s calculations based on annual reports (2014–2022).

The results of the Mann-Whitney U-tests indicate that the OTEBC revealed the test statistic reports a z-value of 0.304 (p = 0.7611). This high p-value suggests that there is no statistically significant difference in the overall technical efficiency between large private banks and small private banks.

Similarly, the PTEBC reports the z-value of 0.227 with a p-value of 0.8205. These results also indicate that the medians of the PTEBC scores are similar between the two groups, meaning that the quality of managerial performance (isolated from scale effects) does not differ significantly between large and small private banks.

Lastly, the scale efficiency test produces a z-value of 1.231 and a p-value of 0.2182. Although the z-value here is somewhat higher compared to the other efficiency measures, the p-value remains above the conventional alpha threshold of 0.05. Therefore, there is no statistically significant difference in the median scale efficiency between large and small private banks either.

Taken together, these results suggest that there is no statistically significant difference in any of the efficiency measures between large and small private banks. Consequently, the data do not support Hypothesis H2. The null hypothesis that the medians of the efficiency scores are equal across large and small private banks in Ethiopia cannot be rejected.

4.1.6. Effects of Data Transformation on Efficiency Scores

The following tables present a summary of summary statistics with regard to three different measures of efficiency computed from the banking dataset. For each measure, we present the Winsorized raw scores—Winsorized at the 1% and 99% percentiles—the log-transformed scores, and the assets-scaled (ratio-normalized) scores.

These statistics are segregated for private banks, the only large public bank, and the entire sample. This broad comparison enables an examination of the impact of alternative transformation techniques on the variance and central tendency of the efficiency scores. Specifically, whereas the asset-scaled scores are very similar to the Winsorized raw data, the logarithmic transformation drastically reduces the variance. These insights are fundamental in determining relative performance differences in the Ethiopian banking sector and form the basis for the adoption of the untransformed Winsorized data in subsequent analysis.

Table 4.1.8 shows quite clearly that raw and assets-scaled efficiency scores are identical, meaning that scaling by total assets does not alter central tendency or dispersion of overall technical efficiency scores. But the log-transformed scores are severely compressed. For example, in private banks the mean increases from 0.863 (raw) to 0.981 (log), and the standard deviation decreases from 0.090 to 0.015. For the public bank, raw efficiency is poorer (mean = 0.742) than for private banks but near perfect efficiency (mean = 0.995) after log transformation. These results imply that while log transformation improves normalization and reduces the effect of outliers, it also reduces differences between units, possibly obscuring subtle performance differences.

Table 4.1.8. Comparative Summary Statistics for Overall Technical Efficiency (OTeBC) Measures by Bank Ownership

Bank Type	Efficiency Measure	N	Mean	SD	Min	Max
Private	OTEBC (Raw)	144	0.863	0.09	0.645	1
	OTEBC_log (Log)	144	0.981	0.015	0.918	1
	OTEBC_ratio (Scaled)	144	0.863	0.09	0.645	1
Public	OTEBC (Raw)	9	0.742	0.148	0.605	1
	OTEBC_log (Log)	9	0.995	0.004	0.988	1
	OTEBC_ratio (Scaled)	9	0.742	0.148	0.605	1
Total	OTEBC (Raw)	153	0.856	0.098	0.605	1
	OTEBC_log (Log)	153	0.982	0.015	0.918	1
	OTEBC_ratio (Scaled)	153	0.856	0.098	0.605	1

Note: "OTEBC" denotes overall technical efficiency. The log-transformed measure (OTEBC_log) compresses the scale to reduce skewness, while the assets-scaled measure (OTEBC_ratio) normalizes the efficiency score by total assets.

Source: Data derived from the annual financial reports of the banks (2014–2022); efficiency scores computed using a Data Envelopment Analysis (DEA) model by the author

The private banks in Table 4.1.9 have moderate raw pure technical efficiency spread with mean = 0.883 and SD = 0.091. Their log-transformed scores, however, are more centrally located (mean = 0.985) with closely grouped values (SD = 0.012). The assets-scaled measure has a lower average efficiency (0.924) with medium spread (SD = 0.054). The single public bank displays maximum efficiency in the unadjusted metric (mean = 1.000), but in the logarithmic and scaled metrics shows some minor variation. The overall sample maintains high levels of efficiency, and the pattern observed is that, as with overall technical efficiency, the logarithmic transformation has a dramatic reduction in variability, whereas the asset-scaling technique retains more of the original variance in performance.

Table 4.1.9. Comparative Summary Statistics for Pure Technical Efficiency (PTeBC) Measures by Bank Ownership

Bank Type	Efficiency Measure	N	Mean	SD	Min	Max
Private	PTEBC (Raw)	144	0.883	0.091	0.646	1
	PTEBC_log (Log)	144	0.985	0.012	0.947	1
	PTEBC_ratio (Scaled)	144	0.924	0.054	0.801	1
Public	PTEBC (Raw)	9	1	0	1	1
	PTEBC_log (Log)	9	0.999	0.002	0.995	1
	PTEBC_ratio (Scaled)	9	0.968	0.042	0.87	1
Total	PTEBC (Raw)	153	0.89	0.092	0.646	1
	PTEBC_log (Log)	153	0.986	0.012	0.947	1
	PTEBC_ratio (Scaled)	153	0.927	0.054	0.801	1

Note: “PTEBC” refers to pure technical efficiency. The log-transformed measure (PTEBC_log) compresses the scale to reduce skewness, while the assets-scaled measure (PTEBC_ratio) normalizes the efficiency score by total assets.

Source: Data derived from the annual financial reports of the banks (2014–2022); efficiency scores computed using a Data Envelopment Analysis (DEA) model by the author

Scale efficiency measures in Table 4.1.10 also demonstrate significant variation across bank categories. Private banks exhibit high scale efficiency levels in the raw data (mean = 0.978, SD = 0.033), which are enhanced following the log transformation (mean = 0.995, SD = 0.009), indicating low scale performance variation among private banks. In contrast, the untransformed scale efficiency of the public bank is much lower (mean = 0.742, SD = 0.148), and there are scale inefficiencies; but the log transformation increases the mean to 0.996 with very little dispersion (SD = 0.004), again demonstrating the compressive effect of the logarithmic function. The assets-scaled values for the two groups are within these limits, retaining more of the original variability than the log-transformed values. In short, the results show that while efficiency scores are not changed substantially when scaled by total assets, the use of a logarithmic transformation significantly reduces variability, which can mask nuances in scale performance across banks.

Table 4.1.10. Comparative Summary Statistics for Scale Efficiency-Based Criteria (SEBC) Measures by Bank Ownership

Bank Type	Efficiency Measure	N	Mean	SD	Min	Max
Private	SEBC (Raw)	144	0.978	0.033	0.762	1
	SEBC_log (Log)	144	0.995	0.009	0.934	1
	SEBC_ratio (Scaled)	144	0.932	0.062	0.762	1
Public	SEBC (Raw)	9	0.742	0.148	0.605	1
	SEBC_log (Log)	9	0.996	0.004	0.992	1
	SEBC_ratio (Scaled)	9	0.765	0.136	0.628	1
Total	SEBC (Raw)	153	0.964	0.072	0.605	1
	SEBC_log (Log)	153	0.995	0.008	0.934	1
	SEBC_ratio (Scaled)	153	0.923	0.078	0.628	1

Note: "SEBC" denotes scale efficiency. The log-transformed measure (SEBC_log) compresses the scale to reduce skewness, while the assets-scaled measure (SEBC_ratio) normalizes the efficiency score by total assets.

Source: Data derived from the annual financial reports of the banks (2014–2022); efficiency scores computed using a Data Envelopment Analysis (DEA) model by the author

In summary, these three tables (Table 4.1.7, Table 4.1.8, and Table 4.1.9) in this section collectively give an overall assessment of the impact of various data preparation methods on banks' efficiency scores. Interestingly enough, overall asset-adjusted efficiency scores—via the ratio-normalized method—closely resemble Winsorized raw data (Winsorized at the 1% and 99% levels), which suggests that this normalization process does not substantially change the central tendencies or dispersion of the efficiency measures. Conversely, the logarithmic transformation will decrease variation in the scores considerably by increasing mean values and attenuating dispersion. While such a reduction enhances statistical properties (for instance, by alleviating skewness), it does so at the expense of masking valuable differences in performance required for fully informed policy-making and managerial decision-making.

A further problem is that our sample includes two basically non-comparable groups: sixteen relatively homogeneous private banks and one large public bank. The extreme difference in size and operating features implies that any transformation aiming to further scale down the data—e.g., the logarithmic transformation—would cancel these inherent disparities. The observed similarity between the Winsorized raw data and ratio-normalized data vindicates the approach of using the untransformed (Winsorized) data. With the Winsorized efficiency scores on the raw data, we maintain the natural variability and actual heterogeneity among the groups. It allows the distinct operational dynamics of the private banking institutions and the big public bank to be represented correctly in our research.

Based on these findings, we have opted to utilize the Winsorized untransformed data in all of our analyses going forward. Not only does this choice preserve the valuable distinctions between the bank groups, but it also offers a sounder foundation for efficiency assessment and policy-making.

4.2: Risks and Bank Specific Factors Affecting the Efficiency of Ethiopian Commercial Banks

4.2.1. Introduction

This section presents the econometric analysis of the determinants of efficiency among Ethiopian commercial banks for the period 2014–2022. We employ a Difference GMM framework to model two key efficiency measures: OTEBC and PTEBC. The choice of Difference GMM is supported by various diagnostic tests and adheres to Bond (2002) rule of thumb for dynamic panel data estimation. This methodology is particularly suitable given the persistence in efficiency levels, the dynamic nature of bank performance, and the potential endogeneity of the explanatory variables.

Both the AR2 P-values (well above the 0.05 threshold) and the Hansen and Sargan statistics indicate that the instruments are valid and that the model is correctly specified[10]. Overall,

[10] The Difference Generalized Method of Moments (GMM) estimator, developed by Arellano and Bond (1991), is particularly suitable for dynamic panel data models where endogeneity, autocorrelation, and unobserved heterogeneity are concerns. It uses lagged levels of endogenous variables as instruments for their differenced forms, thereby mitigating bias from simultaneity and omitted variables. The Arellano-Bond test for second-order serial correlation (AR2) assesses whether the differenced residuals exhibit autocorrelation beyond the first order; a non-significant AR2 p-value (typically > 0.05) suggests no violation of the model's assumptions. The Hansen and Sargan tests evaluate the validity of the instruments used in the GMM

the estimation strategy robustly addresses potential endogeneity and autocorrelation issues, lending credibility to the estimated risk factors and other determinants of both overall and pure technical efficiency. In the following sub section, the study presents the descriptive statistics of main variables used in the estimations and their correlation matrix. The model diagnosis tests and results are presented. Consequently, the determinants of technical efficiencies are presented for OTEBC and PTEBC.

4.2.2. Descriptive Statistics and Correlations of variables used in the studies

The subsequent two sections provide a detailed examination of the determinants influencing the technical efficiency scores of Ethiopian commercial banks. This analysis is followed by an investigation into the effects of these efficiency factors on financial risks, specifically credit risk and liquidity risk. Tables 4.2.1 and 4.2.2 present the descriptive statistics and correlation coefficients for the variables utilized in one or both aspects of the study, offering empirical insights into their relationships.

Table 4.2.1 provides the descriptive statistics for the primary variables employed in the study. The aggregate figures are the means, the standard deviations, and the range (minimum to maximum) for each of the key variables. The efficiency scores—OTEBC, PTEBC, and SEBC—form the foundation for the evaluation of operating performance. Ethiopian commercial banks, on average, exhibit an OTEBC of 0.856, ranging from 0.61 to 1.00 and with a standard deviation of 0.098. PTEBC, which estimates managerial effectiveness alone, is 0.890 on average (SD = 0.092). Scale efficiency, which estimates the degree to which banks are producing at optimal output relative to scale, is relatively high, with a mean of 0.964 (SD = 0.072) Refer to section 4.1 for details.

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framework. A non-significant result in these tests indicates that the instruments are not overidentified and are consistent with the moment conditions, thereby confirming the reliability of the model specification.

Table 4.2.1: Descriptive Statistics of Main Variables used in both or either one of the two Studies

	Mean	SD	Min	Max
OTEBC	0.856	0.098	0.61	1.00
PTEBC	0.890	0.092	0.65	1.00
SEBC	0.964	0.072	0.61	1.00
Credit Risk[11]	0.653	0.905	0.00	7.75
Liquidity risk	53.188	10.499	27.67	77.07
Interest Rate risk	77.635	8.000	48.25	94.16
Profitability	2.685	0.845	0.33	5.13
Size (Ln(TA))	9.888	1.3568	6.7748	13.998
Capital Adequacy	14.105	4.028	3.72	25.95
Market share	5.882	11.407	0.18	62.43
Economic Growth	8.261	1.679	6.10	10.40
Inflation	16.332	8.513	7.50	34.04
Observations	153			

Notes: SD = Standard Deviation. Variables are winsorized at 1st and 99th percentiles.

Source: Author's calculation based on Annual reports (2014 - 2022)

Table 4.2.1 shows some descriptive statistics of the main variables used in our model tests. The technical efficiency scores are relatively high on average. More specifically, OTEBC is 0.856 on average and PTEBC 0.890. Their standard deviations are 0.098 and 0.092, respectively, showing minimal variation. The scores vary almost across the entire range from 0 to 1, with a maximum of 1.00. The mean scale efficiency score (SEBC) is 0.964 with low dispersion (SD = 0.072). This suggests that most banks are producing at or near the optimal scale levels.

[11] The minimum of 0 is due to four cases in the year 2016 & 2017. During these periods, major accounting, regulatory and reporting changes, such as the adoption of compulsory International Financial Reporting Standard (IFRS), were made. Thus, some banks might have significantly reduced their prior loan loss provision upon improved loan quality (Almaw, 2021).

Credit risk displays a mean of 0.653 but a very large spread (SD = 0.905; max = 7.75). This heterogeneity was anticipated: while the average ratio indicates moderate loan loss provision to loan ratio, several banks far exceed prudent thresholds, reflecting divergent underwriting standards and cyclical credit booms during the 2014–2022 period.

Liquidity risk averages 53.19 percent of assets (SD = 10.50), aligning with central-bank guidance that banks maintain liquid buffers above 30 percent. Yet the range (27.67–77.07) reveals that some institutions skirt the lower limit—potentially heightening funding-stress vulnerability—whereas others hold substantial liquidity, perhaps in response to episodic market volatility. This variation supports our hypothesis that differences in asset-liability strategies would materially influence efficiency outcomes.

Interest rate risk is similarly elevated, with a mean repricing gap of 77.63 (SD = 8.00). Such uniformly high exposure was expected given regulated deposit rates and more flexible lending rates in Ethiopia's banking sector. The moderate dispersion suggests that, while all banks face pronounced mismatch risk, a few manage this gap more effectively—presaging heterogeneous impacts on technical efficiency.

Profitability, measured by return on assets, averages 2.69 percent (SD = 0.85). This performance sits above regional averages reported in the literature and corresponds with the robust macro environment (mean GDP growth = 8.26 percent). However, the range from 0.33 percent to 5.13 percent indicates that some banks, likely those with weaker risk controls or higher funding costs, underperform their peers.

Bank size (Ln TA) averages 9.888 (SD = 1.357), confirming a sample that includes both small niche players and large universal banks. This study predicted that size heterogeneity would drive scale-efficiency differences, and these figures set the stage for subsequent regression results.

Capital adequacy averages 14.11 percent (SD = 4.03), comfortably above the 8 percent regulatory floor. Yet the minimum of 3.72 percent highlights outliers potentially subject to regulatory intervention. The study anticipated that better-capitalized banks would exhibit higher technical efficiency, since capital buffers allow smoother operations during downturns.

Market share is highly concentrated (mean = 5.88; SD = 11.41; max = 62.43), confirming that a few large banks dominate the sector. This concentration was expected to create competitive asymmetries, which the study modeled later to show financial risk differentials.

Macro variables exhibit meaningful volatility. Economic growth averages 8.26 percent (SD = 1.68), underscoring a dynamic but uneven expansion consistent with structural reforms. Inflation, at 16.33 percent on average (SD = 8.51; range 7.50–34.04), far exceeds levels in more stable economies and was hypothesized to exert downward pressure on both operational and scale efficiencies through eroded real returns and increased risk premiums.

All variables were winsorized at the 1st and 99th percentiles to dampen outlier effects. Together, these descriptive insights confirm our expectations and set a coherent foundation for the diagnostic tests and efficiency-risk interplay analyses that follow.

Table 4.2.2: Matrix of Correlations among variables used in the studies

	Otebc	Ptebc	Sebc	Crr	Lqr	Irr	Roaa	Size	Cadq	MS	Econgr	Cpi
OTEBC	1.00											
PTEBC	0.71	1.00										
SEBC	0.47	-0.29	1.00									
CRR	0.00	0.25	-0.31	1.00								
LQR	0.59	0.24	0.51	-0.01	1.00							
IRR	0.19	0.39	-0.22	0.27	0.35	1.00						
ROAA	0.29	0.11	0.26	-0.35	-0.17	-0.27	1.00					
SIZE	-0.03	0.31	-0.42	0.18	0.19	0.57	-0.38	1.00				
CADQ	0.18	-0.04	0.29	-0.21	-0.10	-0.42	0.48	-0.81	1.00			
MS	-0.20	0.31	-0.65	0.17	-0.37	0.40	-0.19	0.70	-0.60	1.00		
ECONGR	-0.35	-0.39	0.01	-0.14	-0.59	-0.40	0.23	-0.44	0.18	0.00	1.00	
CPI	0.42	0.46	-0.01	0.15	0.65	0.39	-0.22	0.47	-0.19	0.00	-0.80	1.00

Note: MS= market share in total loans, all other variables are as defined in Table 4.2.1.

Source: Author's calculation based on Annual reports (2014 - 2022)

Table 4.2.2 provides the correlation matrix of the risk–efficiency model variables. OTEBC is highly and positively correlated with PTEBC, with the Pearson correlation coefficient (r) at 0.71. Therefore, banks with high overall performance are also likely to have high managerial efficiency when we consider the impact of scale effects. OTEBC is weakly positively correlated with liquidity risk (r = 0.59). This means that banks that are efficient are also facing high liquidity risk at the same time. This correlation suggests that banks that aim to be more efficient are also using their cash balances to drive better performance as much as possible.

The correlation matrix gives the relationship between two variables and bank financial performance, risk, and efficiency in general. All the diagonal values are 1, which reflects that they are fully correlated with one another. For example, OTEBC and PTEBC are moderately to strongly positively correlated (r = 0.714), i.e., the technical efficiency measures tend to move in the same direction.

OTEBC is positively and significantly related to liquidity risk (r = 0.589), indicating that technical efficiency is higher when the exposure to liquidity risk is higher. SEBC is negatively related to credit risk (r = -0.309), indicating that banks that are near their optimal size have lower levels of credit risk.

Other correlations in the matrix reveal more. Bank size (Ln(TA)) is weakly negatively correlated with OTEBC (r = -0.035) but is strongly positively correlated with market share (r = 0.704) and interest rate risk (r = 0.569). This trend indicates that larger banks may be more powerful in the market while also encountering various forms of risks. In addition, economic growth has a negative correlation with variables such as OTEBC (r = -0.347) and particularly CPI (r = -0.804), reflecting potential impacts on banks' performance from the general economy.

The correlation matrix demonstrates the associations between efficiency measures, risk measures, and economic variables. These bivariate relationships enable us to initiate the process of understanding the multifaceted interactions in the banking sector that necessitate additional examination with a greater number of variables.

4.2.3. Effect of Risk Factors and Other Determinants on the Overall Technical Efficiency

Table 4.2.3 reports the results of the Difference GMM estimations for overall technical efficiency (OTEBC) using both one-step and two-step specifications. In these models, OTEBC is regressed on several explanatory variables, including the lagged efficiency term (L.OTEBC), credit risk, liquidity risk, profitability, bank size (measured in logarithmic terms as Ln(TA)), and capital adequacy. Year dummies ha ve been included to account for temporal effects, and the number of effective observations is 119 after differencing.

The coefficient on the lagged dependent variable (L.OTEBC) is 0.429 in both the one-step and two-step estimations, with t-statistics of 4.52 and 4.54, respectively, all statistically significant at the 1% level. This finding indicates a high degree of persistence in overall technical efficiency: banks that have performed well in the past tend to continue doing so. Credit risk is also a statistically significant determinant, with a coefficient of 0.00686 (t = 2.37 in one-step and 2.41 in two-step, significant at the 5% level), implying that an increase in the measure of credit risk is associated with an improvement in overall technical efficiency, all else held constant.

Liquidity risk exerts a strong positive influence on OTEBC, with coefficients of 0.00732 and 0.00733 (t-statistics of 7.27 and 7.43, respectively), significant at the 1% level. These results suggest that banks with higher liquidity risk tend to operate more efficiently, potentially reflecting risk-adjusted measures in their operational processes. Profitability has a robust positive effect, as indicated by a coefficient of 0.0384 (t = 5.01 in one-step and 5.04 in two-step, significant at the 1% level), showing that more profitable banks enjoy higher levels of efficiency.

In contrast, the coefficient on bank size—measured by the natural logarithm of total assets (Ln(TA))—is negative, with estimates of –0.0837 in the one-step model and –0.0829 in the two-step model. The corresponding t-statistics, –2.06 and –2.20, indicate significance at the 10% and 5% levels, respectively. In practical terms, these negative coefficients imply that larger banks tend to have lower overall technical efficiency. Specifically, the study shows that a unit increase in the size of a bank is associated with an approximately 8.4% decrease in the overall efficiency score in the one-step estimation and an 8.3% decrease in the two-step estimation in short run, ceteris paribus. Capital adequacy, however, is not a statistically significant determinant in either model, with coefficients of 0.00222 and 0.00224, and t-statistics of 0.57 in both cases.

The overall performance of the models is supported by high F-statistics (89.96 for the one-step and 90.46 for the two-step estimation), and the diagnostic statistics are satisfactory: the AR(2) P-values (0.997 and 0.994) and the Hansen and Sargan statistics (0.957 and 0.945, respectively) denote that the instruments used are valid and that the model specifications are appropriate.

Table 4.2.3: Effect of Risk Factors and other determinants on Overall Technical Efficiency of Ethiopian Commercial Banks: Difference GMM

	One-step	Two-Step
L.OTEBC	0.429***	0.429***
	(4.52)	(4.54)
Credit Risk	0.00686**	0.00686**
	(2.37)	(2.41)
Liquidity risk	0.00732***	0.00733***
	(7.27)	(7.43)
Profitability	0.0384***	0.0384***
	(5.01)	(5.04)
Bank Size (Ln(TA))	-0.0837*	-0.0829**
	(-2.06)	(-2.20)
Capital Adequacy	0.00222	0.00224
	(0.57)	(0.57)
Year dummies	Yes	Yes
No. of Obs.	119	119
F-Statistic	89.96***	90.46***
No. of Groups/Instruments	17/14	17/14
AR2 P-value	0.997	0.994
Hansen -Statistic	0.957	0.957
Sargan – Statistic	0.945	0.945

Note: the dependent variable was overall technical efficiency (otebc), L.OTEBC = lagged dependent variable, Ln(TA) = Logarithm of total assets as a measure of banks size, t statistics is reported in parentheses, statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, No. of Obs. = Number of observations reduced from 153 due to variable differencing.

Source: Author's calculation based on Annual reports (2014 - 2022)

4.2.4. Effect of Risk Factors and other determinants on Pure Technical Efficiency

Table 4.2.4 presents the results of the Difference GMM estimation for pure technical efficiency (PTEBC) in Ethiopian commercial banks. In this model, PTEBC serves as the dependent variable, while its explanatory variables include the lagged dependent variable (L.PTEBC), credit risk, liquidity risk, profitability, bank size (expressed as the natural logarithm of total assets, Ln(TA)), capital adequacy, and inflation. Year dummies have been incorporated in the estimation to control for time-specific effects. The sample for this analysis is comprised of 119 observations, reduced from the original sample due to variable differencing. Two sets of estimates are reported: one-step and two-step GMM.

In both specifications, the coefficient on the lagged dependent variable L.PTEBC is positive and statistically significant, with a coefficient of 0.436 ($t = 3.29$) in the one-step model and 0.427 ($t = 2.42$) in the two-step model. This finding clearly indicates that pure technical efficiency is highly persistent, i.e., banks with higher managerial efficiency in a previous period tend to maintain their performance in subsequent periods too. Credit risk is also a positive determinant with coefficients of 0.00785 ($t = 1.85$) in the one-step model and 0.00813 ($t = 1.87$) in the two-step model, both significant at approximately the 10% level, suggesting that an increase in credit risk is modestly associated with an improvement in managerial efficiency in the short run, holding other factors constant.

Liquidity risk exhibits a strong and statistically significant positive influence on PTEBC, where the one-step model reports a coefficient of 0.00614 ($t = 8.06$) and the two-step model finds a similar value of 0.00593 ($t = 6.01$), both significant at the 1% level. This robust positive association implies that banks operating under higher liquidity risk conditions tend to achieve better pure technical efficiency, perhaps reflecting risk-adjusted operational strategies.

Similarly, profitability is found to have a robust positive effect, as indicated by coefficients of 0.0378 ($t = 5.62$) in the one-step and 0.0361 ($t = 5.16$) in the two-step model, underscoring those higher earnings are strongly linked with enhanced managerial performance.

Table 4.2.4: Effect of Risk Factors and other determinants on Pure Technical Efficiency of Ethiopian Commercial Banks: Difference GMM

	One-step	Two-Step
L.PTEBC	0.436***	0.427**
	(3.29)	(2.42)
Credit Risk	0.00785*	0.00813*
	(1.85)	(1.87)
Liquidity risk	0.00614***	0.00593***
	(8.06)	(6.01)
Profitability	0.0378***	0.0361***
	(5.62)	(5.16)
Bank Size (Ln(TA))	-0.0837*	-0.0716
	(-1.99)	(-1.68)
Capital Adequacy	0.00205	0.00256
	(0.42)	(0.44)
Inflation	0.00454**	0.00408*
	(2.13)	(1.81)
Year dummies	Yes	Yes
No. of Obs.	119	119
F-Statistic	137.1***	120.3***
No. of Groups/Instruments	17/14	17/14
AR2 P-value	0.774	0.766
Hansen -Statistic	0.328	0.328
Sargan – Statistic	0.190	0.190

Note: the dependent variable was pure technical efficiency (ptebc), L.PTEBC = lagged dependent variable, Ln(TA) = Logarithm of total assets as a measure of banks size, t statistics is reported in parentheses, statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, No. of Obs. = Number of observations reduced from 153 due to variable differencing.

Source: Author's calculation based on Annual reports (2014 - 2022)

Conversely, bank size, measured as Ln(TA), has a negative impact on PTEBC. The one-step model reports a coefficient of –0.0837 (t = –1.99), while the two-step model shows a slightly smaller negative coefficient of –0.0716 (t = –1.68). Although both estimates suggest that larger banks tend to experience lower pure technical efficiency, the statistical significance in the two-step model is marginal, which indicates that the adverse impact of size on managerial efficiency might be less pronounced when controlling more rigorously for potential endogeneity. Capital adequacy appears to have little to no effect on PTEBC, with coefficients of 0.00205 ($t = 0.42$) and 0.00256 ($t = 0.44$) in the one-step and two-step models, respectively, both of which are statistically insignificant.

Additionally, inflation is a statistically significant positive determinant; the one-step model reports a coefficient of 0.00454 ($t = 2.13$) and the two-step model presents a coefficient of 0.00408 ($t = 1.81$). The significance of inflation, at the 5% level in the one-step and at the 10% level in the two-step model, suggests that in environments with higher inflation, banks may adopt adaptive managerial practices that lead to improved pure technical efficiency. The overall model performance is indicated by robust F-statistics of 137.1 in the one-step and 120.3 in the two-step estimation. The diagnostic tests further support the validity of our instrumentation and model specification, with an AR(2) P-value of 0.774 in the one-step and 0.766 in the two-step models, alongside Hansen and Sargan statistics that confirm proper instrument validity.

4.2.5 Hypotheses Testing and Empirical Findings

This section examines Hypotheses H3 through H7 using a Difference GMM estimation on panel data covering Ethiopian commercial banks over the period 2014–2022. Two dependent variables were considered: overall technical efficiency (OTEBC) and pure technical efficiency (PTEBC). The key explanatory variables include the credit risk ratio (CRR), liquidity risk ratio (LQR), profitability (as measured by return on average assets, ROAA), capital adequacy (CADQ), and bank size (measured by the logarithm of total assets, Ln(TA)). The estimated results for OTEBC are reported in Table 4.2.3, while Table 4.2.4 presents the findings for PTEBC. The discussion below highlights the evidence regarding each hypothesis.

H3: The Relationship between Credit Risk Ratio and Technical Efficiency

Hypothesis H3 predicts a negative effect between credit risk and technical efficiency according to classical banking theory. The theory predicts that higher credit risk—derived from high default rates on loans or lax underwriting practices—would lead to decreased operating efficiency, attributed to higher non-performing loans and financial instability. The empirical findings presented in Table 4.2.3 and Table 4.2.4 reject this hypothesis and determine that credit risk positively relates to overall technical efficiency (OTEBC) as well as pure technical efficiency (PTEBC).

For the OTEBC model, the two-step credit risk coefficient is 0.00686, at the 5% level ($t = 2.41$), suggesting that banks with higher credit risk levels have higher efficiency performance. Similarly, for the PTEBC model, the CRR coefficient is 0.00813, at statistical significance at the 10% level ($t = 1.87$). The same positive impact felt in both efficiency measures shows that, against the initial hypothesis, high credit risk does not hinder efficiency but appears to enhance it in Ethiopian commercial banks.

Several theoretical models could illuminate this apparently contradictory observation. One such explanation is that Ethiopian financial institutions may be adopting aggressive lending practices, expanding their credit portfolios in a bid to increase profitability while sustaining operational efficiency.

A second explanation is linked to the risk-adjusted efficiency hypothesis, which indicates that banks deal with credit risk as a means of efficiency improvement measures instead of experiencing inefficiency from financial exposure. In this regard, Ethiopian commercial banks can rationalize loan processing structures, enhance risk-adjusted returns, and maximize borrower appraisal methods, ensuring that credit growth fuels both increased revenue collection and operational efficiency improvements.

Lastly, the rejection of H3 suggests that higher credit risk does not have to be detrimental to efficiency because Ethiopian banks are perhaps optimizing their loan portfolios while embracing efficiency-oriented risk management.

H4: The Relationship between Liquidity Risk and Technical Efficiency

Hypothesis H4 predicts a negative relationship between technical efficiency and liquidity risk, following the reasoning that financial constraints tighten liquidity, forcing banks to struggle to finance business activities, to postpone credit repayments, and to suffer from higher financial instability. Empirical results, however, reject this hypothesis, as a highly significant positive relationship between liquidity risk and efficiency is found in both estimation models.

In the OTEBC model (Table 4.2.3), the liquidity risk coefficient is 0.00733, statistically significant at 1% ($t = 7.43$) and implying that banks experiencing liquidity stress will tend to have greater operational efficiency. Similarly, in the PTEBC model (Table 4.2.4), liquidity risk continues to have a positive significant effect, with a coefficient of 0.00593 ($t = 6.01$, $p < 0.01$), confirming the trend found in overall technical efficiency estimates.

The results imply that banks with liquidity constraints do not inherently experience losses in efficiency but rather improve their efficiency through adaptation strategies. A possible explanation of this correlation is that banks with liquidity problems may intentionally concentrate on strategies for maximizing efficiency to attain sustainable financial performance. Firms that have stringent liquidity constraints tend to utilize advanced cash flow management strategies, aggressive revenue-generating strategies, and risk-taking loan turnover frameworks that enable them to withstand liquidity volatility using efficiency-enhancing mechanisms.

Besides, Ethiopian commercial banks may be using asset-liability management strategies that enhance short-term operating efficiency despite liquidity shortages. Liquidity shortages may stimulate banks to enhance deposit mobilization strategies, improve the efficiency of interbank lending, and optimize working capital management, ensuring cost-effective use of resources.

H5: The Effect of Profitability (ROAA) on Technical Efficiency

Hypothesis H5 asserts that higher profitability, proxied by ROAA, is positively associated with technical efficiency. The GMM results substantiate this relationship. In the OTEBC model, profitability is associated with an increase in technical efficiency by 0.0384, with a t statistic of approximately 5.04 ($p < 0.01$). Likewise, in the pure technical efficiency model, the coefficient is 0.0361 ($t = 5.16$, $p < 0.01$). The statistical significance and magnitude of these effects provide compelling evidence in favor of H5.

These findings indicate that profitability enhances technical efficiency, as financially strong banks optimize resource allocations, invest in operational refinements, and leverage advanced banking technologies to sustain performance gains. Ethiopian commercial banks appear to utilize profitability-driven efficiency strategies, ensuring that higher earnings contribute to efficiency improvements across operational dimensions.

H6: The Effect of Capital Adequacy on Technical Efficiency

Hypothesis H7 expects a positive relationship between capital adequacy and efficiency, assuming that higher capital buffers provide financial stability, enabling banks to optimize resource allocations and strengthen operational effectiveness. However, the empirical results do not support this hypothesis, indicating that capital adequacy has no significant effect on efficiency.

For the overall technical efficiency model (Table 4.2.3), the coefficient for capital adequacy is 0.00224 with a t value of 0.57, indicating that the effect is statistically insignificant. The pure technical efficiency specifications (Table 4.2.4) yield similar outcomes, with coefficients near zero and low t statistics. Thus, H6 is not supported by the data, and it appears that capital adequacy does not exert a discernible influence on the technical efficiency of Ethiopian commercial banks. This result suggests that Ethiopian banks maintain capital primarily for regulatory compliance rather than for efficiency-driven allocations, reinforcing the argument that Basel I-based capital adequacy measures may not effectively align with efficiency objectives.

H7: The Relationship between Bank Size and Technical Efficiency

Hypothesis H7 posits that larger bank exhibit lower technical efficiency, implying a negative relationship between bank size and efficiency. The overall technical efficiency estimates indicate that bank size is indeed negatively related to efficiency. In Table 4.2.3, the two-step coefficient for Ln(TA) is –0.0829 ($t = -2.20$, $p < 0.05$), supporting the hypothesis. In the model for pure technical efficiency, the one-step estimation reports a coefficient of –0.0837 ($t = -1.99$, significant at the 10% level), although the two-step result (–0.0716, $t = -1.68$) is not statistically significant at conventional levels. Overall, the evidence for H7 can be considered partial, indicating that while larger bank size tends to be associated with lower overall technical efficiency, the relationship is less robust when isolating managerial performance from scale effects.

Generally, these results suggest that as Ethiopian banks expand, efficiency losses may emerge due to higher administrative costs, operational fragmentation, and slow decision-making structures. Institutions with high asset volumes may struggle with coordination inefficiencies, preventing them from fully leveraging size for efficiency optimization. These findings set the foundation for further discussions on policy implications which will be explored in subsequent chapter.

4.3. Effect of Technical Efficiencies on Credit and Liquidity Risks

4.3.1. Introduction

In this section, we discuss the effect of bank efficiency—proxied by overall technical efficiency (OTEBC) and pure technical efficiency (PTEBC)—on two most crucial risk aspects: credit risk and liquidity risk. Totally four model results are presented in this paper. First, the study reports the diagnostic tests confirming the appropriateness of the empirical strategies; and then it displays the estimation results from panel estimates.

4.3.2. Diagnosis Tests: The Multicollinearity Test Result

Table 4.3.1 presents variance inflation factors (VIF) estimated for credit risk models with various efficiency measures as one with overall technical efficiency (OTEBC) and another with pure technical efficiency (PTEBC) as the primary predictor.

The VIF values for the primary predictors are relatively low, from approximately 1.62 to 4.88. For both models, VIFs for Market Share (LAA) are 3.59 in Model 1 and 4.10 in Model 2, and Inflation (CPI) has VIFs of 3.64 and 3.95, respectively. Liquidity Risk (LQR) records a Variance Inflation Factor (VIF) of 4.88 in Model 1 and 3.45 in Model 2. The other predictors, including Economic Growth (ECONGR) and Capital Adequacy (CADQ), all record VIFs below 3, specifically 2.98 and 2.58 in Model 1, respectively, and close values in Model 2. The efficiency measure itself records a VIF of 2.75 in the OTEBC-based and 2.18 in the PTEBC-based model. Profitability (ROAA), Interest Rate Risk (IRR), and Operating Income (OPR), however, have hardly any multicollinearity, with VIF scores between 1.62 and 2.54.

Overall, the mean VIF values of Model 1 (2.94) and Model 2 (2.76) are well below customary thresholds that would indicate serious multicollinearity (typically a VIF of 10 or more). The results indicate that, in both credit risk models, the predictors do not exhibit unhealthily high degrees of collinearity. From a practical perspective, VIF values categorized as low to moderate give assurance about the consistency of the parameter estimates in the models, making it possible to have credible interpretation about the effects imposed by individual predictors on credit risk. Accordingly, this diagnostic analysis underpins the foundation of the validity of the ensuing econometric analysis for the effect of efficiency on credit risk so that the observed relations are not obscured by the presence of extreme multicollinearity among the independent variables.

Table 4.3.1. Variance Inflation Factors for credit risk Models

Predictor	Model 1 (OTEBC) VIF	Model 2 (PTEBC) VIF	Interpretation
Market Share (LAA)	3.59	4.10	Mild
Inflation (CPI)	3.64	3.95	Mild
Liquidity Risk (LQR)	4.88	3.45	Mild
Economic Growth (ECONGR)	2.98	2.97	Mild
Capital Adequacy (CADQ)	2.58	2.62	Mild
Efficiency Measure	**2.75 (OTEBC)**	**2.18 (PTEBC)**	Very Mild
Profitability (ROAA)	2.54	2.11	Very Mild
Interest Rate Risk (IRR)	1.84	1.85	Very Mild
Operating Income (OPR)	1.68	1.62	Very Mild
Mean VIF	**2.94**	**2.76**	**No concerns**

Source: Author’s calculations based on Ethiopian banking data (2014–2022).

Table 4.3.2 presents the variance inflation factors calculated for the two liquidity risk models—one using overall technical efficiency (OTEBC; Model 2) and the other using pure technical efficiency (PTEBC; Model 4) as the primary predictor. In these models, key explanatory variables include Inflation (CPI), Economic Growth (ECONGR), Market Share (LAA), Capital Adequacy (CADQ), Operating Income (OPR), Profitability (ROAA), the efficiency measure of interest (either OTEBC or PTEBC), Credit Risk (CRR), and Interest Rate Risk (IRR). The VIFs for Inflation are 3.55 in Model 2 and 3.56 in Model 4, which are considered mild; similarly, Economic Growth has VIFs of 2.97 in both models, also falling within the mild range. Market Share is associated with very mild multicollinearity, with VIF values of 1.85 in Model 2 and 2.36 in Model 4. In addition, Capital Adequacy registers VIFs of 2.10 and 2.23, while Operating Income displays VIFs of 2.50 and 2.23 in the respective models. Profitability shows VIF values of 2.43 in Model 2 and 2.11 in Model 4, indicating a very mild level of multicollinearity. The efficiency measures themselves have VIFs of 1.97 for OTEBC and 2.13 for PTEBC, which are reassuringly low. Finally, both Credit Risk and Interest Rate Risk have VIFs below 2 (with values of 1.82 and 1.65 in Model 2, and 1.75 and 1.62 in Model 4), indicating minimal collinearity. The average VIF across predictors is 2.32 for Model 2 and 2.33 for Model 4, which reflects an excellent overall level of independence among the explanatory variables.

Table 4.3.2: Variance Inflation Factors for Liquidity Risk Models

Predictor	Model 2 (OTEBC) VIF	Model 4 (PTEBC) VIF	Interpretation
Inflation (CPI)	3.55	3.56	Mild
Economic Growth (ECONGR)	2.97	2.97	Mild
Market Share (LAA)	1.85	2.36	Very Mild
Capital Adequacy (CADQ)	2.10	2.23	Very Mild
Operating Income (OPR)	2.50	2.23	Very Mild
Profitability (ROAA)	2.43	2.11	Very Mild
Efficiency Measure	**1.97 (OTEBC)**	**2.13 (PTEBC)**	Very Mild
Credit Risk (CRR)	1.82	1.75	Very Mild
Interest Rate Risk (IRR)	1.65	1.62	Very Mild
Mean VIF	**2.32**	**2.33**	**Excellent**

Source: Author’s calculations based on Ethiopian banking data (2014–2022).

These VIF findings are strong evidence that the liquidity risk models are not tainted by multicollinearity. Practically, the low-to-moderate VIF values indicate that the estimated coefficients are trustworthy and that the predictors are measured with considerable independence. This diagnostic check confirms the validity of the further interpretations of the effect of bank efficiency on liquidity risk. Lastly, these diagnostic tests provide confidence in the validity of the results so that one can trace the changes in liquidity risk to underlying operating and macroeconomic determinants instead of ascribing them to redundancy of variables-related problems.

4.3.3 Analysis and Selection of Estimation Models

The selection of an appropriate estimation model is critical to ensuring the robustness and reliability of empirical findings. The results summarized in Table 4.3.3 provide statistical validation for the use of the Fixed Effects Model (FEM) over the Random Effects Model (REM) in analyzing the relationship between technical efficiency and risk exposure in Ethiopian commercial banks. The Hausman test, which assesses whether individual bank-specific effects are correlated with explanatory variables, consistently rejects the random-effects assumption, confirming that a fixed effects approach is necessary to control for institutional heterogeneity.

Table 4.3.3: Hausman Test Results for Model Specification

Risk Type	Model	Chi-squared (χ^2)	Prob > χ^2	Preferred Model
Credit Risk (CRR)	Model 1 (OTEBC)	20.64	0.0021	Fixed Effects
	Model 2 (PTEBC)	13.26	0.0390	Fixed Effects
Liquidity Risk (LQR)	Model 1 (OTEBC)	43.44	0.0000	Fixed Effects
	Model 2 (PTEBC)	67.57	0.0000	Fixed Effects

Notes: In all models, the Hausman test produces statistically significant results (**$p < 0.05$**), favoring fixed effects estimation.

Source: Author’s calculations based on Ethiopian banking panel data (2014–2020).

Specifically, the results show that for credit risk (CRR), Model 1 (OTEBC) produces a chi-squared value of 20.64 ($p = 0.0021$), and Model 2 (PTEBC) registers 13.26 ($p = 0.0390$), both of which surpass the conventional significance threshold of 5%. Similarly, for liquidity risk (LQR), Model 1 (OTEBC) yields a chi-squared value of 43.44 ($p = 0.0000$), and Model 2 (PTEBC) produces an even higher value of 67.57 ($p = 0.0000$), further reinforcing the suitability of a fixed effects estimation strategy.

The preference for fixed effects estimation suggests that efficiency-risk trade-offs in Ethiopian banking are strongly influenced by institution-specific characteristics such as ownership structure, governance practices, legal constraints, and operational efficiencies. By adopting a fixed effects model, the study effectively controls for time-invariant institutional characteristics, ensuring that efficiency determinants reflect structural disparities among banks. This approach minimizes estimation bias by eliminating unobserved heterogeneity, allowing for more precise evaluation of efficiency dynamics. The Hausman test results also indicate that efficiency measures (OTEBC and PTEBC) interact differently with risk exposure across banks, necessitating an estimation model that accounts for institutional variations rather than assuming homogeneity across firms.

The implications of using a fixed effects model extend beyond estimation precision, offering valuable insights into policy formulation and banking sector stability. The rejection of random effects suggests that credit risk and liquidity risk are not uniformly influenced by efficiency determinants across all banks; instead, time-invariant characteristics play a critical role. This finding underscores the necessity for bank-specific regulatory policies that acknowledge disparities in operational efficiency rather than applying blanket risk-management measures. For example, state-owned banks may require different oversight mechanisms compared to private banks due to differences in governance structures and risk exposure tendencies. Similarly, financial institutions operating in different market segments—such as retail banking versus corporate lending—may exhibit distinct efficiency-risk interactions that must be accounted for in policy frameworks.

From a practical standpoint, the adoption of fixed effects estimation ensures that efficiency models capture the nuanced relationships between efficiency and risk within Ethiopian banking institutions. By distinguishing the effects of efficiency determinants at the institutional level, this approach strengthens empirical insights into how banks navigate operational performance while managing financial vulnerabilities. The statistically significant results reinforce the need for differentiated efficiency-risk management strategies, ensuring that efficiency-driven banks implement risk mitigation frameworks tailored to their specific operational contexts. These findings provide a strong basis for future policy discussions and financial sector reforms aimed at optimizing efficiency while safeguarding banking stability.

Since efficiency metrics (OTEBC and PTEBC) affect risk with varying degrees depending upon bank-specific characteristics, the application of a fixed effects model ensures that parameter estimates are not confounded by unobserved heterogeneity. Such findings assist in informing a more robust risk exposure and efficiency trade-offs as required for policy prescriptions and banking sector stability improvement.

4.3.4. Empirical Findings: Technical Efficiency and Credit and Liquidity Risks

This sub-section presents regression results that examine the nexus of technical efficiency and financial risk measures of Ethiopian commercial banks. The research employs panel data for the period 2014-2022, with the estimation of technical efficiency through Overall Technical Efficiency (OTEBC) and Pure Technical Efficiency (PTEBC). Financial risk is estimated through credit risk (CRR) and liquidity risk (LQR), giving a clearer picture of the impact of efficiency patterns on financial stability. The findings pertaining to credit risk are provided in Table 4.3.4, and the assessments pertaining to liquidity risk are presented in Table 4.3.5.

4.3.4.1. Effect of Technical Efficiency on Credit Risk

Hypothesis H8 predicts technical efficiency improvements influence credit risk, in that banks optimizing their efficiency of operations can change their lending behaviors, possibly enhancing risk limiting controls or inadvertently heightening risk exposure in the course of attempting to conserve costs. The empirical findings presented in Table 4.3.4 display a statistically significant positive relationship, suggesting banks with greater degrees of technical efficiency are more likely to face increased credit risk.

In Model 1, overall technical efficiency (OTEBC) has a coefficient of 3.154, significant at the 5% level ($t = 3.91$), which supports the finding that efficiency improvements are associated with credit risk build-up. Similarly, in Model 2, pure technical efficiency (PTEBC) presents a positive 3.017 coefficient, also significant at the 5% level ($t = 3.66$). The results suggest that efficiency-oriented operation strategies may enhance risk-taking behavior, particularly in loan issuing and credit extending models.

The interpretation of these findings is in line with efficiency-risk trade-off hypotheses, in which banks that prioritize efficiency may relax underwriting vigilance, streamline lending processes, and reduce precautionary credit buffers, inadvertently heightening risk exposure to non-performing loans. The estimation findings highlight a key element of bank operations—efficiency fosters cost-reduction and performance improvement while requiring more rigorous risk monitoring to maintain financial stability.

Together with efficiency determinants, the return on average assets (ROAA) also indicates a significant negative effect on credit risk, as uncovered by the coefficients of -0.353 in Model 1 ($t = -3.59$, $p < 0.05$) and -0.323 in Model 2 ($t = -2.60$, $p < 0.10$). The finding indicates that more profitable banks are likely to have superior credit risk management practices in place, supporting the contention that financially healthier institutions invest more in risk mitigation initiatives. Conversely, the market share of loans and advances variable (MKT_SHARE_LAA) has a consistently negative coefficient, suggesting that institutions with larger lending portfolios may reduce risk by having diversified credit structures, thereby reducing their exposure to concentrated credit risk positions.

Table 4.3.4: Effect of Bank Technical Efficiency on Credit Risk of Ethiopian Banks

	(1) Model 1		(2) Model 2	
OTEBC	3.154**	(3.91)		
LQR	-0.010	(-0.21)	-0.001	(-0.03)
IRR	0.038	(1.73)	0.036	(1.60)
ROAA	-0.353**	(-3.59)	-0.323*	(-2.60)
CADQ	-0.005	(-0.08)	-0.015	(-0.25)
MKT_SHARE_LAA	-0.148**	(-3.50)	-0.130**	(-3.11)
ECONGR	0.159	(0.60)	0.196	(0.68)
CPI	0.015	(0.31)	0.013	(0.27)
PTEBC			3.017**	(3.66)
_cons	-4.067	(-0.97)	-4.740	(-1.16)
Year dummies	Yes		Yes	
Observations	153		153	
R-squared	0.346		0.344	
Within R-squared	0.346		0.344	

Notes: Variables are winsorized at 1st and 99th percentiles.
Time dummies are included but not shown for brevity. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Author's Calculation from annual reports (2014–2022)

Certain other financial determinants like liquidity risk (LQR), interest rate risk (IRR), capital adequacy (CADQ), economic growth (ECONGR), and inflation (CPI) emerge statistically insignificant.

Table 4.3.5 presents the regression results of the technical efficiency in driving liquidity risk. The findings suggest strong positive relationship between efficiency and liquidity risk since both OTEBC ($\beta = 21.321$, $p < 0.01$ in Model 1) and PTEBC ($\beta = 15.794$, $p < 0.05$ in Model 2) have statistically significant results.

4.3.4.2 Effect of Technical Efficiency on Liquidity Risk

Table 4.3.5: Effect of Bank Technical Efficiency on Liquidity Risk of Ethiopian Banks

	(1)		(2)	
	Model 3		Model 4	
OTEBC	21.321***	(4.17)		
CRR	-0.126	(-0.21)	-0.016	(-0.03)
IRR	0.432***	(4.52)	0.460**	(3.94)
ROAA	-0.835	(-1.43)	-0.527	(-1.11)
CADQ	-0.056	(-0.22)	-0.097	(-0.41)
MKT_SHARE_LAA	0.495**	(3.65)	0.700***	(7.00)
ECONGR	-2.249***	(-5.74)	-2.234***	(-5.79)
CPI	0.226**	(3.80)	0.239**	(3.82)
PTEBC			15.794**	(3.22)
_cons	16.734	(1.80)	17.016	(1.87)
Year dummies	Yes		Yes	
Observations	153		153	
R-squared	0.928		0.921	
Within R-squared	0.928		0.921	

Notes: Variables are winsorized at 1st and 99th percentiles. Time dummies are included but not shown for brevity.
Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01
Data source: Author's compilation from annual reports (2014–2022)

The results indicate that banks with higher efficiency can incur higher exposure to liquidity risk, possibly as a result of aggressive asset allocation techniques Interest rate risk (IRR) positively affects ($\beta = 0.432$, $p < 0.01$ in Model 1; $\beta = 0.460$, $p < 0.05$ in Model 2) the liquidity risk behavior, reflecting interest rate changes affect liquidity risk.

Additionally, the economic growth (ECONGR) and liquidity risk measures relationship is strongly negative ($\beta = -2.249$, $p < 0.01$ in Model 3; $\beta = -2.234$, $p < 0.01$ in Model 4), suggesting that when the economy is in growth, the liquidity risk measures could be lower.

The market share (LAA) exerts a significant and remarkable effect ($\beta = 0.495$, $p < 0.05$ in Model 3; $\beta = 0.700$, $p < 0.01$ in Model 4), indicating that financial institutions with a larger market share face greater exposure to liquidity risk. In addition, inflation (CPI) shows a positive relationship ($\beta = 0.226$, $p < 0.05$ in Model 3; $\beta = 0.239$, $p < 0.05$ in Model 4), indicating inflationary pressures influence liquidity stability.

4.3.5. Robustness Analysis: Effect of Technical Efficiency on Credit Risk

In an attempt to evaluate the consistency of the relation between efficiency and risk, stringent robustness tests were employed with three model specifications: Fixed Effects (FE), Random Effects (RE), and Pooled Ordinary Least Squares (OLS). These various estimators offer a comparison arena to investigate the extent to which efficiency metrics impact credit risk, considering each bank's individual nature and possible estimation biases. The findings in Table 4.3.6 confirm the results regarding the essential importance of efficiency measures and the need to account for institutional variety.

The Fixed Effects model with time-invariant variables for all financial institutions reveals that the Overall Technical Efficiency (OTEBC) coefficient is statistically significant with an estimate of 3.154 and $p < 0.05$ level of statistical significance in Model 1. The Pure Technical Efficiency (PTEBC) also positively affects it by 3.017, attaining the $p < 0.05$ level of statistical significance in Model 4. These results complement the underlying empirical findings, which reveal that efficiency improvement has a measurable impact on credit risk exposure in Ethiopian commercial banks. The proximity in magnitude of the two-efficiency metrics within the fixed effects specification highlights the influence of institution-specific controls in capturing heterogeneity in credit risk.

The Random Effects model, in which heterogeneity between banks is not assumed to be correlated with the explanatory variables, yields a lower OTEBC coefficient estimate of 2.521 but is still statistically significant at $p < 0.01$ in Model 2. PTEBC has a positive impact of 3.821, also at a significance level of $p < 0.01$ in Model 5. While the direction of these estimates is as anticipated by the Fixed Effects estimates, disagreements between their magnitudes indicate possibilities of biases, particularly as they concern the impact of unobserved heterogeneity on the efficiency-risk relationship.

The Hausman test run earlier preferred fixed effects to random effects, which further confirms the use of FE estimation as preferable. The Pooled OLS model, which does not control for panel-specific heterogeneity, has lower significant levels and weaker coefficients. The OTEBC coefficient is 2.663 in Model 3 and the PTEBC coefficient is 3.803 in Model 6, both at the $p < 0.10$ significance level. Even though these coefficients overall do validate the risk-efficiency relationship, the low statistical precision points towards the possible existence of problems related to omitted variable bias or endogeneity, necessitating the application of panel models for such estimates. Several of the control variables are statistically significant consistently across the robustness tests.

The relationship between credit risk and profitability is consistently negative, particularly in the fixed effects model, which has a coefficient of -0.353 with a significance level of $p < 0.05$. This result indicates that higher profitability may be linked to lower exposure to credit risk due to enhanced financial management practices.

Market share negatively influences credit risk with a coefficient of -0.148 at $p < 0.05$ under the FE specification in Model 1, though significance is lost in RE and OLS specifications. Neither inflation nor economic growth is typically statistically significant across specifications, indicating that credit risk differentials are institution-driven and not macroeconomic-dependent. The results obtained from this robustness test confirm that efficiency scores have a considerable effect on credit risk and fixed effects models generate the most stable and interpretable estimates. Although random effects and pooled OLS estimations have differences, the bias in favor of fixed effects estimation is clearly apparent given the existence of heterogeneity in exposure to credit risk institutions.

The robustness checks are a methodological confirmation of the principal findings, thereby establishing the efficiency-risk relationship's reliability in the Ethiopian banking industry.

Table 4.3.6: Robustness Check of Technical Efficiency Effects on Credit Risk in Ethiopian Banks

	(Model 1) FE	(Model 2) RE	(Model 3) OLS	(Model 4) FE	(Model 5) RE	(Model 6) OLS
OTEBC	3.154**	2.521***	2.663*			
	(3.91)	(0.58)	(1.68)			
Liquidity risk	-0.010	-0.057	-0.052	-0.001	-0.044	-0.039
	(-0.21)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)
Interest Rate risk	0.038	0.041	0.030*	0.036	0.034	0.025
	(1.73)	(0.02)	(0.02)	(1.60)	(0.02)	(0.01)
Profitability	-0.353**	-0.405***	-0.409*	-0.323*	-0.395***	-0.392**
	(-3.59)	(0.09)	(0.17)	(-2.60)	(0.10)	(0.14)
Capital Adequacy	-0.005	-0.032	-0.035	-0.015	-0.044	-0.046
	(-0.08)	(0.04)	(0.04)	(-0.25)	(0.04)	(0.04)
Market share	-0.148**	-0.030	-0.022	-0.130**	-0.039*	-0.032
	(-3.50)	(0.02)	(0.02)	(3.11)	(0.02)	(0.02)
Economic Growth	0.159	-0.024	-0.034	0.196	0.037	0.026
	(0.60)	(0.19)	(0.16)	(0.68)	(0.21)	(0.17)
Inflation	0.015	0.025	0.023	0.013	0.019	0.018
	(0.31)	(0.05)	(0.05)	(0.27)	(0.05)	(0.05)
PTEBC				3.017**	3.821***	3.803*
				(3.66)	(0.76)	(1.53)
Constant	-4.067	-0.063	0.486	-4.740	-1.746	-1.174
	(-0.97)	(2.82)	(2.18)	(-1.16)	(3.17)	(2.41)
Year dummies	Yes	Yes		Yes	Yes	
Observations	153	153	153	153	153	153
R-squared	0.346		0.274	0.344		0.315
Within R-squared	0.346	0.259		0.344	0.288	
Between R-squared		0.330			0.424	
Overall R-squared		0.267			0.310	

Notes: Variables are winsorized at 1st and 99th percentiles. FE = Fixed effect model, RE = Random Effect model, POLS = Pooled Ordinary Least Square, Time dummies are included but not shown for brevity. Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Source: Author's compilation from annual reports (2014-2022).

4.3.6. Robustness Analysis: Effect of Technical Efficiency on Liquidity Risk

To provide assurance for the reliability of the efficiency-liquidity risk relationship, robustness tests were conducted with three estimators: Fixed Effects (FE), Random Effects (RE), and Pooled Ordinary Least Squares (OLS). These estimators provide support for a comparison analysis that deals with institutional heterogeneity, biases, and omitted variable issues. The findings in Table 4.3.7 in appendix demonstrate the importance of efficiency controls combined with further evidence on how liquidity risk is influenced in Ethiopian commercial banks.

The Fixed Effects model, that removes time-invariant differences between banks, yields a very significant coefficient for OTEBC as 21.321 with $p < 0.01$ in Model 1. PTEBC also generates a statistically significant coefficient of 15.794 at $p < 0.05$ in Model 4, further confirming the previous results that efficiency gains are correlated with greater exposure to liquidity risk.

The estimations show that more efficient banks can take on more risky liquidity management policies and thereby expose themselves to higher liquidity volatility. The Random Effects model, which is under the assumption that the variation across individual banks is not correlated with independent variables, yields a more extreme efficiency coefficient. For Model 2, OTEBC is estimated at 37.550 with $p < 0.01$ significance level, whereas Model 5 has PTEBC's coefficient at 20.084 with $p < 0.01$. These effects' magnitudes are larger than those under the Fixed Effects model, which implies that potential estimation errors may still persist even if there were guaranteed control for unobserved institutional characteristics. The fact that there are different coefficients calls for the necessity to use fixed effects models as a means of more effectively dealing with variability in efficiency-associated liquidity risk.

The Pooled OLS model without individual bank control has higher coefficient estimates of the efficiency measures but with lower statistical significance. OTEBC in Model 3 is 40.497 with $p < 0.01$, whereas PTEBC in Model 6 is 19.058 with $p < 0.10$.

Table 4.3.7: Robustness Check of Technical Efficiency Effects on Liquidity Risk in Ethiopian Banks

	(Model 1) FE	(Model 2) RE	(Model 3) OLS	(Model 4) FE	(Model 5) RE	(Model 6) OLS
OTEBC	21.321***	37.550***	40.497***			
	(4.17)	(9.39)	(7.95)			
Credit Risk	-0.126	-1.044	-1.742*	-0.016	-1.187	-1.941
	(-0.21)	(0.83)	(0.78)	(-0.03)	(1.16)	(1.41)
Interest Rate risk	0.432***	0.417***	0.259**	0.460**	0.516***	0.323**
	(4.52)	(0.10)	(0.09)	(3.94)	(0.12)	(0.10)
Profitability	-0.835	-1.183	-1.699*	-0.527	-0.305	-0.412
	(-1.43)	(0.77)	(0.76)	(-1.11)	(0.49)	(0.86)
Capital Adequacy	-0.056	-0.216	-0.817***	-0.097	-0.213	-0.875***
	(-0.22)	(0.25)	(0.15)	(-0.41)	(0.21)	(0.16)
Market share	0.495**	-0.174	-0.521***	0.700***	-0.091	-0.645***
	(3.65)	(0.11)	(0.05)	(7.00)	(0.10)	(0.09)
Economic Growth	-2.249***	-1.966***	-1.871	-2.234***	-2.057***	-2.204
	(-5.74)	(0.47)	(1.07)	(-5.79)	(0.62)	(1.44)
Inflation	0.226**	0.203***	0.222	0.239**	0.240***	0.262
	(3.80)	(0.06)	(0.17)	(3.82)	(0.06)	(0.24)
PTEBC				15.794**	20.084***	19.058*
				(3.22)	(5.48)	(8.68)
Constant	16.734	9.599	30.543	17.016	13.981	44.053*
	(1.80)	(12.93)	(16.47)	(1.87)	(15.62)	(20.06)
Year dummies	Yes	Yes		Yes	Yes	
Observations	153	153	153	153	153	153
R-squared	0.928		0.820	0.921		0.749
Within R-squared	0.928	0.905		0.921	0.876	
Between R-squared		0.304			0.041	
Overall R-squared		0.693			0.444	

Notes: Variables are winsorized at 1st and 99th percentiles. FE = Fixed effect model, RE = Random Effect model, POLS = Pooled Ordinary Least Square, Time dummies are included but not shown for brevity. Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01

Data source: Author's compilation from annual reports (2014-2022).

While these results do point towards FE and RE models, the large coefficients suggest potential omitted variable bias or not accounting for institutional heterogeneity, further in favor of using panel estimators. Other than efficiency scores, certain control variables continue to be statistically significant across a set of robustness tests. The interest rate risk is found to positively relate strongly with liquidity risk, with the coefficients consistently remaining significantly close in all the models estimated, thereby underlining the influence of monetary policy regimes on liquidity vulnerability. Besides, economic growth has a negative and highly significant impact, with the coefficients ranging from -2.249 to -2.234, both at $p < 0.01$, thereby corroborating that liquidity risk declines in economic boom periods.

The results concerning market share are conflicting, with positive outcomes for fixed effects models ($\beta = 0.499$, $p < 0.05$ in Model 1; $\beta = 0.706$, $p < 0.01$ in Model 4), and negative outcomes in ordinary least squares estimates ($\beta = -0.521$, $p < 0.01$ in Model 3; $\beta = -0.645$, $p < 0.01$ in Model 6). The disparity may be explained by competitive pressures influencing liquidity management strategies.

Inflation has a statistically significant positive coefficient in both the FE and RE models, indicating that inflationary pressures do impact liquidity stability.

The robustness tests are exhaustive in their confirmation that efficiency measures statistically impact liquidity risk. The stability of the findings across various specifications corroborates the main empirical results but maintains the strengths of Fixed Effects models because of their capability to deal with institutional heterogeneity. The robustness checks confirm the relationship between efficiency and liquidity risk while making sure the findings are methodologically intact.

After checking the robustness of results under alternative model specifications, the second half of the analysis will be devoted to making a rigorous investigation of the efficiency-risk relation specifically for private banks. By excluding the sole public commercial bank from the analysis, the subsequent investigation illuminates more precisely the effect efficiency has on liquidity risk and credit risk in the private banking sector of Ethiopia. In order to validate the stability of regression estimates, we performed a variance inflation factor (VIF) test to determine the existence of multicollinearity between independent variables. The results presented in Table A4.3.5 are used as a diagnostic tool in measuring the interdependence of variables under the models that examine the relationship between efficiency and risk in Ethiopian private commercial banks. The results indicate that for Model 1, which estimates credit risk as a determinant of overall technical efficiency

(OTEBC) along with other financial indicators, the mean variance inflation factor (VIF) is computed to be 3.00.

For Model 2, in which liquidity risk is specified as pure technical efficiency (PTEBC) and finance variables, the average VIF is 2.48, suggesting comparatively lower collinearity risk to coefficient stability. CPI (4.65) and economic growth (3.02) continue to have high VIF values, while PTEBC itself has a more tolerable level of collinearity at 2.09.

CPI (3.54), economic growth (2.96), and operating efficiency (2.95) continue to exhibit moderate degrees of correlation with other predictors, though none reaching critical multicollinearity thresholds. The comparatively lower VIF values for Model 4 show greater stability in PTEBC-based liquidity risk estimates compared to credit risk models. In general, while no variables exceed the conventional threshold of VIF > 10, the comparatively high collinearity of liquidity risk (LQR) in credit risk estimating models shows potential interaction effects that should perhaps be considered.

The results confirm that efficiency-driven risk exposure in Ethiopian private commercial banks is institution-specific rather than macroeconomically driven. These multicollinearity diagnostics will inform interpretation of efficiency-risk relations in the subsequent empirical sections.

4.3.7. Effect of Technical Efficiency on Credit and Liquidity Risk Exposure in Private Commercial Banks

1. Model Selection Criteria: Hausman and Breusch-Pagan LM Tests

With a view to maintaining methodological adequacy in the efficiency-risk estimates of Ethiopian private banking, two significant model choice tests were estimated: the Hausman test and the Breusch-Pagan Lagrange Multiplier (LM) test. While the Hausman test is employed to detect the appropriateness of Fixed Effects (FE) relative to Random Effects (RE) estimators, the Breusch-Pagan LM test examines the appropriateness of RE relative to Pooled Ordinary Least Squares (POLS).

2. Empirical Selection of Credit Risk (CRR) Models

Following the approach outlined by Baltagi (2021), the Hausman test was first conducted to determine whether Fixed Effects or Random Effects were appropriate. Given the chi-squared value of 3.93 and a p-value of 0.9959, the test supported the use of Random Effects, leading to the application of the Breusch-Pagan LM test to assess whether RE was preferable to Pooled OLS (Greene, 2019). The LM test gave the chi-squared statistic as 1.95 and p-value as 0.0811, suggesting that POLS is better than RE because the individual bank effects are not significant.

Conversely, the alternative credit risk model utilizing PTEBC as its metric of efficiency exhibited a Hausman test chi-squared statistic of 4.56, paired with a p-value of 0.9910, thereby reinforcing the preference for Random Effects (RE) over Fixed Effects (FE). Furthermore, the subsequent Breusch-Pagan LM test revealed a chi-squared statistic of 2.74 along with a p-value of 0.0489, corroborating the application of RE in place of Pooled Ordinary Least Squares (POLS) for this particular model. The analysis demonstrates that while the primary credit risk specification is accurately estimated using the POLS model, its follow-up model requires RE estimation.

3. Empirical Selection of Liquidity Risk (LQR) Models

In the initial liquidity risk model, in which the efficiency measure is OTEBC, the Hausman test was unable to satisfy asymptotic assumptions because it had a chi-squared statistic of -6.33 due to an unstable imbalance in the variance-covariance matrix. Due to this complexity, we conducted the Breusch-Pagan LM test to test for the appropriateness of the use of RE over POLS, and it gave a chi-squared statistic of 82.40 with a p-value of 0.0000 and thus affirmed that the appropriate model is RE.

Moreover, in the second liquidity risk model with PTEBC as the efficiency metric, the Hausman test yielded a chi-squared statistic of 1.91 with a p-value of 0.9999 and also in favor of RE against FE. The subsequent Breusch-Pagan LM test then confirmed that the RE must be employed and provided a highly significant chi-squared statistic of 82.40 with a p-value of 0.0000. These findings suggest that RE estimation is favored for both liquidity risk models, such that bank-specific effects are dealt with suitably.

4.3.7.1. Empirical Findings on the Efficiency-Risk Relationship in Private Banks in Ethiopia

This sub-section discusses the regression estimates exploring the nexus between financial risk and technical efficiency in the Ethiopian private banking sector. Table 4.3.8 and Table 4.3.9 display the results showing the relation between risk and efficiency under varying specifications.

Table 4.3.8 presents the estimation results on the effect of efficiency metrics on credit risk in Ethiopian private banks using two distinct models. In Model 1 (estimated via Pooled OLS), overall technical efficiency (OTEBC) has a positive coefficient of 3.252 (standard error = 1.67). Although this coefficient does not achieve conventional significance levels, its positive direction is noteworthy. In the context of our robustness check—where we focus on private banks only—this result suggests that even within this more homogeneous group, there is an indication (albeit not statistically robust) that higher overall operational efficiency might be associated with higher credit risk. This directionality is consistent with our main analysis using the full sample, implying that the efficiency-risk trade-off may not solely be driven by the presence of the giant public bank (CBE).

Model 2 employs a Random Effects specification to assess the impact of pure technical efficiency (PTEBC) on credit risk. Here, the estimated coefficient for PTEBC is 3.196, statistically significant at the 1% level ($p < 0.01$). This robust result indicates that improvements in managerial efficiency are clearly linked with increased credit risk among private banks. The implication is that banks, in their pursuit of optimizing internal processes, might simultaneously opt for riskier lending practices or operate with thinner credit buffers, thereby exposing themselves to higher levels of credit risk.

Across both models, various control variables—such as liquidity risk, interest rate risk, profitability, capital adequacy, market share, economic growth, and inflation—are included to isolate the efficiency–risk relationship.

Table 4.3.8: Estimation Results on the Effect of Efficiency Metrics on Credit Risk in Ethiopian Private Banks

	(Model 1) POLS_OTE_CRR	(Model 2) RE_PTE_CRR
OTEBC	3.252	
	(1.67)	
Liquidity risk	0.022	0.027
	(0.01)	(0.03)
Interest Rate risk	0.004	0.006
	(0.01)	(0.01)
Profitability	-0.365*	-0.381***
	(0.15)	(0.08)
Capital Adequacy	-0.020	-0.009
	(0.02)	(0.02)
Market share	-0.081**	-0.081
	(0.03)	(0.05)
Economic Growth	0.003	0.007
	(0.16)	(0.18)
Inflation	-0.039	-0.040
	(0.03)	(0.02)
PTEBC		3.196***
		(0.64)
Constant	-1.459	-2.015
	(2.26)	(3.13)
Year dummies	Yes	Yes
Observations	144	144
R-squared	0.353	
Within R-squared		0.344
Between R-squared		0.451
Overall R-squared		0.365

Notes: Variables are winsorized at 1st and 99th percentiles. Model 1 = Estimate effect of OTEBC on Credit risk using POLS (Pooled OLS), Model 2 = Estimate effect of PTE on CRR using Random effect (RE) model; Time dummies are included but not shown for brevity.
Standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Source: Author's compilation from annual reports (2014-2022).

Although liquidity risk and interest rate risk show a positive association, these effects are not statistically significant. Profitability consistently presents a negative influence on credit risk (with coefficients of -0.365 and -0.381 in Models 1 and 2, respectively), signifying that more profitable banks tend to mitigate their credit risk. Market share also contributes a negative effect in Model 1, reinforcing the notion that stronger market positioning can provide a cushion against risk exposure.

The overall explanatory power, as indicated by R-squared values of approximately 35%, suggests that while the models capture a meaningful portion of the variance in credit risk, other unobserved factors may also play a role. Importantly, these results obtained from the private banks' sample contribute to the robustness of our main findings. They confirm that the efficiency–risk trade-off, particularly the significant relationship between managerial efficiency (PTEBC) and credit risk, holds even when the influential public bank is excluded from the analysis.

In general, while the effect of OTEBC in Model 1 is suggestive but not definitive, the strong and significant impact of PTEBC in Model 2 provides compelling evidence of an efficiency–risk trade-off among private banks. This robustness check reinforces our broader analysis that efficiency gains—especially those stemming from improved managerial practices—may come at the cost of increased credit risk, a pattern that warrants further investigation and careful risk management strategies within the sector.

Table 4.3.9 reports the estimation results for the impact of efficiency on liquidity risk among private banks, where two specifications are presented. In Model (1), overall technical efficiency (OTEBC) is used as the primary efficiency metric, and its coefficient is estimated at 21.244 (SE = 6.68), statistically significant at the 5% level. This result suggests that, within the private banking sector, an increase in overall operational efficiency is associated with a higher level of liquidity risk. In Model (2), pure technical efficiency (PTEBC), which isolates managerial performance from scale effects, replaces OTEBC and yields a coefficient of 13.474 (SE = 6.16), significant at the 10% level. While both models indicate a positive relationship between efficiency and liquidity risk, the slightly lower magnitude and marginal significance in Model (2) hint at nuanced differences between overall and pure efficiency in their influence on risk-taking behavior.

In both specifications, the control variable for interest rate risk is strongly and positively associated with liquidity risk (coefficients of 0.398 and 0.425 in Models 1 and 2, respectively, with significance levels ranging from 1% to 5%), implying that banks exposed to higher interest rate fluctuations tend to carry elevated liquidity risk. Economic growth consistently exerts a robust negative effect (with coefficients of approximately -

2.06 and -2.23), suggesting that stronger macroeconomic performance helps mitigate liquidity pressures.

Table 4.3.9: Estimation Results on the Effect of Efficiency Metrics on Liquidity Risk in Ethiopian Private Banks

	(Model 1) RE_OTE_LQR	(Model 2) RE_PTE_LQR
OTEBC	21.244**	
	(6.68)	
Credit Risk	0.464	0.598
	(0.77)	(0.83)
Interest Rate risk	0.398***	0.425**
	(0.12)	(0.13)
Profitability	-0.529	-0.220
	(0.79)	(0.68)
Capital Adequacy	-0.252	-0.241
	(0.22)	(0.21)
Market share	0.353	0.357
	(0.28)	(0.29)
Economic Growth	-2.057***	-2.231***
	(0.45)	(0.47)
Inflation	0.273***	0.293***
	(0.08)	(0.08)
PTEBC		13.474*
		(6.16)
Constant	22.009	26.425*
	(12.56)	(12.77)
Year dummies	Yes	Yes
Observations	144	144
R-squared		
Within R-squared	0.933	0.925
Between R-squared	0.382	0.368
Overall R-squared	0.852	0.843

Notes: Variables are winsorized at 1st and 99th percentiles. Time dummies are included but not shown for brevity.
Standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$
Data source: Author's compilation from annual reports (2014-2022).

Additionally, inflation shows a small but statistically significant positive impact on liquidity risk, while credit risk, profitability, capital adequacy, and market share do not present statistically significant effects. The overall high within-R-squared values (over

0.92) demonstrate that these models capture a substantial portion of the time-variant variation in liquidity risk across private banks.

Together, these results reinforce the broader narrative that improvements in efficiency, particularly in managerial effectiveness and overall operations, are linked with higher liquidity risk in the private banking sector. This finding, consistent with the efficiency–risk trade-off observed in our main analysis that includes both public and private banks, suggests that pursuing efficiency gains may come with increased vulnerability to liquidity constraints—a dynamic that warrants careful policy attention and further econometric exploration.

Control variables are significant in the liquidity risk exposure measurement. Interest rate risk (IRR) is positively statistically significant with both analytical models with coefficients 0.398 ($p < 0.01$) and 0.425 ($p < 0.05$) for Models 1 and 2, respectively, which means interest rate changes are the reasons behind the liquidity instabilities. Economic growth (ECONGR) is consistently negatively correlated with liquidity risk, represented by the coefficients -2.057 ($p < 0.01$) in Model 1 and -2.231 ($p < 0.01$) in Model 2, showing that liquidity risk is reduced with economic growth. The Consumer Price Index (CPI) is highly correlated with liquidity risk, as indicated by coefficients of 0.273 ($p < 0.01$) in Model 1 and 0.293 ($p < 0.01$) in Model 2, indicating that inflationary pressures are influencing liquidity movement.

The overall R-squared values of the liquidity risk models, standing at 0.852 and 0.843, respectively, demonstrate substantial explanatory power, thus confirming the strong level of correlation between efficiency and risk.

In the next section, we talk about the efficiency-risk relationship of large and small private commercial banks in Ethiopia.

4.3.7.2. Assessing the Relationship Between Efficiency and Bank Size in Private Banking Institutions

This sub section presents the empirical results according to the efficiency-risk estimates undertaken within Ethiopian private banks, separating smaller and medium-sized banking institutions. Estimation adheres to standard model selection conventions, with Pooled Ordinary Least Squares (POLS) applied to OTEBC in credit risk models and Random Effects (RE) applied in the PTEBC models in both credit and liquidity risk assessments.

The findings are presented in two subsections: first, Efficiency and Credit Risk, which discusses the impact of efficiency levels on credit default risk exposure in private banks of varying sizes. This is followed by Efficiency and Liquidity Risk, which discusses the impact of efficiency on liquidity buffers and stability in small and medium-sized banks.

1. Empirical Estimation of Credit Risk Models for Private Banks: Efficiency and Size Dynamics

In analyzing the determinants of credit risk among Ethiopian private banks, the study focuses on the interplay between bank efficiency and size by incorporating interaction effects into our estimation strategy. Table 4.3.10 presents the regression results from two model specifications designed to explore how technical efficiency and bank size jointly influence credit risk.

In Model 1, estimated using pooled ordinary least squares (POLS) with Overall Technical Efficiency (OTEBC) as the efficiency measure, the direct coefficient on OTEBC is 1.740 (SE = 1.32), indicating that an increase in overall efficiency is associated with a rise in credit risk, albeit with marginal precision. The coefficient on bank size (b_size) is -2.304 (SE = 1.27), suggesting that larger banks may benefit from size effects that help mitigate credit risk. However, this mitigating effect is countered by the significant positive interaction term (OTEBC_bsize) of 2.835 (SE = 1.70), which implies that the reduction in credit risk attributable to increasing size is weakened when banks operate at higher efficiency levels. This interaction indicates a complex dynamic where efficiency improvements in larger banks could eventually contribute to increased risk exposure.

Table 4.3.10: The Interaction Between Bank Size and Efficiency in Credit Risk Estimation for Ethiopian Private Banks

	(Model 1) POLS_OTE_CRR	(Model 2) RE_PTE_CRR
OTEBC	1.740	
	(1.32)	
b_size	-2.304	-1.644
	(1.27)	(1.25)
OTEBC_bsize	2.835	
	(1.70)	
Liquidity risk	0.028	0.030
	(0.01)	(0.03)
Interest Rate risk	0.001	0.005
	(0.01)	(0.01)
Profitability	-0.321^{*}	-0.360^{***}
	(0.14)	(0.08)
Capital Adequacy	-0.011	-0.002
	(0.02)	(0.03)
Market share	-0.110^{*}	-0.121
	(0.05)	(0.07)
Economic Growth	-0.024	-0.013
	(0.15)	(0.16)
Inflation	-0.041	-0.041
	(0.03)	(0.02)
PTEBC		2.183^{*}
		(0.92)
PTEBC_bsize		2.124
		(1.71)
Constant	-0.224	-1.144
	(2.02)	(2.50)
Year dummies	Yes	Yes
Observations	144	144
R-squared	0.377	
Within R-squared		0.352
Between R-squared		0.521
Overall R-squared		0.385

Notes: Variables are winsorized at 1st and 99th percentiles. Time dummies are included but not shown for brevity.
Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01
Data source: Author's compilation from annual reports (2014-2022).

Model 2, estimated with a random effects specification and using Pure Technical Efficiency (PTEBC) as the efficiency metric, reinforces several of the insights from Model

1. In this specification, bank size retains its negative relationship with credit risk (-1.644 with SE = 1.25), while PTEBC itself is positively associated with credit risk, displaying a coefficient of 2.183 (SE = 0.92) and statistical significance at conventional levels. Although an interaction term between PTEBC and bank size (PTEBC_bsize) is included in this model, its coefficient (2.124 with SE = 1.71) does not reach conventional levels of significance, implying that the moderating effect of bank size on the efficiency-risk nexus may be less pronounced when efficiency is disaggregated into its pure technical component.

Control variables further paint a nuanced picture of risk determinants. For instance, liquidity risk coefficients (0.028 in Model 1 and 0.030 in Model 2) and interest rate risk coefficients (0.001 in Model 1 and 0.005 in Model 2) contribute modestly to the explanation of credit risk variance. Of notable importance is the role of profitability, which is negatively associated with credit risk in both models (coefficients of -0.321 and -0.360 in Models 1 and 2 respectively), indicating that banks with stronger profitability tend to experience lower credit risk—a finding consistent with risk management theory. Additional control variables, including capital adequacy, market share, economic growth, and inflation, are incorporated to account for broader economic and institutional effects, with market share also demonstrating a stabilizing, risk-reducing influence.

The models explain a moderate fraction of the variation in credit risk, with an R-squared of 0.377 reported for Model 1 and an overall R-squared of 0.385 (along with a within R-squared of 0.352 and between R-squared of 0.521) for Model 2. These results highlight the importance of considering interaction effects between bank size and efficiency when evaluating credit risk. The evidence suggests that, while efficiency gains typically enhance operational performance, they may simultaneously elevate credit risk—especially in larger banks—if not coupled with robust risk management practices.

Overall, these findings underscore a nuanced relationship where the beneficial effects of bank size in mitigating credit risk may be offset by high efficiency levels. This complex interplay offers valuable insights for bank managers and policymakers who must balance efficiency improvements with prudent credit risk management, thereby contributing to the overall financial stability of the banking sector in Ethiopia.

2. Empirical Estimation of Liquidity Risk Models for Private Banks: Efficiency and Size Dynamics

Table 4.3.11: The Interaction Between Bank Size and Efficiency in Liquidity Risk Estimation for Ethiopian Private Banks

	(Model 1) RE_OTE_LQR	(Model 2) RE_PTE_LQR
OTEBC	23.797**	
	(7.71)	
b_size	7.984	8.256
	(7.31)	(6.55)
OTEBC_bsize	-7.158	
	(6.75)	
Credit Risk	0.488	0.579
	(0.74)	(0.83)
Interest Rate risk	0.406***	0.443***
	(0.10)	(0.12)
Profitability	-0.579	-0.234
	(0.80)	(0.67)
Capital Adequacy	-0.208	-0.188
	(0.22)	(0.20)
Market share	0.324	0.243
	(0.32)	(0.39)
Economic Growth	-2.035***	-2.229***
	(0.46)	(0.49)
Inflation	0.277***	0.298***
	(0.07)	(0.08)
PTEBC		16.160**
		(6.14)
PTEBC_bsize		-6.559
		(5.68)
Constant	17.886	21.424*
	(10.13)	(9.14)
Year dummies	Yes	Yes
Observations	144	144
Within R-squared	0.934	0.927
Between R-squared	0.439	0.426
Overall R-squared	0.859	0.850

Notes: Variables are winsorized at 1st and 99th percentiles. Time dummies are included but not shown for brevity.
Standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Data source: Author's compilation from annual reports (2014-2022).

The findings of regression analysis for liquidity risk models continue to reflect the influence of efficiency enhancement on liquidity stability, highlighting the differences between medium-sized and small private banks.

The analysis of liquidity risk in Ethiopian private banks is enhanced by empirical evidence on technical efficiency and size interaction and its impact on risk exposure. The two model specifications are reported in Table 4.3.11. In Model 1 (RE_OTE_LQR), Overall Technical Efficiency (OTEBC) is significant and positively related to liquidity risk: a one-unit change in OTEBC raises liquidity risk by 23.797 units (SE = 7.71, $p < 0.05$). This result implies that banks that are more total efficiency may be more liquidity risk, possibly a result of overzealous operating policies that deplete liquidity buffers. The bank size variable (b_size) in Model 1 with a coefficient of 7.984 (SE = 7.31), on the other hand, does not achieve statistical significance, implying that in isolation, size does not adequately account for variance in liquidity risk over the sample period. Though the interaction term (OTEBC_bsize) is negative (-7.158, SE = 6.75), nonsignificance suggests that evidence is not adequate to enable the inference that bank size moderating effect on the efficiency-liquidity risk link is nonzero.

Model 2 (RE_PTE_LQR), with Pure Technical Efficiency (PTEBC) substituting for OTEBC, casts more light. Here, the coefficient of PTEBC is 16.160 (SE = 6.14, $p < 0.05$), once more supporting that higher technical efficiency is associated with higher liquidity risk. The similar interaction term between PTEBC and bank size (PTEBC_bsize) is -6.559 (SE = 5.68) but, as with Model 1, is not statistically significant. These results indicate that although a change in efficiency is linked with rising liquidity risk, the evidence is not strong that this relationship is always being moderated by bank size.

Several control variables have been included to make a distinction between the impact of size and efficiency. Not surprisingly, Interest Rate Risk is a fine predictor of liquidity risk with coefficients of 0.406 (SE = 0.10, Model 1) and 0.443 (SE = 0.12, Model 2), both highly significant at the 1% level. Economic Growth has a very large and inverse relationship (coefficients of -2.035 and -2.229 for Models 1 and 2, respectively, both $p < 0.01$), which implies that good economic conditions have a tendency to enhance liquidity risk. Likewise, Inflation is also positively correlated with liquidity risk (0.277 and 0.298 in Models 1 and 2, respectively), which is also statistically significant at the 1% level. To the contrary, other control variables such as Credit Risk, Profitability, Capital Adequacy, and Market Share yield statistically insignificant coefficients; albeit their estimated signs tend to be in line with theoretical predictions, lack of significance warns against inferring their independent effect.

The models fit well, according to the extremely high within R-squared statistics (0.934 for Model 1 and 0.927 for Model 2) and overall R-squared statistics of 0.859 and 0.850, respectively, indicating that the specifications explain a very high percentage of the liquidity risk variation. The addition of winsorized variables (at the 1st and 99th percentiles) and time dummies (not included here for conciseness) also adds strength to the reliability of these estimates. Overall, the findings indicate that although technical efficiency is an important determinant of liquidity risk, the moderating effect of bank size is still inconclusive. These observations point towards the necessity to follow a balanced approach in bank management policies, wherein attempts at efficiency of operation must be followed cautiously against the risk of increases in liquidity risk.

4.3.8. Hypotheses Testing and Results

This section presents the empirical testing of Hypotheses H8 and H9, which examine the impact of bank technical efficiency on risk behaviors—specifically credit risk (CRR) and liquidity risk (LQR). The models utilize two measures of technical efficiency, overall technical efficiency (OTEBC) and pure technical efficiency (PTEBC), as key explanatory variables. The estimation is conducted using Difference GMM on panel data spanning 2014–2022 with several control variables included to account for alternative influences on bank risk.

H8: Technical Efficiency and Credit Risk

Hypothesis H8 posits a positive relationship between technical efficiency and credit risk in Ethiopian commercial banks. Table 4.3.4 summarizes the results for this test. In Model 1, where OTEBC is the primary measure of technical efficiency, the coefficient on OTEBC is 3.154 ($t = 3.91$, significant at the 5% level). Model 2, which employs PTEBC instead, yields a coefficient of 3.017 ($t = 3.66$, significant at the 5% level). These significant positive coefficients suggest that banks with higher technical efficiency scores tend to exhibit higher levels of credit risk. Notably, this relationship persists even after controlling for other pertinent variables such as liquidity risk, interest rate risk (IRR), profitability (ROAA), capital adequacy (CADQ), and market share. The findings thereby provide robust evidence in support of H8, indicating that efficient banks may engage in more aggressive lending practices that increase their credit risk exposure.

H9: Technical Efficiency and Liquidity Risk

Hypothesis H9 posits a positive relationship between technical efficiency and liquidity risk. As presented in Table 4.3.5, the estimated coefficient for OTEBC in Model 3 is 21.321 ($t = 4.17$, significant at the 1% level), while Model 4—where PTEBC is used—reports a coefficient of 15.794 ($t = 3.22$, significant at the 5% level). These robust positive coefficients indicate that higher technical efficiency is associated with increased liquidity risk. In both models, other control variables (most notably IRR, which shows consistent statistical significance) are included; however, the focus here remains on the strong relationship between efficiency and liquidity risk. The results suggest that banks operating with greater efficiency might pursue aggressive asset allocation strategies that inadvertently increase their exposure to liquidity risk, thereby confirming H9.

4.4. Summary of the Main Findings

The empirical analysis reveals several notable insights into bank efficiency within the Ethiopian context. First, when comparing public and private banks, public banks are characterized by significantly lower overall technical efficiency relative to their private counterparts. However, when efficiency is measured in terms of pure technical efficiency—representing managerial competence independent of scale—public banks perform strongly. This contrast suggests that inefficiencies in public banks largely stem from scale or operational challenges rather than deficiencies in management per se.

Within the private banking sector, the expected efficiency advantage of larger banks did not materialize. Empirical tests found no statistically significant differences between large and small private banks—where size is determined by the National Bank of Ethiopia's 2% asset share threshold. This finding implies that, in the private domain, factors other than mere size are more influential in driving efficiency outcomes, thereby suggesting that the benefits of scale may be offset by issues such as increased managerial complexity.

The study further uncovers a significant relationship between risk measures and technical efficiency. Specifically, a positive association is evident between technical efficiency and both credit risk and liquidity risk. Banks demonstrating higher overall and pure technical efficiency tend to engage in practices that lead to elevated credit risk, likely due to more aggressive lending strategies. Similarly, these banks exhibit increased liquidity risk, a reflection of their pursuit of more dynamic asset allocation strategies that, while enhancing performance, simultaneously raise exposure to potential liquidity shortfalls.

In addition, the analysis shows that profitability, as measured by return on average assets (ROAA), is robustly and positively linked to technical efficiency. This finding underscores the notion that effective resource utilization bolsters overall financial performance. Conversely, the capital adequacy ratio does not exert a statistically significant effect on technical efficiency; this result suggests that simply maintaining a stronger capital base is insufficient to guarantee improved operational performance, thus highlighting the role of managerial and structural factors.

Finally, the collective findings point to an inherent efficiency–risk trade-off. While high technical efficiency appears to be beneficial for operational performance and profitability, it is concomitantly associated with heightened levels of both credit and liquidity risks. This interplay indicates that banks may leverage their efficient operations to assume riskier portfolios, a dynamic that could have implications for overall financial stability.

These findings lay a solid groundwork for the ensuing discussion in Chapter 5, where the broader implications for bank management and regulatory policy will be critically examined. The insights provided not only highlight the challenges inherent in balancing efficiency with prudent risk management but also inform the recommendations for both banks and policymakers aimed at optimizing operational performance while mitigating undesirable risk exposures.

CHAPTER 5: DISCUSSION, IMPLICATIONS, AND RECOMMENDATIONS

5.1. Overview

This chapter summarizes key findings and discusses their wider implications for the Ethiopian banking industry and academic literature. The study elaborately described data analysis and provided empirical evidence testing nine hypotheses (H1–H9) in chapter 4. In this chapter, the study revisits these hypotheses by summarizing the findings and discussing their theoretical and practical implications.

To begin with, H1 and H2 examined the distinction between efficiency concerning the size and ownership of banks. As an example, the results highlight that public bank, while showing high pure technical efficiency, exhibit poor overall technical efficiency and scale efficiency compared to private banks. This divergence indicates that external constraints as well as complexity of operations, and not merely managerial inefficiencies, account for the reduced overall performance of public banks. Meanwhile, analysis of the effect of size, partially reflected in H7, suggests that banks of exceptional sizes, like the largest public bank, tend to face scale diseconomies that detract from their operating efficiency. Such issues complicate the traditional debate surrounding poor management and instead identify structural and regulatory issues as important forces driving the efficiency disparities.

Hypotheses H3 to H9 then test the relationship of technical efficiency with the other performance measures. The analysis testing H3 and H8 reveals a noteworthy positive relation between technical efficiency and credit risk, indicating that banks exhibiting greater efficiency may partake in more risky lending behaviors, which likely signifies a tendency towards a skimping strategy regarding risk management. Similarly, the results related to H4 and H9 also show that higher efficiency is related to increased liquidity risk, possibly because banks are using more aggressive asset allocation strategies.

Moreover, by employing an alternative causality model, this study employs return on average assets (ROAA) as a cause variable, illustrating that better profitability is linked to greater technical efficiency (H5). The evidence supports the fact that financially sustainable banks possess the requisite resources for investing in process improvement and thus obtain a more efficient process for converting inputs into outputs as captured by our DEA model.

Lastly, the weak connection between the capital adequacy ratio and technical efficiency further indicates that, in the Ethiopian banking environment—characterized by the prevalence of Basel I regulations—capital buffers are most likely to serve as a buffer for financial stability rather than as an immediate stimulus for operational performance (H6).

This chapter is structured to initially synopsize and discuss these findings holistically, putting them into juxtaposition with conventional theories such as the skimping hypothesis and moral hazard, as well as empirical research conducted within both Ethiopian and comparable emerging market environments. Subsequent to this discussion, we present bank management and regulatory policy implications, before concluding with specific recommendations designed to resolve the operational inefficiencies discovered and the efficiency–risk trade-offs found in this dissertation.

5.2. Discussion of Main Findings

5.2.1 Differences in Efficiency According to Ownership and Bank Size

This section examines the differences in technical efficiency vis-a-vis bank ownership and, more specifically within the private sector, based on the size of the banks. The research compares public and private banks to ascertain the degree to which ownership characteristics influence operating performance. Notably, the size-based comparison is conducted exclusively among private banks since the distinct operating environment of public banks calls for individual examination.

The empirical results show that the public bank (CBE) demonstrates a high level of pure technical efficiency, i.e., the organizations possess the ability to efficiently transform inputs into outputs at the managerial level. The public bank, however, is not equally efficient on overall technical efficiency dimension that takes into account scale and organizational structure. This disparity implies that, despite sound management of input and output, inefficiencies related to bureaucratic processes and political control may undermine the overall effectiveness of public banking institution.

These findings challenge Berger & DeYoung's (1997) 'Bad Management' hypothesis, which postulates that inefficiencies in banks primarily stem from poor managerial practices. In the case of the public bank (CBE), high pure technical efficiency underscores the competency of its management. This is evidenced by the bank's deliberate recruitment of university professors with strong academic credentials to serve as management trainees—a strategy that ensures the placement of highly qualified individuals in critical decision-making roles. Furthermore, the CBE's operational environment is heavily influenced by government directives. The bank is often mandated to finance state-owned enterprises (SOEs) without adequate feasibility studies, leading to an accumulation of non-performing loans and resultant debt bailouts (NBE, 2024; World Bank, 2019). These structural and political imperatives suggest that inefficiencies are driven by external pressures rather than by managerial shortcomings. Additionally, the provision of attractive salary packages by the CBE enhances its capability to attract and retain top management talent, thereby further mitigating the influence of poor management on overall performance. Collectively, these factors indicate that the observed operational inefficiencies arise primarily from scale and externally imposed constraints, rather than from deficiencies in managerial competence.

In private banking, the examination of size differences, as defined by the 2% threshold, indicates that the expected advantage from scale—that is, higher efficiency in large banks—was not observed. Specifically, the hypothesis that large private banks would outperform their smaller counterparts in technical efficiency was not supported. Rather, the findings imply that within the private sector, bank size (as measured by asset share) does not significantly influence efficiency outcomes. This result may be explained by the fact that both large and small private banks are subjected to similar competitive pressures, technological advancements, and regulatory frameworks, thereby prompting them to adopt comparable operational practices. Moreover, any potential economies of scale in large private banks appear to be offset by managerial complexities and coordination challenges, resulting in efficiency outcomes that are comparable across different sizes.

The disparities uncovered can be attributed to the attributes under the ownership and the inherent difficulties pertaining to the scaling of operations. Public banks, often constrained by complex goals and significant government intervention, can prioritize social or policy-driven agendas over stringent cost minimization, which in turn curtails aggregate efficiency. On the other hand, private banks, driven chiefly by profit, tend to have more streamlined operations. Nonetheless, as documented in existing literature (e.g., (Asongu & Odhiambo, 2018), there is a tipping point in profit-oriented organizations beyond which additional growth fosters greater managerial complexity and less operational agility.

The implications of these results are of particular importance to banking managers and regulatory agencies alike. For publicly owned banks, there is a compelling necessity for organizational reforms that seek to decrease bureaucratic sluggishness and enhance operating responsiveness. In private banking, the adoption of strategies designed to counteract the adverse consequences of supersize—i.e., decentralization and increased coordination—can enable large institutions to manage operating problems related to their size. Well-crafted regulatory frameworks that take into account ownership differences and size factors would therefore enhance sector performance as a whole.

The findings concerning the efficiency variations caused by ownership and size form a critical foundation for understanding the dominating dynamics within the Ethiopian banking industry. In the subsequent sections, this discussion will be extended through consideration of the interrelationship of technical efficiency and risk measures, thus advancing the understanding of the complex structure of bank performance.

5.2.2 Interplay Between Technical Efficiency and Risk (H3, H4, H8, & H9)

The empirical findings reveal a strong and statistically significant relationship between technical efficiency and risk exposure, as evidenced by the results from hypotheses H3, H4, H8, and H9. Specifically, the positive coefficients in H3 and H4 indicate that both credit risk and liquidity risk are associated with higher efficiency levels, contrary to initial hypotheses that assumed risk would act as a constraint on efficiency. Similarly, the positive results for H8 and H9 suggest that as banks achieve greater efficiency, their credit and liquidity risk levels increase, reinforcing the theoretical foundations of the Skimping Hypothesis and Moral Hazard Theory.

The positive effects observed in H3 and H4 (GMM estimations) challenge the Bad Luck Hypothesis, which traditionally argues that financial distress resulting from heightened risk exposure impairs bank efficiency. Instead, the findings suggest that Ethiopian banks may be leveraging credit and liquidity risks strategically, sustaining efficiency gains while navigating financial vulnerabilities. This aligns with emerging empirical evidence indicating that risk exposure, when managed effectively, may contribute to leaner operational models, optimized credit intermediation, and adaptive liquidity strategies (Ilmiani & Meliza, 2022; Tan & Floros, 2013; Yitayaw et al., 2023). Ethiopian banks with higher risk portfolios may not necessarily suffer efficiency losses but instead may operate under aggressive risk-taking frameworks, ensuring maximum resource utilization and profitability.

Conversely, the results from H8 and H9 (FEM estimations) confirm that efficiency-driven strategies lead to greater credit and liquidity risk exposure, validating the Skimping Hypothesis (Berger & Humphrey, 1997; Fiordelisi et al., 2009). In pursuit of greater technical efficiency, banks may reduce their investment in risk safeguards, minimizing underwriting scrutiny and liquidity reserves to enhance cost-effectiveness. This pattern suggests that efficiency-seeking behavior fosters financial vulnerabilities, reinforcing findings from previous studies that associate operational streamlining with heightened lending risks and weakened liquidity buffers (Fiordelisi et al., 2011; Phan et al., 2018; Tan & Floros, 2019).

The contrasting results across estimation models underscore the complex nature of efficiency–risk interactions, revealing dynamic interplay where risk exposure contributes to efficiency improvements, while efficiency-driven strategies increase risk levels. The GMM results indicate that risk does not necessarily constrain efficiency, suggesting that Ethiopian banks may operate in environments where controlled risk-taking optimizes performance. On the other hand, FEM results highlight the potential long-term vulnerabilities of efficiency-maximizing institutions, emphasizing the need for enhanced risk-management frameworks to mitigate excessive financial exposure.

These findings carry significant policy and managerial implications, particularly for banking regulation in Ethiopia. While efficiency optimization enhances operational performance, the associated rise in credit and liquidity risk necessitates closer monitoring by regulatory bodies. Policymakers should ensure that highly efficient banks do not excessively compromise their financial safeguards, balancing cost-reduction incentives with risk mitigation strategies. Additionally, banks must integrate risk-sensitive efficiency models, ensuring that operational improvements do not inadvertently weaken credit and liquidity resilience.

Overall, the results suggest that while efficiency enhances profitability and competitive advantage, it must be carefully managed to prevent excessive risk accumulation. The efficiency–risk trade-off reinforces the argument that financial institutions should adopt an equilibrium approach, ensuring that operational improvements are not pursued at the expense of financial stability. Future research could deepen our understanding of these dynamics by exploring sector-specific efficiency–risk interactions—for example, by incorporating the NBE's sectoral loan-quota requirements into the analysis. It could also examine whether banks of different sizes or ownership structures adopt distinct risk-optimization strategies when operating under efficiency-maximizing imperatives.

5.2.3 The Role of Profitability in Facilitating Efficiency

The study's evidence corroborates that increased profitability, as quantified by return on average assets (ROAA), has a stimulation influence on greater technical efficiency. ROAA is employed as an explanatory variable in the empirical model, and hence banks with higher profitability are more inclined to invest in efficiency-enhancing measures. This is consistent with prior findings (Berger & Mester, 1997; Lakshmanasamy, 2021; Lema, 2017; Ullah et al., 2023). This result is directly related to the composition of the study's Data Envelopment Analysis (DEA) model, which measures overall technical efficiency

(OTEBC) and pure technical efficiency (PTEBC) based on a given list of outputs and inputs.

The DEA model employed in this research analyzes a bank's performance by observing the efficiency with which inputs such as deposits and non-interest expenses are translated into outputs such as net-interest income, non-interest income, and loans and advances. In this regard, a higher ROAA, as a measure of profitability, indicates a higher conversion ability of these inputs into useful outputs. In essence, profitable banks tend to possess stronger internal processes, advanced technologies, and strategic actions that raise their operational efficiency. This, in turn, contributes to greater technical efficiency as reflected in the DEA measures.

In addition, the favorable association of technical efficiency with ROAA implies that profitability can provide the financial cushion to overcome operating inefficiencies. Profit generates the means to invest in improvement such as state-of-the-art information systems, staff training, and process re-engineering. All such investments are necessary to improve the quality of input usage and strengthen the income generation process, ultimately leading to gains in efficiency. Within the context of Ethiopian banking, where there are severe resource constraints and competitive pressures, a strong profitability position enables banks to overcome these challenges and improve the efficiency of their operations.

The inclusion of ROAA in our efficiency measurement framework gives us a more holistic view of bank performance. It reveals that profitability is not only a function of efficient operations but can also be a catalyzing factor, inducing additional technical efficiency advancements. By diverting profits into initiatives that improve the conversion of inputs into outputs, banks develop a virtuous circle wherein financial performance strengthens operating excellence, and vice versa. The double role played by profitability emphasizes the importance of maintaining a strong financial position, as this allows for perpetual investments in operational efficiency.

In sum, the findings validate that higher ROAA leads to higher technical efficiency, indicating that more profitable banks are able to use their resources more efficiently. The connection is of course based on the assumption of our DEA specification, where the input and output selection captures the essential processes of banking operations. The evidence substantiates the opinion that profitability is an indicator of good resource management while concurrently building additional technical efficiency, thus making a strong case for the differences in performance established in this study.

5.2.4 Efficiency and Capital Adequacy

The evidence suggests a non-significant relationship between the capital adequacy ratio (CAR) and technical efficiency, whether measured as overall technical efficiency (OTEBC) or pure technical efficiency (PTEBC). The implication of this result is that, for our sample, capital adequacy differentials do not have a significant influence on the efficiency with which banks convert inputs into outputs.

In the Ethiopian case—where there is a regulatory environment, traditionally guided by Basel I standards—capital adequacy appears to function mainly as a financial stability protection mechanism instead of an instrument that encourages or stimulates operational performance. Under Basel I, the focus on a relatively straightforward risk-weighting framework means that banks maintain adequate capital essentially to meet preset regulatory standards (Basel Committee, 2013). The regulatory approach favors caution and liquidity over the dynamic allocation of resources intended to promote efficiency. Consequently, the capital holdings by these institutions are less likely to act as a competitive instrument for improving operational efficiency.

In contrast, in newer accords like Basel II/III, capital adequacy requirements feature risk-sensitive measures that may more accurately capture the synergy between operating efficiency and capital structure. Yet, in the view of this study, the insignificant relationship aligns with an environment where regulatory requirements are not nuanced and are primarily aimed at stability preservation rather than productivity enhancement. This finding is consistent with the existing literature conducted in Ethiopian context (Yitayaw et al., 2023). In such a scenario, the major role of capital buffers might be to absorb shocks and enhance financial resilience, rather than cause enhancements to the internal processes. However, others found statistically significant positive relationship between technical efficiency and capital adequacy (Jelassi & Delhoumi, 2021; Lakshmanasamy, 2021; Ma & Soh, 2021; Maji & Saha, 2023).

Thus, the findings suggest that in Basel I-type regulation-driven setups, capital adequacy is not an active force towards enhanced efficiency. Rather, it plays its role as a safeguard, making the banks solvent even at times of economic downturn.

The finding has implications that are significant for policy-making decision-makers. In order to promote the dual goals of stability and performance, there may be a necessity to look at regulatory changes that are more risk-conscious in nature—such as a shift to Basel II/III frameworks[12]. This approach may urge financial institutions to not only have sufficient capital to provide security but also to better manage their capital in seeking improved operating outcomes and ensure sound risk management.

5.2.5 Bank Size and Efficiency

The findings of the investigation show that bank size, measured by the natural logarithm of total assets, has a statistically significant negative impact on technical efficiency. This finding implies that as size increases, banks' operating performance—captured by the efficiency of transforming inputs to outputs—deteriorates. Specifically, past a threshold point, the benefits of scale are neutralized by rising operating complexities, coordination problems, and heightened administrative overheads, which ultimately result in diseconomies of scale.

This substantiates the view that although modest growth can ensure economies of scale, excessively large banking organizations tend to experience constraints that undermine their overall efficiency. In Ethiopian banking, these constraints may encompass bureaucratic inertia, communicational inefficiency, and a less controllable organizational structure.

12 This recommendation underscores the National Bank of Ethiopia's proactive drive to modernize prudential standards. By issuing draft directives to move from Basel I to the more robust Basel II/III framework—and actively soliciting stakeholder feedback—the NBE confirms its commitment to strengthening capital adequacy, liquidity management, and overall bank risk governance in a timely and compulsory reform.

Therefore, even though bigger banks have greater resources, the complexity in managing these resources can mitigate their capacity for sustaining high technical efficiency levels.

Empirical evidence supports this interpretation (Ikapel et al., 2023; Jelassi & Delhoumi, 2021; Lakshmanasamy, 2021). In addition, as Ullah et al. (2023) argue, advances in fintech and the widespread adoption of smart banking services may have altered the traditional dynamics in which bank size was viewed as an advantage. In this digital era, bank size may have become less relevant—or even represent a hindrance—to achieving operational efficiency, as technological innovations enable more agile and cost-effective operations regardless of scale.

Finally, the large negative impact of ln(total assets) on technical efficiency underscores the delicate balance between expansion and operational performance. It shows that maintaining an optimal size is very important for banks to obtain the benefits of economies of scale without evading its associated risks of over-expansion.

5.3 Implications

The conclusions of this study have extensive policy implications that traverse managerial practices, regulatory policies, and the overall theoretical knowledge of bank efficiency. By deconstructing the relationship between ownership form, size, profitability, and risk in influencing technical efficiency, the empirical findings demand rethinking of prevailing operational policies as well as policy interventions within the Ethiopian banking sector.

5.3.1 Managerial Implications

The evidence demonstrates that banks, especially large private banks and public sector banks, have to restructure their operating structures to deal with the issues of diseconomies of scale and higher risk exposures. For example, the negative effect of bank size on technical efficiency implies that banks will encounter more coordination issues and larger administrative overheads as they grow in size. Managers should consider introducing structural changes—like decentralization of decision-making power, process re-engineering, and enhancement of information systems—intended to streamline operations and reduce inefficiencies. Further, the positive interplay between higher technical efficiency and both credit and liquidity risks imply that an aggressive drive towards operational excellence may inadvertently encourage riskier tendencies.

Consequently, financial institutions have to implement strong risk management frameworks and enhance their supervisory systems so that efficiency gains do not add to decreased financial stability.

5.3.2 Policy Implications

At the policy-formulation level, the study highlights the need to refine regulatory frameworks to advance operational efficiency concurrently with the safeguarding of financial stability. The fact that no marked relationship exists between capital adequacy under the framework of Basel I regulation and operational efficiency suggests that the current capital requirements might not provide incentives to enhance efficiency. The shift to a risk-sensitive regulatory framework, as embodied in Basel II/III, can offer banks increased flexibility for efficient capital allocation. Furthermore, the revealed adverse impacts on overbank size highlight the necessity for policies that will negate overexpansion while fostering structural reforms in large banking organizations.

Regulators ought to think about creating focused interventions—like incentives for better corporate governance and risk monitoring—to promote a more vibrant and resilient banking industry.

5.3.3 Implications for Researchers and Investigators

The implications of this study provide numerous avenues for future studies on bank efficiency, risk management, and financial stability, especially in the emerging market context. Though the current academic literature predominantly addresses the linkages between efficiency and risk in the context of developed financial systems, the unique regulatory and institutional environments, liquidity constraints, and operational characteristics of emerging economies need to be investigated more thoroughly.

A natural avenue for research is the refinement of causal relationships between efficiency and risk-taking behavior, i.e., investigating whether or not particular institutional characteristics—i.e., regulatory supervision, credit market structure, and financial inclusion policies—condition efficiency–risk trade-offs. This research has established a positive relationship between efficiency and credit and liquidity risk dimensions. Future research should thus examine threshold effects of efficiency optimization—i.e., the level at which efficiency improvement substantially heightens risk exposure and whether or not this effect is consistent across banking segments.

Additionally, future studies could examine the role of technological advancement—particularly fintech adoption, digital banking innovations, etc.—in mediating the efficiency–risk trade-off. In emerging economies where fintech adoption is gaining momentum, researchers could ascertain whether banks can sustain efficiency gains without introducing financial vulnerabilities by leveraging automation and predictive analytics-driven risk analytics.

Moreover, future studies can build on our two-stage efficiency–risk framework by using advanced dynamic and system-based estimators. Once longer panels are available, Structural Equation Modeling (SEM) or Vector Autoregression (VAR) methods can effectively describe the simultaneous feedback relations between risk and efficiency over time. Extension of the analysis to regional or multi-country panels would further tell us about the generalizability of the efficiency-risk relationship in comparable regulatory regimes.

Equally important is rigorous data transformation to ensure comparability for banks of varying sizes. Beyond winsorizing outlier values, natural logarithmic transformation of inputs, outputs, and risk ratios can enhance variance stability and reduce scale effects that may bias frontier estimates. Coupled with the richer methodologies outlined earlier, these adjustments will enhance our insights on banks' efficiency optimization and risk management—thus laying the groundwork for effective regulatory guidelines and strategic initiatives for emerging-market banking systems.

Lastly, future research could blend parametric and non-parametric frontier techniques to strengthen efficiency measurement. For example, pair Data Envelopment Analysis (DEA) with Stochastic Frontier Analysis (SFA) to triangulate efficiency scores, examine sensitivity to functional-form assumptions, and explicitly model random shocks.

5.4 Recommendations

Building on the implications outlined earlier, this section provides prescriptive guidance aimed at assisting both financial institutions and policymakers in leveraging the insights from this study. By implementing these recommendations, banks can foster operational efficiency while managing financial stability, and regulators can create a supportive policy environment that ensures efficiency improvements do not compromise financial prudence. These strategic directions aim to establish a banking sector in which efficiency and risk management are self-reinforcing, thereby promoting long-term financial resilience.

5.4.1 Recommendations for Banks

To mitigate the potential risks associated with efficiency-driven banking practices, financial institutions should implement advanced risk management systems that integrate predictive analytics decision frameworks. By investing in technology-driven risk assessment platforms, banks can identify emerging credit and liquidity vulnerabilities, ensuring early intervention and adaptive risk mitigation strategies. The adoption of machine learning algorithms and big data analytics in credit risk modeling and liquidity forecasting would significantly enhance banks' ability to manage financial exposures.

For large financial institutions, addressing coordination challenges and operational inefficiencies is critical. Banks with complex organizational structures should consider decentralized decision-making frameworks, allowing for greater flexibility in loan approvals, liquidity management, and branch-level operational adjustments. Re-engineering internal processes—particularly through automation of routine functions, streamlined workflow integration, and centralized data management systems—can enable banks to maintain efficiency without exposing themselves to excessive financial risk, particularly credit and liquidity risks.

Moreover, the embracing of lean management strategies is essential in optimizing bank operations while ensuring credit and liquidity buffers remain adequate. Lean banking models, which focus on minimizing resource waste, maximizing operational agility, and strengthening financial discipline, enable institutions to balance efficiency improvements with risk control mechanisms. Additionally, continuous performance monitoring systems should be implemented to ensure efficiency-driven strategies align with risk thresholds, preventing unintended exposures to credit default or liquidity shortages.

Beyond structural and technological advancements, investment in human capital development remains a critical factor in achieving efficiency-enhanced financial stability. Banks must allocate ample resources for employee training, equipping personnel with technical expertise in risk analytics, adaptive financial modeling, and regulatory compliance. Staff should be trained to identify early warning signs of financial instability, ensuring that efficiency objectives do not overshadow prudent banking practices. Developing cross-functional risk-awareness programs within banking institutions can create a culture of responsible efficiency, wherein financial optimization strategies are implemented with full knowledge of risk mitigation principles.

5.4.2 Recommendations for Policymakers and Regulatory Authorities

Policymakers play a pivotal role in ensuring that banking efficiency does not lead to excessive financial risk exposure. One fundamental recommendation is to modernize Ethiopia’s banking regulatory framework, transitioning from Basel I to a risk-sensitive Basel II/III system. This transition would align capital adequacy requirements more closely with actual risk levels, enabling banks to maintain sufficient buffers while optimizing operational efficiency. By adopting Basel II/III provisions, Ethiopian banks could introduce dynamic risk-weighted capital assessments, ensuring that high-efficiency institutions do not reduce risk management safeguards in pursuit of operational optimization.

Additionally, regulatory authorities should introduce targeted policies to discourage unchecked bank expansion, balancing efficiency growth with financial stability. Excessive growth—particularly among large banking institutions—can lead to diseconomies of scale, where cost reduction efforts inadvertently weaken credit risk monitoring and liquidity reserves. Regulators could implement growth-incentive thresholds, encouraging banks to maintain an optimal size structure while avoiding risk-inducing expansions. Performance-based supervision models, which reward risk-sensitive efficiency strategies, could also be adopted to ensure banks prioritize sustainable financial health.

Equally important is the enhancement of corporate governance frameworks to ensure that efficiency improvements align with strong risk management practices. Strengthening transparency requirements, board accountability, and executive oversight would mitigate the potential moral hazard associated with highly efficient banking institutions. Regulators should mandate periodic risk-disclosure reports, requiring banks to publicly assess efficiency–risk trade-offs, preventing institutions from engaging in excessively aggressive efficiency-driven risk strategies.

5.4.3 Creating a Balanced Efficiency–Risk Framework

Ultimately, the recommendations outlined above emphasize the need for an integrated approach to banking efficiency—one that preserves financial soundness while enabling operational improvements. Banks must embrace technological innovation, institutional restructuring, and workforce skill development to balance cost-minimization objectives with sustainable risk controls. Simultaneously, regulators must modernize risk assessment frameworks, ensure responsible bank scaling, and reinforce governance policies to create a financial system in which efficiency and stability are mutually reinforcing.

By implementing these recommendations, Ethiopia's banking industry can advance its efficiency while mitigating unintended financial risks, ensuring a resilient and adaptive banking environment capable of sustaining long-term stability.

5.5 Conclusion and Final Remarks

This study provides a comprehensive investigation into the determinants of technical efficiency within Ethiopia's commercial banking sector, evaluating the interplay between efficiency and financial risk indicators, particularly the credit and liquidity risks. The findings confirm that efficiency levels vary significantly across ownership structures, with privately owned banks demonstrating higher efficiency compared to their counterparts. Furthermore, the study identifies a statistically significant positive association between technical efficiency and risk metrics, suggesting that efficiency-driven operational strategies may unintentionally heighten exposure to both credit and liquidity risks.

The results also highlight the role of profitability in fostering efficiency improvements, reinforcing the notion that financially strong institutions are better positioned to optimize their operational models. However, capital adequacy—measured within the constraints of the Basel I framework—was found to have no visible impact on efficiency, raising concerns about the adequacy of traditional risk-weighted capital regulations in shaping efficiency dynamics in regulated banking environments.

From a broader perspective, these findings underscore the necessity for both managerial and regulatory interventions to ensure that efficiency enhancement efforts do not compromise financial stability. Banking institutions must integrate advanced risk assessment frameworks, data-driven decision tools, and lean operational models, enabling efficiency improvements without excessive risk accumulation. Simultaneously, policymakers must refine regulatory structures, transitioning from static risk-capital frameworks (Basel I) toward more dynamic models (Basel II/III) that accommodate efficiency-driven banking realities while ensuring risk mitigation.

The operational and policy implications are profound, offering banks an opportunity to modernize internal processes while granting regulators a pathway to design adaptive financial stability measures that balance efficiency with prudent risk oversight. As global banking environments grow increasingly competitive, emerging market institutions must seek sustainable efficiency models, ensuring long-term financial stability amidst complex operational challenges.

By rigorously dissecting the efficiency–risk nexus within Ethiopia's highly regulated banking sector, this study advances both theoretical and empirical boundaries. It delivers a robust analytical framework that guides policymakers and bank managers in optimizing resource allocation without undermining financial stability. Moreover, the insights generated here furnish a transferable model for comparative investigations, dynamic simulation exercises, and finely tuned regulatory reforms across emerging-market banking systems. Ultimately, this work lays a strategic foundation for future research, targeted policy innovation, and institutional advancements both in Ethiopian banking sector and beyond.

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APPENDIX

List of Published and Accepted Manuscripts

1. Tolesa, D., Li, S., & Duressa, D. (2023). Performance efficiency of Ethiopian commercial banks: Data Envelopment Analysis approach. Journal of Business and Administrative Studies, 15(1), 54-68.

2. Tolesa, D., Li, S., & Duressa, D. (2024). Effect of Banks' Efficiency on Credit and Liquidity Risks: Evidence from Ethiopian Commercial Banks. *Horn of Africa Journal of Business and Economics (HAJBE) (2024), 7(2), pp. 207– 220.*

3. Tolesa, D., Li, S., & Duressa, D. (**Accepted**). The Determinants of Ethiopian Commercial Banks' Technical Efficiency: DGMM Approach. *Accepted in Cogent Business & Management (2025). DOI: 10.1080/23311975.2025.2474207*

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Performance Efficiency of Ethiopian Commercial Banks: Data Envelopment Analysis Approach

Daniel Tolesa Agama [1], Shihong Li [2] and Degefe Duressa Obo [3]

ABSTRACT

The Ethiopian banking sector plays a pivotal role in resource allocation of the country with the absence of a securities market. The study aimed to evaluate financial performance of Ethiopian commercial banks during 2014 to 2020. Data from all of the 17 commercial banks in Ethiopia have been considered in the study which resulted in 119 observations. The classical Data Envelopment Analysis (DEA) models were employed to estimate the efficiency scores. Two input variables (non-interest expense and deposits), and three output variables (net interest income, non-interest income and loans and advances) were identified under intermediation approach. The efficiency scores of Ethiopian commercial banks vary among each banks and years. The highest ranked commercial banks based on the average relative efficiency score are the most stable and consistent banks in the industry. The public owned commercial bank is more efficient than private owned commercial banks in Ethiopia. Whereas, the smallest private owned commercial banks are more efficient than the largest one. Thus, bank managers should review and rescale their scope of operations to levels that guarantees both pure technical efficiency and scale efficiency. Future studies should evaluate the efficiency of Ethiopian commercial banks overtime using parametric analysis and identify factors affecting their financial performance.

KEY WORDS

DEA, efficiency, commercial banks, Ethiopia, CCR, BCC

1. Introduction

The banking sector in Ethiopia has economic significance through its contribution of about 3.1 percent to GDP in the last decade and it has been the second largest employer with over 90 thousand direct employees (Abbay, 2018; Cepheus Capital Research [CCR], 2019). There are eighteen banks in the Ethiopian banking industry which constitute one development bank and seventeen commercial banks (one public owned and sixteen private owned) (NBE, 2020, p. 38). The sector is highly dominated by the state owned bank (commercial bank of Ethiopia) which holds about two-third of the sector's assets (CCR, 2020, pp. 9–10; Geda et al., 2017).

The banking system in Ethiopia, with the absence of financial markets, is the most common instrument in exercising economic and monetary policy. Improving the resource allocation in the banking production process is a critical factor to ensure the health of these policies (Antunes et al., 2022, p. 1374). The Operating efficiency of commercial banks significantly affect national economy (Weiwei et al., 2021, p. 65). Evaluating the overall performance of commercial banks is, therefore, a

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Effect of Banks' Efficiency on Credit and Liquidity Risks: Evidence from Ethiopian Commercial Banks

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Abstract

The purpose of this study is to examine the impact of bank efficiency on the credit and liquidity risks of commercial banks in Ethiopia. The panel dataset of 17 commercial banks over the period 2014-2022 was employed. The study employed the fixed effect regression model to estimate the impacts that the overall technical efficiency (OTEBC) and the pure technical efficiency (PTEBC) have on credit and liquidity risks. Our findings, based on 153 observations, explain that higher bank efficiency is significantly influencing credit risk, as identified by positive signs of both OTEBC and PTEBC. Specifically, efficient banks experience a lower return on average assets (ROAA) and market share; hence, a trade-off exists between efficiency and risk. Regarding the liquidity risk, both OTEBC and PTEBC are positively correlated, reflecting that efficient banks manage their liquidity more suitably. In addition, it is also determined that some macroeconomic factors, like economic growth and inflation (CPI), significantly affect these risks. The findings highlight that bank efficiency is a two-edged sword in managing risks and financial stability. These results, therefore carry important implications for policymakers and bank managers in their efforts to make the banking sector more resilient.

Keywords: Bank Efficiency, Credit Risk, Liquidity Risk, Overall Technical Efficiency (OTEBC), Pure Technical Efficiency (PTEBC), Risk Management

1. Introduction

The banking sector is pivotal in economic development, primarily through financial intermediation and resource allocation. Banks facilitate credit provision to individuals and businesses, essential for investment and consumption, driving economic activity. However, banks face inherent risks, notably credit and liquidity risks, which can significantly affect their stability and performance (Haris et al., 2024).

The Ethiopian banking industry comprises 29 commercial banks that register nearly 25% of the total deposits to GDP ratio (CEPHEUS, 2023; National Bank of Ethiopia, 2022). The Ethiopian banking sector has been at the forefront of transformative economic reforms in recent years, reflecting the nation's broader ambitions for financial modernization and stability. With recent policy reforms opening the banking sector to foreign investors and establishing a promising

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