Factors Affecting Technical Efficiency: Evidence from the Banking Industry in Ethiopia

By:

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Declaration

I, Getnet Zemene Muche, declare that this thesis, titled "Factors Affecting Technical Efficiency: Evidence from the Banking Industry in Ethiopia," was completed by myself under the supervision of Tilahun Teklu (Ph.D.) and that it has not been submitted for any other institution or university for any degree. I also confirm that all sources of information used in this thesis have been properly mentioned and credited.

Declared by: Getnet Zemene Muche

Signature: _____ _____

Date: _____June 10/2023____

Certification

This is to certify that Getnet Zemene Muche worked on the research paper "Factors Affecting Technical Efficiency: Evidence from the banking industry in Ethiopia" under my supervision. I certify that this thesis is his original work and can be used to fulfill a partial of the requirements for the award of a master's in international business.

Approved by Board of Examiners

Dr.Tilahun Teklu _____ _____ _____June 10/2023___

Advisor Signature Date

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External Examiner Signature Date

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Abstract

The efficacy of private banks in Ethiopia from 2016 to 2021 was the focus of this research, investigating the factors impacting their technical efficiency. Output variables such as loan, investment, and net profit were considered to gauge technical efficiency, while input

variables like paid-up capital and total deposit were used. A binary logistic regression was used to identify the technical efficiency predictors of the banks. The results revealed that only five of the sixteen banks studied (31.3%) met the technical efficiency standards, while the majority (68.7%) performed beneath the optimal production frontiers. Consequently, these banks may need to prioritize enhancing their productivity to improve their operations. The efficiency trends of private banks were not consistent, showing better efficiency in 2017, then sharply declining in 2018 and 2019, and gradually improving in 2021. Furthermore, tier I banks were relatively efficient than tier II and tier III banks. In addition, a positive and significant relationship was found between returns on assets and technical efficiency measure of private banks. On the other hand, a negative statistically significant relationship was observed between solvency and technical efficiency, which implies that the higher the debt obligation for a unit asset, the less likely that the bank is technically efficient. Therefore, banks may need to increase loan creation capacity and improve return on assets to enhance their technical efficiency. Additionally, careful planning of the solvency ratio of banks is also recommended.

Keywords: technical efficiency; intermediation approach; data envelopment analysis; logistic regression; commercial banks in Ethiopia

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Acronyms

TE: Technical efficiency

BCC: Banker Coopers

DEA: Data Envelop Analysis

LP: Linear Programming

ROA: Return on Asset

ROE: Return on Equity

SPF: Stochastic Frontiers

DMU: Decision-Making Unit

VRS: Variable Return to Scale

CRS: Constant Return to Scale

CHAPTER ONE

Introduction

This chapter introduces the topic of the research and its purpose. Introducing the concept, formulating the problem statement, setting out the research questions, identifying the objectives, putting the importance and range of the investigation, providing definitions of key terms employed in the research.

1.1. Background of the Study

Previously the banking sector in Ethiopia was limited, heavily regulated, and restricted, resulting in a closed and uncompetitive banking sector.

The banking business was characterized by limited accessibility; traditional products and services. In addition, it was serving a very low credit supply for households and firms, inadequate financial market infrastructure, and limited capacity in banking skills. Loans are often made based on personal connections (rather than business plans. According to Precise Consult (2021), currently, there are 16 private banks, one public commercial bank, one development bank, and more than 17 new upcoming private banks. The public-owned commercial bank Commercial Bank of Ethiopia (CBE) is the dominant bank in the industry as it has more than 1,800 branches across the country.

On the other hand, the 16 operational private banks have 4,729 branches combined. More than 34.0 percent of the commercial banks' branches are in the capital city, Addis Ababa. In terms of bank accounts, commercial banks in Ethiopia have more than 55 million customer deposit accounts, while the numbers of credit accounts are less than 300 thousand (NBE ,2021)

In its new home-grown economic reform program, the Ethiopian government has been easing entry into the sector for all interested and capable actors. The industry recently embarked on a series of economic reforms to liberalize the sector. With these reforms, the sector has already opened to foreign investors, and new financial products and institutions were permitted.

Liberalization of the sector will bring all types of banks (commercial, private, and specialized) to compete with each other. Therefore, the banking system will force inefficient

banks to be out of the market, they will be replaced by the more efficient banks. Therefore, it is highly timely to measure the technical efficiency of existing banks.

A review of the literature has identified the choice between parametric (Stochastic Frontier Analysis (SFA) and nonparametric (Data Envelop Analysis) for technical efficiency measurement. The studies argue that a researcher can safely choose any of the methods since there are no significant differences between the estimated results. DEA may be a better choice when random disturbances are less of an issue and price information is unavailable (Kuosmanen T, Johnson A, Saastamoinen A 2014, Murillo Zamorano LR 2004, Wang M, Wang MH 2002). Consequently, this study chooses DEA over the SFA.

So far, the literature is lacking in determining the banking technical efficiency in Ethiopia (Tesfaye, 2019, Tadesse, 2017). This paper provides a comparative analysis of the performance of the banking sector in Ethiopia over the period 2016 to 2021 by following a two stages approach: estimating technical efficiency scores in the first stage and using logistic regression to identify technical efficiency determinants in the second stage

1.2. Statement of the problem

Banking in Ethiopia was tightly controlled and confined, leading to a shut and non-competitive banking sector.

Access to banking was very limited particularly in rural areas, banking products was homogeneous and there exist inadequate credit supply. According to Tesfaye (2014), the banking industry was lacking financial market infrastructure and expertise. Thus, banks usually lend using collateral than business plans.

Despite, NBE report (August 9,2022) was indicated the remarkable growth of banks with number of banks increased from 16 to 30 , branches reached 8,944 ratio of branches per population reached 1:11,516 and total deposit reached of 1.7 trillion birr, the reform by government allows all eligible and competent actors to get access. Moreover, permitting foreign investors to enter and introducing new financial products and institutions.

Opening the banking sector will allow specialized banks to compete, hence driving out inefficient banks and replacing them with efficient banks. Therefore, measuring technical efficiency of banks will have significant contributions.

Previous studies were tried to identify the options between parametric (Data envelopment Analysis (DEA) and Non- parametric Stochastic Frontier Analysis (SFA) for assessing technical efficiency. The two approaches have a correlated result (Kuosmanen T, Johnson A,

Saastamoinen A 2014, Murillo Zamorano LR 2004, Wang M, Wang MH 2002). However, this study has chosen DEA over SFA and the drivers of TE were identified using Binary logistic regression.

So far, the works are scant in measuring technical efficiency in Ethiopia. The two studies are Tesfaye, (2019), Tadesse, (2017).

This paper investigates the relative performance of private banks in Ethiopia from 2016 to 2021, by applying the two steps first to describe their technical efficiency then applying binary logistics to in order identify drivers of technical.

1.3. The Research Question

- What is the relative efficiency score of private banks?
- What impact does profitability have on the efficiency of private banks?
- Does credit risk affect the efficiency of private banks?
- How does efficiency of utilizing assets affect efficiency of private banks?
- What is the effect of bank size on private banks?
- What impact does credit risk has on the efficiency of private banks?
- Does market share affect efficiency of private banks?
- What effect does income diversification affects the efficiency of private banks?
- How did capital adequacy affect efficiency of private banks?
- How did solvency affect the efficiency of private banks?
- How did management efficiency affect efficiency of private banks

1.4. Objective of the study

4.1.1. General objectives of the study

The main goal of this paper is to measure the technical efficiency level of private banks then to investigate the driving factors of that efficiency for the period 2016 to 2021.

4.1.2. Specific objectives of the study

- To measure the technical efficiency level of private banks.
- To examine the impact of profitability on technical efficiency of private banks.

- To determine the effect of credit risk on technical efficiency of private banks.
- To investigate the impact of asset utilization on technical efficiency of private banks.
- To study the impact of bank size on the technical efficiency of private banks.
- To investigate the effect of credit risk on the technical efficiency of private banks.
- To determine the effect of market share on the technical efficiency of private banks.
- To identify the effect of Income diversification on technical efficiency of private banks
- To examine the impact of paid up capital on technical efficiency of private banks.
- To study the effect of solvency on the technical efficiency of private banks.
- To investigate the impact of management effectiveness on the technical efficiency of private banks.

1.5. Significance of the Study

This research is beneficial for multiple entities involved in the banking industry in Ethiopia, such as government officials, policy makers, regulators, investors, and bank managers.

For the management of entities under consideration, it is of particular importance to measure the technical efficiency as a basis for undertaking adequate steps to improve the performance of the inefficient units. The study will have contributions for different academicians and practitioners as it suggested alternative measurement approaches to measuring efficiency. Additionally it has suggested inputs and outputs through which technical efficiency can be measured and finally it indicated possible sources of bank's technical efficiency level.

1.6. The Scope of the study

This paper is restricted in assessing the technical efficiency level of benchmarking private banks and its determinants. Due to data constraints, the Commercial Bank of Ethiopia (state-owned) was not included.

Moreover, the study used two phases of analysis: Data Envelope Analysis used to describe technical efficiency level of private banks while Binary Logistics applied for identifying efficiency drivers.

1.7. Limitations of the study

Further research can be done by including other variables, such as organizational cultures, as predictors. The strength of the two different approaches for technical efficiency measurement models such as DEA and SFA can be tested by other researchers.

1.8. Definition of key words used in this study

- ✓ **Deposit** =the sum of saving, time and demand deposit and it is the liability of banks .
- ✓ **Loan:** Include real estate loan, commercial loan, industrial loan and consumer loan.
- ✓ **Other Investment** made on other assets such fixed assets and investments in different shares.
- ✓ **Technical efficiency** is the effectiveness with which a given set of inputs is used to produce an output. A firm is said to be technically efficient if a firm is producing the maximum output from the minimum quantity of inputs, such as labour, capital, and technology.
- ✓ **Level of capitalization** is the ratio between Capital adequacies Equity to total asset (Tadesse ,2017)
- ✓ **Market share**: is ratio of total asset of a bank divided by total asset of all banks. Market share is the percentage of the total revenue or sales in a market that a company's business makes up.
- ✓ **Return on asset:** The return on assets is a cross-financial statement ratio. It makes use of "net income" derived from the income statement and "total assets" obtained from the balance sheet Bank size.
- ✓ **Bank size** revealing the nature and size of the value of total assets of systemic risk of individual banks. It is also measured as the natural logarithm Natural Log of Total asset
- ✓ **Credit Risk:** Credit risk is the possibility of losing a lender holds due to a risk of default on a debt that may arise from a borrower failing to make required payments. In the first resort, the risk is that of the lender and includes lost principal and interest, disruption to cash flows, and increased collection costs.
- ✓ **Diversification of Income**: Drawing earning from two or more sources rather than from just one job Income it can protect against the loss and the equation is a diversified Income from non interest divide by interest income

- ✓ **Solvency ratio**; A solvency ratio indicates whether a company's cash flow is sufficient to meet its long-term liabilities and thus is a measure of its financial health. An unfavourable ratio can indicate some likelihood that a company will default on it's the formula is total deposit (liability) to total asset
- ✓ **Management quality**: it helps an organization achieve greater consistency in tasks and activities and It increases efficiency in processes, reduces wastage.

1.9. Organization of the study

The paper is organized with five sections. The first part gives an overview that contains essential details such as articulating the study, problem, objectives, research questions, its importance, the research scope, and definitions of essential terms employed in the study. The second chapter contains a review of the previous studies. Then the third section focused on method employed in the study. In chapter four, the results presented, interpreted and analysed. Indeed, chapter five puts the study's conclusion and recommendation.

CHAPTER TWO

Literature review

2.1 Theoretical Review

A theoretical analysis examines notions that concentrate on the subject matter being investigated, helping to attain a greater comprehension of the topic while also furnishing a reasonable justification for the on-going exploration. Furthermore, it is a typical practice to articulate the explanation and connection of the study's dependent and independent variables.

2.1.1.Basic Banking Function

Even though the basic function of banks is termed as intermediation in general, it comes with banking functions which includes range of activities that take place within the banking system. These functions include providing banking services such as accepting deposits, making loans, and facilitating payments. Banks also manage investments, provide advice to customers, and protect deposits. Banking has grown in complexity over time as a result of technological advances, deregulation, globalization, and other economic factors. This requires banks to be increasingly efficient in order to remain competitive (Mishkin & Serletis, 2018). The efficiency of banking functions is critical for ensuring the health of the entire financial system. Inefficiencies can lead to higher costs and reduced access to banking services, limiting the ability of individuals and businesses to participate in the economy and causing losses to bank depositors. As such, it is essential for banks to constantly seek ways to increase efficiency, such as through automation, leveraging new technologies, streamlining processes, and better managing resources. The efficiency of banking functions is critical for ensuring the health of the entire financial system. Inefficiencies can lead to higher costs and reduced access to banking services, limiting the ability of individuals and businesses to participate in the economy and causing losses to bank depositors. As such, it is essential for banks to constantly seek ways to increase efficiency, such as through automation, leveraging new technologies, streamlining processes, and better managing resources (Mishkin & Serletis, 2018).

2.1.2.Approaches of measuring efficiency

Technical efficiency is defined as a measure of the productive use of resources (inputs) relative to the outcome generated from their use. It is typically measured as the ratio of a firm's output/outputs relative to its inputs. In the economic and business literature, technical efficiency has been studied extensively.

Broadly speaking, there are two main theoretical approaches to measuring technical efficiency. The first approach is derived from production economics and focuses on the assessment of the technical efficiency of firms according to the maximal possible output for given levels of inputs (Farrell, 1957); (Aginer, Lovell, & Schmidt, 1977). The second approach is the resource-based view of firms (Penrose & Pitelis, 1959); (Wernerfelt, 1984), which seeks to understand the sources and capabilities of firms that lead to superior performance. This approach is more concerned with understanding the drivers of technical efficiency than estimating the magnitude of production losses due to inefficiencies.

The production view and resource view to measuring bank efficiency are both approaches used to assess a bank's performance. The production view focuses on the output of a bank, taking into account its loans and deposits, while the resource view looks at the utilization of a bank's resources, such as staff and capital. Generally, banks strive to achieve a balance between the two (Aikaeli, 2006). Overall, banks might strive to find a balance between production and resource views in order to maximize their efficiency and bottom line. In doing so they must remain competitive in terms of cost, whilst also ensuring that their products and services are attractive to customers and generate sufficient profit.

In analysing financial performance, different studies have sought many different ways to measure technical efficiency the two important approaches are (DEA) and SFA. In the choice between the two methods there is no accepted guide line Kuosmanen T, Johnson A, Saastamoinen A (2014). According to Murillo Zamorano LR (2004), Parametric and nonparametric techniques are dissimilar techniques that have been used to estimate technical efficiencies, yet the decision of which strategies to use remains uncertain Ahmed MH (2015).

In contrast, Toma P et al. investigated that the parametric and non-parametric efficiency measures have correlated outcomes. Besides, research on efficiency assessments suggests that either plan can be selected without concern as there are no meaningful discrepancies between the estimated results. A random inference is not relevant and price information is not available, DEA is the preferred choice. Thus, this study use DEA for technical efficiency descripts and SFA for Identify the drivers of efficiency.

2.1.2.1. The Production view of Efficiency Measurement

The production view, also known as the "profits and losses" approach, evaluates a bank's performance by looking at the number of loans and deposits that it is able to generate. This approach considers the bank's net income or profits as well as its return on assets (ROA) and return on equity (ROE). It also takes into account the composition of a bank's portfolio, including the types of products and services it provides, as well as the degree of liquidity and risk associated with them (Aikaeli, 2006). These ratios can be used to gauge the overall financial strength of a bank and its management's technical and operational efficiency Chen and Yen (1997).

2.1.2.2. The Resource view of Efficiency Measurement

The resource view, also known as "cost control", examines how efficiently a bank manages its resources. It looks at the amount of staff, capital, and other resources the bank has, as well as how it utilizes them. This approach evaluates a bank's efficiency by measuring the cost-effectiveness of its operations, and can include analyses of its personnel costs, operating expenses, and asset utilization ratios (Aikaeli, 2006).

Determinants of banking efficiency include factors such as bank size, capital adequacy, technology adoption, asset quality, and the overall operating efficiency of the banking system. Addressing these determinants through a stochastic approach requires a process of dynamic optimization in order to maximize banking efficiency.

In order to achieve this goal, banks must continually adjust their strategies in response to the changing banking environment. For example, banks can use stochastic programming methods to optimize their capital structure and maintain appropriate levels of capital adequacy. Additionally, banks can apply stochastic control theory to optimize their portfolio selection and balance risk and return.

2.1.3.Overview of Data Envelope Analysis (DEA)

It is a non-parametric method that utilizes linear programming to measure the level of efficiency of comparable decision-making units (DMU) by employing multiple inputs and outputs. DEA occasionally called frontier analysis is a performance measurement technique which can be used for analysing the relative efficiency of productive units in the case of Banks are branches, having the same multiple inputs and multiple outputs.

2.1.4.Basic Types of DEA Model

The two basic assumptions of constant return to scale (CCR) and variable return to scale (BCC) (Charnes et al.1984) suggests for measuring the relative efficiencies of various banks. BCC model represents more optimistic figures about the relative efficiencies of various banks.

The envelopment surface will differ depending on the scale assumptions that underpin the model. Two scale assumptions are generally employed: constant returns to scale (CRS), and the BCC model by Banker-Charnes-Cooper altered the Constant Return to Scale (CRS) notion to Variable Return to Scale (VRS). The latter encompasses both increasing and decreasing returns to scale. CRS reflects the fact that output will change by the same proportion as inputs are changed (e.g. a doubling of all inputs will double output); VRS reflects the fact that production technology may exhibit increasing, constant and decreasing returns to scale.

2.1.4.1. Input and Output Orientation

The focuses of DEA model might be input minimization or output maximization If the concern is input minimization the objective is to calculate the amount of inputs use that can be minimized without varying the output quantity. A fixed factor couldn't be minimized; therefore, output-focused DEA is better option to measure potential output of a firm given its inputs when operating efficiently. This measurement is similar with neo-classical production functions, which tells as the maximum output achievable with given input quantities (Färe, Grosskopf, and Lowell et al. 1994, p. 95).

2.1.5. Stochastic approach to explain banking efficiency

The theoretical literature surrounding stochastic approaches to banking efficiency includes works such as (Ocampo, Bongo, Alinsub, & Ruselle, 2017) who proposed a stochastic decentralized control framework for the banking industry; and (Anderson & Wincoop, 2003), who conducted a study on the effects of macroeconomic uncertainty on bank managerial decisions. Additionally, there are various works in the literature that discuss how stochastic methodologies can be used to help banks improve their operational efficiency. Overall, a stochastic approach to banking efficiency is useful for maximizing the performance of banks because it allows institutions to optimize their strategies in response to changes in the

banking environment. In addition, the theoretical literature provides guidance on the types of models and techniques that should be used by banks in order to maximize their efficiency (Ocampo, Bongo, Alinsub, & Ruselle, 2017).

2.1.5.1. Determinants of bank Efficiency

Bank efficiency is determined by a variety of factors. According to (Ignacio, Gabriel , & Francisco, 2019), bank efficiency is affected by group of internal and external variables. These variables are; market structure, GDP per capita, domestic credit as %age GDP, population density, rate, size, ownership structure (foreign vs domestic), public or private, competition, loan to asset, Loan loss reserves to total assets. The authors explain that larger banks are typically more efficient than smaller banks due to economies of scale. Banks with higher ownership concentration are also more efficient, while market competition can drive down efficiency. Risk management practices can increase efficiency by managing potential losses, while well-capitalized banks have better financial performance. Additionally, technological advancements have enabled banks to reduce costs, as well as increase their speed of operations: strategic decisions such as mergers and acquisitions and outsourcing can further increase efficiency.

2.2 Empirical Review

Adusei, M. in 2016 Investigated the technical efficiency of Ghanian 101 community banks by employing DEA and Binary logistic regression tools. In his finding only 20 banks were efficient and their efficiency drivers were: bank size, profitability and liquidity. Jeon and Miller et al (2005) and Sufian et al (2009), in their joint study has argued income diversification positively affected technical efficiency. It is evidence that when banks diversify source of their revenue TE improves (Sufian, 2009).

Similar studies by Hasan &Marton, (2003, Sufian, (2009) investigated Profitability as a proxy of return on asset positively and significantly affects technical efficiency. While the contribution by Majid K. in 2012 using DEA concluded that various technical efficiency scores are scored in Indian banks while public banks were more performing than Private banks. On the other hand, Rosman in 2014 studied the positive contribution of capital on technical efficiency.

Alrafadi, Kamaruddin, and Yusuf, M. in 2014 studies bank performance using DEA and Tobit Model, they analysed 17 banks in libya. Their finding suggests that specialized banks have higher technical performance than commercial and private banks. Furthermore, In the Tobit model, the significant drivers of technical efficiency were: ROA, size, Capital Adequacy and government ownership.

Duygun M, and Pasiouras, F. (2009) , presents a comprehensive review of 179 studies that employ operational research (O.R.) and Artificial Intelligence (A.I.) techniques in the assessment of bank performance. They first discuss numerous applications of data envelopment analysis which is the most widely applied O.R. technique in the field. Then they discuss applications of other techniques such as neural networks, support vector machines, and multi-criteria decision aid that have also been used in recent years, in bank failure prediction studies and the assessment of bank creditworthiness and underperformance

The two technical efficiency studies contributed in Ethiopia were:

Sufian (2009) provides evidence in support of the skimping hypothesis with a study that reports a negative statistically significant relationship between credit risk and bank TE.

Jeon and Miller et al (2005) and Sufian et al (2009), find that diversification positively affects Technical efficiency. The implication is that as banks generate more income from non-interest sources their TE improves (Sufian, 2009). Thus, there is a positive relationship between firm diversification and firm efficiency.

Berger and DeYoung (1997) , has developed that the bad management hypothesis postulates that management quality/technical efficiency should negatively affect TE. Bad managers are unable to sufficiently monitor and control their operating expenses

Tesfaye in 2016 and Tadesse in 2017. Both researches were used the DEA techniques for measuring technical efficiency of banks while Tadesse included the Tobit model to investigate the technical efficiency determinates. Both researchers indicated that banks in Ethiopia have variations in efficiency levels while the later one concluded added the positive and significant impact of paid up capital, liquidity risk and market share have a positive and substantial influence on the technical efficiency

Literature gap: the performance of banks has been an issue of major interest for various stakeholders such as depositors, regulators, customers, and investors. While bank performance has been traditionally evaluated based on financial ratios, there has been very little empirical research on banks in Ethiopia using technical efficiency. (Tadesse, 2017, Tesfaye, 2016).

Thus, this study will fill the gaps that advanced operational research (O.R.) and artificial intelligence (A.I.) have resulted in a shift towards the use of such state-of-the-art techniques for bank performance measurements.

2.1. *The relationship of dependent and Independent variable is summarised as (Hypothesis)*

Return on Assets (ROA): Return on Asset is proxy measure of banks. Positive relationship is expected with technical efficiency (Sufan, 2009; Adusei, 2016).

H o: Profitability is negatively related with bank Technical efficiency and,

H α: Profitability is positively related to bank efficiency

Credit Risk: The risk with poor bank credit management that negatively affects bank technical efficiency (Taddese, 2016).

H o: Credit risk is negatively related to bank efficiency, and

H α: Credit risk is positively related to bank efficiency

Bank size: Bank size has a positive advantage when the operation is modernized (Sufian, 2009). We develop the following hypothesis about the size of the operation and bank efficiency:

H o: Large size negatively related to efficiency, and

H α: Large size is positively related to efficiency

Market share: Total deposit as sum of saving, time and demand deposit is to measure the approximately of maket share (Tadesse, 2016). The hypothesis can be developed:

H o:: Market share is negatively related to bank efficiency, and

H α:: Market share is positively related to bank efficiency.

Income diversification: Jeon and Miller et al. (2005) and Sufian et al (2009) studies the positive impact of income diversification on technical efficiency of banks. We then write hypothesis:

H o: Income diversification is negatively related to bank efficiency, and

H α: Income diversification is positively related to bank efficiency.

Capital adequacy: According to Sufian, (2009), capital is measured by dividing total book value of shareholders equity by total asset. Then hypothesis is whether:

H o: Capital adequacy is negatively related to bank efficiency, and

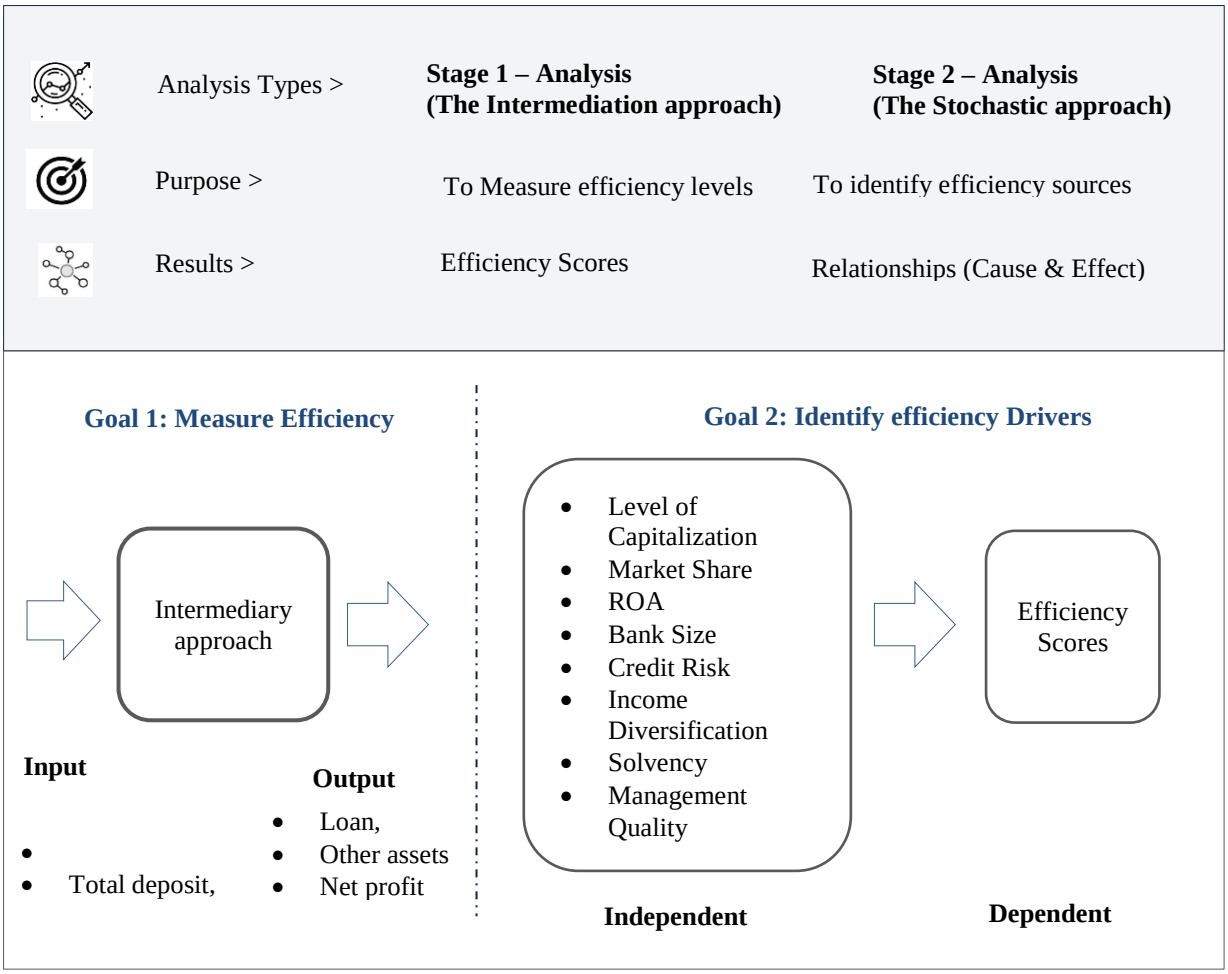
H α: Capital adequacy is positively related to bank efficiency.

Solvency ratio: The debt-to-assets ratio is a measure of a firm's total debt in comparison to its total assets. It is an indicator of company's commitment for future finance and debt obligations. The hypothesis can be:

H o: solvency is negatively related to bank efficiency, and

H α: solvency is positively related to bank efficiency

4.1.3. Conceptual Framework (Two Stage Analysis)



Source: Author Compilation

3. CHAPTER THREE

Methodology

From summary of the literature review, the bank performance measurement, are traditional ratio technics are (ROA, ROE) and the advanced measurements of bank performance are (DEA) and (SFA). While determinates can be identified using various regression models such as Binary Logistics and Tobit regression.

3.1. Research Design

This study combined descriptive and explanatory research designs. Descriptive research is good for characterizing the current situations as its (Koul, 1997). On the other hand, explanatory research is employed when limited information is available about the topic. Therefore, both descriptive and explanatory strategies will be utilized in this study.

3.2. Research approaches

The research approaches are vital issues to achieve the research objectives and it can be qualitative or quantitative.

3.3. Quantitative Research Approach

Quantitative studies rely on numerical or measurable data, and data collection involves gathering numeric information (Bryman, 2009). Therefore, this research adopted quantitative approaches in order to support with strong evidence.

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3.4. Source of data

Seven years panel data were collected from National Bank and analysed from private 16 banks. DEA and Jamovi open statistical software were employed to study the gathered information.

3.5. Variables Descriptions

This research utilizes a deterministic approach to appraise the relative effectiveness of banks. While selecting the input and output variables, bank Intermediation efficiency was the concern of this study. Thus, in the analysis:

1. Outputs are: loan, other assets, and net profit
2. Inputs: total deposit, paid-up capital

Table 1 portrays the variables in the DEA and Binary Logistic Regression models.

Table 1: List of Variables in Input-Output and Binary Logistics Regression

DEA Input & Output				
#	**Inputs**	**Outputs**	**Sign**	**Expected Results**
1	Deposit	Saving ,time and demand deposit	DD	Efficiency Levels of decision units (Private Banks)
2	Equity	Sum of paid-up capital	E	
1	Loan	All outstanding loans	L	
2	Other Investments	Investments other than loans. E.g., Investments in fixed assets and investments in different shares.	IO	
3	Profit after tax	Net Profit after deductions	P	
The drivers of bank performance in the Binary logistics model				
#	**Variables**	**Measurements**	**Sign**	**Expected relationship**
1	Level of capitalization (Capital adequacy)	Equity to total asset	LC	Positively
2	Market share	Total asset of a bank divided by Total asset of all banks	MS	Positively
3	Return on asset as proxy of profit	Net income divided by total assets	ROA	Positively
4	Bank size	Natural Log of Total asset	BS	positive/negative
5	Credit Risk	Outstanding loan divide by total assets	CR	Negatively
6	Diversification of Income	Income from non interest divide by interest income	DI	positive/negative
7	Solvency ratio	Total deposit (liability) to Total asset	SR	Negatively
8	Management Quality	Administrative cost to total income	MQ	Positively

3.6. Model Specifications

We execute a two-stage of examination. First, we compute the technical proficiency rating using DEA and then analysed the drivers of technical efficiency using binary logistic regression.

3.7. First-stage DEA Technical Efficiency Estimation

While applying the DEA to measure multiple inputs and outputs, TE is calculated by comparing the weighted sum of outputs to the weighted sum of inputs. The weights are measured on the basis of constraint that each units ratio must be less than or equal to one. Hence, combining the two, TE is calculated by dividing the weighted outputs by the weighted inputs. Following the work by Adusei (2016), VRS technology is used to maximize our objective. The objective function is portrayed below:

$$\max h_c = \sum_{r=1}^{s} u_r\, y_r c \Big/ \sum_{i=1}^{m} v_i\, x_i c$$

Subject to (1)

$$\sum_{r=1}^{s} u_r\, y_{ri} \Big/ \sum_{i=1}^{m} v_i\, x_{ij} \le 1; \quad u_r, v_i \ge 0 \quad r = 1 \dots s; \quad i = 1, m, \quad j = 1 \dots n$$

where c denotes a specific private bank to be evaluated, y_{rj} is the amount of output r from the private bank, x_{ij} is the amount of input i to private bank j, u_r is the weight chosen for output r, v_i is the weight chosen for input i, n is the number of private banks, s is the number of outputs, and m is the number of inputs.

The mathematics study has objective to increase the ratio of weighted outputs to weighted inputs while ensuring that none of the banks in the sample have a higher technical efficiency score than one based on the weights. Adusei et al (2016), Tadesse (2017). The weights, however, are undetermined but acquired through optimization.

3.7.1.Input Output Definitions

The production and intermediation approaches are the basic for identifying the objective function. According to Avkiran,(2006), banks production are various services and produce revenue. While the Intermediation concept depicts that banks allocate funds from depositors

to Investors with shortage (Adusei, M. 2016, Mostafa, et al 2007; Rosman et al., 2014), the intermediation approach was adopted.

To measure technical proficiency, we made use of data on three outputs and two inputs - loan (L2), Other Asset (OA2), and Profit after tax (P3) and Paid up capital (LC1) and Total deposit (DD2) (Alrafadi, Kamaruddin, and Yusuf, M. 2014; Adusei, 2016; Drake, Hall, and Simper et al. 2009; Mostafa, 2007).

3.8. Second stage – Logistic Regression Model

A two-step approach, as suggested by previous studies, is to measure private banks' technical efficiency.

According to Adusei (2014), DEA scores can range from 0 to 1, with 0 being the lower limit and 1 being the upper limit of the dependent variable. As the DEA scores do not exclude any observations and limited 1, this is considered a dichotomous classification or case of censoring the technical efficiency scores at 1 for efficient providers Girma (Novemer 2020) Therefore, logistic or Tobit regression can be used as a choice to OLS regression in the second-stage analysis (Ozcan, 2014). Binary logistic regression is preferred due to the TE scores from the first stage being coded in to binary data, this is adopted by Coelli et al. (1998), Rosman et al. (2014), and Adusei (2016). Scores from the DEA are bounded by 0 and 1, the binary logistic is deemed suitable for the multivariate analysis. The relationships between the explanatory variables (Profitability, Size, Credit Risk, Management Quality, Income Diversification, Equity Capitalization, and Solvency) and TE are presented in below equation.

$$\mathbf{TE = \beta 1ROA + \beta 2CreditRisk + \beta 3lnBankSize + \beta 4MarketShare + \beta 5IncomeDiversity + \beta 6CapitalAdequacy + \beta 7Solvency + \beta 8ManagementQuality}$$

CHAPTER FOUR

Result and Discussion

4.2. Descriptive Statistics

4.2.1. First–Stage Results: DEA Technical estimate

In this research, 16 private banks that have been operational were chosen as decision-making units. Consequently, the DEA model used to analyse considering six-year data of paid-up capital and total deposit as an input and six-year of data of banks loan and advance, net profit and other investments as an output. In the assumption, the VRS technology is chosen over the CRS.

4.2.2. Input Output (DEA) Validity test

According to Adusei (2016), technical efficiency needs an isotonicity test on the data to validate the DEA model specification. It describes correlations between inputs and outputs must be statistically significant correlations between inputs and outputs. Thus, the result showed positive significance among all inputs (equity and deposit) and output variables (loan, profit after tax, and other investments). The test result is depicted below.

Table 2: Correlation between Inputs and Outputs

Correlation Matrix								
		Loans & Advance		Profit After Tax		Other Investment		Total Deposit	Equity
Loans & Advance	Pearson's r	—							
	p-value	—							
Profit After Tax	Pearson's r	0.816	***	—					
	p-value	< .001		—					
Other Investment	Pearson's r	0.559	***	0.307	**	—			
	p-value	< .001		0.006		—			
Total	Pearson's r	0.990	***	0.804	***	0.581	***	—	

Deposit										
	p-value	< .001		< .001		< .001		—		
Equity	Pearson's r	0.943	***	0.829	***	0.537	***	0.932	***	—
	p-value	< .001		< .001		< .001		< .001		—

Note. * p < .05, ** p < .01, *** p < .001

From the correlation table it is observed that both the input factors (i.e. deposit and equity are significantly associated with the output factors: even though the direction of relationship is positive for some variables and negative for the others. The relationship among input and output factors indicates that the variability in input factors can have the possibility to explain the variability in output factors which in turn gives the confidence to proceed in to studying the efficiency level of private banks with the set of given inputs and outputs.

In the correlation matrix, strong positive linear relationships can be seen between Loans & Advance and Total Deposit (Pearson's r = 0.990, p < .001), Profit After Tax and Equity (Pearson's r = 0.829, p < .001), and Other Investment and Total Deposit (Pearson's r = 0.581, p < .001). This suggests that an increase in one variable will lead to an increase in the other, while a decrease in one will lead to a decrease in the other. Further, strong negative linear relationships can be observed between Other Investment and Equity (Pearson's r = -0.537, p < .001) and Profit After Tax and Total Deposit (Pearson's r = -0.804, p < .001). This suggests that an increase in one variable will lead to a decrease in the other, while a decrease in one will lead to an increase in the other.

4.2.3. Overall efficiency scores

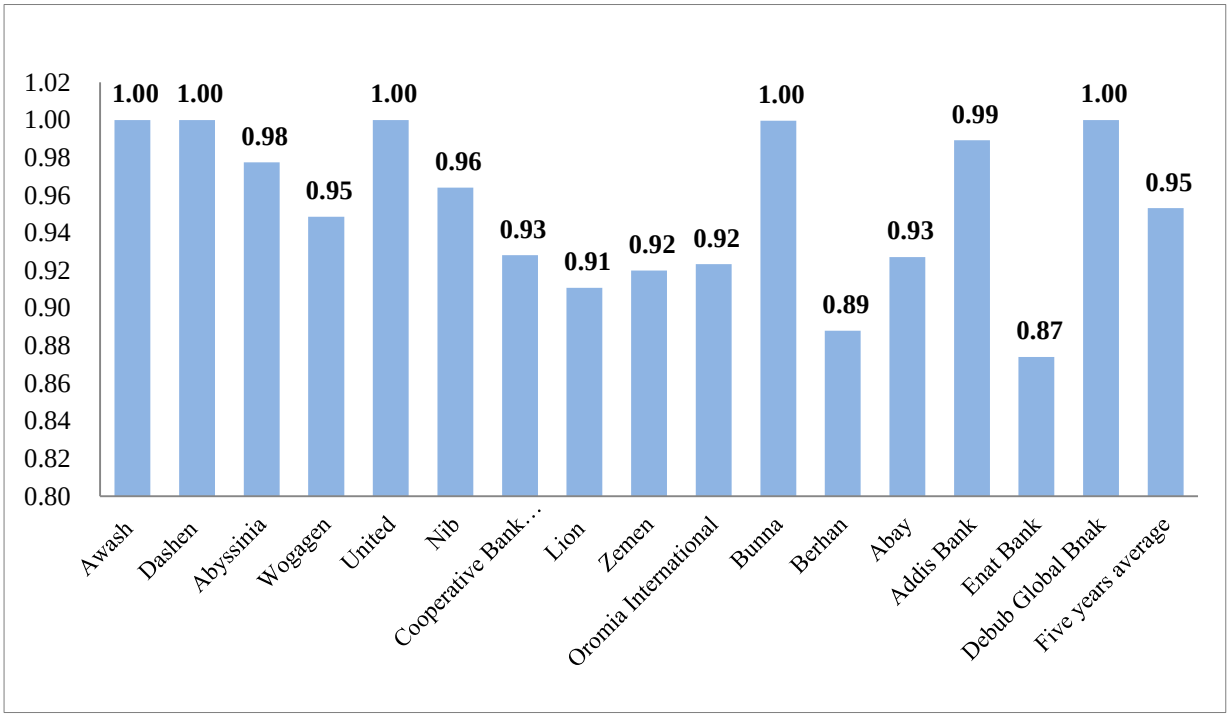
The overall technical efficiency score ranges between 87% and 100%.

The overall result shows that out of 16 banks, only 5 (31.3%) are technically efficient, while most banks (68.7%).

According Getnet (2019), in this case, significant number of banks is operating below the best practice production frontiers and can improve their productivity.

Moreover, this paper revealed that banks that opened during an early period or first tier banks (Awash, Dashen, Abyssinia, Wegagen, and United) have better average technical efficiency as compared with tier II and tier III banks.

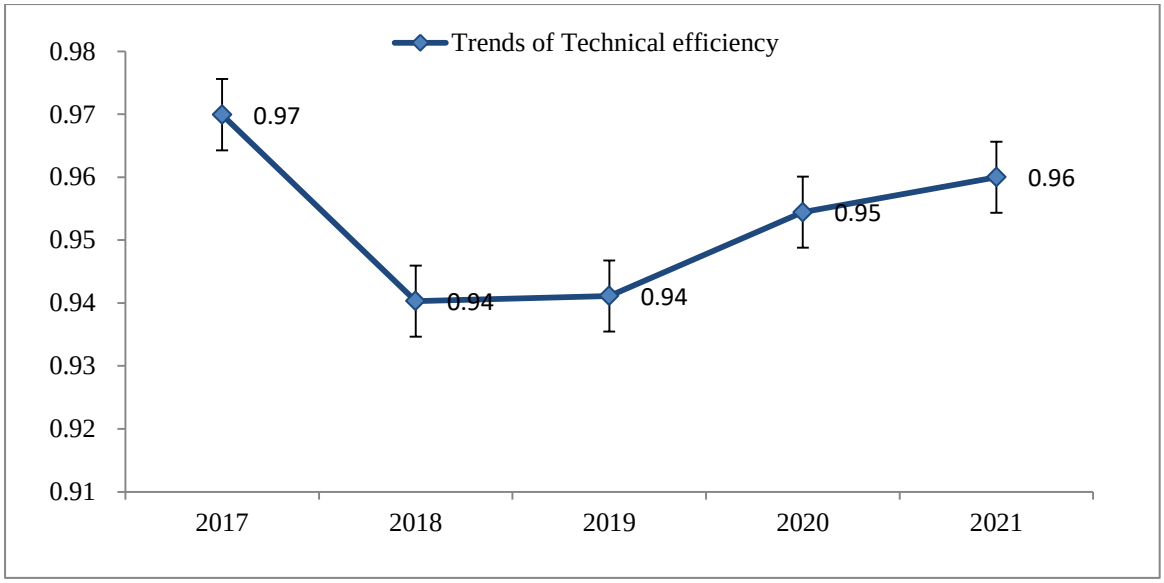
Figure 1. Average Technical efficiency score for 16 private banks



4.2.4. Efficiency Trends

Table 1, presents efficiency trends of private bank, whether it has constant, increasing or declined with time. Figure 2 shows better efficient result 97 % in 2017 sharply declined to 94 % from 2018 to 2019 and gradually improved to 96 % in 2021.

Figure 2: Trends in the technical efficiency of private banks



4.2.5. Second Stage: Logistic regression on the determinates of technical efficiency

An examination of the correlations between the explanatory variables is displayed in the Table. Bank size and total deposit (market share) have a strong relationship, signifying that caution should be taken when incorporating the two variables into the same model, as it could lead to issues with multicollinearity. The correlations between the other explanatory variables are within the acceptable range.

Table 3: Correlation among explanatory variables

		CAD	ROA	Size	Credit Risk	Management Quality	**Income diversification**	**deposit fund**	
CA	Pearson's r	—							
	p-value	—							
ROA	Pearson's r	0.230	—						
	p-value	0.024	—						
Size	Pearson's r	-0.486	-0.247	—					
	p-value	< .001	0.015	—					
Credit Risk	Pearson's r	-0.163	-0.159	0.637	—				
	p-value	0.112	0.121	< .001	—				
Management Quality	Pearson's r	0.017	-0.221	0.144	0.302	—			
	p-value	0.867	0.030	0.161	0.003	—			
Income diversification	Pearson's r	0.060	0.154	-0.631	-0.635	-0.063	—		
	p-value	0.559	0.135	< .001	< .001	0.541	—		
Solvency ratio	Pearson's r	-0.424	-0.308	0.514	0.306	0.078	-0.370	—	
	p-value	< .001	0.002	< .001	0.002	0.450	< .001	—	
Market share (Total deposit)	Pearson's r	-0.499	-0.259	0.998	0.633	0.142	-0.633	0.567	—
	p-value	< .001	0.011	< .001	< .001	0.167	< .001	< .001	—

4.2.6. Multicollinearity

When two independent variables in a regression equation are highly correlated, it can affect the predictions of the parameters. This is known as multicollinearity (Kutner, Nachtsheim, Neter, & Wasserman, 2004). Adeboye, Fagoyinbo, & Olatayo (2014) suggest that when the VIF is above 4 or the tolerance is below 0.25, multicollinearity may be present and further investigation is needed. Fortunately, in this case, all the VIFs are below 4 and the tolerance is above 0.25, indicating that multicollinearity is not present.

Table 4:Collinearity test

	VIF	**Tolerance**
Management Quality	1.20	0.830
Income diversification	3.10	0.322
ROA	1.71	0.584
Size	3.43	0.291
CA	3.15	0.318
Credit Risk	2.13	0.469
deposit fund	1.84	0.543

Based on Table 4., it can be shown that there is no multicollinearity between any of the independent variables, as all of the tolerance levels are greater than 0.4 and the VIF is less than 2.50.

4.3. Predictions

The accuracy of the model's prediction was assessed by creating a contingency table. Assessment showed that 83% of the banks in the sample were correctly classified as efficient.

Table 5: Classification Table

	Predicted		
Observed	**0**	**1**	**% Correct**
0	28	15	65.1
1	9	44	83.0

Note. The cut-off value is set to 0.5

4.4. Interpretation of significant model coefficients

The results of the binary logistic regression help us determine which explanatory variables affect on how to affect technical efficiency of banks. A total of 16 banks were studied in the analysis.

The Binary logistic (Liklihood ratio) test explained in below table 3 reported that 33% of the variation in technical efficiency and correctly classified 87.8 of cases. As a result the joint null hypothesis $HO{:}\beta 1 = \beta 2 = \beta 3 = \beta 4 = \beta 5 = \beta 6 = \beta 6 = \beta 7 = 0$ was rejected at the 5% level of significance (Prob $\chi 2 < 0.05$), implying that our model fits.

Table 6: Model coefficients of Technical Efficiency

Model Coefficients – TE

						95% Confidence Interval	
Predictor	Estimate	SE	Z	P	Odds ratio	Lower	Upper
Intercept	10.824	8.792	1.231	0.218	50218.105	0.00165	1.53e+12
Management Quality	0.336	0.825	0.407	0.684	1.399	0.27746	7.053
Income diversification	1.342	1.130	1.187	0.235	3.825	0.41778	35.023
ROA	2.592	1.205	2.150	0.032	13.358	1.25803	141.843
Size	0.671	0.504	1.332	0.183	1.956	0.72892	5.251
CA	-1.904	1.774	-1.073	0.283	0.149	0.00461	4.818
Credit Risk	4.877	2.891	1.687	0.092	131.299	0.45427	37949.600
Solvency ratio	-13.469	6.195	2.174	0.030	1.41e-6	7.54e-12	0.265

Model Fit Measures

					Overall Model Test		
Model	Deviance	AIC	R^2_{CS}	R^2_N	χ^2	df	P
1	104	120	0.250	0.334	27.6	7	< .001

N.B. Estimates of log odds of "TE = 1" vs. "TE = 0", P < 0.05, P<.1, P<0.01

The significance codes indicate the level of significance of the coefficients: Highly significant with (p < 0.01), Significant (p < 0.05) and moderately significant (p < 0.1

Moreover, significant coefficients in the logistic regression model are listed below:

- **Profitability measured as a proxy of return on asset**: (Estimate: 2.592, p-value: 0.032, Significance: **), It was found that, holding all other predictor variables constant, the odds of (technical efficiency) occurring increased) by 35 per cents, at 95 % CI with a lower and upper limit of (25 %, 84 %) for a one–unit increase in return on equity. Besides, the p-value is 0.032 (less than 0.05); we can say that the relationship is statistically significant at the 5% level. The result is in line with studies by Hasan and Marton, 2003, Rosman et al2014, Singh and Fida 2015, and Sufian 2009, Adusi, Tadesse ,2017).

- **Solvency ratio (liability to asset ratio**): (Estimate: -13.469, p-value: 0.0.00633, negative, Significance: ***), the result indicated that holding all other predictor variables constant, as the liability to asset ratio increases, the odds of the dependent variable (TE) occurring decrease. The higher the ratio, the higher the degree of leverage and, consequently, the higher the risk of investing in that bank and causing inefficiency. The p-value is 0.00633 (less than 0.01), indicating that the variables have statistically significant relationship at the 5% level. Indeed, other variables do not appear to significantly affect the odds of the dependent variable.

CHAPTER FIVE

Summary, Conclusion and Recommendation

5.1. Summary

An investigation into the factors that affect TE in the banking industry in Ethiopia was conducted between 2016 and 2021, using panel data from 16 private banks. DEA model was used to measure TE of private banks. The output variables for in measuring TE were loan, investment, and net profit while the input variables were paid-up capital and total deposit. The TE score was coded in to binary data, with a value of 1 assigned for TE bank and 0 to each technically inefficient private bank. Then Binary logistic regression is performed to investigate the driving factors of TE of private banks. Accordingly, the results revealed that 5 out of 16 banks (31.3%) were technically efficient, that means significant number of banks have the possibility for TE improvements. The TE trends indicated unsteady, with better efficiency in 2017, a sharp decline in 2018 and 2019, and gradual improvement in 2021. Tier I banks were found to be more efficient than tier II and tier III banks.

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5.2. Conclusion

According to our input output technical efficiency analysis, most of the private banks were exhibiting technical inefficiency. Their efficiency trend was unstable.

Indeed, in the Binary logistics regression, returns on asset and solvency ratio were significant predictors of TE in the private banking industry. The positive and statistically significant relationship between returns on assets and technical TE indicates that banks should strive to improve their operational excellence. On the other hand, the negative and statistically significant relationship between solvency and TE suggests that a higher debt obligation for a unit asset may have a negative effect on the bank's performance.

5.3. Recommendation

The findings of the research indicate that private banks require efficiency-enhancement measures. In addition to deposit collection, the surveyed banks may also need to concentrate on enhancing their credit capacity and investing in other ventures. Moreover, the efficiency

of the banks positively and significantly affected by return on asset . Thus, steps should be taken to augment the return on assets. On the contrary, banks need to have a comprehensive understanding of their solvency ratio as it can significantly and adversely affect their technical efficiency.

5.4. Feature Research Directions

Further research can be done by including other variables, such as organizational cultures, as predictors. The strength of the two different approaches for technical efficiency measurement models such as DEA and SFA can be tested by other researchers.

References

Adeboye, N. O., Fagoyinbo, I. S., &Olatayo, T. O. (2014). Estimation of the effect of multicollinearity on the standard error for regression coefficients. Journal of Mathematics, 10(4), 16-20.

Adusei, M. (2016). Determinants of bank technical efficiency: Evidence from rural and community banks in Ghana. Cogent Business & Management, 1199519.

Ahmed MH (2015) Measuring technical, economic and Allocate efficiency of maize production in subsistence

Alrafadi,K. and Kamaruddin, B. and Yusuf ,M. (2014), Technical efficiency and determinates in Libyan Banking. International Journal of Business and Social Science,Vol. 5, No. 5;

Berger, A. N., & DeYoung, R. (1997). Problem Loans and Cost Efficiency in Commercial Banks. Journal of Banking and Finance, 21, 849-870. http://dx.doi.org/10.1016/S0378 …

Berger, A. N., & DeYoung, R. (1997). Problem Loans and Cost Efficiency in Commercial Banks. Journal of Banking and Finance, 21, 849-870

Bryman, A., & Cramer, D. (2009). Quantitative data analysis with SPSS 14, 15 & 16: A guide for social scientists

Cephus Research and Analytics (2020). Ethiopia's Banking Sector report.

Charnes, A., Cooper, W.W. and Rhodes, E. (1978). Measuring the Efficiency of Decision Making Units. European Journal of Operational Research, 2, 429-444.

Coelli, T., Rao, D. P., O'Donnell, C.J. and Battese, G.E. (2005). An Introduction to Technical Efficiency and Productivity Analysis, New York: Springe

Creswell, J.W. (2003) Research Design: Qualitative, Quantitative, and Mixed Method Approaches

Duygun M., Pasiouras F. (2009). Assessing Bank Performance with Operational .Research and Artificial Intelligence Techniques: A Survey. School of Management, Working Paper Series

farming : Evidence from the central rift valley of Ethiopia. Applied Studies in Agribusiness and Commerce 9(3): 63-74.

Farrell, M. J., (1957). The Measurement of Productive Efficiency. Journal of the Royal Statistical Society, Series A, 120, 253-290

Fida, (2015). for Omani banking sector as it is small banking sector having only sixteen banks. Study analyzes the technical efficiency of …Author: Tankiso Moloi Publish Year: 2017

Getnet Z . Muche (2019). Efficiency Analysis of Commercial Bank Branches: The Case of Berhan Bank Sh. Co. Journal of Business and Administrative Studies (2019), Vol. 11, No.2

Getnet Z. Muche (2019). Cost Efficiency of Private Commercial Banks in Ethiopia. Research and Knowledge Mangement Office - St. Mary's University, 67-76.

Girma J. Duguma (2020). Effect of deposit mobilization on the technical efficiency of rural saving and credit cooperatives: Evidence from Ethiopia

Hasan and Marton, (2003). Development and efficiency of the banking sector in a transitional economy: Hungarian experience, Journal of banking and Finance 2003, vol. 27, issue 12, 2249-2271http://dx.doi.org/10.1016/0377-2217(78)90138-8

Kuosmanen T, Johnson A, Saastamoinen A (2014) stochastic nonparametric approach to efficiency analysis : A unified framework. In: Zhu J (Ed.), Handbook on data envelopment analysis, Springer, New York, USA, pp. 49

Kutner, M. H., Nachtsheim, C. J., Neter, J., & Wasserman, W. (2004). Applied linear regression models (Vol. 4, pp. 563-568). New York: McGraw-Hill/Irwin.

Kutner, Neter, Nachtsheim, Wasserman, Applied Linear Regression Models

Majid, K. (2012). Technical efficiency analysis by using Data Envelop Analysis Model: Evidence from Indian Banks. The Islamic Azad University of Saravan Aligarh, Uttar Pradesh, India,2002

Maryam DuygunFethi, (2009). Assessing Bank Performance with Operational Research and Artificial Intelligence Techniques: A Survey FotiosPasiouras School of Management, University of Leicester, UK School of Management, University of Bath, UK

Mohammed, S. A. (2002). Finance-growth nexus in Sudan: an empirical assessment based on an application of the autoregressive distributed lag (ARDL) model. Arab Planning. Institute in Kuwait, API/WPS 0803.

Mostafa (2007). cited in Osamwonyi and Imafidon (2015), defines efficiency as a dynamic concept that involves a firm being able to operate with the minimum level of resources or inputs such as capital, labour and materials to produce outputs and yet remain highly competitive over an extended period.

Murillo Zamorano LR (2004) Economic efficiency and frontier techniques. Journal of Economic Surveys 18(1): 33-77

Pasiouras F., (2008a), International evidence on the impact of regulations and supervision on banks' technical efficiency: an application of two-stage data envelopment analysis, Review of Quantitative Finance and Accounting, 30, 187-223

Pasiouras, F. (2008) . Estimating the Technical and Scale Efficiency of Greek Commercial Banks: The Impact of Credit Risk, Off-Balance Sheet Activities, and International Operations. Research in International Business and Finance, 3, 301-318.

Precise Consult (2021). Access to Credit for MSEs and Credit Information System in Ethiopia Policy Environment and Regulatory Issues

Precise Consult (2021).Why Ethiopia Must Strengthen Its Credit Information System and Ensure Access to Credit for Micro and Small Scales Enterprises? Position paper.

Rosman., (2014) . Efficiency of Islamic banks during the financial crisis: An analysis of Middle Eastern and Asian countries

Sealey, C. and Lindley, J.T. (1977). Inputs, outputs, and a Theory of Production and Cost at depository financial Institutions, Journal of Finance, 32 (4), 1251-66.

Sealey, C. and Lindley, J.T. (1977). Inputs, outputs, and a Theory of Production and Cost at depository financial Institutions, Journal of Finance, 32 (4), 1251-66.

Sealey, C. and Lindley, J.T. (1977). Inputs, outputs, and a Theory of Production and Cost at depository financial Institutions, Journal of Finance, 32 (4), 1251-66.

Singh and Fida (2015). Technical efficiency and its determinants: an empirical study on banking sector of Oman. Problems andPerspectives in Management, 13(1-1), 168-17

Sufian (2009) explicated the bank profitability determinants of commercial banks in Malaysia.

Tadesse, Z. (2017), Determinants of bank technical efficiency: Evidence from commercial banks in Ethiopia.

Tesfaye (2014), Efficiency in the Ethiopian Banking System: An Application of Data Envelopment Analysis.

Tesfaye B. (2016). Determinants of commercial banks efficiency: Evidence from selected commercial banks of Ethiopia.International Journal of Scientific and Research Publications,6, 551–556

Tesfaye, Rahel (2018). Determinants of the Financial Performance of a Private Commercial Bank in Ethiopia

Wang M, Wang MH (2002) Comparison of economic efficiency estimation methods : Parametric and nonparametric techniques. The Manchester School 70(5): 682-709

https://www.pwc.in/assets/pdfs/finance-effectiveness/banking_

profitability.pdf,BankingProfitability,andPerformance Management. PricewaterhouseCoopers Pvt. Ltd

https://www.economicshelp.org/blog/glossary/technical efficiency/#:~:text=Technical%20efficiency%20is%20the%20effectiveness%20with%20which%20a,technology.

APPENDIX

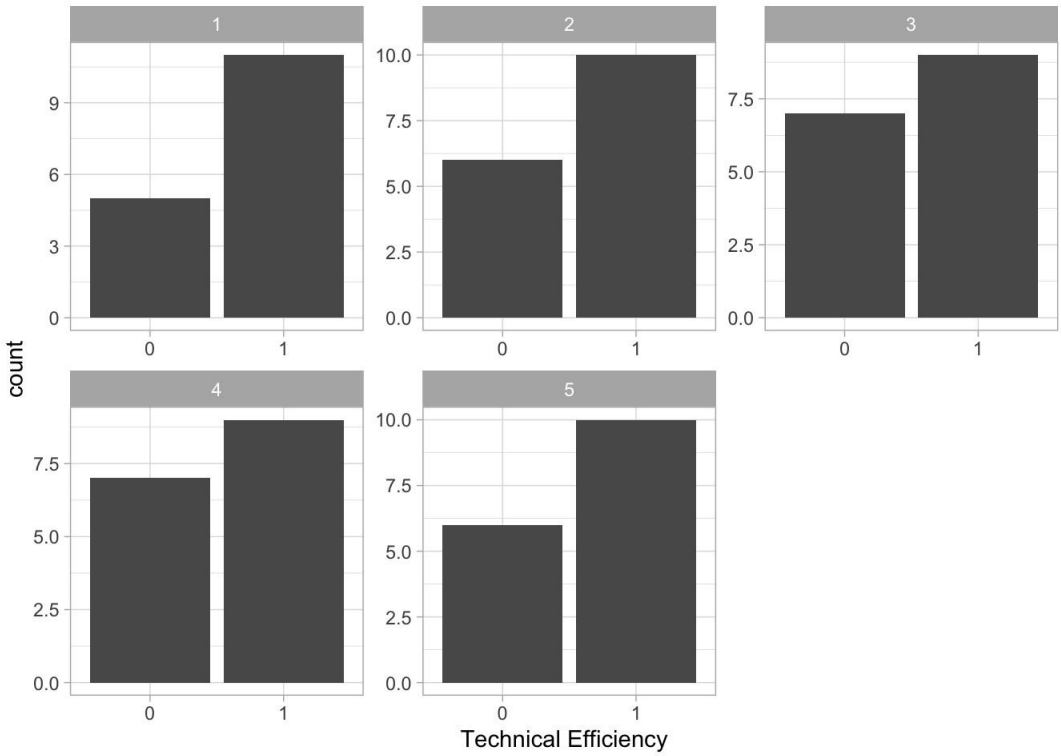
Table :1 Trends in Technical efficiency of Private banks

	TE under CRS	TE under VRS	TE under Scale
AIB	1.00	1.00	1.00
DB	1.00	1.00	1.00
BOA	0.96	0.97	0.99
WB	0.93	0.95	0.98
UB7	1.00	1.00	1.00
NiB	0.93	0.95	0.98
CBO	0.90	0.94	0.96
LIB	0.91	0.93	0.98
ZB	0.89	0.90	0.99
OIB	0.88	0.92	0.96
BUNNA	1.00	1.00	1.00
BRIB	0.90	0.91	0.99
ABAY	0.90	0.93	0.97
ADDIS	0.96	0.99	0.97
ENAT	0.87	0.88	0.98
DGB	1.00	1.00	1.00
Six years average	**0.94**	**0.95**	**0.98**

Table 2 : Technical efficiency score of private

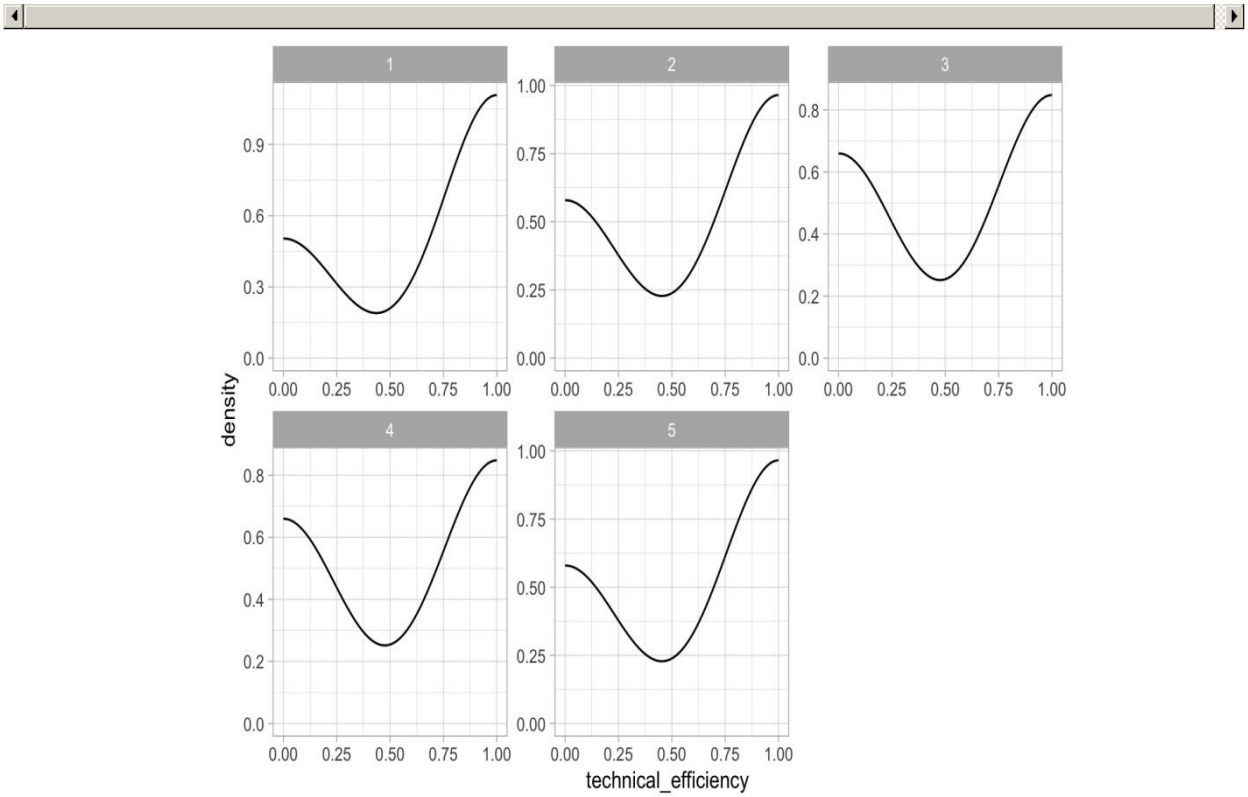
Banks	Years					
	2016	2017	2018	2019	2020	2021
Banks	TE (VRS technology)	TE (VRS technology)	TE (VRS technology)	TE (VRS technology)	TE (VRS technology)	TE (VRS technology)
Awash	1.00	1.00	1.00	1.00	1.00	1.00
Dashen	1.00	1.00	1.00	1.00	1.00	1.00
Bank of Abyssinia	0.92	0.94	0.94	1.00	1.00	1.00
Wogagen	0.96	1.00	1.00	0.83	0.92	0.99
United	0.99	1.00	1.00	1.00	1.00	1.00
Nib	0.87	1.00	1.00	0.82	1.00	1.00
Cooperative bank of Oromia	0.98	1.00	1.00	0.97	0.90	0.78
Lion	1.00	0.92	0.88	0.90	0.91	0.95
Zemen	0.79	1.00	0.67	0.95	0.98	1.00
Oromia International	0.90	0.88	1.00	0.91	0.93	0.90
Bunna	1.00	1.00	1.00	1.00	1.00	1.00

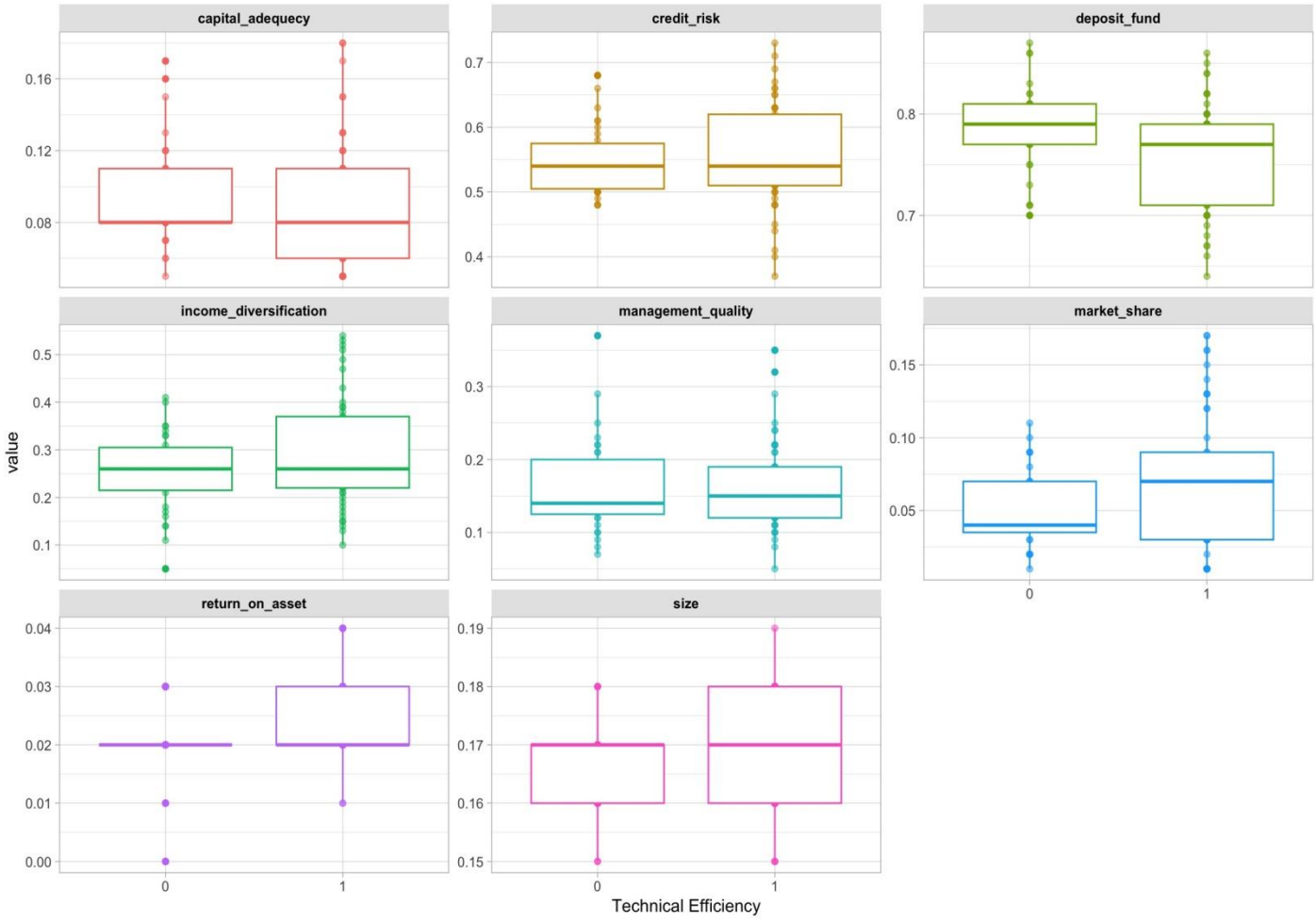
Berhan	1.00	1.00	0.87	0.82	0.87	0.88
Abay	0.92	0.90	0.86	1.00	0.89	1.00
Addis	1.00	1.00	0.95	1.00	1.00	1.00
Enat	0.93	0.88	0.88	0.87	0.89	0.87
Debub Global	1.00	1.00	1.00	1.00	1.00	1.00



Mean result	**0.95**	**0.97**	**0.94**	**0.94**	**0.95**	**0.96**

Figure A1: Histogram of technical efficiency of banks


1
2
3
4
5
density
technical_efficiency


capital_adequecy
credit_risk
deposit_fund
income_diversification
management_quality
market_share
return_on_asset
size
value
Technical Efficiency