Addis Ababa University
አዲስ፡አበባ፡ዩኒቨርሲቲ
SEEK WISDOM, ELEVATE YOUR INTELLECT AND SERVE HUMANITY !

SCHOOL OF GRADUATE STUDIES

COLLEGE OF BUSINESS AND ECONOMICS

DEPARTMENT OF ECONOMICS

CREDIT RISK AND TECHNICAL EFFICIENCY IN ETHIOPIAN COMMERCIAL BANKS

BY: TAMRAT MEKONEN CHANE

JUNE, 2022

ADDIS ABABA

ETHIOPIA

ADDIS ABABA UNIVERSTY

FACULITY OF BUSSINESS AND ECONOMICS

DEPARTEMENT OF ECONOMICS

CREDIT RISK AND TECHNICAL EFFICIENCY IN ETHIOPIAN COMMERCIAL BANKS

By:

Tamrat Mekonen

tamr.meko@gmail.com

A THESIS SUBMITTED TO THE DEPARTMENT OF ECONOMICS SCHOOL OF GRADUATE STUDIES OF ADDIS ABABA UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN ECONOMICS (DEVELOPMENT ECONOMICS).

ADVISOR: Guta Legesse (PhD)

JUNE, 2022

ADDIS ABABA

ETHIOPIA

Declaration

I, the undersigned, declare that this project paper (**Credit Risk and Technical Efficiency in Ethiopian Commercial Banks**) is my original work, which has never been submitted for a degree at another university, and all sources of information used in the project have been properly recognized.

Declared by:

Tamrat Mekonen Signature _______________ Date __________

Confirmed by advisor:

Guta Legesse (PhD) Signature _______________ Date __________

Certification

Addis Ababa University

School of graduate studies

This is to certify that the thesis prepared by Tamrat Mekonen Chane entitled: **Credit Risk and Technical Efficiency in Ethiopian Commercial Banks** in partial fulfillment of the requirements for the Master of Science in Economics (development economics) degree, complies with University regulations and meets the accepted standards in terms of originality and quality.

By: Tamrat Mekonen Chane

Approved by board of examiners:

1. Guta Legesse (PhD) _______________________
   Advisor Signature

2. Misgina Asmelash (PhD) ______________________
   External Examiner Signature

3. Gebeyehu Manie (PhD) _____________________
   Internal Examiner Signature

Acknowledgment

First and for most, I would like to say thanks to "God" and his Holy mother, "Virgin Mary", who helped me to successfully complete not only this paper but also all my life to be what I am today. Along with, I would like to convey my heartfelt gratitude to my advisor, Dr. Guta Legesse, for his expert guidance, helpful criticism, useful recommendations, and encouragement at every stage during the completion of this work. It was a pleasant and inspiring experience for me to work under her guidance.

My special thanks and appreciation go to my friend and my classmate for their useful advice and provision of necessary skills. I would like to thank them again for their effort to make me passionate about undertaking research and appreciate it. This research would not have been accomplished without the participation and assistance of a significant number of people, including some whose identities may not be recorded.

Finally, I would like to thank my family and fiancée(kidist) for supporting me in a way I needed to successfully complete my academic career and to all my friends for being there whenever I needed their assistance.

Contents

List of Acronyms

CRS……………………..Constant Return to Scale

DEA................................Data Envelopment Analysis

DMU……………………Decision Making Unit

NBE……………………..National Bank Ethiopia

OTE……………………..Overall Technical Efficiency

PTE……………………..Pure Technical Efficiency

ROA…………………….Return on Asset

SE………………………Scale Efficiency

VIF……………………...variance inflation factor

VRS…………………….. Variable Return to Scale

List of Tables

List of figures

Abstract

This study examined the relationship between credit risk and technical efficiency of Ethiopian commercial banks in the period from 2012/13 to 2017/18. The two-stage data envelopment analysis model was used to obtain efficiency scores. The estimated result of the constant returns to scale assumption indicates that the commercial bank of Ethiopia and Dashen bank are inefficient, whereas Debub Global bank, Addis International bank, and Zemen bank are more than efficient compared to the other. Similarly, the estimated result of variable return to scale assumption showed that Commercial bank of Ethiopia and Dashen bank are shown to be inefficient, whereas Addis International bank, Development bank of Ethiopia and Debub Global bank are found to be more efficient. It is also found that, in compared to the commercial banks included in the study, united bank and Debub global bank are the most scale efficient commercial banks in Ethiopia, whereas Bunna international bank and Ethiopian Development Bank are the least scale efficient banks. In the second stage to estimate the relationship between credit risk and technical efficiency score of commercial banks as we used Tobit model. The finding indicates that credit risk has negative and statistical significant effect on Ethiopian commercial bank's technical efficiency. The higher the credit risk is the lower the efficiency scores and those commercial banks that manage to maintain their continuity in the market and diversify their products had higher efficiency scores, however generating greater benefits to their shareholder. Furthermore, the findings also indicate that liquidity risk, return on asset and capitalization have positive and significant effects on the technical efficiency score of the commercial banks under study, whereas ownership structure have negative and significant effects, but market share is a positive and insignificant variable under this study.

Keywords: Data envelopment analysis, Tobit Model, Technical Efficiency, Bank, Credit risk.

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Banks are crucial to an economy's growth and stability. They help to route household savings to enterprises and industries, where they can be put to the best possible use for the country's development. As a result, financial institutions serve as intermediates, and if this financial intermediation is effective, it will provide value to the economy as a whole. As a result, the banking system's performance is crucial and a source of issue for all stakeholders. For all economies, whether developed or developing, bank performance measurement is critical. Financial ratios or efficiency measurements can both be used to assess a bank's performance. The output-to-input ratio of a company is characterized as efficiency (Dharmendra and Bashir, 2015). The management of a company always expects proper and efficient resource or input utilization to achieve the target amount and quality of output.

Economic efficiency, often known as business efficiency from a firm's perspective, is a broader term that encompasses productive efficiency. According to the proportions on which the concept of economic efficiency is built, finance, machinery, materials, human capital and time are the precious resources from which one can produce. The firm's resources are limited and can be put to other uses; human capital, machines, materials, finance, and time are all limited resources from which to produce. Due to the scarcity of these resources and the numerous purposes for which they might be used, it is only logical for a prudent business to make the most of them (Barthwal, 1984). Banks, in particular, must be efficient because they are major participants in the financial system and benefit from efficient operations. Market performance is fundamentally a product of the system's flow in terms of pricing efficiency and flexibility to respond to changing situations.

The efficiency and development of banking systems are directly related to the productivity of the economy. Measuring the efficiencies of banks one can provide a valuable insight into the banking system and the potential of that country (Gishkori and Ullah, 2013). Therefore, the determinants of banking efficiency are necessary for the design and implementation of better strategies and public policies (Staub et al., 2010).

A large number of studies discuss banking efficiency and its determinants. In recent years, studies investigating the efficiency of banks with parametric and nonparametric frontier techniques have expanded significantly (Sufian, 2009). The most widely used approach for measuring banking efficiency scores is Data envelopment analysis (DEA), introduced by Charnes et al. (1978). The method is a non-parametric method for assessing the relative efficiency of several decision-making units (DMUs). DEA enables the measurement of managerial performance (Pure Technical Efficiency) and provides managers with a way to choose the optimum size of resources (scale efficiency) (Kumar and Gulati, 2008; Sathye, 2003).
Credit risk in financial institution is the subject of several studies. Salas and Saurina (2002) evaluated the drivers of problematic loans from Spanish commercial and savings banks from 1985 to 1997, taking macroeconomic and individual bank level variables into consideration. The findings indicated that GDP growth rate, family indebtedness, rapid expansion of credit or branches, inefficiency, portfolio composition, size, financial margin, capital index, and market dominance are all factors that influence credit risk. Commercial and savings banks differ significantly, demonstrating the importance of the institutional form in credit risk management.

Financial institutions face a variety of risks, but credit risk is the most critical for the majority of them. Credit risk is defined by the Bank for International Settlements (BIS) as the possibility that a bank borrower or counterparty would fail to meet its obligations in line with agreed terms. Credit risk management is to increase a bank's risk-adjusted rate of return while keeping credit risk exposure below acceptable limits. Banks must manage both the overall credit risk of their portfolio and the risk of individual transactions. Credit risk management is a vital component of a comprehensive risk management strategy and is critical to any banking organization's long-term success (BIS).
Fiordelisi, Marques-Ibanez, and Molyneux (2011) examined the relationship between European commercial banks' efficiency, capital, and risk. According to the findings, lower banking efficiency in relation to costs and revenues leads to increased banking risk, and increases in banking capital come before cost efficiency improvements. According to the findings, more efficient banks become more capitalized, and higher capital levels have a beneficial effect on efficiency levels. The authors point out that such findings have significant implications for bank prudential supervision and emphasize the need to achieve long-term efficiency gains in order to achieve financial stability goals.

The relationship between bank efficiency and risk, according to the research, is debatable. There is empirical evidence in Europe that shows a negative relationship between bank efficiency and risk-taking. A bank that is inefficient holds more capital and take on fewer risks (Altunbas et al., 2007). Sarmiento and Galán(2017) presented research on the impact of risk on banking efficiency in emerging markets, highlighting the variety in how risk affects banks with various characteristics. Risk has different implications on efficiency depending on the size and affiliation of the organization. The study also found that large and international banks gained the most from increased credit and market risk exposure, while domestic and local banks were better capitalized.

Some researchers have looked into the relationship between risk and efficiency on a global scale. Pastor and Serrano (2005) examined bank efficiency and credit risk in the European area's major economies and concluded that risk adjustments are relevant for profit efficiency but not for cost efficiency. Altunbas et al. (2007) examined the relationship between capital, risk, and efficiency for a sample of European banks between 1992 and 2000. The authors found no existence of a relationship between inefficiency and banking risk. In the case of cooperative banks, they found that capital levels were inversely related to risk and that inefficient banks had lower levels of capital. AlKhathlan and Abdul (2008) evaluated Saudi banks' relative efficiency between 2003 and 2008. They used both the constant return to scale and variable return to scale DEA models, and it was concluded that Saudi banks manage their resources efficiently.

Rahim et al. (2013) used DEA based on the intermediation approach to examine the efficiency of Islamic banks in Middle Eastern and North African (MENA) and Asian countries. They found that the scale of operations was the primary source of technical inefficiency among Islamic banks. Debasish (2006) evaluated the relative performance of Indian banks using the output-oriented CRR DEA model. The author used nine input factors and seven output variables to look at the relative efficiency of commercial banks from 1997 to 2004.

Hughes and Moon (1995) proposed that banking efficiency should be included in empirical models examining the determinants of bank risk and capital, because banks' efficiency is likely to influence their capital and risk levels (Hughes and Mester, 1998). Kwan and Eisenbeis (1997) explored the relationship between operating efficiency and banks' risk-taking for a sample of 352 US banking organizations. They found that inefficiency affects interest rate risk and credit risk positively, while it has a positive effect on capitalization. Altunbas et al. (2007) examined the relationship between risk, capital, and efficiency using a large sample of European banks for the time period 1992–2000. They argued that there is not a strong relationship between inefficiency and bank risk-taking, while a positive relationship between risk and liquidity (in terms of capital) is also found.

Franco, David and Phil (2010) investigate the effect of efficiency on bank risk in the European banking industry. They also considered whether bank capital affects this relationship and used the inter-temporal relationships model among efficiency, capital, and risk for a large sample of commercial banks in the European Union. They observed that cost and revenue efficiencies increase banks' future risks, lending credence to the bad management and efficiency versions of the moral hazard hypotheses. Bank efficiency improvements, on the other hand, help to strengthen bank capital levels. They indicate that banks that are falling behind in terms of efficiency can expect higher risk and lower capital positions in the near future.

In comparison to the past, today's banking business faces fierce competition, and the risk of bankruptcy is considerable due to the globalization of financial markets. Because of integration risk, a problem in one region of the world can easily spread to the rest of the world. In this uncertain situation, it is critical to assess the credit risk and technical efficiency of these banks, as well as it's determinate of the Ethiopian commercial banks.

1.2 Statement of the problem

Commercial banks play a vital role in the economy and financial system. Because they efficiently transfer funds from depositors to borrowers, banks are critical components of the financial system. They provide specialized financial services that make obtaining knowledge about saving and borrowing possibilities more affordable. These financial services contribute to the overall efficiency of the economy.

In various parts of the world, studies have been carried out to examine the factors that influence banking efficiency. For example, Sufian (2009) used a multivariate Tobit regression to examine the determinate of Malaysian banks' efficiency. The author used three different methods: intermediation, operating and value-added. The result intermediation method indicates the size of the banks' total assets has a positive and significant effect on bank efficiency, wereas bank deposits, bank management quality, and bank size have negative and significant effects. In the second, the result of operating method showed that bank loan intensity, bank risk, and diversification towards non-interest income are found to have a positive and significant effect on bank efficiency, whereas bank management quality, return on assets, and GDP have a negative and significant effect on bank efficiency. According to the results based on the value-added approach those variables :- bank loan intensity, diversification toward non-interest income, and return on assets have a positive and significant effect on bank efficiency, whereas bank management quality, total book value of shareholders' equity over total assets, and GDP have a negative and significant effect.

Sufian & Habibullah (2010) aim to examine the efficiency of the Thailand banking sector during the period of 1999–2008. The results suggest that banks with higher loan intensity and those better capitalized tend to exhibit higher efficiency levels. On the other hand, credit risk is inversely related to bank efficiency. Despite many attempts to examine the factors that influence bank efficiency in various regions of the world, there are few studies on commercial banks in Ethiopia.

The study conducted by Zenebe (2017), used Data Envelopment Analysis and the Tobit regression model to assess the determinants of technical efficiency of commercial banks in Ethiopia. To evaluate the technical efficiency score of Ethiopian commercial banks, the author considered three alternative assumptions: constant-return to scale, variable-return to scale, and scale efficiency. As a result, Abay bank, Construction and Business bank, and Oromia Cooperative Bank are found to be less efficient under the Constant-Return to Scale assumption, but Oromia International Bank and Nib International Bank are shown to be more efficient. In the variable returns to scale assumption, Construction and Business Bank, Abay Bank, and the Oromia Cooperative Bank are found to be less efficient, but Oromia International Bank, Wegagen Bank, and Awash International Bank are found to be more efficient. Based on the scale efficiency assumption, the most scale efficient commercial banks in Ethiopia are Oromia International Bank and Nib International Bank, whereas Berhan International Bank and Awash International Bank are the least scale efficient banks. The determinants of technical efficiency score were investigated using the Tobit regression model. The technical efficiency score is influenced by capitalization, liquidity risk, return on asset, and market share, all of which are determined to have a positive and substantial impact; however, bank size, market concentration, credit risk, and ownership structure have no impact. Those variables are main determinate of technical efficiency but, the author conclude that credit risk is no impact for technical efficiency of Ethiopian commercial banks.

Tesfaye and Abdurezak (2016) use cost models to analyze the cost efficiency of Ethiopian banks for the long period data (1999-2015). The authors used the Data Envelopment Analysis score to look at bank efficiency in both constant and return of scale scenarios. They found that bank efficiency levels differed significantly between bank groups. The study also concludes that the efficiency of state banks has consistently been on the efficiency frontier, indicating the banks' considerable dominance in the Ethiopian financial sector. The parametric and non-parametric tests also reveal that state and private banks have different management and technological capabilities. Despite the state banks' size advantage; they claimed that disparities in management and technical capabilities contributed to higher efficiency results. On the other hand, a statistical analysis of efficiency variables reveals that deposit growth rate, loan size, and earning asset growth are all positively and significantly related to efficiencies. Branch size and fixed asset growth rate, on the other hand, are negatively and insignificantly connected to efficiency. In line with this fact, the benchmarking methodology implies that banks with excessive deposits that limit their intermediation activities are disadvantaged when it comes to relying on their efficiency results.

There are several literatures exist on banking efficiency of developed economies and its relationship with banking risk; however, there have been few studies focusing on the analysis determinants of banking technical efficiency of the Ethiopian banking industry. So far, to the best of my knowledge, there is limited empirical research assessing the technical efficiency and it’s determinate in Ethiopian commercial banks. As a result, the purpose of this study was to evaluate the credit risk and technical efficiency of sixteen commercial banks operating in Ethiopia using a two-step procedure. Then, DEA is used to measure technical efficiency scores and the Tobit model is used to assess the determinants of technical efficiency. Then, by using of technical efficiency score result from DEA model we use to assess the determinate of technical efficiencies of commercial banks. In this thesis one of the main determinates of technical efficiency is credit risk so by using of Tobit regression model we analyze the relationship between technical efficiency score and credit risk is positive or negative relation and is its one of the main factor that affect commercial banks technical efficiency in Ethiopia.

In addition, the scope of this paper is to close this gap in the literature using bank-level data from two government-owned banks and fourteen privately-owned banks in Ethiopia. The researcher wants to show whether the technical efficiency score of each commercial bank in Ethiopia is good or not under the study period. According to some empirical evidence, the relationship between banks' efficiency and risk is controversial. There is a negative relationship between banks' efficiency and risk-taking in European countries. However, in Ethiopian commercial banks, there is no empirical evidence that indicates there is a negative or positive relation between credit risk and technical efficiency score; hence this study seeks to fill the gap by including private banks that were not included in previous studies by using most recent possible data. Therefore, the main purpose of the study is to examine the credit risk and technical efficiency of commercial banks in Ethiopia for the period from 2012/13 to 2017/18.

1.3 General objective of the study

In the context of the problems highlighted above, the general objective of the study is to examine the relationship between credit risk and technical efficiency score of the sampled Ethiopian commercial banks for the period of 2012/13 to 2017/18.

1.4 Specific objectives

The specific objectives are: -

- ✓ To measure technical efficiency score of Ethiopian commercial banks by using BCC and CCR model assumption for the period under study.
- ✓ To examine the determinates of technical efficiency score Ethiopian commercial banks.
- ✓ To examine the relationship between credit risk and technical efficiency score of Ethiopia commercial banks.

1.5 Research question

This study will answer question of credit risk how to relate with technical efficiency score of Commercial bank of Ethiopia. As a result, the study will answer the following research Questions;

- Is the Ethiopian commercial banks for the period from 2012/13 to 2017/18 is technically efficient?
- What are the main determinates of technical efficiency of Ethiopian commercial banks?
- What is the effect of credit risk on technical efficiency score of Ethiopian commercial banks?
- Is there positive or negative relation between credit risk and technical efficiency score of Ethiopia commercial banks?

1.6 Scope and delimitation of the study

The scope of the study is restricted to the relationship between credit risk and technical efficiency score of the commercial banks that are found in Ethiopia by using six years' (2012/13-2017/18) audited financial statements data of each commercial bank in order to include more recently established new banks. There are 22 commercial banks in Ethiopia. The study comprises all commercial banks that started their operations before 2012. As a result, it includes two state-owned banks and the other 14 private commercial banks.

The study used decision-making units of three input variables (interest expense, operating expense, and deposit) and three output variables (interest income, non-interest income, and total loan) in to estimate the technical efficiency of Ethiopian commercial banks. In order to determine the factor that affects the technical efficiency score of each commercial bank as a dependent variable and seven independent variables, that means level of capitalization, credit risk, liquidity risk, return on assets, , ownership structure, and market share. Therefore, this study is limited to 16 commercial banks from the period 2012/13–2017/18 and focuses on bank-specific factors that affect banks' technical efficiency.

The limitation of the study is that the decision-making units (DMUs) considered in the study may not be the only factors influencing the technical efficiency of input and output variables. There may be other factors driving technical efficiency as well, and if they were considered, they may have influenced the result of the study. In addition, civil war tension, my own work load and availability of data in some commercial banks It is not comprehensive study on the issue concerned and in-depth research is required to investigate the technical efficiency and its determinate of banking sector of Ethiopia and the relation between credit risk and technical efficiency score that makes significant to study the commercial banks of Ethiopia.

1.7 Significance of the study

The study tries to add some value to the existing literature by offering recent empirical evidence on credit risk and technical efficiency Ethiopian commercial banks. The following would be the research's significance: First, the study would draw some conclusions and identify the major factors that have a significant impact on Ethiopian banks’ technical efficiency. As a result, it will send a signal to bank management and policymakers to focus on the main determinants of commercial banks' technical efficiency in order to achieve organizational goals and take corrective action. Second, other researchers will find the study beneficial as a source of reference and a stepping stone for those who want to do more research in the field of technical efficiency in the future. Finally, this research has a significant role to play in providing insight on how to better understand what determines financial institutions' technical efficiency in Ethiopia, especially commercial banks, and its relationship with credit risk.

1.8 Organization of the Study

This study is divided into five chapters with various sections and sub-sections, and it is organized as follows: Chapter one contains an introduction to the main part of the study, a statement of the problem, a research question, and the study's objective, as well as the scope, limitations, and significance of the study. Chapter two reviews the most significant theoretical literature and empirical evidence. Chapter three presents methodology of the study. Chapter four provides data analysis and presentation of econometric model outcomes. Finally, Chapter five presents summary, conclusion and recommendation with further research direction.

CHAPTER TWO

Theoretical Framework and Empirical Evidence

This section of the paper were discussed the overall theoretical framework and empirical evidence including the definition and concepts of baking efficiency, measurers (approaches) of banking efficiency, drivers of banking efficiency, risk and efficiency in the financial institution, risk assessment of Ethiopian commercial banks, empirical evidence, and a brief discussion of the study's conceptual framework.

2.1 Theoretical literature review

2.1.1 Definition and concepts banking efficiency

Banks are regarded as the financial system's backbone; they play an important role in economic development by acting as an intermediary to transfer funds from surplus units to deficit units. As a result, banking efficiency is critical and should be prioritized. The concept of efficiency as a general performance indicator for all types of businesses was first formulated in the early works of Edgeworth (1881) and Pareto (1927) and recorded its empirical realization in Shephard's book (1953). In economics, efficiency is defined as the maximum possible ratio between the output and input of a product development process, showing the appropriate distribution of available resources that would allow the maximum potential to be realized (Cvilikas & Jurkonyte-Dumbliauskiene 2016). According to Drucker (1963), efficiency can be defined as the ability of an organization to achieve its output from the minimum input level. It can also define Efficiency as the measure of effectiveness that produces the minimum waste of time, effort, and skill.

However, the term efficiency is different from the term effectiveness; both are used to describe the performance of an entity but according to Jouadi & Zorgui (2014), efficiency summarizes the idea of producing in the best possible way, which means efficiency is focused on the use of minimal inputs to produce the best output, or in other words, the optimal use of resources to generate the best products at the lowest possible cost. Efficiency in management can be defined as the study of the firm's optimal use of internal elements. The effectiveness idea, on the other hand, summarizes the yield of elements and the achievement of a goal without taking into account the way and efficient use of resources.

According to, Isrova (2010) stated that efficiency supports the effectiveness of implemented macroeconomic policies, resulting in long-term development, economic growth, and social welfare; this is the same meaning as McKnley & Banaian (2000), who define efficiency in terms of cost minimization and profit maximization. Several classification methods are demonstrated in the literature. Yudistira (2004) distinguishes two types of banking efficiency: the first, known as scale efficiency, is the relationship between a bank's per unit average production cost and volume; the second, known as X-efficiency, was first introduced by Leibenstien (1966), and it represents a deviations from the cost-efficient frontier, which reflects the lowest production cost for a given amount of output.

Drawing inspirations from Koopmans (1951) and Debreu (1951), Farrell was the first to empirically assess efficiency. According to Farrell (1957), Technical efficiency (TE) and allocative efficiency (AE) are two components of efficiency measurement. Another way to categorize banking efficiency is to divide it into the five groups listed below:

a. Technical efficiency

In a production unit, technical efficiency refers to maximizing potential output from a limited number of factor inputs while taking physical production relationships into account (Farrell, 1957). Management's role in the manufacturing process is frequently associated with technical efficiency. Due to the structure of managers' and workers' preferences, firms may fail to produce on the outside edge of their production surface, resulting in changes in the level of "X efficiency," according to Liebenstein (1966). It's also about completing a work in the most cost-effective way feasible, which means producing a certain level of output from the fewest possible combination of inputs or producing the highest output given the level of inputs used. It measures a company's or a decision-making unit's capacity to get the most out of a given set of inputs. As a result, a technically efficient production could either create the same output with fewer inputs or produce more output with the same input (Green, 1993). The relationship between observed production and some ideal or potential production characterizes a firm's level of technical efficiency.

b. Scale efficiency

Scale efficiency is the ability of large companies to spread fixed expenditures such as advertising, expenses, and technological costs across a larger volume of output. It also tells you if decision-making entities (like banks) are operating at the bottom of their long-run average cost curve. It focuses on technical efficiency, or a bank's capacity to generate the most output from a given set of inputs in a given amount of time (Adongo et al., 2005). Data from all banks in the sample is often used to calculate scale economies, rather than merely data from all banks. Scale economies are only theoretically applicable to production potential frontiers where businesses are completely X-Efficient and cost-minimize at all output scales (Berger and Humphrey, 1994).

c. Allocative efficiency

Allocative efficiency is also known as price efficiency. It refers to a company's capacity to choose the best input combination given input pricing (Farrell, 1957). A corporation becomes cost efficient when it achieves both technical and allocative efficiency (overall efficient). The capacity to attain the best combination of inputs while accounting for their relative values, or to provide the right mix of outputs given a set of prices, is referred to as allocating efficiency (Kumhaker and Hevell, 2000). It measures a company's capacity to use inputs in the best possible proportions, given their prices and production technologies.

d. Cost efficiency

Cost efficiency is determined by how close a bank's costs are to the efficient cost frontier for a given technology, according to Steven and Anita (2004). Two conditions determine the efficient frontier: technical efficiency (using as few inputs as possible) and allocative efficiency (optimal mix of inputs given relative factor prices). A deviation from cost minimization occurs in the absence of either technical or allocative efficiency (or even both), resulting in inefficiency. However, because cost functions are unknown and cannot be directly observed, inefficiencies must be measured in relation to a data-driven efficient cost frontier. As a result, rather than a technologically feasible efficient frontier, the measurement of inefficiency is based on deviations from the data's minimal costs. Bank cost inefficiency is defined as the difference between observed costs and predicted minimum costs for a given scale and mi x of outputs, factor prices and other country-level variables.

e. Scope efficiency

Sharing information, such as knowledge of customer habits, across product lines may result in scope efficiency. It refers to a shift in product mix due to cost considerations. It occurs when producing two or more items together in a single manufacturing unit is more cost efficient than producing the products separately in separate specialist enterprises. The distribution of fixed costs across a broader product mix and cost complementary assets in the manufacture of diverse products are two sources of scope economies. Spreading fixed costs happens when a bank's or a branch's fixed capital is better employed by issuing a variety of deposits to local citizens rather than opening separate offices to meet demand for transaction accounts, savings accounts, consumer loans, and business loans. When several types of services require essentially the same sort of computer, accounting system, and other fixed inputs of a branch, and there is insufficient local demand to support a completely specialized branch for each of the services, this type of economic cost spreading happens. Deposits and loans have cost redundancy. On the other hand, when payment flow information created in the provision of deposit services is utilized to lower the costs of obtaining credit information and monitoring loans for the same customer, this is referred to as. However, using the trans log cost/profit function or another multiplicative specification to evaluate scope economies presents a problem.

2.1.2 Measures (Approaches) of banking efficiency

The primary types of efficiency measurement approaches appear to be parametric and non-parametric (Leon, 2014). Data Envelopment Analysis is the most extensively used non-parametric method (DEA). DEA is different from a simple efficiency ratio in that it takes into account many inputs and outputs and provides a lot more information on where efficiency gains can be made and how big they can be. It also accomplishes so without requiring knowledge of the relative values of the outputs and inputs that ratio analysis requires (Cooper, Seiford and Tone, 2000).

The lack of limits on the functional form, as well as the numerous variables and values (e.g., ratios) that can be employed is one of the most significant advantages of the DEA technique.

Those variables can be measured in a variety of units, and any departures from the efficiency frontier are obvious (Thanassoulis 2001). The stochastic frontier model is another alternative used to address some of DEA's acknowledged flaws. The contemporary dispute among scholars over the frontier model, on the other hand, boils down to a preference for the lesser of two evils.

Non-parametric studies put less structure on the frontier, but they fail to account for random error due to chance, data difficulties, or other measurement flaws. If there is random error, these random deviations from the true efficiency frontier may cause measured efficiency to be skewed. As a result, no consensus has been formed on which efficiency-measuring border is best (Berger and Humphrey, 1997; Goddard et al. 2001). As a result, the conceptual framework of the study is based on the DEA approach, which is validated by the DEA methodology's most significant benefits. It includes things like the lack of functional form requirements, the ability to measure variables in different units, and the fact that any departures from the efficiency frontier are visible (Thanassoulis, 2001). Because of the advantages listed above, the study will be able to use a variety of inputs measured in different units (for example, numerical measures such as branch size, staff, etc. and others, such as loans and deposits, are measured in monetary terms).

a) Input-Output Specifications

When it comes to generating efficiency scores, the most difficult challenge an analyst faces is choosing the correct inputs and outputs for anticipating bank behavior. It's worth noting that there's no consensus on what inputs and outputs a bank should have (Casu and Girardone, 2002; Sathye, 2003). DEA models can be input- or output-oriented, depending on whether the goal is to minimize inputs while maintaining a certain output level or to maximize outputs given input levels. Which of the alternative measuring orientations is the best is a point of contention in the theoretical literature (Goddard et al. 2001).

However, it's worth noting that both output- and input-oriented models will use the same frontier, resulting in the same set of efficient banks. Because of the intangible character of bank production and a theoretical void in the banking literature on multi-input-multi-output structures, output measurement is ambiguous. In the literature on banking efficiency, there are basically two approaches to selecting a bank's inputs and outputs: the production method and the intermediation approach (Humphrey, 1985; Hjalmarsson et al., 2000). Traditional microeconomic theory is applied to banking in both approaches, with the only difference being the description of banking activities.

b) Production Approach

According to Benston (1965) started the production model, which views banks as clients' service providers. This method's output represents the services provided to clients, and it's best measured in terms of the number and type of transactions, papers handled, or specialized services provided during a given time period. Data on the number of deposits and loan accounts is used as a substitute for the degree of services given if full transaction flow data is not available. This strategy includes physical variables (such as labor, material, space, or information systems) and their associated costs. This strategy just examines operating costs and completely disregards interest payments.

In addition to the above, Banks are thought to be primarily concerned with providing services to account holders. They are characterized as enterprises that construct various sorts of deposit and lending accounts using capital and manpower. Customers' loan applications, credit reports, and payment instruments are processed by them. Total expenses are the operating costs utilized to manufacture these products, whereas outputs are the number of deposit and loan accounts or transactions executed on each type of product. Banks are thought to offer two kinds of services: money deposits and fund users. Each method, though, has its own set of benefits. The production technique may be marginally better for measuring the efficiency of bank branches because branches primarily process client paperwork for the institution as a whole, and branch managers often have minimal influence over bank funding and investment decisions.

c) Intermediation Approach

Banks are typically thought of as money middlemen between savers and investors; they are financial services intermediates rather than loan and deposit account providers. Due to the rarity of service flow data, the flows are normally considered to be proportional to the stock of financial value in the accounts, such as the quantity of dollars in loans and deposits (Berger and Humphery, 1991). The input and interest cost of money should be included in the study because they are the fundamental 'raw material' converted in the financial intermediation process. Banks provide intermediation services by collecting deposits and other liabilities and transferring them to interest-earning assets (Isik and Hassen, 2002). Deposits are considered as a third input, along with capital and labor. As a result, operating and interest costs are factored into the production process.

Banks' twin responsibilities as transaction (document processing) service providers and financial intermediaries who transmit cash from savers to investors are overlooked in both models. Each method, though, has its own set of benefits. Because branches largely process customer papers for the institution as a whole, branch managers frequently have little effect on bank funding and investment decisions. Because it incorporates interest expenditures, which often account for one-half to two-thirds of total cost, the intermediation technique may be more appropriate for evaluating entire institutions. Furthermore, because profit maximization necessitates the minimization of total costs, not just production expenses, the intermediation technique may be superior for measuring the importance of frontier efficiency to the bank's efficiency.

2.1.3 Drivers of Banking Efficiency

According to Harker & Zinos (2000), the three drivers of bank efficiency are strategy, execution of strategy, and last the environment, and these three categories comprise the engine of banking success, based on their research.

Strategy: A bank's product mix, client mix, geographic location, distribution techniques, and organizational structure are all strategic considerations that must be made. These decisions represent not only the Bank's approach to providing services to clients, but also its willingness to accept financial risks. Making a good strategic client mix selection requires matching a specified customer segment with well-priced merchandise.

Execution of Strategy: Human resource management, technology, and process design are all tools that can be used to put a strategy into action. The bank's strategy execution can be evaluated using X-efficiency.

Environment: Banks use lobbying, marketing, and research and development to try to alter environmental issues. Information technology, client preferences, and government regulation are examples of environmental influences (Kablan, 2010). In terms of banking efficiency determinants, both regulatory-specific variables (e.g., bank type, ownership status, and geographic region) and bank-specific variables (e.g., size, capital adequacy, asset quality, expenses, and age) can influence the process of producing outputs from inputs in explaining variations in bank efficiency estimates.

2.1.4 Risk assessment of Ethiopian commercial banks

An effective internal control program cannot be designed without a thorough understanding of the bank's risks and exposures, as well as a robust risk management process. Risk management refers to a bank's ability to identify measure, monitor, assess, and control risks. The Bank, through its Board, Management, and RMCD, is able to respond to changing circumstances and address risks that may arise as a result of: changing business or economic conditions; a decline in the effectiveness of internal controls; the start-up of new business activities; or the introduction of new products and services. The risk assessment process begins with an assessment of the inherent risk. Risks are classified into four types, as detailed below.

Credit Risk: - The risk of loss arising from a borrower's, issuer's, or counterparty's failure to meet their financial obligations to the bank is known as credit risk. The bank alleviates this risk by imposing a strict set of credit-granting criteria. It ensures that loan activities are conducted in accordance with strict underwriting standards and KYC (know your customer) principles, confining its dealings to high-credit-worthy institutions and individuals, and ensures that counterparty exposures are appropriately secured. Taking into consideration expected returns, the external environment, and changes in the structure of the bank's balance sheet, the bank have a high-risk appetite for credit risk. Financial statement analysis, risk identification technique, stress testing risk identification method, and audit approach risk identification method are the key credit risk identification methods employed by commercial banks in Ethiopia.

In rare cases, Ethiopian Commercial Bank applies the incident investigation risk identification method to identify credit risk. The bank applies five levels of qualitative measurement of credit risk in order to measure credit risk impact. These measurement levels are scales that range from very low for risk that has insignificant consequences, low for risk that has minor consequences, medium for risk that has moderate consequences, very high for risk that has extreme consequences. The level of the risk is measured by taking into account the credit risk appetite of the bank, NBE limits, internal credit risk limits, and based on the bank's risk management program.

Liquidity risk: - is the possibility that the bank may be unable to satisfy its maturing commitments when they are due, at a fair cost, and on time. The Asset Liability Management Committee, which has overall responsibility for liquidity risk, is entirely responsible for managing liquidity risk at the bank. The bank's liquidity risk framework's principal goal is to retain sufficient liquidity to ensure that maturing obligations are met.

Prudent liquidity risk management entails keeping enough cash on hand and having enough funding available to cover liabilities as they fall due, in both normal and stressful circumstances, without incurring unacceptable losses or jeopardizing the bank's image. Borrowings have resulted in indebtedness for the bank. On a regular basis, the bank assesses its ability to meet its obligations. The bank develops methods to control its liquidity risk based on these assessments.

Market risk: - is fluctuate because of changes in market risk factors such as interest rates, foreign exchange rates, equity prices, credit spreads and their volatilities. Market risk can arise in conjunction with the trading and non-trading activities of a financial institution. Because there are no active markets in Ethiopia, the bank does not normally engage in trading activity.

Operational risk: - The risk of losses caused by failed procedures, rules, systems, or incidents that disturb business operations is known as operational risk. Employee errors, criminal behavior likes as fraud, and natural disasters are just a few of the things that might put your business at danger. Most companies understand that their personnel and procedures may make mistakes from time to time, resulting in inefficient operations. When considering operational risk, practical remedial methods should be considered in order to eliminate exposures and assure successful responses. If left handled, operational risk can result in financial loss, competitive disadvantage, employee or customer-related concerns, and business failure.

2.2 Empirical Evidence

Banking efficiency has a rich literature, where it includes its drivers or determinants, its effects or impacts and its measures efficiency. Parametric and non-parametric techniques can be used to assess efficiency. The use of non-parametric techniques outnumbers that of parametric ones (Berger and Humphrey, 1997). Among other non-parametric techniques, DEA models are widely used. In banks, the DEA is estimated using both CRS and VRS assumptions. However, there is disagreement about which of the two approaches should be used. VRS proponents argue that CRS is only acceptable when all firms are working at optimal scale (Fiorentino et al., 2006). As a result, expecting perfection in bank operations all of the time may be unrealistic. Other studies, however, argue in favor of CRS because it allows for comparisons between small and large banks (Miller and Noulas, 1997). The input-oriented approach is used in banking studies to estimate efficiency scores. This is most likely due to the fact that a bank's output can be predicted based on the level of its input. A bank, for example, can generate more loans by mobilizing deposits.

Furthermore, Banks are thought to have stronger control over inputs than outputs. Studies that take an output-oriented approach are also available (Ataullah Le, 2006). Under CRS, the input and output oriented measures always provide the same value. When they are computed under the VRS assumption, there may be some variation (Coelli et al., 2005). As a matter of fact, in many cases, the orientation chosen has only a minor impact on the DUM scores obtained (Coelli et. el, 1999). According to Berger and Humphrey (1997) the intermediation strategy is the most widely employed in the literature. The difficulty in acquiring the detailed transaction flow information required is a criticism of the production approach. As a result, the intermediation method is the one that has received the most attention in the literature.

Deposits, permanent assets, and staff are some of the most frequent DEA inputs (Casu and Girardone, 2004). In certain research, however, additional or alternative variables such as branches (Chen, 2001), loan loss provisions (Drake et al., 2003), and equity (Sturm and Williams, 2004) are included. Several studies rely on two outputs, which are often loans and other revenue-generating assets (Casu and Molyneux, 2003). The number of branches is treated as an additional output by Canhoto and Dermine (2003), presuming that it offers value to retail customers. Finally, recent studies have added non-interest income or off-balance-sheet items as additional outcomes (Weil, 2004).

Sathye (2003) uses the (DEA) method to assess bank efficiency in India and finds that public sector banks have a higher mean efficiency score than private sector and foreign commercial banks in India. Milind (2003) carries out the bank's efficiency analysis in India on the basis of two models. Model A inputs are: interest expenses, non-interest expenses, and outputs: net interest income, net non-interest income, and model B inputs are: deposits, employees, and outputs: net loans, noninterest income).

Bhattacharya et al. (1997) examined the efficiency of Indian banks by applying the DEA technique, followed by a stochastic frontier approach to explain variation in efficiencies. The authors used an intermediation approach to select interest and operating expenses as two inputs and deposits, advances, and investments as three outputs. Similarly, according to Mokhtar et al. (2008) was used intermediation approach to select input and output variables. The author used the DEA technique to measure the technical and cost efficiency of Islamic banks in Malaysia from 1997 to 2003. They used the Intermediation approach and came to the conclusion that conventional banks are more efficient than Islamic banks.

Data envelopment analysis (DEA) was used by Dharmendra S. and Bashir A. (2015) to investigate the degree of technical, Purely technical, and scale efficiencies in commercial banks in Oman. The contribution of scale inefficiency to overall technical inefficiency was shown to be larger than that of pure technical inefficiency across the time period investigated. The returns-to-scale data show that the most common type of scale inefficiency is diminishing returns-to-scale.

According to the report, Bank Dhofar and Ahli Bank have maintained their performance over time since they are the two most efficient banks. The largest bank in Oman, Bank Muscat, is experiencing declining returns-to-scale. After that, the predicted efficiency scores are regressed against a variety of explanatory variables, such as bank size, profitability, capital adequacy, and liquidity (using the Tobit model). According to the findings, bank size is insignificant; however, profitability and liquidity are significant positive explanatory variables.

In their study, San, O. et al. (2011) examined the relative efficiency of domestic and foreign banks in Malaysia. The author used 9 domestic and 12 foreign banks from 2002 to 2009. They used the intermediation approach, followed by the Tobit model, to determine the determinants of efficiency. According to the findings of this study, domestic banks are more efficient than foreign banks operating in Malaysia. Hassan and Hussein (2003) analyzed the efficiency of 17 Sudanese banks from 1992 to 2000. A range of parametric and non-parametric data envelopment analysis (DEA) measures were employed to analyze cost and profit efficiency, as well as cost, allocative, technical, pure technical, and scale efficiency. The studies demonstrated that technological flaws were at the root of Sudanese Islamic banks' total cost inefficiencies (managerial underperformance).

Kumar and Gulati (2008) used DEA to evaluate the technical scale efficiencies and pure technical of India's public sector banks. They concluded that Indian banks have an overall technical efficiency (OTE) of 88.5 percent and that exposure to off-balance-sheet activities has a positive impact on OTE. Using DEA, Pastor et al (1997) concluded that the values of efficiency parameters vary by country. Spain, Belgium, and France have the most efficient banking systems, while Austria, Germany, and the United Kingdom have the least efficient. Sharma and Dalip (2014) examine the post-reform performance of the Indian banking sector in terms of efficiency and productivity, as well as their causes. Poor technical efficiency has experienced with scale efficiency change exerting dominant factors.

Ariff and Can (2008) used DEA approach to compute cost and profit efficiency of the Chinese banking industry and a Tobit regression model. Private and medium-sized banks were revealed to be the most efficient. Sufian (2009) used the DEA method to assess the efficiency of Malaysian banks and found high levels of inefficiency, especially one year after the East Asian crisis. The study's findings also show a negative relationship between efficiency and economic conditions, as well as a positive relationship between efficiency with loan volume. Jia et al. (2009) analyses the technical efficiency from 1995 to 2005 for Chinese banks with a stochastic distance function. According to their findings, banking efficiency has improved, and joint-stock ownership is related to greater performance than state ownership.

Katib & Mathews (2000) studies the characteristics of the management structure and technical efficiency of the Malaysian banking sector from 1989 to 1995. The results indicate that technical inefficiency in Malaysian banking is due to scale inefficiency. Besides, banks with more market power (measured by their ratio of deposits to market deposits) tend to exhibit higher technical efficiency. Darrat , Topuz & Yussef (2002) investigates the inefficiency sources in Kuwaiti banks using DEA and finds that inefficiency is related to both allocative and technical efficiency.

Moreover, small banks appear to be more allocative and technically efficient compared to larger banks.

Novickyte and Drodz (2018) recently investigated the efficiency of Lithuanian banks using the DEA method. The efficiency scores were computed using a non-parametric frontier input-oriented DEA technique with variable and constant returns to scale (VRS) assumptions. Based on the VRS assumption, the efficiency analysis of Lithuanian banks shows that local banks achieve better results. According to the technical efficiency analysis based on the CRS assumption, larger Lithuanian banks used a more appropriate business model than smaller (local) banks operating in Lithuania between 2012 and 2016.

Several other studies have been conducted on a global scale to investigate the relationship between risk and efficiency. Pastor and Serrano (2005) examined the efficiency and credit risk of banks in the euro zone's major economies and discovered that risk adjustments are important in the case of profit efficiency but not in the case of cost efficiency. Between 1992 and 2000, Altunbas, Carbo, Gardener, and colleagues (2007) examined the relationship between capital, risk, and efficiency in a sample of European banks. The authors found no evidence of a link between inefficiency and banking risk. In the case of cooperative banks, they discovered that capital levels were inversely related to risk, with inefficient banks having lower capital levels.

Fiordelisi, Marques-Ibanez, and Molyneux (2011) examined the relationship between European commercial banks' efficiency, capital, and risk. According to the findings, lower banking efficiency in terms of costs and revenues leads to increased banking risk, and increases in banking capital precede improvements in cost efficiency. According to the findings, more efficient banks become more capitalized, and higher levels of capital tend to have a positive effect on efficiency levels. The authors emphasize the significance of such findings for bank prudential supervision and the importance of achieving long-term efficiency gains to support financial stability objectives.

Sarmiento and Galán (2017) presented evidence on the impact of risk on banking efficiency in emerging markets, identifying heterogeneity in how risk affects banks with varying characteristics. The impact of risk on efficiency varies according to size and affiliation. Another finding of the study was that large and foreign banks benefited more from increased credit and market risk exposure, whereas domestic and small banks were better capitalized. Tan and Floros

(2018) investigated the interdependence of risk, competition, and efficiency in the Chinese banking sector between 2003 and 2013.

According to the findings, the most efficient Chinese commercial banks had higher credit and insolvency risk, but lower risk liquidity and capital. According to (Lemonakis et al.,2015) the relationship between efficiency, capital and risk of MENA region's banking industry using external and internal to the firm factors and panel data econometric modelling. The results indicate that bank capitalization is positively related to efficiency and profitability and negatively to size; amount and quality of loans and risk measured with Altman's *Z*-score but, Efficiency and risk are also negatively related.

Franco, David and Phil (2010) analysis efficiency and risk in the European banking. They used inter-temporal relationships among efficiency, capital and risk for a large sample of commercial banks operating in the European Union. They found that reductions in cost and revenue efficiencies increase banks future risks thus supporting the bad management and efficiency version of the moral hazard hypotheses. Sufian and Habibullah (2010) intend to investigate the efficiency of Thailand's banking sector from 1999 to 2008. According to the findings, banks with a higher loan intensity and better capitalization tend to be more efficient. On the other hand, credit risk is negatively associated with bank efficiency.

There are some studies in Ethiopia commercial banks related with banking efficiency. For instance, Tesfaye and Abdurezak (2016) propose to study the cost efficiency of the Ethiopian banking sector from 1999 to 2015. Deposit growth rate, loan size, and earning asset growth are all favorably and significantly associated to efficiency, according to the statistical test results. On the other side, branch size and fixed asset growth rate are both adversely and insignificantly connected to efficiency. According to a study, Ethiopia's state and private banks have differing management and technical capacities. The study also indicated that the efficiency of state banks is constantly above the efficiency frontier.

According to Zenebe (2017) investigate the factors that influenced commercial banks' technical efficiency in Ethiopia from 2011 to 2014. The author used secondary data from annual reports of commercial banks in Ethiopia to study input variables [interest expense, operating expense, and deposit] and output variables [interest income, non-interest income, and loan]. DEA The author used three assumptions to calculate the technical efficiency score: constant returns to scale, variable returns to scale, and scale efficient for DEA model. The author examined the drivers of technical efficiency score as a dependent variable and level of capitalization, liquidity risk, return on asset, bank size, credit risk, ownership structure, market share, and market concentration as independent variables using the Tobit model. They conclude that level of capitalization, liquidity risk, return on asset and market share are found to have positive and significant effect on the technical efficiency score. In this study the author used in Tobit model as of pure technical efficiency is limited dependent variable by using of BCC model assumption of VRS but, the author does not use scale efficiency and overall technical efficiency score as censored dependent variable so this is one gap of the author. In addition to this Tesfaye and Abdurezak (2016) propose to study the cost efficiency of the Ethiopian banking sector from 1999 to 2015. They used as grouping of state and private owned commercial banks to measure cost efficiency in this study they does not explain each and every commercial banks cost efficiency result for the study period.

2.2.1 Risks and Efficiency in Financial Institutions

Commercial banks are vulnerable to risks when it comes to financial intermediation, owing to banking's reputation as a high-risk activity. They must adhere to the appropriate management of the risks that come with their work, even if they are not in business to make money, but rather to deliver services to their consumers. Lack of risk management has a direct impact on the level of security and assurance offered by operations, causing them to deviate from their core purpose of assuring efficiency in service delivery (FREITAS, AMARAL and BRAGA, 2008; PEREIRA, 2006).

Several studies have been conducted on credit risk in financial institutions. Salas and Saurina (2002) compared the determinants of problematic loans from Spanish commercial and savings banks from 1985 to 1997 at the international level, taking into account macroeconomic and individual bank level variables. The findings indicated that GDP growth rate, family indebtedness, rapid expansion of credit or branches, inefficiency, portfolio composition, size, financial margin, capital index, and market power are variables that explain credit risk. They also note that there are significant differences between commercial and savings banks, confirming the importance of the institutional form in credit risk management.

Risk management is critical to the survival and stability of financial systems. As Stiglitz (1994) and Jorion (1994) point out, it is one of the primary concerns of both institutions and global banking supervision (2003). Credit risk is associated with the possibility of the borrower failing to fulfill the payment promise made at the time of contracting or with the potential financial loss resulting from loan default (HUSCHER, 2017; SATHYE, 2005). This type of risk has been more closely associated with bank failure issues, and it is also one of the most common, because the activity of organizations such as credit unions and commercial banks consists in granting loans (STUCHI, 2004).

According to CMN Resolution No. 4,557 (BRASIL, 2017), financial institutions must maintain a continuous and integrated risk management structure that is compatible with the business model, nature of operations, and complexity of products, services, activities, and institution's processes. Financial institutions face a variety of risks, but credit risk is the most significant for the majority of them, and thus the focus of the Basel Accord (1988). Sarmiento and Galán (2017) presented findings from their research on the impact of risk on banking efficiency in emerging markets, concluding that risk affects banks differently depending on their characteristics. The impact of risk on efficiency varies depending on the size and affiliation of the company. Despite the fact that domestic and local banks were better capitalized, the study found that increased credit and market risk exposure benefited large and international banks more than domestic and local banks.

According to Pastor and Serrano (2005) they analyzed the efficiency and credit risk of banks in the major economies in the euro area and found that risk adjustments are important for profit efficiency but not for cost efficiency. Altunbas, Carbo, Gardener, et al. (2007) investigated the relation between risk, capital, and efficiency for a sample of European banks for the period 1992 to 2000. The authors did not find a positive relationship between inefficiency and banking risk. In the case of cooperative banks, they found that capital levels were inversely related to risk and that inefficient banks had lower levels of capital.

In the work of Tabak, Craveiro, and Cajueiro (2010) investigated the relationship between non-performing loans and bank efficiency in Brazilian institutions. The authors discovered that an increase in the level of non-performing loans can be explained by a decrease in efficiency, which is most likely manifested in failures in risk assessment management. Carneiro, Salgado Junior, and Macoris (2016) evaluated the efficiency of 99 Brazilian financial institutions operating in the Brazilian financial market in 2013. The authors identified 22 with a higher degree of efficiency, with heterogeneity in terms of capital origin, size, and industry sector of activity. Furthermore, an indication was identified that there is a directly proportional positive relationship between the credit rating and the efficiency of the institutions examined.

Similarly, Cava, Salgado, Branco, and colleagues (2016) assessed the efficiency of banks operating in the Brazilian market in 2013. According to the findings, large banks have the highest average score, implying that they are more efficient. When compared to other banks, federal public banks had the highest average efficiency score. Those who had foreign capital and participation scored well on average. Those who used foreign currency had the highest average efficiency scores. In terms of risk classification, those classified as AAA had higher average efficiency scores, implying that banks that provide better services have more solid results and are classified better.

Table 2.1 Summary of some empirical analysis results and conclusions

Author	Study area	Methodology	Conclusion
Technical efficiency and its determinant an empirical study on banking sector			
Dharmendra Singh and Bashir Ahmad Fida (2015)	Banking sector of Oman	DEA model	The author was investigated the degree of technical, pure technical, and scale efficiencies in Oman's commercial banks. The author concludes that scale inefficiency has been found to contribute more to overall technical inefficiency than pure technical inefficiency.
		Tobit model	The author used a number of explanatory variables, including bank size, profitability, capital adequacy, and liquidity; nonetheless, the researcher determines that bank size is negligible, while profitability and liquidity are significant positive explanatory variables.
Tadesse Zenebe	Banking sector	DEA model	According to the author, the status of bank efficiency is comparable under both hypotheses. That is, banks that are shown to be inefficient under the CRS assumption are likewise found to be inefficient under the VRS assumption. Under the assumptions of the BCC and CCR models.

Lema (2017)	of Ethiopian	Tobit model	The author indicates that capitalization, liquidity risk, return on asset, and market share have a positive and significant impact on the technical efficiency score, but that bank size, credit risk, ownership structure, and market concentration are irrelevant variables.
Zaniah Santos et.al (2020)	Brazilian credit unions	Tobit model	They observed that the higher the credit risk, the lower the efficiency scores and those credit unions that can maintain their market continuity and diversify their products have higher efficiency scores, resulting in greater benefits to their members.
Tesfaye Boru Lelissa and Abdurezak Mohammed Kuhil (2016)	Banking sector of Ethiopian	Cost efficiency model	According with author, the efficiency level of banks varies greatly across bank groups. They also observed that the efficiency of state banks has consistently been on the cutting edge, indicating the banks' dominance in the Ethiopian banking sector. Furthermore, they believe that small private banks' efficiency is improving over time, whereas medium-sized private banks' efficiency is harder to improve.
Lemonakis, C., Voulgaris, F., Vassakis, K. and	Middle East	DEA model using panel data	The findings further showed that banks in Oman, Qatar, and the UAE had the highest efficiency scores. Furthermore, according to Z-score values, banks in Oman, Qatar, and Israel were found to be more stable.

Christakis, S. (2015)	and North Africa (MENA) Countries	EGLS econometric model	The author concludes that capital, efficiency, and stability have a strong and positive relationship. They found strong relationship between bank efficiency and risk-taking. There is a positive relationship between risk (Z-score), efficiency, and capital. As a result, banks with higher levels of capital adequacy are more stable (lower insolvency risk) and efficient.
Elfy Deba Bangagnan Yanga (2020)	Economic and Monetary Community of Central Africa (CEMAC)	Tobit Model	The author concludes that CEMAC banks are inefficient in terms of cost, and that the efficiency of these banks is harmed by credit risk, as measured by the ratio of bad debts to loans given.

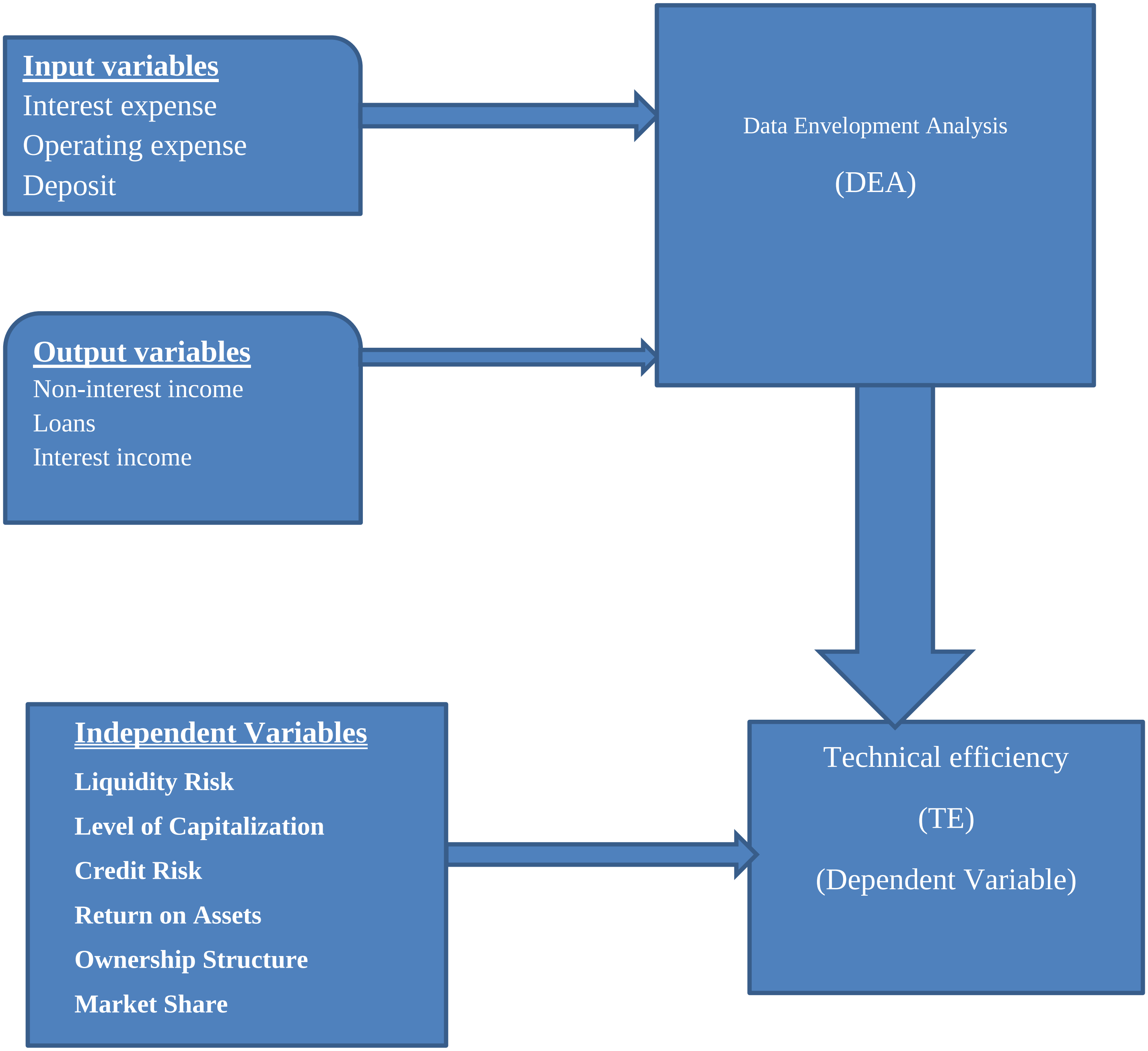
2.3 Conceptual frameworks of Banking Technical Efficiency

The main aim of this study is to examine the credit risk and technical efficiency of the Ethiopian commercial banks. The measurement of efficiency would enable us to know the status of the individual banks' efficiency and how it is compared among them. While substantial literature has been generated to evaluate banking efficiency in the United States and Europe, it should be remembered that he was the first to bring forward the idea of assessing efficiency (Farrell, 1957). According to Farrell (1957), technical efficiency is a company's ability to get the most output from a given set of inputs. In this study we will use the technical efficiency concepts to measure Ethiopian commercial banks' technical efficiency.

Under this study, the conceptual framework of banking technical efficiency is stated in Figure (1) as the Data Envelopment Analysis (DEA) model as input and output variables of decision making units, which makes that analysis the determinant of the technical efficiency score of Ethiopian commercial banks. As stated in the figure below, we will determine the main determinates of the technical efficiency of Ethiopian commercial banks by using the Tobit regression model as defined in the conceptual framework of this study. In general, in this study, the relationship between the result from DEA analysis of technical efficiency score and credit risk is either positive or negative relation by using the Tobit regression model as stated below.

This conceptual framework is based on the analysis of Mokhtar, AlHabashi, and Abdullah (2006).

Figure 1 Conceptual Framework of Banking Technical Efficiency



Source: authors' self-construction

CHAPTER THREE

METHODOLOGY

The overall methodology of the study were discussed in this section of the paper, including data sources and variables, data analysis methodologies, empirical model formulation, and a brief discussion of variables and their predicted sign.

3.1 Data Source and Variables

The Ethiopian financial system consists of 22 commercial Banks, of which 20 are private banks as of 2021 G.C (Abay Bank (AB), Addis International Bank (AIB), Awash Bank (AWB), Bank of Abyssinia (BOA), Berhan Bank (BRB), Bunna Bank (BUB), Cooperative Bank of Oromia (CBO), Dashen Bank (DB), Debub Global Bank (DGB), Enat Bank (EB), Hijra Bank(HB), Lion International Bank (LB), Nib International Bank (NIB), Oromia International Bank (OIB), Shabelle Bank (SHB),), Sinqee Bank (SB), United Bank (UB), Wegagaen Bank (WB), Zamzam Bank (ZZB), Zemen Bank (ZB) and the remaining two are state-owned banks (Commercial Bank of Ethiopia (CBE) and Development Bank of Ethiopia (DBE)). Under this, EB, ZZB, HB, SB, OIB, and SHB are not included in this study due to a lack of data and some commercial banks are established after 2012/13. This study examines the credit risk and technical efficiency of the remaining 16 commercial banks in Ethiopia over the period of six years (2012/13-2017/18 G.C). For this study, secondary data on input variables (interest expense, operating expense and deposit) and output variables (interest income, non-interest income and loan) were collected from the National Bank of Ethiopia (NBE) annual report, income statement and balance sheet of those commercial banks for DEA analysis. The censored dependent variable in the Tobit model is the technical efficiency (TE) scores obtained in the first step, and six independent variables: level of capitalization, liquidity risk, return on assets, credit risk, ownership structure, and market share are also collected from the income statement and balance sheet of the aforementioned commercial banks, as well as the annual report of the National Banks of Ethiopia.

3.2 Methods of Data Analysis

Descriptive statistics such as mean, standard deviation, minimum, and maximum was used to describe variables in the DEA model, Tobit regression model, and the estimated technical efficiency score distribution of the commercial banks in Ethiopia under study. The DEA model used to estimate each commercial bank under investigation's technical efficiency score. The

Tobit model used to investigate the factors that influence Ethiopian commercial banks' efficiency scores and how they relate to credit risk for the period under study.

3.3 Empirical Model Specification

3.3.1 Data Envelopment Analysis

The parametric (econometric) and non-parametric (mathematical) techniques are both commonly used to assess the efficiency of DMUs. A common parametric technique is the Stochastic Frontier Approach (SFA), whereas Data Envelopment Analysis (DEA) is a popular non-parametric technique (Raphael, 2013). The fact that it does not assume any random mistake, such as measurement error is a DEA's basic problem, especially when contrasted to the SFA (Raphael, 2012). However, the underlying technology does not need to be specified in advance, and DEA can accept a wide range of inputs and outputs. It does not require a prior specification of the underlying technology (Raphael, 2013). As a result, in technical efficiency evaluations of DMUs, notably banks and financial institutions, it is favored. DEA entails utilizing linear programming to create a non-parametric piece-wise frontier over data (Rpkova, 2015). DEA can be input-oriented or output-oriented. In the first case, efficiency is defined as the maximum proportional reduction in input use given output, and in the second scenario, efficiency is defined as the largest proportional rise in output given input (Coelli & Rao, 2005). Because banks have greater control over the input than the output, input-oriented DEA was used in this study. Assuming M inputs and N outputs for each of i firms, the mathematical programming problem to maximize the efficiency measure for the ith firm is (Coelli & Rao, 2005)

$$\mathbf{Max}\ V,U\left(\frac{V'qj}{U'Xi}\right) \qquad \mathbf{Eq\ (1)}$$

$$St\ \frac{V'qj}{U'Xj} \leq 1 \quad j = 1, 2, 3 \ldots i$$

$$V, U \geq 0$$

Where, v is an $N \times 1$ vector of output weight and u is $M \times 1$ vector of input weight. The problem with Equation (1) is that it has an infinite number of solutions. To address this problem, the following formulation is considered imposing the constraint $u'x_i = 1$.

$$Max\ V,U\ (V'q_i) \qquad Eq\ (2)$$

$$St\ u'^{xi} = 1$$

$$v'q_j - u'x_j \leq 0, j = 1, 2 \ldots I$$

$$v, u \geq 0$$

Where, *v* and *u* are the same with the *v* and *u* in Equation (1). Based on the concept of duality, an equivalent envelopment form of the above linear programming model is given by Equation (3).

$$\text{Min}_{\theta,\lambda}\,\boldsymbol{\theta} \qquad \text{Eq (3)}$$

$$\text{St.} \quad -q_i + Q\lambda \geq 0$$

$$\theta X_i - X\lambda \geq 0$$

$$\lambda \geq 0$$

Where θ is scalar, $\boldsymbol{\lambda}$ is an $I \times 1$ vector of constants and $\theta \leq 1$. In the Charnes, Cooper, and Rhodes (1978) (CCR) model, where the scale of operation and the efficiency of DMUs are unrelated, a constant return to scale (CRS) is assumed. As a result, the model calculates a technical efficiency score (Řepkova, 2015). The CRS assumption holds true when all DMUs are working at optimal scale. DMUs, on the other hand, may suffer either scale economies or scale diseconomies in practice. Scale efficiencies will contaminate the CCR model's predicted technical efficiency score when not all DMUs are running at optimal scale (Řepkova, 2015). This was addressed in the Banker, Charnes, Cooper (1984) (BCC) model by assuming a VRS, as illustrated in Equation (4).

$$\textbf{Min}_{\theta,\lambda}\,\boldsymbol{\theta}, \qquad \text{Eq (4)}$$

$$\text{St.} \quad -qi + Q\lambda \geq 0$$

$$\theta X_i - X\lambda \geq 0$$

$$I1'\lambda = 1$$

$$\lambda \geq 0$$

Where I1 is an $I \times 1$ vectors of ones. The BCC approach divides the technical efficiency score into two parts: pure technical efficiency and scale efficiency (Alrafadi et al., 2014). Technical efficiency is represented by CRS, and pure technical efficiency is represented by VRS. Let the efficiency scores of a DMU's CCR and BCC models be θ_k *CRS* and θ_k, *VRS* respectively. Then the scale efficiency (SE) is given by, $SE = \frac{\theta k,CRS}{\theta k,VRS} = \frac{\theta k,CCR}{\theta k,BCC}$. Overall technical efficiency score on the other hand is given by $OTE = PTE \times SE$.

3.3.2 Tobit Regression Models

To explain a non-negative dependent variable's relationship with an independent variable, James Tobin proposed the Tobit model. Tobit was derived from Tobin's name by truncating and adding it, similar to the Probit model. The presence of a latent variable is assumed in the model. This variable is dependent linearly on a parameter that defines the relationship between the independent and latent variables. A normally distributed error term is also included to account for random influences on this relationship. When the observed variable is greater than zero, it is equal to the latent variable; otherwise, it is zero. Where is the consistency of the latent variable? The resulting ordinary least squares regression estimator is inconsistent if the relationship parameter is estimated by regressing the observed on. It will produce a downward biased estimate of the coefficient's slope and an upward biased estimate of the intercept. For this model, Tekshi Amemiya demonstrated that the maximum likelihood estimator suggested by Tobin's is consistent.

The DEA model is used to determine the technical efficiency score, which ranges from 0 to 1, i.e., $0 \leq \theta \leq 1$; thus, it is a censored dependent variable. Tobit is an ideal model to utilize because it is thought to handle the features of the efficiency score distribution (Sufian, 2009). Equation (5) gives the Tobit model to be estimated (Henningsen, 2010).

$$Z^*_{it} = X^*_{it}\beta + \epsilon_{it} = X'_{it}\beta_i + \mu_i + v_{it} \qquad Eq(5)$$

$$z_{it} = \begin{cases} L, \text{ if } z^*_{it} < L \\ Z^*_{it}, \text{ if } L < Z^*_{it} > U \\ U, \text{ If } z^*_{it} > U \end{cases}$$

Where z_{it} is observed dependent variable, $z*\ it$ is a latent variable, x_{it} is a vector of explanatory variables, $\boldsymbol{\beta}_i$ are parameters to be estimated, L is the lower limit, U is the upper limit, $i = 1, 2, \ldots, N$ representing individuals, $t = 1, 2, \ldots, T_t$ indicates the time period, T_t is the number of time periods, μ_t is time invariant individual specific effect and v_{it} is a random term. The empirical regression model is specified as:

$$Z = \alpha + \beta_1 LC + \beta_2 LR + \beta_3 RA + \beta_4 CR + \beta_5 OS + \beta_6 MS + \epsilon_i \qquad \text{Eq (6)}$$

Were LC = Level of capitalization LR = liquidity risk

RA = Return on asset CR = Credit risk

OS = Ownership structure MS = Market share

Z is the technical efficiency score of the DMUs. Technical efficiency score and the other independent variables for the Tobit regression model are described below.

3.4 Description of Variables and Measures

3.4.1 Description of Variables in the DEA Model

According to Milind (2003) carries out the bank's efficiency analysis in India on the basis of two models by using DEA. Model A inputs are: interest expenses, non-interest expenses, and outputs: net interest income, net non-interest income, and model B inputs are: deposits, employees, and outputs: net loans, noninterest income) and Bhattacharya et al. (1997) used DEA model to analysis the Indian banks sector efficiency. The authors used an intermediation approach to select as two inputs such as interest and operating expenses and three outputs such as deposits, advances, and investments. Depending on the previous studies, to analysis the technical efficiency score Decision making units of DEA model variables which can be grouped into the following categories such as input variables (interest expense, operating expense and deposit) and output variables (non-interest income, interest income and loans).

a) Input Variables

Interest Expenses:

The total of payments made on fixed deposits, savings accounts, and demand deposits. The cost incurred by a company for borrowing money. Interest expense is a non-operating expense shown on the income statement. It represents interest payable on any borrowings bonds, loans, convertible debt, or lines of credit.

Operating Expenses

Operating expenses include salaries and benefits, administrative and general expenses, provision for doubtful debt and other expenses, and audit fees. A business incurs through its normal business operations. It includes rent, equipment, inventory costs, marketing, payroll, insurance, step costs, and funds allocated for research and development.

Deposits

The sum of demand, time, and savings deposit a financial institution maintains a bank account in which a customer can deposit and withdraw funds. Deposit accounts can be savings accounts, current accounts, or any of the other types of accounts described further below. Deposit account transactions are recorded in a bank's books, and the resulting balance is recorded as a liability of the bank, representing the amount owed by the bank to the customer. Some financial institutions charge fees for transactions made on a customer's account.

b) Output Variables

Interest Income

It is the sum of interest on loans and advances, interest on deposits, interest on treasury and NBE bills. It is generated by savings accounts, CDs, and other investments that pay some form of interest. Net interest income is the difference between the revenue generated by assets loans, mortgages, and securities and the interest costs on liabilities, such as deposits in checking and savings accounts and CDs.

Non-interest Income

Commissions, fees and charges on letters of credit, letters of guarantee, local transfers, and other sources of revenue are non-interest income. Any income that banks earn from activities other than their core intermediation business (taking deposits and making loans) or from their investments is classified as non-interest income. This type of income is often referred to as "fee income" since fees constitute the majority of non-interest income.

Loan

Real estate loans, commercial loans, industrial loans, and consumer loans are all examples of loans. A loan is a financial transaction in which one or more individuals, organizations, or other entities lend money to other individuals, organizations, or entities. The borrower incurs a debt and is normally responsible for paying both interest and the principal amount borrowed until the obligation is repaid.

3.4.2 Description of Variables in the Tobit Model

Based on Dharmendra and Bashir (2015) that examined technical efficiency and its determinate commercial banks in Oman, the author used explanatory variables, including bank size, profitability, capital adequacy, and liquidity and overall technical efficiency score as limited dependent variable by using the Tobit model. Based on the literature in this study we used Tobit model the technical efficiency (TE) scores achieved from the first step are used as limited dependent variable from DEA analysis and six variables: level of capitalization, liquidity risk, return on assets, credit risk, market share and ownership structure are selected as independent variable.

Dependent variable

Technical Efficiency Score (TE)

As we define the difference between observed quantity of input and output variables with respect to optimal quantity of input and output variables. An efficient bank can achieve a maximum value of one in comparison to an inefficient bank, which can reduce to the level of zero. According to Cooper et al. (2011), to measure efficiency in the banking sector, the DEA model (input-oriented) with variable return to scale (VRS) and constant return to scale (CRS) assumptions was adopted. It measures efficiency based on minimizing the input values. The BCC mode is with the assumption of VRS and the CCR mode is with CRS assumption. The BCC models assumption that is VRS that measure pure technical efficiency score and the CRR model assume that CRS measures technical efficiency of those aforementioned commercial banks in Ethiopia. The DEA model is used to determine the technical efficiency score, which ranges from 0 to 1, i.e., $0 \leq \theta \leq 1$; thus, it is a censored dependent variable. Then the scale efficiency (SE) is given by, $SE = \frac{\theta k,CRS}{\theta k,VRS} = \frac{\theta k,CCR}{\theta k,BCC}$. In this study we used technical efficiency score as a limited dependent variable is given by: overall technical efficiency (OTE) = PTE*SE

Explanatory Variables

This subsection describes the independent variables that are used in the Tobit model to estimate the dependent variable (TE).

A. **Level of Capitalization: -** This variable is defined as the ratio of equity to total assets. It is an important indicator used to explain the performance of financial institutions. The expected effect of the capital on bank profitability is positive. It refers to the company's capital structure. Capitalization can refer to the book value cost of capital, which is the sum of a company's long-term debt, stock, and retained earnings. The ratio of equity to total assets.

$$\textbf{Level of Capitalization}(\textbf{LC}) = \frac{\textbf{Equity}}{\textbf{\textit{Total Asset}}}$$

B. **Liquidity Risk: -** Defined as the risk of incurring losses resulting from the inability to meet payment obligations in a timely manner when they become due or from being unable to do so at a sustainable cost. The ratio of loans to deposits.

$$\textbf{Liquidity Risk (LR)} = \frac{\textbf{Total Loan}}{\boldsymbol{Deposit}}$$

C. **Return on Asset: -** It is a measure of profitability that estimated as a ratio of net income to total assets of the banks. It shows the efficiency of bank management in generating net income by using the bank resources. ROA is a ratio calculated by dividing the net income to total assets. ROA have been used in most of the studies for the measurement the profitability of the banks (Khrawish, 2011) we expect a positive relationship with bank efficiency (Sufian, 2009). This study used ROA as measure of explanatory variable which is calculated by dividing net income to total asset.

$$\textbf{Return on Asset (ROA)} = \frac{\textbf{Net income}}{\boldsymbol{Total\ Asset}}$$

D. Credit Risk: - The measure of the creditworthiness of a borrower. In calculating credit risk, lenders are gauging the likelihood that they will recover all of their principal and interest when making a loan. Borrowers considered to be low credit risks are charged lower interest rates. In addition to this, according to the Bank for International Settlements (BIS), credit risk is simply defined as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms. Finally, we can calculate the ratio of total loans to total assets.

$$\textbf{Credit Risk (CR)} = \frac{\textbf{Total Loan}}{\textbf{Total Asset}}$$

E. **Ownership Structure**: - This variable was created to investigate the impact of various ownership structures on efficiency. Each deposit bank, both private and state-owned, generates a dummy variable. If the bank is state-owned, it has a value of 1; otherwise it has a value of 0.

F. Market Share: - The percentage of an industry or a market's total assets, that is earned by a particular company over a specified time period. It calculated by taking the company's total assets over the period and dividing them by the total assets of the industry over the same period. It calculates total assets of one bank to the total assets of all banks.

$$\textbf{Market Share (MS)} = \frac{\textbf{Total Asset of one bank}}{\boldsymbol{Total\ Assets\ of\ all\ bank}}$$

3.5 Variables Expected Sign

Table 3.1 Variables Expected sign in the Tobit model

Variables	Expected sign
Level of capitalization	Positive
Liquidity risk	Positive
Return on asset	Positive
Credit risk	Negative
Ownership structure	Negative
Market share	Positive

CHAPTER FOUR

RESULTS AND DISCUSSIONS

This chapter deals with the analysis and presentation of the regression results of the study. The data was analyzed using Stata software. The descriptive statistics of the input and output variables, as well as the econometric analysis of the DEA model are presented. Secondly, there were descriptive statistics for the dependent and independent variables, as well as the Tobit model regression analysis. Then, diagnostic tests on the Tobit model were conducted using econometric tests and finally, we present a discussion and a summary of the analysis.

4.1 Descriptive Statistics of the data

4.1.1 Descriptive Statistics of Variables in the DEA Model

The most difficult challenge an analyst faces when generating efficiency scores is selecting the appropriate inputs and outputs for forecasting bank behavior. It should be noted that there is no agreement on what constitutes a bank's inputs and outputs (Casu and Girardone, 2002; Sathye, 2003). There are two approaches to selecting a bank's inputs and outputs in the literature on banking efficiency: the intermediation approach and the production approach (Humphrey, 1985; Hjalmarsson et al., 2000).

Both approaches apply traditional microeconomic theory to banking, with the only difference being how banking activities are classified. According to Berger and Humphrey (1997), neither of these models is perfect because they fail to convey the dual role of banks as a document processing service providers and financial intermediaries. They did, however, recommend that the intermediation method be used to examine bank-level efficiency, while the production method is used to examine branch-level efficiency. As a result, in order to compute the various efficiency ratings for sampling commercial banks in Ethiopia, input and output variables were used. We used the intermediation technique rather than the production approach, as has been done in the majority of empirical literature. Under this we present the outcomes of descriptive statistics for input and output variables used in the study for the sampled commercial banks. The input variables used in the study were interest expense, operating expense, and deposit, while the output variables were interest income, non-interest income, and loan.

The secondary data collected from income statement and balance sheets of those commercial banks are used for DEA analysis. The descriptive analysis is based on the statistical summary of the DEA data. For each variable under consideration the table 4.1 presents the mean, standard deviation, minimum and maximum value for the input and output variables for the sample banks used in the study over the period 2012/13 to 2017/18.

Table 4.1 Descriptive statistics summary of variables in the DEA model

Variables	Obs	Mean	Std. dev.	Min	Max
Interest expense in millions of Birr	96	787.121	1,922.039	1.171	14,750.251
Operating expense in millions of Birr	96	906.942	1,784.661	27.990	12,659.476
Deposit in billions of Birr	96	26,178.022	71,510.276	158.366	450,680.91
Interest income in millions of Birr	96	2,181.259	5,376.361	7.054	37,328.464
Noninterest income in millions of Birr	96	661.231	1,089.343	7.821	5,466.708
Loan in billions of Birr	96	14,587.344	29,790.810	99.414	172,687.492

Source: Authors' self calculation

As stated in the above table 4.1, all variables contained 96 observations (panel data of 16 commercial banks for 6 years) and indicate that the summary of descriptive statistics of selected input and output variables for Ethiopian commercial banks over the period of 2012/13 to 2017/18. According to the input data, the commercial banks under investigation incurred an average interest expenditure of Birr 787 million over the study period and a standard deviation of 1,922.039 with a minimum value of birr 1.17 million observed in Debub Global Bank in 2013 and a maximum value of birr 14.750 billion observed in CBE in 2018, which means the variables have great variation across the bank. The average operating expense of Ethiopia's commercial banks is estimated to be Birr 906 million, with a minimum value of birr 27.990 million observed in DGB in 2012/13 and a maximum value of birr 12.659 billion observed in CBE in 2017/18. With these expenses, they are able to mobilize an average of birr 26.178 billion, with a standard deviation of 71,510.276. In addition to this, the minimum value of this variable is birr 158.366 million, observed in DGB in 2012/13, and a maximum value of birr 450.680 billion, recorded in CBE in 2017/18.

On the other hand, with these inputs variables, the sampled commercial banks earned an average of Birr 2.181 billion in interest income and Birr 661 million in non-interest income during the study period. Furthermore, they recorded the minimum value of those variables as birr 7.054 million and birr 7.821 million, observed in Bunna international bank and Brhan international bank in 2015/16, and a maximum value of birr 37.32 billion and birr 5.466 billion, recorded in

CBE in 2017/18, respectively. In this statistical summary, the sampled commercial banks under this study, they disbursed loans totaling birr 14.586 billion on average over a six-year period, with the lowest value being birr 99.414 million recorded in DBG 2012/13 and the highest value being birr 172.687 billion recorded in CBE 2017/18.

4.1.2 Descriptive Statistics of Variables in the Tobit model

It is critical to acquire information about the sources of efficiency or inefficiency before considering interventions to increase the technical efficiency score. This was addressed in this study using the estimation of a Tobit model. This section presents the outcomes of descriptive statistics for dependent and independent variables used in the study for those commercial banks selected for in this study. The dependent variables used in the study is technical efficiency score under VRS assumption , while the independent variables were level of capitalization, liquidity risk, return on asset, credit risk, ownership structure and market share. The table 4.2 presents the mean, standard deviation, minimum and maximum value for the dependent and independent variables for commercial banks used in the study over the period 2012/13 to 2017/18. This section contains a statistical summary of the explanatory variables in the Tobit model.

Table 4.2 Descriptive statistics of variables in the Tobit model

Variables	Obs	Mean	Std. dev.	Min	Max
Technical efficiency	96	0.884	0.057	0.757	1.000
Level of capitalization	96	0.145	0.048	0.034	0.297
Liquidity risk	96	2.769	8.545	0.383	55.21
Return on asset	96	0.023	0.011	-0.037	0.051
Credit risk	96	0.457	0.073	0.200	0.570
Ownership structure in %	96	0.125	0.332	0.000	1.000
Market share	96	0.062	0.145	0.001	0.629

Source: Authors' self calculation

As stated in the above table 4.2, all variables contained 96 observations (panel data of 16 commercial banks for 6 years) and the efficiency measure used in the study as dependent variable, namely, TE, under the assumption of variable return to scale, indicates that the Ethiopian commercial banks' technical efficiency, on average, there has been an increasing return to scale for their efficiency for about the last six years. For the total included sample of the commercial banks in the study, the mean of TE was 88.4% with a minimum of 75.7 % technical efficiency score recorded in CBE 2015/16 and a maximum of 100% was recorded in AIB and DGB for the year 2012/13 and ZB, DBE, and AWB for the year 2014/15, the most efficient banks in the study period. That means the most efficient bank among the sampled banks in the study used all the inputs efficiently. On the other hand, the least inefficient bank of the sampled inefficient banks uses the input inefficiently. The data set has a standard deviation of (0.057), which indicates that the efficiency variation between the selected banks in the study was very small. The above result shows that these banks need to optimize the utilization of their inputs to increase their efficiency.

Concerning the explanatory variables of the Tobit model, there are some statistics that have to be mentioned. The level of capitalization, which is measured by total capital divided by total assets, has a mean value of 14.5% with a maximum and minimum value of 3.4% and 29.5%, respectively. The mean value indicates that, on average, 14.5% of the total assets are capital for sampled commercial banks. The standard deviation statistic for the level of capitalization was 0.048, which shows the existence of a relatively lower variation in capital to asset ratio between the selected banks compared to the variation in technical efficiency.

The second independent variable used in the study was liquidity risk, which is measured by total loan divided by total deposit and has a mean value of 2.769 with a maximum and minimum value of 0.383 and 55.21 respectively. The liquidity measure of the study indicates that the Ethiopian commercial banks have, on average, a higher liquidity position, which was somewhat higher than the minimum requirement set by NBE. In addition, the standard deviation of liquidity risk was 8.545, which shows there is higher variation in liquidity among sampled banks.

The third independent variable used in the study was return on assets, which is measured by net income divided by total assets, and has shown a mean of 2.3% with a maximum of 5.1% and a minimum value of -3.7% in the study period undertaken. The standard deviation has registered a value equal to (0.011). The fourth independent variable used in the study was credit risk, which is measured by total loan dived by total assets and has a mean value of 45.7% with a maximum and minimum value of 57% and 20% respectively. The data set of credit risk has experienced a standard deviation of equal to (0.073), which shows the existence of less variation among the Ethiopian commercial banks in diversifying their sources of credit risk.

The fifth variable used in the study was ownership structure, with a mean value of 0.125. The minimum and maximum value of the ownership structure in the given data set is 0.000 and 1.00, respectively, which indicates that banks are state-owned and privately-owned commercial banks. The data set shows the standard deviation of this variable is equal to (0.332). The other variable employed in this study is market share, which is measured by the total assets of one bank to the total assets of all banks. On average, they share 6.2% of the market with a maximum and minimum value of 62.9% and 1%, respectively. The standard deviation is 0.145. There is high variation among those commercial banks under the study period.

4.2 Empirical analysis of the DEA Model

A data envelopment analysis model is a method for evaluating DMU efficiency that employs linear programming techniques to envelop observed input-output vectors as tightly as possible (Boussofiane, Dyson, and Thanassoulis 1991). It enables the consideration of multiple input-output pairs at the same time without making any assumptions about data distribution. Efficiency is measured in each case as a proportional change in inputs or outputs. DEA models can be further subdivided into input-oriented models, which minimize inputs while satisfying at least the given output levels, and output-oriented models, which maximize outputs without requiring any more of the observed input values.

According to Charnes, Cooper, and Rhodes (1978), the CCR model was first proposed by the assumption of constant returns to scale (CRS), in which all DMUs operate at their optimal scale, which measures technical efficiency (overall technical efficiency). Banker, Charnes, and Cooper (1984), on the other hand, introduced the BCC model under the assumption of variable returns to scale (VRS), which measures pure technical efficiency. This model allows for the breakdown of efficiency into technical and scale efficiencies. During all sample banks for the time under study, we explain the outcomes of the DEA model estimate, technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) as follows:-

4.2.1 Overall Technical efficiency score estimates results under CRS Assumption

According to Dharmendra and Bashir (2015), the overall technical efficiency (OTE), which measures inefficiencies by input/output configuration and process scale, is represented by the technical efficiency metric. However, the CRS assumption is only valid when all DMUs are running at their maximum capacity. Imperfect competition and other commercial reasons, on the other hand, may force a DMU to run at a scale that is not ideal. According to the CCR model assumption of CRS, out of the sixteen sample banks evaluated for this study table 4.3 shows the findings of the DEA model, i.e. overall technical efficiency (OTE), for all of the selected banks from 2012/13 to 2017/18.

Table 4.3 Technical efficiency estimates under CRS assumption

S.no	*Banks*	***TE under CRS Assumption***					
		2012/13	*2013/14*	*2014/15*	*2015/16*	*2016/17*	*2017/18*
1	*DB*	*0.851*	*0.812*	*0.773*	*0.791*	*0.797*	*0.760*
2	*NIB*	*0.882*	*0.847*	*0.823*	*0.823*	*0.826*	*0.794*
3	*AB*	*0.949*	*0.788*	*0.870*	*0.869*	*0.840*	*0.837*
4	*AIB*	*1.000*	*0.854*	*0.924*	*0.900*	*0.882*	*0.873*
5	*BOA*	*0.906*	*0.781*	*0.767*	*0.838*	*0.812*	*0.833*
6	*BRB*	*0.980*	*0.845*	*0.827*	*0.890*	*0.854*	*0.868*
7	*BUB*	*0.911*	*0.849*	*0.841*	*0.699*	*0.869*	*0.884*
8	*CBE*	*0.769*	*0.722*	*0.729*	*0.632*	*0.754*	*0.764*
9	*CBO*	*0.878*	*0.847*	*0.829*	*0.754*	*0.813*	*0.853*
10	*DGB*	*1.000*	*0.960*	*0.937*	*0.859*	*0.899*	*0.946*
11	*LB*	*0.932*	*0.890*	*0.963*	*0.796*	*0.845*	*0.842*
12	*UB*	*0.883*	*0.855*	*0.933*	*0.787*	*0.826*	*0.825*
13	*WB*	*0.780*	*0.875*	*0.943*	*0.775*	*0.840*	*0.833*
14	*ZB*	*0.859*	*0.935*	*1.000*	*0.848*	*0.896*	*0.886*
15	*DBE*	*0.872*	*0.826*	*1.000*	*0.841*	*0.878*	*0.912*
16	*AWB*	*0.809*	*0.769*	*0.949*	*0.798*	*0.766*	*0.839*

Source: Authors' self-evaluation using Stata SE14.0.

According to the two stages DEA analysis tables 4.3 displayed above, based on the assumption of constant return to scale of the CCR model. It is observed that out of the sixteen sample banks considered for this study, Addis International Bank and Debub Global Bank were technically efficient in 2012/13 and Zemen Bank and Development Bank of Ethiopia were technically efficient in 2014/15 for about 100%, whereas Bunna International and Commercial Bank of Ethiopia recorded 69.9% and 63.2% were inefficient banks in the study period respectively in 2015/16. The other commercial banks, on the other hand, are technically less efficient. Furthermore, Commercial Bank of Ethiopia is Ethiopia's largest state-owned bank in terms of assets and employees, but it was inefficient in terms of technology during the study period and its technical efficiency score declined from 76.9% to 76.4% recorded for the study period 2012/13-2017/18.

With an average technical efficiency score of 93.7 percent, 90.5 percent, and 90.4 percent, respectively, Debub Global Bank, Addis International Bank, and Zemen Bank are deemed to be more efficient over the study period under consideration, whereas Dashen Bank and Commercial Bank of Ethiopia are found to be the least efficient with a technical efficiency score of 79.7% and 72.8%, respectively (see appendix B). The technical efficiency measure under the CRS assumption is overall technical efficiency (OTE), which measures inefficiencies owing to input/output configuration and operation size. However, the CRS assumption is only valid when all DMUs are running at their maximum capacity. Imperfect competition and other commercial reasons, on the other hand, may force a DMU to run at a scale that is not ideal. Pure technical efficiency and scale efficiency are separated from overall technical efficiency.

4.2.2 Pure Technical efficiency score estimates results under VRS Assumption

Based on the BCC model assumption of VRS, Table 4.4 displays the results of the DEA model pure technical efficiency (PTE) for all sample banks from 2012/13 to 2017/18. Based on appendix B, Debub Global Bank and Development Bank are determined to be more efficient with an average of 95.4 percent and 94.3 percent, respectively, in the study's pure technical efficiency score, while Commercial Bank of Ethiopia and Dashen Bank are found to be the least efficient with a pure technical efficiency score of 83.1% and 77.1%, respectively, as we compared to the other commercial banks under the study period. There are commercial banks in Ethiopia in the study that are technically inefficient on average. This means that on average it indicates managerial underperformance. However, we can check each and every year our sampled Ethiopian commercial banks technical efficiency detailed see the below table 4.4

Table 4.4 Pure Technical efficiency estimates under VRS assumption

S.no	Banks	PTE under VRS Assumption					
		2012/13	2013/14	2014/15	2015/16	2016/17	2017/18
1	DB	0.863	0.847	0.833	0.827	0.814	0.807
2	NIB	0.889	0.869	0.859	0.852	0.843	0.832
3	AB	0.949	0.911	0.896	0.886	0.867	0.862
4	AIB	1.000	0.957	0.938	0.922	0.907	0.898
5	BOA	0.907	0.872	0.859	0.846	0.827	0.836
6	BRB	0.987	0.930	0.907	0.895	0.863	0.870
7	BUB	0.950	0.918	0.897	0.876	0.875	0.887
8	CBE	0.796	0.776	0.767	0.757	0.765	0.768
9	CBO	0.896	0.877	0.846	0.835	0.836	0.855
10	DGB	1.000	0.978	0.953	0.930	0.919	0.947
11	LB	0.945	0.916	0.978	0.873	0.865	0.855
12	UB	0.899	0.869	0.950	0.842	0.837	0.831
13	WB	0.874	0.877	0.958	0.843	0.844	0.833
14	ZB	0.940	0.949	1.000	0.897	0.905	0.892
15	DBE	0.928	0.932	1.000	0.920	0.941	0.941
16	AWB	0.858	0.847	1.000	0.826	0.811	0.840

Source: Authors' self-evaluation using Stata SE14.0.

According to the DEA analysis table 4.4 displayed above, based on the assumption of variable return to scale. Out of the sixteen sample banks considered for this investigation, it was discovered that Addis International Bank and Debub Global Bank were technically efficient in 2012/13 and Zemen Bank, Awash Bank, and Development Bank of Ethiopia were technically efficient in 2014/15. The other commercial banks, on the other hand, are technically inefficient Commercial Bank of Ethiopia is Ethiopia's largest bank in terms of assets and personnel; however it was inefficient in terms of technology during the study period. It recorded 75.7% in the year of 2015/16. Pure technical efficiency (PTE) is a measure of inefficiencies caused solely by management underperformance, and it corresponds to the VRS assumption. This indicates that there is no issue with input management or, in other words, managerial underperformance. Inefficient bank resources are the cause of inefficiency for those listed banks that are inefficient. A bank's size, whether it's too big or too tiny, can occasionally be a source of technical inefficiency.

4.2.3 Scale efficiency estimates result

There are numerous causes of technical inefficiency. Scale inefficiency occurs when a company operates at an inefficient size (either too small or too large). Table 4.5 displays the results of the DEA model scale efficiency (SE) for all sample banks from 2012/13 to 2017/18.

Table 4.5 Scale efficiency estimated result

S.no	*Banks*	*Scale efficiency*					
		2012/13	*2013/14*	*2014/15*	*2015/16*	*2016/17*	*2017/18*
1	DB	0.986	0.958	0.928	0.956	0.978	0.942
2	NIB	0.992	0.9750	0.958	0.966	0.979	0.953
3	AB	0.999	0.864	0.971	0.981	0.969	0.970
4	AIB	1.000	0.892	0.984	0.976	0.972	0.971
5	BOA	0.998	0.896	0.893	0.989	0.981	0.995
6	BRB	0.992	0.908	0.912	0.994	0.990	0.997
7	BUB	0.959	0.924	0.938	0.797	0.993	0.997
8	CBE	0.966	0.930	0.950	0.835	0.986	0.995
9	CBO	0.979	0.966	0.980	0.902	0.972	0.997
10	DGB	1.000	0.982	0.983	0.924	0.978	0.999
11	LB	0.986	0.971	0.984	0.911	0.976	0.983
12	UB	0.982	0.983	0.982	0.934	0.986	0.993
13	WB	0.892	0.997	0.984	0.919	0.995	0.999
14	ZB	0.913	0.985	1.000	0.945	0.990	0.993
15	DBE	0.938	0.885	1.000	0.913	0.932	0.969
16	AWB	0.943	0.908	0.949	0.965	0.945	0.998

Source: Authors' self-evaluation using Stata SE14.0.

According to the DEA analysis table 4.5 displayed above the estimated result of scale efficiency. Out of the sixteen sample banks considered for this investigation, it was discovered that Addis

International Bank and Debub Global Bank are scale efficient in 2012/13, and Zemen Bank and Development Bank of Ethiopia are scale efficient in 2014/15 compared to the other selected commercial banks under the study period while under the study period Bunna internatioan bank is recoreded the least scale inefficient bank that is 79.7% in the year of 2015/16. The other commercial banks, on the other hand, are scale inefficient. Commercial Bank of Ethiopia is the largest bank in Ethiopia in terms of asset size and number employee. The decreasing return-to-scale inefficiency of Ethiopian commercial banks means that a bank is too big to fully benefit from scale, or in other words, it is a case of scale diseconomies.

Commercial banks in Ethiopia also have varying scale efficiency scores, as indicated in Appendix B. Bunna International Bank and Development Bank of Ethiopia, for example, were found to be the least scale efficient of the commercial banks studied, with average scores of 93.4 and 93.9 percent, respectively, due to the choice of scale of operation. In general all commercial banks under the study period there is good scale efficiency recorded compared to the technical and pure technical efficiency under the study period.

4.3 Test for Multicollinearity

Table 4.6 Empirical results VIF

Variable	VIF	1/VIF
Ownership Structure (OS)	3.13	0.319
Liquidity risk(LR)	2.87	0.348
Level of capitalization (LC)	1.73	0.579
Credit risk(CR)	1.54	0.648
Return on Asset(lnROA)	1.29	0.773
Market share (lnMS)	1.02	0.983
Mean VIF	1.93	

As see from the above table 4.6 the variance inflation factor (VIF) and the tolerance level (1/VIF) are used to quantify the problem of multicollinearity in estimations. If there is no correlation between the explanatory variables, the VIF value will be 1. When VIF exceeds 10 and (1/VIF) falls below 0.1, there is a severe problem of multicollinearity. According to (Asteriou, Dimitros, and Hall, 2007), a VIF of less than 10 is acceptable. As a result, the results of table 4.6 show that there is no problematic multicollinearity in the model because the values of VIF are less than 10 and the values of 1/VIF are greater than 0.1.

4.4 Empirical analysis Tobit model

The technical efficiency score (under the variables returns to scale assumption) is regressed on capitalization, liquidity risk, return on assets, credit risk, ownership structure, and market share in the Tobit model. It is crucial to determine whether a panel model is acceptable for estimating the aforementioned relationship before moving on to the main study. As a result, the Likelihood ratio test is employed to see if the panel estimator and the pooled estimator are different. The test results show that the model has no panel level effect that indicated this result (see appendix D)

Likelihood-ratio test of $\sigma_u = 0$: $\bar{\chi}^2(01) = 14.06$

Prob. $\geq \bar{\chi}^2 = 0.000$

The panel-level variance component is negligible when rho is zero, and the panel estimator is identical to the pooled estimator. This is tested using a likelihood-ratio test at the bottom of the output. The Tobit estimator is officially compared to the panel estimator in this test. We reject the null hypothesis that there are no panel-level effects in this situation (see Appendix D). As a result, the conclusion of this study is based on the results of the Tobit model. The Tobit model regression results are consistent. The robust standard error option is used to calculate robust standard errors and solve the Heteroscedasticity problem, goodness fit and other model specification problems of our model. The estimation result is present in table 4.7.

Table 4.7 Tobit model estimation result

TE	*Coef.*	*Robust Std. Err.*	*T*	*P>|t|*	*[95% Conf. Interval]*	
LC	*0.534*	*0.098*	*5.42*	*0.000*	*0.338*	*0.729*
LR	*0.004*	*0.001*	*4.04*	*0.000*	*0.002*	*0.007*
ROA	*0.028*	*0.009*	*3.02*	*0.003*	*0.009*	*0.047*
CR	*-0.193*	*0.055*	*-3.48*	*0.000*	*-0.303*	*-0.082*
OS	*-0.071*	*0.019*	*-3.67*	*0.000*	*-0.110*	*-0.033*
MS	*0.003*	*0.002*	*1.49*	*0.141*	*-0.001*	*0.009*
Constant	*1.014*	*0.053*	*18.93*	*0.000*	*0.907*	*1.120*
σ Constant	*0.037*	*0.004*			*0.029*	*0.046*

Source: Author's self estimation by using stata/SE14.0

Tobit model estimation result of the above table 4.7 shows that variables like level of capitalization, liquidity risk, and return on assets had a positive relationship with technical efficiency as far as their coefficients were (*0.534*), (0.004), and (*0.028*) respectively. This indicates that there was a direct relationship between the three independent variables and TE. On the other hand, credit risk and ownership structure have a negative coefficient of -0.193 and -0.071, respectively, which indicates that there was an inverse relationship between credit risk and ownership structure with TE. Thus, the increase in these variables will lead to a decrease in TE. In general, as per the regression results provided in above table 4.7, among the 6 explanatory variables used in the study, five of them were significant, but market share is a positive and insignificant variable to Technical efficiency.

According to the above Tobit model estimation results presented in Table 4.7, it can be seen that Level of capitalization, liquidity risk, Return on assets, credit risk, and ownership structure are found to have a significant effect on the technical efficiency score of commercial banks in Ethiopia at a 1% level of significance. The estimation result is presented in detail in the next section below.

4.5 Discussion of the study

Based on the outputs presented in the above regression analysis result table 4.7 the next section tries to present the analysis with respect to each technical efficiency determinant.

Level of capitalization

The coefficient of level of capitalization (LC), which is measured by the ratio of equity to total assets, is 0.534 and the P-value is 0.000, according to the aforementioned regression analysis in table 4.7. Increasing the level of capitalization (LC) by one percent increases the technical efficiency of sampled Ethiopian commercial banks by 53.41 percent, which is statistically significant at the 1% level. This suggests that the relation is positive, as expected, and that there is insufficient evidence to demonstrate a negative relationship between TE and capitalization level, as suggested by Repkova's study (2015). The degree of capitalization of Ethiopian commercial banks and banking efficiency were shown to be positively related. This result confirms the conclusion of Grigorian and Manole (2002), Altunbas et al. (2007), Chortareas, Girardone, and Ventouri (2009) and Vu and Nahm (2013) in banking sectors.

Liquidity risk

The coefficient of liquidity risk, which is measured by the ratio of total loans to total deposits, was positive as expected and statistically significant at the 1% significance level (p-value = 0.000). Holding other independent variables constant at their average value, when liquidity risk (LR) is increased by one percent, the technical efficiency of Ethiopian commercial banks would be increased by 0.47%. Moreover, the coefficient of the ratio of total loans to total deposits is (0.004), which was high, which shows that an increase in total loans will result in increased technical efficiency. This is in line with the expectation that loans are one of the main sources of interest income for the banks. According to the study, liquidity concerns have a favorable and significant effect on technical efficiency of commercial banks at a 1% level of significance Repkova's study (2015).

Return on assets

This variable is explained in the model as a ratio of net income to total assets, and it is a primary measure of technical efficiency. Based on the above table 4.7, the coefficient of return on assets (ROA) measured by net income to total assets is *0.028 and* its P-value is 0.003. Holding other independent variables constant at their average values, increase return on assets (ROA) by one percent increases technical efficiency (TE) of sampled Ethiopian commercial banks by 2.86%, which is statistically significant at the 1% level of significance. That is, Alrafadi et al. (2014) and Adusei (2016) discovered that return on assets is positive and significantly related to technical efficiency score, while Repkova (2015) discovered that return on assets is positive and significantly related to bank technical efficiency score, which is consistent with the findings of this study.

Credit risk

Concerning credit risk, the regression results of this study suggest that the relation between credit risk and TE is negative and significant effect at the 1% significance level (p value = 0.000). Holding other independent variables constant at their average values, increasing credit risk (CR) of banks by one percent reduces technical efficiency (TE) of sampled Ethiopian commercial banks by 19.32%. In other words, there is a significant negative relationship between credit risk (CR) and technical efficiency (TE) of sampled Ethiopian commercial banks. Therefore, the researcher fails to reject the hypothesis which states there is a negative relationship between credit risk and technical efficiency.

In the literature, there is no conclusive evidence of a link between credit risk and efficiency. Several study the relation between credit risk and efficiency of the institution. TABAK, CRAVEIRO, and CAJUEIRO, 2010; ALTUNBAS, CARBO, GARDENER et al., 2007; BRANCO, SALGADO, CAVA et al., 2017; TABAK, CRAVEIRO, and CAJUEIRO, 2010). Wang, and Zhang (2014); Tan and Anchor (2017); and Tan and Floros (2018), on the other hand, discovered a link between higher credit risks and higher institution efficiency. According to Lua Syrma Z et al..(2020) they studied the credit risk and technical efficiency of the Brazilian credit union. The author concludes that the relation between credit risk and efficiency is inversely related that means the higher the credit risk and the lower the efficiency scores.

This negative link between credit risk and efficiency could indicate that risk-averse managers would raise operating expenses for loan review and monitoring in an attempt to control the increase in defaults, which would have a negative impact on the bank's efficiency measure. The relationship between credit risk and technical efficiency of the bank shows that when the credit risk ratio increases the technical efficiency of commercial banks decreases in opposite direction. In addition, this result has been supported by various studies; Sufian and Habibullah (2010) conclude that credit risk is negatively associated with bank efficiency. It indicates that there is a negative relation between banks' efficiency and risk-taking in European countries. Inefficient banks hold more capital and take on less risk (Altunbas et al., 2007). So in this study, technical efficiency and credit risk are negatively related. That means if the ratio of total loan to total asset increases by 1 percent, the technical efficiency of commercial banks declines by 19.32 percent. Therefore, credit risk exists as one of the major determinant factor that can influence Ethiopian commercial banks technical efficiency.

Ownership structure

Ownership structure is another important determinant of the commercial banks technical efficiency. Concerning ownership structure, the regression results of this study suggest that the relation between ownership structure and TE is negative and significant at the 1% significance level (p value = 0.000). In other words, there is a significant negative relationship between ownership structure (OS) and technical efficiency (TE) of sampled Ethiopian commercial banks. Therefore, the researcher fails to reject the hypothesis which states there is a negative relationship between ownership structure and technical efficiency.

Market share

The regression analysis in table 4.7 shows that, the coefficient of market share which measured by Total assets of one bank to the total assets of all banks is *0.003* and its P-value is 0.141. Holding other independent variables constant at their average value, when market share (MS) increased by one percent, technical efficiency (TE) of sampled Ethiopian commercial banks would be increased by 0.3876%, but statistically insignificant at 5% of significance level. There is insignificant positive relationship between Market share (MS) and technical efficiency (TE) of sampled Ethiopian commercial banks. In addition, the insignificant parameter of market share indicates that the market share does not affect Ethiopian banks technical efficiency. According to some previous studies, the results concerning market share are mixed. The impact of market share on bank technical efficiency scores has been found to be negative and significant (Seelanatha, 2012), which is not the case in this study. That is, market share is found to be positively and insignificantly related to Ethiopian commercial banks' technical efficiency score.

4.6 Summary of Analysis

The following table 4.8 presents the summary of hypothesized expected sign and actual sign for the relationship between the independent variables and banks technical efficiency.

Table 4.8 Summary of expected and actual signs of explanatory variables on the Dependent Variables

Explanatory Variables	Expected Relationship	Actual relationship	Statistical significance Test
Level of capitalization	Positive	Positive	Significant at 1%
Liquidity risk	Positive	Positive	Significant at 1%
Return on asset	Positive	Positive	Significant at 1%
Credit risk	Negative	Negative	Significant at 1%
Ownership structure	Negative	Negative	Significant at 1%
Market share	Positive	Positive	Insignificant

Source: own computation

As expected level of capitalization, liquidity risk, return on asset and market share affects banks technical efficiency positively. On the other hand, the expected result of credit risk and market share with bank technical efficiency is negatively associated. This chapter discussed the analysis of the results of Tobit model of the study. To summarize the above data analysis all bank specific factors included in the study are the major determinant of Ethiopian banks technical efficiency except market share.

CHAPTER FIVE

SUMMARYS, CONCLUSIONS AND RECOMMENDATIONS

This chapter discusses the conclusions and recommendations based on the findings of the previous chapter's result. The sections that followed discussed the study's final conclusion remarks and relevant recommendations. As a result, this chapter is divided into four sections. The first section contains a summary of the major findings, the second section contains the conclusions, and the third section contains recommendations. Finally, directions for future research were made.

5.1 Summary of Major Findings

The finding of the study display that out of the sixteen sample banks considered for this study for Data envelopment analysis only Addis International Bank and Debub Global Bank were technically efficient in 2012/13, and Zemen Bank, Awash bank and Development Bank of Ethiopia were technically efficient in 2014/15 for about 100% for both CRS and VRS assumption, but the other commercial banks, on the other hand, are technically inefficient. Addis International Bank, Debub Global Bank in 2012/13, and Zemen Bank and Development Bank Ethiopia in 2014/15 were the most scale efficient banks.

In the Tobit model finding indicate that level of capitalization; liquidity risk, return on asset, credit risk, and ownership structure are the major significant determinants of commercial banks' technical efficiency in Ethiopia. According to this study, the listed explanatory variables have a significant positive effect on the technical efficiency of the banks at a 1% level, but market share have an insignificant positive effect on the technical efficiency of commercial banks. This implies that the technical efficiency of Ethiopia commercial banks is determined by a combination of capitalization, liquidity risk, Return on asset, credit risk, and ownership structure.

5.2 Conclusions

The goal of this study was to use a two-step process to assess the technical efficiency of sixteen commercial banks in Ethiopia. A two-stage DEA model is used to measure technical efficiency scores in the first stage and the Tobit model is used to assess the credit risk and technical efficiency in the second step. The degree of capitalization, liquidity risk, return on assets, credit risk, market share, and ownership structure were included as independent factors in the analysis, For the period 2012/13 to 2017/18, under both the CRS and VRS assumptions, data envelopment analysis is utilized to calculate technical efficiency scores for all institutions under consideration. The findings of the investigation revealed that, despite slight variances, the conclusions regarding bank efficiency under both hypotheses are equivalent. Commercial banks that are shown to be inefficient under the CRS assumption are likewise found to be inefficient under the VRS assumption. Technical efficiency is recorded on average for the sampled commercial banks under the study period 88.4%. Commercial bank of Ethiopia and Dashen bank are found to be less efficient under the CRS assumption, whereas Debub Global bank and Zemen bank are found to be more efficient. Addis International Bank, Development Bank of Ethiopia and Debub Global Bank are shown to be more efficient, under the VRS assumption, whereas Commercial Bank of Ethiopia and Dashen Bank are found to be less efficient. It is also proven that, in comparison to the commercial banks included in the study, united bank and Debub global bank are the most scale efficient commercial banks in Ethiopia, whereas Bunna international bank and Ethiopian Development Bank are the least scale efficient banks. The findings reveal that technical inefficiency in the Ethiopian banking sector is linked to both inefficient input utilization (managerial inefficiency) and failure to operate at the most productive scale level.

The study used an acceptable econometric methodology for the estimate of variables coefficient under Tobit regression models to meet the research purpose. The necessary data was gathered from secondary sources, mostly from the commercial banks annual report and each bank through document analysis in order to identify and measure the factors of banks' technical efficiency. A Tobit model is calculated since the major goal of this study is to investigate the factors that influence the technical efficiency score of commercial banks in Ethiopia their relationship between with credit risk.

The Tobit model does not have a panel level effect (see Appendix d), as stated in the preceding chapter. As a result, the Tobit model result was used to explain the association between technical efficiency score and credit risk in this study. The results showed that level of capitalization, liquidity risk and return on asset have positive and significant effect, whereas the credit risk and ownership structure have negative and significant effect on the technical efficiency score of the commercial banks under study. However, market share is positive and insignificant variables.

Frist, The level of capitalization has a positive impact on technical efficiency with a strong significance coefficient. This positive relationship suggests an improved level of equity relative to the respective total assets. From this result, the researcher concludes that banks that have more equity generate more efficiency than banks with less equity. As a result, the level of capitalization is an important factor in determining the technical efficiency of commercial banks. Second, as expected, liquidity risk has a positive impact on technical efficiency with a strong significance coefficient. This shows that maximizing commercial banks' total loans in Ethiopia would certainly improve the bank’s technical efficiency.

Third, the result showed that there is a positive relationship between return on assets and commercial banks' technical efficiency as expected with strong statistical significance. The coefficient of the ratio of net income to total assets is relatively the highest compared to other variables in the study, showing that an increase in net income will result in increased technical efficiency.

Fourth, as expected, credit risk has a negative impact on technical efficiency with a strong significance coefficient. The finding also indicates that credit risk is negative and significant effect on Ethiopian commercial banks technical efficiency. The higher the credit risk, the lower the efficiency scores. As we conclude that the government of Ethiopia said the distribution of loan is low as the whole country due to this commercial banks give more loan to their customer. However, the ratio of total loan to total asset of sampled commercial banks indexed as credit risk in this study so the relation between technical efficiency is negative due to managerial under performance and their procedural policy of commercial banks related with collateral. Lastly, the ownership structure also has statistically significant and negative relationship with Commercial banks technical efficiency.

5.3 Recommendations

It is critical to understand the determinant that most affects the technical efficiency of Ethiopian commercial banks in order to sustain financial stability in the country. According to the study's findings, Ethiopian commercial banks' efficiency is primarily influenced by internal variables. Because the bank's management has control over the bank's unique characteristics, it's possible to boost the bank's efficiency by focusing more on the recognized elements including level of capitalization, liquidity risk, return on asset, credit risk, and ownership structure. Therefore management bodies of Ethiopian commercial banks should strive to strengthen the bank specific factors. Since, they are found to be the most significant factors that affect technical efficiency of

Ethiopian commercial banks. As a result of the study's findings, the following possible recommendations have been forwarded:-

- The conclusions of this study should offer policymakers with useful information for enhancing and maximizing the use of valuable resources in various banks.
- According to the findings suggested that inefficient banks can significantly enhance their performance by adopting the right input-output mix and scale size.
- The efficiency of Ethiopian banks is positively connected with their return on assets. As a result, measures should be undertaken to improve asset return.
- Level of capitalization is one of the significant factors affecting technical efficiency; banks should increase their equity by minimizing their shareholder of dividend to increase their level of capitalization. Therefore, banks need to develop a strategy that enables them to increase their equity to improve technical efficiency.
- Credit risk is a significant factor influencing technical efficiency as inversely in this study. This is due to managerial under performance, political instability and their loan procedural manual of those commercial banks. Therefore, banks need to develop a strategy that enables them to improve their technical efficiency Ethiopian commercial banks increase their staff managerial performance and amend their loan procedural manual and collateral evaluation technics flexible.
- The Ethiopian banks under investigation should strengthen their lending capabilities in addition to deposit mobilization.

5.4 Direction for future research

The goal of the study was to look into the factors that influence commercial banks' technical efficiency in Ethiopia. However, the statistical research did not take into account all of the elements that can affect Ethiopian banks' technical efficiency. As a result, future study may cover previously unknown bank-specific and macroeconomic data, as well as interest-free banking of Ethiopian commercial banks.

References

Alrafadi, K. M., Kamaruddin, B. H., & Yusuf, M. (2014). Efficiency and determinants in Libyan banking: *International Journal of Business and Social Science*.

Altunbas, Y., Carbo, S., Gardener, E.P.M. and Molyneux, P. (2007). Examining the relationships between capital, risk and efficiency in European banking: *European Financial Management.*

Ariff, M. and Can, L. (2008). Cost and profit efficiency of Chinese banks: a non-parametric analysis; *China Economic Review*.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*.

Barry, T.A., Dacanay, S.J., Lepetit, L. and Tarazi, A. (2010). Ownership structure and bank efficiency in six Asian countries: *Philippine Management Review*, Vol. 18, pp.19–35.

Berger, A. & Humphrey, D. (1997). Efficiency of Financial Institutions: International Survey and Directions for Future Research. *Journal of Operational Research* 98, 175–212.

Charnes, A., Cooper, W. & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research*, 2, 429–444.

Chu, S. & Lim, G. (1998). Share Performance and Profit Efficiency of Banks in an Oligopolistic Market: Evidence from Singapore. *Journal of Multinational Financial Management.*

Coelli, T. J., & Rao, D. S. (2005). Total factor productivity growth in agriculture: A Malmquist index analysis of 93 countries, 1980–2000. *Agricultural Economics*, *32*, 115–134.

Cvilikas, A. & Jurkonyte-Dumbliauskiene, E. (2016). Assessment of Risk Management Economic Efficiency Applying Economic Logistic Theory. *Transformations in Business & Economics* 15, 207–19.

Darrat, A., Topuz, C. & Yousef, T. (2002). Assessing Cost and Technical Efficiency of Banks in Kuwait. *Proceedings of the ERF's Annual Conference, Cario*, 1-22.

Debreu, G. (1951). The Coefficient of Resource Utilisation. *Econometrica* 19 (3), 273-292.

Dharmendra S., and Bashir A. (2015). Technical efficiency and its determinants: an empirical study on banking sector of Oman. *Problems and Perspectives in Management*.

Diallo, B., (2018). Bank efficiency and industry growth during financial crises. *Economic Modelling* 68: 11–22.

Drucker, P. (1963). Managing for Business Effectiveness. *Harvard Business Review*. 41(3).

Edgeworth, F. (1881). Mathematical Psychics: An Essay on the Application of Mathematics to the Moral Sciences. *Mathematical Physics*.

Farrell, M. J. (1957). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society*, 120 (3) 253–81.

Fiordelisi, F.; Marques-Ibanez, D.; Molyneux, P. (2011). Efficiency and risk in European banking. *Journal of Banking & Finance*, v. 35, n. 5, p. 1315-1326.

Freixas, X. and Rochet, J.C. (2008) Microeconomics of Banking, 2nd ed., MIT Press, Boston, MA

Gishkori, M.A. and Ullah, N. (2013). Technical efficiency of Islamic and commercial banks: evidence from Pakistan using DEA model (2007–2011)', *IOSR Journal of Business and Management (IOSR-JBM),* Vol. 7, No. 4, pp.68–76.

Harker, P. & Zenios, S. (2000) Performance of Financial Institutions, Efficiency, Innovation, Regulation.Cambridge, UK: Cambridge University Press. 259–311.

Henningsen, A. (2010). Estimating censored regression models in R using the censReg Package. Kobenhavn: University of Copenhagen.

Irsova, S. (2008). Measuring Bank Efficiency. *Charles University in Prague*.

Jaouadi, S. (2014). Exploring the Effectiveness and Efficiency of Banks in Switzerland. *International Journal of Academic Research in Business and Social Sciences*. 4, 313-325

Jia, C. (2009). The effect of ownership on the prudential behavior of banks the case of China. *Journal of Banking & Finance*, Vol. 33, pp.77–87.

Kablan, S. (2009). Banking Efficiency and Financial Development in Sub-Saharan Africa. *African Finance Journal*, 11(2), 28–50.

Katib, M. & Mathews, K. (2000). A Non-Parametric Approach to Efficiency Measurement in the Malaysian Banking Sector. *The Singapore Economic Review* 44, 89-114.

Keatinge, T. (2014). The role of public and private sector banking in ethiopia's future economic growth. Policy brief. *Global Center on Cooperative Security: Building Strong Partnerships for a more secure world*.

Kim, M., Kristiansen, E.G. and Vale, B. (2005). Endogenous product differentiation in credit markets: what do borrowers pay for. *Journal of Banking and Finance*, Vol. 29, pp.681–699.

Koopmans, T. (1951). An Analysis of Production as an Efficient Combination of Activities. *Int. C.Koopmans (Eds) Activity Analysis of Production and Allocation, Cowles Commission for Research in Economics*, Monograph No.13, New York.

Kumar, S. and Gulati, R. (2008). An examination of technical, pure technical, and scale efficiencies in Indian public sector banks using data envelopment analysis. *Eurasian Journal of Business and Economic*, Vol. 1, No. 2, pp.33–69.

Leibenstein, H. (1966). Allocative Efficiency Vs' X-Efficiency. *American Economic Review*, 56, 392–415

Lemonakis, C., Voulgaris, F., Vassakis, K. and Christakis, S. (2015). Efficiency, capital and risk in banking industry: the case of Middle East and North Africa countries. *Int. J. Financial Engineering and Risk Management*, Vol. 2, No. 2, pp.109–123.

Mckinley, V. & Banian, K. (2000). Central Bank Operational Measurement: Meaning and Measurement. *Central Bank Publications* 45-81

Milind, S. (2003). Efficiency of Banks in a Developing Economy: The Case of India. *European, Journal of operational Research* 148, 662–671.

Pareto, V. (1927). *Manuel d'Economie Politique*. Giard et Brier, 2nd Edition.

Pastor, J. M.; Serrano, L. (2005). Efficiency, endogenous and exogenous credit risk in the banking systems of the Euro area. *Applied Financial Economics,* v. 15, n. 9, p. 631-649.

Raphael, G. (2012). Commercial banks efficiency in Tanzania: A non-parametric approach. *European Journal of Business and Management*, 55–67.

Raphael, G. (2013). Efficiency of commercial banks in east Africa: A non-parametric approach. *International Journal of Business and Management, 8*, 50–64.

Řepkova, I. (2015). Banking efficiency determinants in the Czech banking sector. *Economics and Finance, 23*, 191–196.

Salas, V.; Saurina, J. (2002). Credit risk in two institutional regimes: Spanish commercial and savings banks. *Journal of Financial Services Research*, v. 22, n. 3, p. 203-224.

Sarmiento, M.; Galán, J. E. (2017). The influence of risk-taking on bank efficiency: evidence from Colombia. *Emerging Markets Review*, v. 32, p. 52-73.

Sathye, M. (2005). The impact of internet banking on performance and risk profile: evidence from Australian credit unions. *Journal of Banking Regulation,* v. 6, n. 2, p. 163-174.

Sealey, C. & Lindley, J. (1977). Inputs, Outputs and Theory of Production Cost at Depository Financial Institutions. *Journal of Finance* 32 (4) 1251-1266.

Seelanatha, Lalith, (2012). Drivers of Technical Efficiency of Sri Lankan Commercial Banks: *International Journal of Applied Economics*.

Shephard, R. W. (1953). Cost and Production Functions. *Princeton University Press.*

Staub, R.B., Souza, G.D.S. and Tabak, B.M. (2010). Evolution of bank efficiency in Brazil: a DEA approach: *European Journal of Operational Research*, Vol. 202, No.

Sufian, F.(2009). Determinants of bank efficiency during unstable macroeconomic environment: Empirical evidence from Malaysia. *Research in International Business and Finance, 23*, 54–77. http://dx.doi.org/10.1016/j.ribaf.2008.07.002

Sufian and Habibullah (2010). Bank-specific, Industry-specific and Macroeconomic Determinants of Bank Efficiency: Empirical Evidence from the Thai Banking Sector; the *Journal of Applied Economic Research*.

Tadesse Z. (2017). Determinants of bank technical efficiency: Evidence from commercial banks in Ethiopia. *Cogent Business & Management*, 4:1, 1268356

Tan, Y. and Floros, C. (2013). Risk, capital and efficiency in Chinese banking: *Journal of International Financial Markets, Institutions and Money*, Vol. 26, pp.378–393.

TAN, Y.; ANCHOR, J (2017). The impacts of risk-taking behavior and competition on technical efficiency: evidence from the Chinese banking industry. *Research in International Business and Finance.*

Waheed, A. & Younus, N. (2010). Effects of Financial Sector's Development and Financial Sector's Efficiency on Economic Growth: Empirical Evidence from Developing and Developed Countries. *International Journal of Economic Perspectives* 4: 449–58.

Appendix’s

Appendix-A

Technical efficiency estimates under CRS and VRS assumptions and scale efficiency

DMU	*Year*	*TE under CRS*	*PTE under VRS*	*TE under NIRS*	*Scale efficiency*	*Return to scale*
DB	*2013*	*0.851459*	*0.863369*	*0.959220*	*0.986205*	*IRS*
NIB	*2013*	*0.882616*	*0.889183*	*1.000000*	*0.992615*	*IRS*
AB	*2013*	*0.949669*	*0.949930*	*1.000000*	*0.999724*	*IRS*
AIB	*2013*	*1.000000*	*1.000000*	*1.000000*	*1.000000*	*CRS*
BOA	*2013*	*0.906724*	*0.907975*	*1.000000*	*0.998622*	*IRS*
BRB	*2013*	*0.980548*	*0.987543*	*1.000000*	*0.992917*	*IRS*
BUB	*2013*	*0.911807*	*0.950221*	*0.996499*	*0.959573*	*IRS*
CBE	*2013*	*0.769740*	*0.796812*	*1.000000*	*0.966025*	*IRS*
CBO	*2013*	*0.878379*	*0.896699*	*1.000000*	*0.979569*	*IRS*
DGB	*2013*	*1.000000*	*1.000000*	*1.000000*	*1.000000*	*CRS*
LB	*2013*	*0.932658*	*0.945662*	*0.983556*	*0.986248*	*IRS*
UB	*2013*	*0.883953*	*0.899357*	*0.938888*	*0.982872*	*IRS*
WB	*2013*	*0.780436*	*0.874793*	*0.899685*	*0.892137*	*IRS*
ZB	*2013*	*0.859891*	*0.940937*	*1.000000*	*0.913867*	*IRS*
DBE	*2013*	*0.872033*	*0.928756*	*1.000000*	*0.938926*	*IRS*
AWB	*2013*	*0.809995*	*0.858365*	*0.859130*	*0.943649*	*IRS*
DB	*2014*	*0.812118*	*0.847713*	*0.879327*	*0.958011*	*IRS*
NIB	*2014*	*0.847594*	*0.869289*	*0.852805*	*0.975044*	*IRS*
AB	*2014*	*0.788560*	*0.911791*	*1.000000*	*0.864847*	*IRS*
AIB	*2014*	*0.854125*	*0.957267*	*1.000000*	*0.892254*	*IRS*
BOA	*2014*	*0.781695*	*0.872199*	*0.913234*	*0.896235*	*IRS*
BRB	*2014*	*0.845292*	*0.930075*	*0.894760*	*0.908843*	*IRS*
BUB	*2014*	*0.849361*	*0.918663*	*0.871454*	*0.924562*	*IRS*
CBE	*2014*	*0.722418*	*0.776704*	*0.779572*	*0.930107*	*IRS*
CBO	*2014*	*0.847913*	*0.877727*	*0.848041*	*0.966033*	*IRS*
DGB	*2014*	*0.960691*	*0.978189*	*1.000000*	*0.982112*	*IRS*
LB	*2014*	*0.890258*	*0.916646*	*0.903017*	*0.971213*	*IRS*
UB	*2014*	*0.855869*	*0.869920*	*0.887253*	*0.983848*	*IRS*
WB	*2014*	*0.875284*	*0.877741*	*0.923556*	*0.997200*	*IRS*
ZB	*2014*	*0.935793*	*0.949821*	*1.000000*	*0.985231*	*IRS*
DBE	*2014*	*0.826149*	*0.932735*	*1.000000*	*0.885727*	*IRS*
AWB	*2014*	*0.769923*	*0.847200*	*0.825479*	*0.908786*	*IRS*
DB	*2015*	*0.773501*	*0.833004*	*0.865581*	*0.928569*	*IRS*
NIB	*2015*	*0.823983*	*0.859771*	*0.874128*	*0.958375*	*IRS*
AB	*2015*	*0.870678*	*0.896083*	*0.894256*	*0.971649*	*IRS*
AIB	*2015*	*0.924207*	*0.938967*	*0.934034*	*0.984281*	*IRS*
BOA	*2015*	*0.767636*	*0.859441*	*0.842351*	*0.893180*	*IRS*
BRB	*2015*	*0.827560*	*0.907380*	*0.849259*	*0.912032*	*IRS*
BUB	*2015*	*0.841951*	*0.897439*	*0.872370*	*0.938171*	*IRS*
CBE	*2015*	*0.729057*	*0.767245*	*0.786744*	*0.950228*	*IRS*
CBO	*2015*	*0.829925*	*0.846800*	*0.861347*	*0.980072*	*IRS*
DGB	*2015*	*0.937735*	*0.953714*	*0.944903*	*0.983245*	*IRS*
LB	*2015*	*0.963674*	*0.978626*	*1.000000*	*0.984722*	*DRS*
UB	*2015*	*0.933981*	*0.950966*	*1.000000*	*0.982139*	*DRS*
WB	*2015*	*0.943739*	*0.958374*	*1.000000*	*0.984729*	*DRS*
ZB	*2015*	*1.000000*	*1.000000*	*1.000000*	*1.000000*	*CRS*
DBE	*2015*	*1.000000*	*1.000000*	*1.000000*	*1.000000*	*CRS*
AWB	*2015*	*0.949359*	*1.000000*	*1.000000*	*0.949359*	*DRS*
DB	*2016*	*0.791093*	*0.827181*	*1.000000*	*0.956372*	*IRS*
NIB	*2016*	*0.823985*	*0.852937*	*0.971759*	*0.966057*	*IRS*
AB	*2016*	*0.869920*	*0.886749*	*1.000000*	*0.981021*	*IRS*
AIB	*2016*	*0.900627*	*0.922239*	*0.933239*	*0.976566*	*IRS*

BOA	***2016***	***0.838135***	***0.846811***	***0.898767***	***0.989754***	***IRS***
BRB	***2016***	***0.890971***	***0.895617***	***0.923858***	***0.994813***	***IRS***
BUB	***2016***	***0.699506***	***0.876980***	***1.000000***	***0.797630***	***IRS***
CBE	***2016***	***0.632838***	***0.757181***	***1.000000***	***0.835781***	***IRS***
CBO	***2016***	***0.754298***	***0.835819***	***1.000000***	***0.902466***	***IRS***
DGB	***2016***	***0.859774***	***0.930449***	***1.000000***	***0.924041***	***IRS***
LB	***2016***	***0.796128***	***0.873285***	***0.904720***	***0.911648***	***IRS***
UB	***2016***	***0.787583***	***0.842402***	***0.855164***	***0.934926***	***IRS***
WB	***2016***	***0.775526***	***0.843864***	***0.808112***	***0.919017***	***IRS***
ZB	***2016***	***0.848333***	***0.897371***	***1.000000***	***0.945354***	***IRS***
DBE	***2016***	***0.841567***	***0.920895***	***1.000000***	***0.913858***	***IRS***
AWB	***2016***	***0.798044***	***0.826843***	***0.856115***	***0.965170***	***IRS***
DB	***2017***	***0.797257***	***0.814714***	***0.826699***	***0.978573***	***IRS***
NIB	***2017***	***0.826228***	***0.843261***	***0.840338***	***0.979801***	***IRS***
AB	***2017***	***0.840528***	***0.867119***	***0.873657***	***0.969334***	***IRS***
AIB	***2017***	***0.882329***	***0.907017***	***0.895692***	***0.972782***	***IRS***
BOA	***2017***	***0.812526***	***0.827902***	***0.832819***	***0.981428***	***IRS***
BRB	***2017***	***0.854699***	***0.863179***	***0.868480***	***0.990176***	***IRS***
BUB	***2017***	***0.869287***	***0.875375***	***0.912475***	***0.993045***	***IRS***
CBE	***2017***	***0.754380***	***0.765009***	***0.807442***	***0.986106***	***IRS***
CBO	***2017***	***0.813004***	***0.836322***	***0.829270***	***0.972119***	***IRS***
DGB	***2017***	***0.899847***	***0.919230***	***0.903189***	***0.978914***	***IRS***
LB	***2017***	***0.845017***	***0.865440***	***0.854935***	***0.976401***	***IRS***
UB	***2017***	***0.826179***	***0.837767***	***0.861540***	***0.986168***	***IRS***
WB	***2017***	***0.840668***	***0.844222***	***0.850911***	***0.995790***	***IRS***
ZB	***2017***	***0.896944***	***0.905198***	***1.000000***	***0.990882***	***IRS***
DBE	***2017***	***0.878373***	***0.941468***	***1.000000***	***0.932983***	***IRS***
AWB	***2017***	***0.766949***	***0.811577***	***1.000000***	***0.945011***	***IRS***
DB	***2018***	***0.760494***	***0.807189***	***0.845701***	***0.942152***	***IRS***
NIB	***2018***	***0.794185***	***0.832718***	***0.925034***	***0.953726***	***IRS***
AB	***2018***	***0.837272***	***0.862510***	***1.000000***	***0.970739***	***IRS***
AIB	***2018***	***0.873162***	***0.898811***	***0.899395***	***0.971463***	***IRS***
BOA	***2018***	***0.833319***	***0.836831***	***1.000000***	***0.995803***	***IRS***
BRB	***2018***	***0.868705***	***0.870657***	***1.000000***	***0.997757***	***IRS***
BUB	***2018***	***0.884735***	***0.887179***	***1.000000***	***0.997245***	***IRS***
CBE	***2018***	***0.764836***	***0.768277***	***1.000000***	***0.995521***	***IRS***
CBO	***2018***	***0.853764***	***0.855643***	***1.000000***	***0.997804***	***IRS***
DGB	***2018***	***0.946536***	***0.947135***	***1.000000***	***0.999367***	***IRS***
LB	***2018***	***0.842077***	***0.855965***	***0.911526***	***0.983775***	***IRS***
UB	***2018***	***0.825802***	***0.831139***	***0.904137***	***0.993579***	***IRS***
WB	***2018***	***0.833898***	***0.833962***	***0.880242***	***0.999923***	***DRS***
ZB	***2018***	***0.886274***	***0.892127***	***1.000000***	***0.993438***	***IRS***
DBE	***2018***	***0.912873***	***0.941251***	***1.000000***	***0.969851***	***IRS***
AWB	***2018***	***0.839301***	***0.840790***	***0.873819***	***0.998229***	***IRS***

Where

IRS = increasing returns to scale

DRS = decreasing return to scale

CRS = constant return to scale

Appendix-B

Estimation result of TE, PTE and SE score of commercial banks

S.no	*Banks*	*OTE under CRS*	*PTE under VRS*	*SE*
1	*DB*	*0.797*	*0.831*	*0.958*
2	*NIB*	*0.832*	*0.857*	*0.970*
3	*AB*	*0.858*	*0.895*	*0.959*
4	*AIB*	*0.905*	*0.937*	*0.965*
5	*BOA*	*0.822*	*0.857*	*0.958*
6	*BRB*	*0.877*	*0.908*	*0.965*
7	*BUB*	*0.842*	*0.900*	*0.934*
8	*CBE*	*0.728*	*0.771*	*0.943*
9	*CBO*	*0.829*	*0.857*	*0.966*
10	*DGB*	*0.933*	*0.954*	*0.977*
11	*LB*	*0.878*	*0.905*	*0.968*
12	*UB*	*0.851*	*0.871*	*0.976*
13	*WB*	*0.841*	*0.871*	*0.964*
14	*ZB*	*0.904*	*0.930*	*0.971*
15	*DBE*	*0.88*	*0.943*	*0.939*
16	*AWB*	*0.821*	*0.863*	*0.951*

Appendix-C

Tobit model estimation result Robust

```
. tobit pte LC LR CR OS lnROA lnMS, ll(0) ul(1) robust

Tobit regression                                  Number of obs     =         94
                                                  F(   6,      88)  =      29.90
                                                  Prob > F          =     0.0000
Log pseudolikelihood =  161.15184                 Pseudo R2         =    -0.3154

------------------------------------------------------------------------------
             |               Robust
         pte |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          LC |   .5341068   .0985299     5.42   0.000     .3382994    .7299142
          LR |   .0047816   .0011839     4.04   0.000     .0024288    .0071345
          CR |  -.1932658   .0555679    -3.48   0.001    -.3036953   -.0828363
          OS |  -.0719371   .0195827    -3.67   0.000    -.1108536   -.0330207
       lnROA |   .0286985   .0095073     3.02   0.003     .0098047    .0475924
        lnMS |   .0038761   .0026074     1.49   0.141    -.0013054    .0090577
       _cons |   1.014218   .0535891    18.93   0.000     .9077207    1.120715
-------------+----------------------------------------------------------------
      /sigma |   .0377844   .0041346                      .0295679     .046001
------------------------------------------------------------------------------
             0  left-censored observations
            90     uncensored observations
             4 right-censored observations at pte >= 1
```

Appendix-D

Panel Tobit model estimation Result the panel data

```
Random-effects tobit regression                 Number of obs     =         94
Group variable: year                            Number of groups  =          6

Random effects u_i ~ Gaussian                   Obs per group:
                                                              min =         15
                                                              avg =       15.7
                                                              max =         16

Integration method: mvaghermite                 Integration pts.  =         12

                                                Wald chi2(6)      =     139.24
Log likelihood  =  168.18408                    Prob > chi2       =     0.0000

------------------------------------------------------------------------------
         pte |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          LC |   .5773982   .1019664     5.66   0.000     .3775478    .7772487
          LR |   .0041299   .0007411     5.57   0.000     .0026773    .0055825
          CR |   -.123146   .0668285    -1.84   0.065    -.2541274    .0078354
          OS |  -.0649372   .0190726    -3.40   0.001    -.1023188   -.0275556
       lnRoA |   .0131102   .0099719     1.31   0.189    -.0064343    .0326546
        lnMS |   .0035992   .0026799     1.34   0.179    -.0016533    .0088518
       _cons |   .9169229   .0620096    14.79   0.000     .7953862     1.03846
-------------+----------------------------------------------------------------
    /sigma_u |   .0196434   .0069236     2.84   0.005     .0060734    .0332133
    /sigma_e |   .0329724   .0025774    12.79   0.000     .0279207     .038024
-------------+----------------------------------------------------------------
         rho |   .2619492   .1408618                      .0687405    .5833775
------------------------------------------------------------------------------
LR test of sigma_u=0: chibar2(01) = 14.06             Prob >= chibar2 = 0.000

             0  left-censored observations
            90     uncensored observations
             4 right-censored observations
```

Undertaking Letter

I was used the income statement and balance sheet report of those sampled commercial banks as they announced to the public for each year ended. So, this financial report is already known to the public. If there is commercial banks complain due to, mentioning the names of banks may have legal implications. I will take the responsibility.

Signature:_____________

Date : June, 2022

Place: Addis Ababa