# A three-stage DEA analysis and a black-box approach of the performance of commercial banks in Ghana: an evaluation of efficiency, competition and profitability

by

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## DECLARATION: PLAGIARISM

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## ABSTRACT

This thesis measures the efficiency of banks, ascertains the determinants of bank efficiency, and evaluates the relationship between efficiency, competition, and profitability of 18 commercial banks in Ghana from 2008 to 2019.

The first empirical paper estimates and compares efficiency scores using both the black-box and the three-stage dynamic network DEA models. Both models incorporate a slack variable and bootstrap technique, with the dynamic network DEA model measuring efficiency of the deposit mobilisation, intermediation and revenue generation activities of banks in Ghana. The results show that commercial banks in Ghana are inefficient, with efficiency scores estimated by the dynamic network model being significantly lower than scores measured by the black-box model. The commercial banks are also most efficient in intermediation and least efficient in revenue generation.

The second empirical chapter uses both the truncated bootstrap and the Tobit regression models to determine the impact of internal and external factors on the efficiency scores measured by the three-stage network dynamic DEA model. Results show that Capital Adequacy Ratio (CAR) and Non-Performing Loans (NPL) ratio have a significant negative impact on production and intermediation efficiencies while liquidity ratio has a negative and positive impact on production and intermediation efficiencies respectively. Inflation rate also has a negative effect on production efficiency and size, a significant positive impact on both production and intermediation efficiencies. ROA, OC/OI and inflation rate positively affects the revenue generation processes of commercial banks assessed, while foreign ownership is seen to be detrimental to revenue generation.

To ascertain the impact of competition on bank efficiency, the Boone indicator is used to measure competition. Banks in Ghana are competitive for all the years assessed using the Boone Indicator and when regressed on the efficiency types, the study observed a positive association between competition and all the types of efficiencies measured. The positive relationship between revenue generation efficiency and competition however does not yield a significant observation, indicating a lower persistence in profits across the industry as banks are unable to earn abnormal profits.

The final empirical chapter uses both the efficiency– profitability matrix and the GMM regression model to assess the impact of the efficiency scores on profitability measures (ROA and ROE). Using the GMM model, all three efficiency types largely have positive impacts on both ROA and Return on Equity (ROE). The study also found that foreign ownership has a significant impact on ROA, while liquidity ratio and competition have a negative and a positive impact on ROE respectively.

With the efficiency– profitability matrix, foreign-owned banks are largely classified in the high profitability, high-efficiency quadrant (Stars or Lucky), while domestic banks were mostly categorised under the low profitability, low-efficiency quadrant (Unlucky or Underdogs).

Based on the findings, the study highlighted relevant implications for policy.

***Keywords**: Efficiency, Profitability, Black-Box Data Envelopment Analysis, Dynamic Network Data Envelopment Analysis, Slack-Based Model, Bootstrap, Boone-indicator, Efficiency–Profitability Matrix*

## OPSOMMING

Hierdie tesis toets die doeltreffendheid van banke, bepaal die determinante van bankdoeltreffendheid en evalueer die verband tussen doeltreffendheid, mededinging en winsgewendheid van 18 handelsbanke in Ghana van 2008 tot 2019.

Die eerste empiriese hoofstuk skat en vergelyk die tellings van doeltreffendheid met behulp van beide die swartboks- en die drie-fase dinamiese netwerk DEA-modelle. Albei modelle bevat 'n oortolligheidsveranderlike en hermonstering tegniek, met die dinamiese netwerk DEA-model wat die doeltreffendheid van die deposito-mobilisering, intermediëring en inkomstegenereringsaktiwiteite van banke in Ghana meet. Die resultate toon dat kommersiële banke in Ghana ondoeltreffend is, met doeltreffendheidstellings wat deur die dinamiese netwerkmodel beraam word, en aansienlik laer is as tellings gemeet deur die swartboksmodel. Die handelsbanke is ook die doeltreffendste in intermediëring en die minste doeltreffend in inkomstegenerering.

Die tweede empiriese hoofstuk gebruik beide die besnoeide hermonstering en die Tobit-regressiemodelle om die impak van interne en eksterne faktore op die doeltreffendheidstellings soos gemeet deur die drie-fase netwerk dinamiese DEA-model te bepaal. Resultate toon dat die verhouding tussen Kapitaaltoereikendheidsratio (CAR) en Nie-Doeltreffende Lenings (NPL) 'n beduidende negatiewe impak op produksie- en intermediëringdoeltreffendheid het, terwyl likiditeitsverhouding 'n negatiewe en positiewe impak op onderskeidelik produksie- en intermediëring doeltreffendheid het. Inflasiekoers het ook 'n negatiewe uitwerking op produksiedoeltreffendheid en -grootte, en 'n beduidende positiewe impak op beide produksie- en intermediëringdoeltreffendheid. Die Opbrengs op Bates (ROA), Bedryfskoste tot Bedryfsinkomste (OC/OI) en die inflasiekoers beïnvloed die inkomstegenereringsprosesse van kommersiële banke wat beoordeel word positief, terwyl buitelandse eienaarskap as nadelig vir inkomstegenerering beskou word.

Om die impak van mededinging op bankdoeltreffendheid vas te stel, word die Boone-aanwyser gebruik om mededinging te meet. Banke in Ghana is mededingend vir die tydperk wat met behulp van die Boone-aanwyser beoordeel is en wanneer op die doeltreffendheidstipes regresseer, het die studie 'n positiewe verband tussen mededinging en al die tipes doeltreffendheid getoon.Die positiewe verband tussen inkomstegenereringsdoeltreffendheid en mededinging is egter nie beduidend nie, wat dui op 'n laer bestendigheid in winste regoor die bedryf, aangesien banke nie abnormale winste kan verdien nie.

Die laaste empiriese hoofstuk gebruik beide die doeltreffendheid- winsgewendheidsmatriks en die GMM-regressiemodel om die impak van die doeltreffendheidstellings op winsgewendheidsmaatreëls (ROA en ROE) te bepaal. Met behulp van die GMM-model het al drie doeltreffendheidstipes grootliks 'n positiewe impak op beide ROA en Opbrengs op Eienaarsbelang (ROE). Die studie het ook bevind dat buitelandse eienaarskap 'n beduidende impak op ROA het, terwyl likiditeitsverhouding en mededinging onderskeidelik 'n negatiewe en 'n positiewe impak op ROE het.

Met die doeltreffendheid- winsgewendheidsmatriks word banke in buitelandse besit grootliks geklassifiseer in die hoë winsgewendheid, hoë-doeltreffendheid kwadrant (Stars of Lucky), terwyl binnelandse banke meestal onder die lae winsgewendheid, lae-doeltreffendheid kwadrant (Unlucky of Underdogs) gekategoriseer is.

Op grond van die bevindinge het die studie relevante implikasies vir beleid uitgelig.

***Sleutelwoorde:*** *Doeltreffendheid, winsgewendheid, Black-Box Data Envelopment Analysis, Dynamic Network Data Envelopment Analysis, Slack-Based Model, Bootstrap, Boone-aanwyser, Doeltreffendheid-Winsgewendheid Matriks*

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# DEDICATION

The thesis is dedicated to the Almighty God, my husband, Mr. Ishmael Oku, my children, Ethan, Elliz Rose and Eda Eleanor Oku, my parents, Mr. Sampson Hammond and Mrs. Sabina Hammond and my bosses Mrs. Elsie Addo Awadzi and Dr. Joseph France.

## DECLARATION: LANGUAGE EDITING

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Dear Sir/Madam,

**Declaration of language editing**

I, Sheila Hicks, hereby declare that I have personally read through the research assignment of Barbara N.A. Oku and have highlighted language errors.

Yours sincerely

Sheila Hicks

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| | |
|---|---|
| ADB | Agricultural Development Bank |
| AT1 | Additional Tier 1 |
| ATM | Automated Teller Machine |
| BCC | Banker, Charnes And Cooper |
| BI | Boone Indicator |
| BoG | Bank Of Ghana |
| CET1 | Common Equity Tier 1 |
| CCR | Charnes, Cooper And Rhodes |
| CAR | Capital Adequacy Requirement |
| CRS | Constant Returns To Scale |
| DEA | Data Envelopment Analysis |
| DFA | Distribution Free Approach |
| DGP | Data Generating Process |
| DRS | Decreasing Returns To Scale |
| DMU | Decision-Making Unit |
| EBRD | European Bank For Reconstruction And Development |
| EFFIP | Intermediation Efficiency |
| EFFPS | Production Efficiency |
| EFFRG | Intermediation Efficiency |
| ESH | Efficiency Structure Hypothesis |
| EU | European Union |
| FDH | Free Disposal Hypothesis |
| FINSAP | Financial Sector Adjustment Programme |
| GCB | Ghana Commercial Bank |
| GCC | Gulf Cooperation Council |
| GDP | Gross Domestic Product |
| GMM | Generalised Methods Of Moments |
| HHI | Herfindahl–Hirschman Index |
| IFRS | International Financial Reporting Standards |
| IMF | International Monetary Fund |
| IP | Intermediation Process |
| IRS | Increasing Returns To Scale |
| IT | Inflation Targeting |
| IT | Information Technology |
| MC | Marginal Cost |

| | |
|---|---|
| MENA | Middle East And North Africa |
| NBFIs | Non-Bank Financial Institutions |
| NFIDS | National Financial Inclusion And Development Strategy |
| NIB | National Investment Bank |
| NIM | Net Interest Margin |
| NIRS | Non-Increasing Returns To Scale |
| NPART | Non-Performing Assets Recovery Trust |
| NPAs | Non-Performing Assets |
| NPL | Non-Performing Loans |
| NSCB | National Savings And Credit Banks |
| OC | Operating Cost |
| OI | Operating Income |
| OLS | Ordinary Least Square |
| OTE | Overall Technical Efficiency |
| PBT | Profit Before Tax |
| PNDC | Provisional National Defense Council |
| POS | Point Of Sale |
| PS | Production Stage |
| PTE | Pure Technical Efficiency |
| RG | Revenue Generation Stage |
| ROE | Return On Equity |
| ROA | Return On Assets |
| SBM | Slack-Based Model |
| SCP | Structural Conduct Performance |
| SFA | Stochastic Frontier Analysis |
| SE | Scale Efficiency |
| SME | Small And Medium Scale Enterprises |
| SSB | Social Security Bank |
| TC | Total Cost |
| TD | Total Deposits |
| TFA | Thick Frontier Approach |
| TL | Total Loans |
| UMB | Universal Merchant Bank |
| VRS | Variable Returns To Scale |
| WAEMU | West African Economic Monetary Union |

# CHAPTER 1
# INTRODUCTION

## 1.1 *Background and Motivation*

Globally, the financial sector is noted for its significant role in developing both the micro and macro economies of nations (de Abreu et al., 2019; Levine, 2002). According to Kalpana and Rao (2017) and Berger and Humphrey (1997), the banking sector, in particular, is credited for bridging the financial gap between net savers and borrowers by facilitating the growth of businesses through the provision of credit for short- and long-term purposes, supporting investment in infrastructure and increasing the disposable income of households.

Irrespective of the significance of the expected contribution of the banking sector to economic development, the sector if not well regulated may lead to a recession in the economy as experienced in the 2007–2008 financial crisis. Management of banks was criticised for engaging in inefficient ventures in the years before the financial crisis, as they sought short-term profits regardless of long-term consequences (Dallas, 2011). Banks consequently became less efficient, with lower profits and higher liquidity and credit risks (Barrell and Davis, 2008). Specifically, banks during the crisis were criticised for engaging in high-risk transactions which saw a great mismatch between the increase in debt demand and the increase in deposits, requiring banks to look at other external sources of funding and increasing their liquidity risks (Norgren, 2010). With an increase in credit and liquidity risks, banks, were heavily undercapitalised, with poor asset quality (Altunbas et al., 2012). Ultimately, following the global financial crisis in 2007–2008, the public has become increasingly distrustful of the banking sector owing to the significant bailout by governments to ensure the sustainability of some banks in the sector (Stix, 2013).

To avoid the replay of the situation that existed before the 2007–2008 financial crisis, supervisors and managers of banks have in the past decade taken a keen interest in improving the operations of banks to ultimately enhance their efficiencies.

Globally, one key attempt made by supervisors in recent times to improve bank efficiency has been the increase in the quality and quantity of the capital that banks are expected to retain. This measure, proposed by the Committee on Banking Regulations and Supervisory Practices (Basel Committee), created standards for the measurement of regulatory capital. Following the stipulations of the Basel Committee, the regulatory capital has been defined as the summation of variables classified as Common Equity Tier 1 (CET1), Additional Tier 1 (AT1), and Tier 2 capital. CET1 is derived from ordinary shares, retained earnings, and statutory reserves; AT1 from debt instruments (issued and paid-up capital, subordinated to deposits, general creditors, and subordinated debt); and Tier 2 capital from revaluation reserves, general provisions, subordinated term debt, and hybrid capital instruments

(BASEL Committee, 2011). Components of additional Tier 1 are very similar to the components of Tier 2 capital. Whereas additional Tier 1 capital is used to support the bank while still under operation (going-concern basis), the Tier 2 is used when the bank is being liquidated (gone-concern basis). Moreover, banks were encouraged to include in their regulatory capital, additional capital buffers: the capital conservation buffer and the countercyclical buffer. The capital conservation buffer is set at 2.5 percent[1] of common equity and the countercyclical buffer is expected to range from 0 percent to 2.5 percent of common equity[2].

Another attempt made by supervisors and bank managers globally to minimise the likelihood of any future crisis and improve efficiency in the banking sector is the enhancement of corporate governance structures (Dallas, 2011). This attempt is to control the behaviour of executive management and shareholders, by aligning their actions to safeguard the assets and continuity of banks. In this regard, following the 2007–2008 financial crisis most countries have instituted new directives to monitor and control the powers and authorities of the executive management and shareholders of banks. Researchers have also become increasingly interested in assessing how well managers handle resources to maximise output of banks. In the literature, this assessment is done by estimating the technical efficiency of banks.

Technical efficiency, which is further categorised into pure technical and scale efficiency, assesses the ability of management to convert input into output, with more output per unit of input implying an increase in efficiency (Charnes et al., 1978; Sherman and Zhu, 2006). In assessing technical efficiency, academia and policymakers have sought to investigate the sources of inefficiencies in the banking sector (Mostafa, 2007). In this regard, existing studies have identified several factors that may influence the efficiency of banks. These largely include size (Hughes et al., 2001), ownership type (Berger and DeYoung, 2001), managerial competence (Alber et al., 2019a), and availability of capital (Altunbas et al., 2007).

Generally, to estimate the technical efficiency of banking sectors, most studies have in the past decade adopted frontier methodologies as opposed to the traditional financial ratio analysis such as Return on Equity (ROE) and Return on Assets (ROA) (Berger et al., 2009; Tone and Tsutsui, 2009; Kablan, 2010; Adjei-Frimpong et al., 2014; Alber et al., 2019). The increasing preference for the frontier methodologies in the banking sector is largely founded on the ability of these measures to assess the performance of multiple input and output firms as opposed to the traditional financial ratios which are most conducive for firms that operate under a single input and output condition (Mousa, 2015). Banks, as pointed out by Kinsella (1980), are multi-product firms as most of their services are joint

[1] This buffer is to assist banks to withstand future periods of stress.
[2] This is to protect banks from excessive growth in credit which poses the threat of high NPLs.

or interdependent, meaning that providing one service may involve providing another service that cannot be independently priced.

A review of literature on the frontier methodologies used to assess efficiency shows that the most applied frontier estimation technique is Data Envelopment Analysis (DEA) (Emrouznejad and Cabanda, 2013; Liu et al., 2012). DEA, a non-parametric estimation approach, is well known for measuring the efficiency of firms with multiple inputs and outputs (Sherman and Zhu, 2006). Existing literature has noted several advantages of DEA. First, the preference for the DEA model is based on the ease of variable selection as this estimation technique selects data mainly on availability and not the importance of the variable (Ahn and Le, 2014). Secondly, the DEA, unlike other efficiency estimation models, does not impose a universal production function on all units in its dataset, making it possible to compare the efficiency of a single unit to other units in the dataset.

Despite the benefits of DEA, the current empirical literature has raised some concerns about the accuracy of its estimations. Primarily, many empirical papers have used the DEA black box approach[3] which has been criticised for ignoring the recently growing developments in the structure and functions of banks (Shi et al., 2021). Post-crisis, banks have evolved via the adoption of new technologies and the emergence of large connected universal banks which not only provide intermediary services but facilitate payment settlement, transactions services and insurance coverage (Davies et al., 2010). With such multiplicity in the functions of banks, there are also various subsections (which are broadly categorised as cost and profit centres) that facilitate the current roles of banks. In effect, bank management is required not only to excel in providing intermediation but to ensure that both profit and cost centres are efficient in their daily operations (Tsai et al., 2020). Therefore, to examine the efficiency of banks, it is prudent to assess management in their various capacities which may include increasing profitability, reducing bureaucracies in processing transactions, improving marketability or reducing costs through superior financial abilities. Unfortunately, the black-box approach, which is the model originally estimated under the DEA technique, is unable to assess the technical efficiency of management in this regard (Tsai et al., 2020).

To overcome the above challenge, recent studies have used the network dynamic DEA model (Fukuyama and Matousek, 2017; Liu and Tone, 2008a; Seiford and Zhu, 1999; Wanke et al., 2019). First, unlike the black-box approach, the network dynamic DEA splits the production system of banks into connected sub-processes, providing more accurate efficiency evaluation of the units within a bank (Färe et al., 2007). Secondly, the network DEA model addresses the existing issue of the classification of variables as either inputs or outputs. Originally, as argued by Berger and Humphrey (1997), researchers view bank liabilities as having input characteristics as they serve as raw materials

[3] Also known as the traditional CCR and BCC models.

for loanable and investable funds. On the other hand, bank assets are seen to be outputs as they generate the bulk of the bank's revenue. Such classification of variables is not clear, particularly for the treatment of deposits. For banks that acquire funds through large depositors and other banks (with interest payments), the classification of deposits as an input variable is adequate. However, most banks not only acquire funds from depositors but also provide other relevant services (which could be classified as outputs) to depositors. These services include liquidity, payments, and safekeeping, informing the classification of deposits as an output variable.

Under the black-box approach, deposits are either classified as inputs or outputs, negating their dual role. The network DEA resolves this challenge by treating deposits as both output and input of different production processes, providing a more accurate assessment of the function of banks (Ebrahimnejad et al., 2014; Fukuyama and Matousek, 2017; Lin and Chiu, 2013; Wang et al., 2019). Also, in the attempt to establish the interlinkages between the bank processes some studies have used the network DEA to treat other variables as outputs in one period and inputs in another period (Akther et al., 2013; Fukuyama and Weber, 2015). This use of the network DEA provides a more detailed analysis of bank performance and is more appropriate for identifying areas of inefficiencies since the functions of banks are reviewed independently taking into consideration the interlinkages between the processes.

Empirically, although there has been an increasing number of studies on bank efficiency in Africa (Adusei, 2015; Alhassan and Ohene-Asare, 2016; Erasmus, 2014; Kablan, 2010; Raphael, 2013), most of these studies have used the black-box approach, giving little or no information about the efficiency of the individual bank processes. Despite the identified benefits, most studies that have used the network DEA model have focused on banks in the North American, European, and Asian continents (Fukuyama and Matousek, 2017; Huang et al., 2014; Liu and Tone, 2008a; Seiford and Zhu, 1999).

Ghana recently faced a banking sector crisis (from 2017 to 2018) which culminated in the liquidation of seven commercial banks in the country. Similar to the reasons provided for the financial crisis in 2007–2008 which originated from the USA, the Bank of Ghana attributed the failure of banks largely to poor corporate governance practices which emanated from the board and senior-level management being either inactive or engaging in activities that conflicted with their roles in the growth of their banks (Benson, 2019; Torku, 2018). Considering the role played by management in the current banking crisis in Ghana, there is a need to assess banking sector efficiency, specifically to examine the effectiveness of bank management in handling the resources of banks in Ghana.

Surprisingly, studies on bank efficiency using DEA have been quite extensive in Ghana, even before the onset of the banking crisis in 2017 to 2018 (Adusei, 2015; Alhassan and Ohene-Asare, 2016;

Alhassan and Tetteh, 2017; Saka et al., 2012; Sarpong and Winful, 2017; Tetteh, 2014). As mentioned above, almost all studies on bank efficiency in Ghana have used the traditional black-box approach, ignoring the current roles played by banks and the efficiency of sub-processes within banks. Currently, commercial banks in Ghana are not only functioning as intermediaries between net borrowers and savers but are engaged in several operational processes to increase value to customers. This diversity in the functions of banks in the country can be traced to the rapid development of technology adopted by the banks (Genberg, 2008). For example, as of December 2018, total registered mobile money accounts were 32.55 million with a value of GH¢223.21 billion. In that same period, the number of registered mobile banking customers stood at 3,891,269 with the value of transactions increasing to GH¢5.66 billion (Payment Systems Oversight Report, 2018). The cumulative number of Automated Teller Machines (ATMs) and Point of Sale (POS) terminals deployed by banks numbered 2,139 and 8,253 respectively at end-December 2018 (Bank of Ghana, Payment Systems Report). Such an increase in digitisation has not only increased the revenue base of banks in the country but has created strong competition among players, requiring banks to constantly create products and diversify operations to enhance customer experience. There is therefore a need to assess not only the intermediation function of banks, which is mainly represented by the black-box approach, but to explore the efficiency of all other processes of the banks.

### *1.2 Importance of Study*

This thesis uses the most recently available bank data to address the lack of studies that have used the network DEA to model the efficiency of banks in Africa, particularly in Ghana.

Specifically, this study is the first attempt at using a three-stage dynamic network DEA model to assess the efficiency of commercial banks in Ghana. Specifically, this study uses the network dynamic DEA model to assess production (deposit mobilisation), intermediation (lending) and revenue generation (increased interest and non-interest income) efficiencies of commercial banks in Ghana. With the three-stage network DEA, managers are likely to ascertain more information on the performance of sub-processes and account for the interlinkages and interdependencies between sub-processes within a bank.

By using the three-stage network DEA, an attempt is made to resolve one key issue in bank efficiency literature, which is whether to treat deposits as an input or output. With the network DEA, the study treats deposits as both input (to ascertain intermediation efficiency) and output (to measure production efficiency), accounting for the dual role played by deposits as both an input and output variable.

This study also compares the efficiency scores estimated for technical efficiency, pure technical efficiency and scale efficiency, and of scores derived from the black-box approach and the three-stage dynamic network DEA. First, as argued by Farrell (1957), comparing technical, pure technical and scale efficiency scores provides insight into the impact of managerial skills (pure technical efficiency) and size (scale efficiency) on bank performance. Such analysis addresses a significant gap of research in Ghana as most studies have not drawn a comparison between these categories of efficiencies. Second, a comparison between results obtained from a black-box model and a network DEA model provides additional information on the performance of banks as a whole or as sub-processes. Currently, no study in Ghana has attempted to perform this comparison.

Finally, in modelling the DEA, this study is the latest and one of the few attempts in Ghana to account for slack variables or undesirable outputs in the examination of bank efficiency. According to Tone (2003), the traditional black-box model examines the relative efficiency scores of institutions by assuming that an increase in input results in a proportionate increase in output. This notion ignores the effects of input excesses or output shortfalls (also known as slack), which results in the overestimation of efficiency scores. This study attempts to solve this challenge by incorporating slack variables (specifically non-performing loans (NPLs)) in the network DEA model used. It is anticipated that the inclusion of slack or undesirable variables will improve the accuracy of scores estimated for commercial banks in Ghana.

Overall, this thesis makes a general contribution by critically evaluating the standard and current empirical approaches that have been used to estimate the efficiency of banks globally. It highlights the various approaches used for measuring efficiency, and discusses extensively the various variable selection approaches introduced by literature. In doing this, the thesis provides insight into the effect of models and variables on efficiency scores estimated for banks.

Following the estimation of the DEA efficiency scores, this thesis also makes an additional contribution to the existing literature in several ways.

First, this study is the first research work to provide insights into the determinants of banks' efficiency scores derived from the network dynamic DEA model. Specifically, this thesis identifies factors that drive deposit mobilisation (production efficiency), lending (intermediation efficiency) and revenue generation (revenue-generating efficiency) processes of commercial banks in Ghana.

To identify the determinants of efficiency the study includes as an explanatory variable, a measure of competition, in order to ascertain the impact of reforms that were implemented to liberalise the entry requirement of foreign banks into Ghana's banking sector. In Ghana, studies such as Saka et al. (2012) and Aboagye (2012) have used the Herfindahl–Hirschman index (HHI) to measure competition of banks. With the exception of Alhassan and Ohene-Asare (2016), this study is the only paper that assesses the relationship between competition and efficiency by using the Boone indicator as a measure of competition. The choice of the Boone indicator is based on the assertions of Dadzi and Ferrari (2019) and Cobbinah et al. (2020) who argued that the Boone indicator resolves the challenges of the HHI which fails to consider the complexities of banking operations in a way that allows for an accurate assessment of competition.

In relation to the regression models used to identify the determinants of efficiency, several studies regressed independent variables on efficiency scores using the Ordinary Least Square (OLS) (Karimu Tossa, 2016), panel regression (Tetteh, 2014), and random and fixed effects Tobit regression models (Saka et al., 2012).

Studies such as Simar and Wilson (2007) and Fernandes et al. (2018) maintained that the above mentioned regression models pose significant challenges. Two significant challenges identified, which are further discussed in this thesis, are the inability of the Tobit, panel and OLS regression models to address issues of endogeneity and serial correlation. In respect of the issue on endogeneity, the researchers argued the efficiency scores estimated are not directly observed, but based on data which could be used as explanatory variables in the regression models. Regarding the issue of serial correlation, the researchers contended that error terms derived from the estimation of efficiency scores may also be serially correlated as observations on the efficiency frontier may in all cases influence the efficiencies estimated for all the Decision-Making Units (DMUs) in the dataset.

To address the issue of serial correlation, Simar and Wilson (2007) proposed a double-bootstrapped truncated regression technique. This technique incorporates in the regression model an underlying data generation process that yields estimated standard errors and confidence intervals that do not suffer from bias due to estimated efficiency scores being correlated. In effect, Simar and Wilson argued that the double-bootstrapped truncated regression technique improves on the accuracy of estimation, providing bias-corrected efficiency scores.

This study attempts to validate the argument of Simar and Wilson (2007) by using both the bootstrap truncated regression model and the Tobit regression to determine banking sector efficiency in Ghana. These two regression models are employed to assess whether there are differences in the regression results and also to attest which model is valid and statistically accurate.

Secondly, following the identification of the determinants of efficiency, this study is the first to investigate the impact of production, intermediation and revenue generation efficiency on the profitability of commercial banks in Ghana. Using the efficiency–profitability matrix, this study juxtaposes the efficiency scores of banks to the profitability ratios of banks.

Finally, the period of analysis in this thesis coincides with the current restructuring exercise in Ghana’s banking sector (from 2017 to 2018). While there is evidence to show that the capital asset base of banks has grown after the restructuring of Ghana’s banking sector, little is known of the impact of the restructuring exercise on bank efficiency in recent times. From a policy perspective, the period of analysis in this thesis considers the most recent state of development of Ghana's banking sector and provides up-to-date information on bank efficiency. It particularly assesses the efficiency of banks with regard to the recent restructuring exercise.

### *1.3 Objectives of the Study*

- To provide an in-depth understanding of the evolution of Ghana's commercial banking sector;
- To summarise the theoretical and empirical literature on parametric and non-parametric measures of efficiency in the banking sector, focusing on the transition of measures from the traditional models to more complex methods;
- To discuss gaps in studies that have used the DEA non-parametric technique to assess bank efficiency and to estimate and compare the efficiency scores of Ghanaian commercial banks derived by using both the traditional black-box model and the three-stage network dynamic DEA model. The three-stage network dynamic DEA model is used to measure efficiency scores for deposit mobilisation, intermediation and revenue generation;
- To ascertain the determinants of bank efficiency (for deposit mobilisation, intermediation and revenue generation) by employing a two-step model where varying internal and external factors are regressed on bank efficiency scores estimated;
- To use the Boone Indicator to measure the level of competition in Ghana's commercial banking sector and examine the impact of competition on efficiency and profitability of banks in Ghana; and
- To establish whether increased efficiency of banks results in improved profitability by employing the efficiency–profitability matrix and the two-step dynamic Generalised Method of Moments (GMM) approach.

### *1.4 Organisation of the Study*

Ultimately, following the objectives and discussions stated above, this thesis is structured as follows;

*Chapter 2*

This chapter describes and provides a historical account of commercial banking policies enacted post-independence and before the enactment of the Financial Sector Adjustment Programme (FINSAP) in Ghana in 1989. In this section, the effect of policies enacted are discussed and analysed and reasons are provided for the trend in the financial performance of the commercial banking sector in this period. The second sub-objective is to describe and provide a historical account of commercial banking in Ghana after the implementation of FINSAP, which is also known as the deregulation period[4]. The impact of these policies on the financial performance of banks is also examined. The

[4] Policies discussed include the recent directives issued by the Bank of Ghana, including the most recent banking act, ACT 930.

third sub-objective focuses on the financial performance of banks and the macroeconomic conditions in Ghana from 2008 to 2019. The financial performance of banks is assessed using the financial soundness indicators and a relationship is established between the macroeconomic conditions and the performance of the commercial banking sector. Also, under this section, the macroeconomic and financial performance of Ghana is compared to that of some other countries in Africa: Nigeria, Kenya, and South Africa. This comparison provides a relative review of the performance of Ghana's commercial banking sector, providing in-depth contextual background on the performance of banks in Ghana.

*Chapter 3*

Chapter 3 provides a conceptual definition of efficiency and the various approaches used in estimating the efficiency scores of firms. In this chapter, we introduce the various types of efficiency (technical[5], allocative and cost efficiency) and the broad categories for measurement of efficiency (parametric and non-parametric measurement methods). We further provide reasons for the selection of the preferred measurement type, which is the non-parametric approach. Consequently, the study focuses on the DEA methodology (the most used non-parametric approach), providing an account of DEA from the traditional black-box model to newly introduced models such as the bootstrap technique proposed by Simar and Wilson (1998, 2000), Fuzzy DEA introduced by Cooper et al. (2000), the Slack-Based Measure (SBM) by Fukuyama and Weber (2010) and the network DEA. Discussions on the various variable selection approaches (production, intermediation (asset and profit approach), value-added, cost user) and orientations (input or output orientation) used in DEA estimations are also presented.

*Chapter 4*

This chapter discusses gaps in studies that have used the DEA technique to assess bank efficiency in Ghana and estimates the efficiency scores of Ghanaian commercial banks by using models that seek to resolve some of the identified gaps.

Following the review of the existing empirical studies, this thesis first estimates efficiency scores of 18 commercial banks in Ghana by using both a black-box DEA model with the bootstrap technique and a three-stage dynamic network DEA slack-based model. Variables selected for the black-box DEA model are based on the intermediation approach, and the three-stage network DEA also introduces a slack variable[6]. The slack variable is represented by the inclusion of NPLs as a bad or

[5] Technical efficiency measures are further classified into pure technical efficiency and scale efficiency.

[6] According to Tone (2002), the original model for estimating technical efficiency ignores the effects of input excesses or output shortfalls (also known as slack). In comparing a DMU against the efficiency frontier, a DMU with a perfect score of 1 with no slack is referred to as efficient. The efficiency score which ignores the slack variable is overestimated. To solve this challenge, Tone introduced the SBM model. This model sought to improve the accuracy of scores by considering both input and output slacks in the estimation of efficiency scores.

undesirable output in stage 2 of the model and as a primary input in stage 3. By way of contribution, the estimation of efficiency scores under both the black-box approach and the network DEA model provides an extensive view of the performance of banks when categorised as a whole or by different sub-processes.

Secondly, for both the black-box and network DEA models, technical efficiency scores are decomposed into pure technical (assessing the impact of management) and scale (assessing the impact of size) efficiencies. This segregation further provides in-depth information on the impact of managerial expertise or size of firm on bank performance in Ghana.

*Chapter 5*

The key objective of Chapter 5[7] is to address a key gap of the DEA model, which is its inability to provide information on the causes of inefficiencies. In this respect, most research that has used the DEA model to estimate bank efficiency ascertains the causes of inefficiencies by employing a two-step model where varying internal and external factors are regressed on bank efficiency scores estimated (Casu and Molyneux, 2003; Naceur, 2003; Ofori-Sasu et al., 2019; Podpiera and Weill, 2008). For the purposes of this study, the authors explore the sources of inefficiency at each stage of the network DEA measured in Chapter 4 by using the truncated bootstrap and Tobit regression models. By using these techniques, this chapter regresses both bank-specific and macroeconomic variables on the efficiency scores estimated. Inclusive in the explanatory variables used is the measure of competition which is estimated with the Boone Indicator. Additional explanatory variables regressed on the efficiency scores are size, ownership, and origin, inflation, and Gross Domestic Product (GDP) per capita.

*Chapter 6*

This chapter seeks to ascertain whether increased efficiency of banks results in improved profitability (efficiency structure theory). Employing the efficiency–profitability matrix and the two-step dynamic Generalised Method of Moments (GMM) approach, Chapter 6 examine the effect of production, intermediation and revenue generation efficiency scores on the profitability of banks. Control variables used in this estimation are the ownership type (foreign or domestic banks), NPL ratio, liquidity ratio (total loans as a ratio of total deposits) and the Boone Indicator measure of competition. This analysis will provide empirical contribution on which processes banks would have to improve to increase their profitability.

[7] Chapter 5 addresses Objective 4.

*Chapter 7*

Finally, Chapter 7 concludes the study and provides policy implications for supervisors, bank managers, and relevant stakeholders. Suggestions are also made for future research in this area.

# CHAPTER 2
# THE EVOLUTION AND PERFORMANCE OF GHANA'S COMMERCIAL BANKING SECTOR

## 2.1 *Background and Motivation*

The impact of a country's financial system on its economic development is predominantly determined by the efficiency of banks in the allocation of resources (Allen et al., 2018, 2013; Buchs and Mathisen, 2005). In a well-functioning economy, banks tend to significantly contribute towards economic development by acting as intermediaries that channel savings into investment, as well as providing financial services to businesses and households (Levine, 1997; Allen et al., 2013; Allen et al., 2018).

In Ghana, the financial sector remains dominated by banks although it includes other key players from the Fund Management, Insurance, Non-Bank Financial Institutions (NBFIs), Pensions, and Stock Exchange sectors. According to the Government of Ghana Ministry of Finance reports on National Financial Inclusion and Development Strategy (NFIDS) 2018–2023, in 2017 commercial banks accounted for 59 percent of total assets of the financial sector. For the same year, fund management sector accounted for 15 percent of total assets of the financial sector, pension funds 12 percent, NBFIs 11 percent, and insurance sector 3 percent. In 2019, the commercial banking sector accounted for 70 percent of the total financial sector asset, which represented 38 percent of GDP (IMF Report).

Considering the significant contribution of the commercial banking sector to Ghana's financial sector, this chapter focuses on the performance of the commercial banking sector, which includes only deposit-taking financial institutions, but excludes rural banks, savings and loans companies, and other non-bank financial institutions that are permitted to take deposits.

Empirically, data from the Bank of Ghana (BoG) reveals significant challenges with the commercial banking sector. Inferring from the Financial Soundness Indicators (FSIs) measured by the World Bank and International Monetary Fund (IMF), the commercial banking sector in Ghana over the past decade has encountered significant liquidity challenges which have required the liquidation of some banks and the restructuring of the entire sector. The sector is plagued with relatively high NPLs compared to other key countries in Africa, with reported profitability indices fluctuating from one period to another.

In examining the impact of financial sector reforms instituted in Ghana, Antwi-Asare and Addison (2000) attributed the challenges faced by the commercial banking sector to the economic and regulatory conditions faced by Ghana as far back as the late 1970s. This period was characterised by extensive government control on the banking sector and extended periods of economic crisis, which impaired the financial system, leading to the decline in the performance of banks.

To minimise the effects of the crisis period mentioned by Antwi-Asare and Addison (2000), several reforms have been implemented since the 1980s. One key reform which has commonly been discussed by existing literature is FINSAP. FINSAP sought to address inefficiencies in the financial system by restructuring distressed banks and reforming prudential regulations that eased restrictions on foreign banks and resulted in increases in minimum capital requirements.

Following FINSAP, very few studies have examined the changing dynamics of regulations in Ghana's commercial banking sector against its performance, even though such analysis may provide useful information for future policy formulation and implementation and give an indication of the success of FINSAP and other important policies in the banking sector. Examples of notable studies that have attempted to address this issue are Brownbridge and Gockel (1996), Antwi-Asare and Addison (2000), Owusu-Antwi (2009) and Dadzie and Ferrari (2019).

Using financial statement data from 1970 to 1995, Brownbridge and Gockel (1996) sought to assess the effectiveness of financial sector reforms by addressing whether the effects of these reforms (financial liberalisation, prudential reforms, bank restructuring) had enhanced the efficiency and competitiveness of Ghana's banking sector. Although the authors acknowledged that financial sector reforms in Ghana post the early 1990s had a positive impact, they also noted that the sector was still very shallow and plagued with very little intermediation between borrowers and savers, especially in the private sector. They further observed that in 1994, credit to the private sector only amounted to 5.3 percent of GDP, representing a major source of financial instability in the country. Brownbridge and Gockel (1996) attributed the reduced intermediation of banks to high inflation rates which depleted the positive real interest rates earned from most interest-bearing deposits, discouraging savings in banks. The authors also explained that the high statutory reserve requirement restricted monetary growth in Ghana and increased the desire of banks to lend to less risky sectors, resulting in the crowding out of the private sector.

Antwi-Asare and Addison (2000) also aimed at investigating the effect of financial sector reforms on bank performance in Ghana by using data from 1980–1986 and 1990–1996. These periods reflect the pre-financial reform era and the period that the Banking Law of 1989 took effect. These authors found that, despite the increase in financial intermediation post reforms, the share of deposits and loans in the balance sheet of banks had reduced. The profitability of banks increased on the back of increased statutory reserves held by banks in the form of government securities and bills. Like Brownbridge and Gockel (1996), Antwi-Asare and Addison (2000) noted that the share of private sector deposits declined significantly with banks attracting insufficient deposits to engage in longer-term lending.

Owusu-Antwi (2009) investigated the pre- and post-financial reform eras in Ghana to ascertain whether policies enacted in the post-reform period had enhanced the effectiveness of the financial sector. Extending the data from 1980 to 2007, this research work found that post the financial reforms instituted in the early 1990s, Ghana's banking sector experienced significant growth in assets and profitability and attained a strong capital position. Owusu-Antwi (2009) also observed that in the 2000s Ghana's banking sector became increasingly sound as a result of credit expansion, targeted regulation, adoption of advanced technologies, and more risk-focused management for commercial banks. Despite these gains, Owusu-Antwi (2009) noted that there are still institutional gaps in terms of the services and products provided by financial institutions in Ghana, stating that there has been minimal innovation in the banking services provided by commercial banks in Ghana.

More recently, Dadzie and Ferrari (2019) investigated whether the macroeconomic environment and the level of financial development in Ghana have impacted the effectiveness of policy reforms in the country's commercial banking sector since the 2000s. The researchers concluded that, with the exception of the removal of entry restrictions, most policy reforms have had little or no impact on bank efficiency. Dadzie and Ferrari (2019) also found no improvement in competition, asserting that macroeconomic and institutional lapses in the country continue to negatively affect the performance of banks in the country.

Overall, the studies discussed above have demonstrated a rise and fall in the performance of commercial banks in Ghana during periods of changes in financial sector reforms. These inconsistencies do not provide a clear interpretation of the impact of financial sector policies and reforms in the banking sector, which makes studies on the impact of financial sector reforms still relevant for further empirical investigation.

Also, the above research has not accounted for reforms in the banking sector since 2007. Ghana, like most countries in Africa, has undergone significant changes in its banking sector since 2007. For example, in 2008, the minimum capital requirement of commercial banks was revised upwards from GH¢60 million to GH¢120 million. Subsequently, the Banks and Specialised Deposit-Taking Institutions Act, 2016 (Act 930), enacted in 2016, again increased the minimum paid-up capital for existing banks and new entrants from GH¢120 million to GH¢400 million (a 233.33 percent increase). The Corporate Governance Directive was issued in 2018 to control the recruitment and assess the performance of directors and management of banks.

The primary objective of this chapter is therefore to provide additional empirical evidence on financial sector reforms and policies by systematically reviewing the evolution and historical development of financial sector reforms (both historical and recent) against the performance of commercial banks in Ghana. Using data from 1970–1989 (pre-financial sector reform) and 1990 to 2020 (post-financial sector reform), we seek to assess how effective financial sector reforms in Ghana have been in creating a sound banking sector. We anticipate the period covered will reflect the current happenings in Ghana's commercial banking sector and enhance policy discussions that will further improve the performance of the commercial banking system in Ghana.

This chapter also explores the challenges facing the banking sector in Ghana and sets the contextual stage for the empirical chapters (Chapters 4, 5 and 6) which focus on empirical evaluation of the efficiency of commercial banks in Ghana.

The rest of this chapter is organised as follows: Section 2.2 presents the historical evolution of commercial banking in Ghana and the impact of banking policies enacted before the deregulation period. Section 2.3 presents and discusses the impact of policies enacted during and post-FINSAP (the deregulation period). Section 2.4 provides information on the current structure and financial performance of Ghana's commercial banking sector and Section 2.5 provides a summary of the chapter and the way forward.

## 2.2 *Evolution of Commercial Banking in Ghana Post-Independence and before FINSAP*

### 2.2.1 *Commencement of Commercial Banking in Ghana and Summary of Policies*

Commercial banking in Ghana dates to the early 1950s. From the 1950s to the 1980s, banks that existed were mostly state-owned banks with extensive government control. In 1953, the government of Ghana established the Ghana Commercial Bank to provide banking services to the indigenes, and the BoG was subsequently set up in 1957 to replace the West African Currency Board[8] which supervised the activities of banks in Ghana, Gambia, Nigeria, and Sierra Leone.

Several state-owned banks were set up between the years 1957 and 1988. The National Investment Bank (NIB) was established in 1963 to provide long-term financing to industries, the Agricultural Development Bank (ADB) was founded in 1965 to provide loans to farmers and promote the agricultural project, and the Merchant Bank Ghana, now known as the Universal Merchant Bank (UMB) was set up in 1972 to boost merchant banking by forming a joint venture between a foreign investor, the government, and other public sector institutions (Owusu-Antwi, 2009). The Bank for Housing and Construction was set up in 1974 to facilitate loans for the construction of buildings, and the Social Security Bank (SSB) was established in 1977 to provide banking services for workers. The National Savings and Credit Banks (NSCB) (originally known as the Post Office Savings Bank) and the Cooperative Bank were founded in 1975 to grant credit facilities to small-scale enterprises and cooperatives (Brownbridge and Gockel, 1996). Also in the 1970s, the government acquired a 40

[8] The West African Currency Board was established in 1912.

percent stake in two existing foreign-owned banks, Standard Chartered Bank and Barclays Bank, that operated to provide trade finance and banking services mainly to the expatriates in the country (Adjei-Frimpong et al., 2014).

In addition to the increased government stake in banks in the 1950s to the 1980s, the banking system in Ghana during this period boasted a controlled exchange and interest rate regime. The Central Bank of Ghana regulated both the deposit and lending rates and imposed fixed exchange rates (Brownbridge and Gockel, 1996). The objective of this policy was to reduce credit cost (by reducing interest rates), allocate credit to some deprived sectors[9], and enhance benefits from savings (by increasing deposit rates) (Daumont et al., 2004; Owusu-Antwi, 2009). Consequently, banks were compelled to submit customer information to the government during the period 1979 to 1982. Customers that held funds over GH¢5.00 (then ¢50,000.00) had their accounts frozen and were required to provide more information on the source and use of funds. According to Owusu-Antwi (2009), the limit on deposits was to control the money supply, inflation, and fraud in the banking sector.

The first banking law was also enacted during this period, the Banking Act (1970) (Act 339). Under this Act, banks were required to keep a minimum paid-up capital and maintain capital reserve requirements amounting to 5 percent of total deposits.

### 2.2.2 *Impact of Policies Enacted Before FINSAP (the 1950s to 1980s)*

Policies that existed in the 1950s to the 1980s resulted in significant challenges in the banking sector. According to Brownbridge and Gockel (1996), the banking system in this period was characterised by severe financial repression with negative real interest rates and excessive lending to the public sector. Like most countries, the extensive control of interest and exchange rates in Ghana left little room for innovation in the financial sector and reduced intermediation in the banking sector (Aziakpono and Wilson, 2013).

Ghana's economic performance in the 1950s to the 1980s also exacerbated the challenges of banks. During this period, the broad money/GDP ratio in Ghana dropped significantly from a high of 29 percent in 1976 to 12.5 percent in 1984, with inflation increasing from 18.80 in 1975 to 31.40 in 1988.

Particularly in the banking sector, the dominance of state-owned banks, the extensive control of the government on bank operations, and the move by the government to regulate amounts deposited in bank accounts, negatively impacted the performance of the sector. In detail, Aryeetey and Gockel

[9] Although these restrictions were not strictly enforced, banks were required to grant a minimum of 20 percent of their loans to the agricultural sector and foreign companies were also required to seek permission from the Bank of Ghana before accessing loans from the local banks (Brownbridge and Gockel, 1996).

(1991) and Owusu-Antwi (2009) argued that the extensive influence of government in the 1950s to 1980s reduced competition and the confidence of the general public in the banking sector, further plummeting intermediation in the formal commercial system. They further claimed that the adverse effects of government intervention in the sector in these times caused a decline in bank deposits to GDP from 19.5 percent in 1977 to 7.4 percent in 1984. Also, according to Leite (1982), increased government restrictions on the interest rate paid on deposits[10] and the high reserve requirements imposed on commercial banks deterred commercial banks from active deposit mobilisation and further discouraged them from channelling funds into loan products.

Although banks such as ADB and NIB were set up to support priority areas, credit amounts advanced by commercial banks to such areas in the 1950s to 1980s were reduced (Aryeetey and Gockel, 1991). According to Owusu-Antwi (2009), commercial banks did not benefit from the credit structure set for these priority areas as the BoG did not account for the high-risk profiles of these sectors (particularly the agricultural sector) and the poor economic conditions experienced by the country in these times. Commercial banks that lent to these sectors therefore mostly lent at rates that resulted in losses.

Another basis for the decline in bank performance in the 1950s to 1980s was the crowding out by government's borrowings which significantly reduced loans granted to the private sector (Owusu-Antwi, 2009). In 1977, credit to the private sector (including both priority and non-priority sectors) amounted to 3.6 percent of GDP while that to the government amounted to 9.8 percent. The situation worsened by 1983, when domestic credit to the government amounted to 87 percent of total domestic credit (World Bank, 2015).

Overall, commercial banks just before the onset of FINSAP in the late 1980s were mostly in financial distress. All banks in this period were classified as insolvent and the BoG was compelled to bail out 62 billion cedis worth of non-performing assets (NPAs)[11] with BoG bonds (Owusu-Antwi, 2009).

## 2.3 *Evolution of Commercial Banking in Ghana During and Post the FINSAP Era*

### 2.3.1 *Policies Enacted During the FINSAP Era*

Financial sector reforms were introduced in Ghana in the late 1980s to curb the challenges identified in the pre-reform era. A key financial sector policy document implemented in Ghana in this era was the FINSAP (Brownbridge and Gockel, 1996). The FINSAP was a World Bank-supported policy introduced in 1989 which sought to restructure the banking sector, reform the supervisory process, liberalise the market and promote the privatisation of state-owned banks.

[10] According to (Owusu-Antwi, 2009), contrary to government direction, most banks refused to open new savings accounts and to pay interest on deposits above a certain limit.
[11] This at that time was equivalent to $170 million representing approximately 4 percent of GDP.

The first phase of FINSAP was introduced in 1989 to restructure the balance sheets of distressed banks. Following the pre-reform era, most existing banks were carrying high NPAs which impaired their capitalisation and profitability. The FINSAP, therefore, introduced the Non-Performing Assets Recovery Trust (NPART) in 1991 which took over the NPAs. According to the World Bank Country report (1994), NPART was able to recover 14.1 billion cedis out of the total of recovered 50 billion cedis received. This enhanced the capital position of most banks and enabled them to meet the minimum capital of 6 percent as stipulated by the 1989 Banking Law.

Following the sector restructuring, FINSAP put in place measures to enhance the prudential regulation of Ghana's commercial banking sector. This informed the enactment of the Banking Act, 1989 (PNDCL 225) which established a minimum capital adequacy ratio of 6 percent of adjusted risk assets and required banks to hold reserve funds (Owusu-Antwi, 2009). The Banking Act, 1989 set the rules for the conduct of internal and external audits by the BoG and the commercial banks. Commercial banks were compelled to regularly submit prudential data[12] to the BoG, and they were to set up internal audit units that facilitated the internal and external audit of the operations of the banks. The BoG was also mandated to carry out annual audits on each commercial bank (Owusu-Antwi, 2009).

The Banking Act, 1989, also put in place measures to improve the credit appraisal, monitoring, and recovery processes. Based on these measures, banks were banned from using their own shares as collateral to advance credit, and accounting rules were set for the classification of loan provisions for NPAs and nonaccrual unpaid income (Aryeetey et al., 1996; Owusu-Antwi, 2009).

FINSAP also facilitated a conducive environment for the operations of foreign banks and introduced budgetary and performance appraisal processes. To provide a conducive environment, the government eradicated controls on interest rate and lending activities; banks were therefore able to independently price loans and deposits using market rates. The shareholding structure of most state-owned banks was also altered. Government shares at SSB were reduced (from 100 to 70 percent) and 30 percent of its shares in GCB were sold to the general public (Brownbridge and Gockel, 1996). Also, as an effect of the budgetary and performance appraisal processes, staff levels in the entire banking sector reduced by 38 percent between 1988 and 1992, and some branches of commercial banks were closed in a bid to cut costs (Owusu-Antwi, 2009).

Whereas governments in periods before FINSAP used credit ceilings and fixed exchange rates to control the money supply, during the FINSAP era the BoG was given the mandate to implement monetary policy in the country. During this period, the BoG used reserve money and money supply

[12] Such as information on NPA, large exposures, deposits, etc.

(M2+)[13] to regulate the amount of money and prices of goods in the economy (Antwi-Asare and Addison, 2000; Brownbridge and Gockel, 1996).

Overall, irrespective of the benefits of FINSAP, which includes reduced government control and privatisation of the banking sector, Owusu-Antwi (2009) argued that one key challenge that surfaced during the implementation of FINSAP was the effect of the high reserve ratio imposed on commercial banks. Such high ratios resulted in financial constraints and limited the amount of money available for lending, significantly reducing the volume of credit. Also, in terms of the monetary policy framework that existed in the FINSAP period, Quartey and Afful-Mensah (2014) argued that as the banking sector developed, the use of reserve money and money supply (M2+) by the BoG to regulate the amount of money and prices of goods in the economy became less effective. The emergence of new substitutes for money such as credit and debit cards significantly reduced the demand for cash in daily transactions and ultimately altered the monetary transmission mechanism (Kovanen, 2011). Reliance on money aggregates to control the transmission mechanism therefore became redundant and misleading (Addison, 2008).

### 2.3.2 *Regulatory Changes after FINSAP*

To address the challenges that still existed after the implementation of the FINSAP, the BoG continued to revise financial sector reforms. Key reforms instituted after the FINSAP included:

- The Bank of Ghana, Act 2002 (Act 612).
- The Banking Act, 2004 (Act 673).
- The Banking (Amendment) Act 2007 (Act 378).
- The institution of the Inflation Targeting Framework in 2007.

The Bank of Ghana Act, 2002 (Act 612) further enhanced the supervision and examination authority of the BoG and formed the basis for the set-up of the Banking Supervision Department within the Central Bank. This department was created to enforce prudential regulations by commercial banks in Ghana and is mandated to examine each commercial bank at least once a year.

The Banking Act, 2004 (Act 673) informed the eradication of secondary reserves and stipulated the minimum capital requirement of banks at GH¢70 million (US$7,752.17)[14]. The required capital aimed at widening the capacity of banks to undertake the various banking activities[15] without acquiring separate licences (PricewaterhouseCoopers, 2008). Another key directive in this Act was the increase in the minimum capital adequacy ratio from 6 percent to 10 percent. Act 673 prohibited banks from voluntarily winding up and granted the BoG the right to be the sole entity that revoked

[13] Known as the monetary targeting framework.
[14] This figure is converted at US$1 to GH¢9,029.73 as at December 2004.
[15] These include retail, merchant, development, and/or investment banking.

the licences of banks that have eroded their required capital base. The procedures for the revocation of licences were not well laid out and the decision of the BoG could be disputed and overturned by the judicial system. Also, with Act 673, the Central Bank could not directly close unlicenced institutions: the BoG had to rely on security agencies to carry out this act.

The Bank of Ghana Act, 2007 (Act 378), introduced a risk-based supervision framework that mandated commercial banks to set up a risk management department. Act 378 further classified banks into Class 1 (universal banking), Class 11 (investment banking and granted the permission for foreign banks to open branches in Ghana), and Class 111 (operating a mix of Class 1 and Class 11). The universal banking licence allowed banks to operate as both retail and merchant banks and improved the range of financial services that banks could provide. According to Aziz (2007), the increase in universal banking increased bank penetration, branch operations, and enhanced competition in the banking sector.

Ghana's banking sector and economy also underwent significant reform in 2007. The country's currency, the cedi, was redenominated[16] to address challenges faced by the banking sector. Before the redenomination, commercial banks in Ghana were reported to be inundated with high cash transactions which increased the risk of fraud. Bank customers were becoming increasingly uncomfortable carrying large amounts of cash, and the statistical departments in the country were facing challenges in keeping the statistical records owing to the increasing digits of values to be recorded by statistical software (Aziz, 2007). The redenomination was therefore expected to reduce the cost of handling cash and the risk associated with transferring cash from one point to another and make statistical data compliant with industry-acceptable software.

Lastly, to resolve the challenges associated with using money supply to regulate prices, Ghana, like most countries, in 2007 abandoned the monetary targeting framework to use the Inflation Targeting (IT) framework as the instrument for conducting monetary policy (Sowa and Abradu-Otoo, 2009). In May 2007, the BoG formally adopted an IT framework together with a flexible exchange rate regime, making Ghana the second African country after South Africa to adopt the IT. The main instrument employed by this framework is the Monetary Policy Rate (MPR) which is expected to guide the rate of change in market interest rates to attain price stability (Lim, 2001; Aziakpono and Wilson, 2013).

### 2.3.3 *Policies Enacted After the year 2007 and the Implications of these Policies on Bank Performance*

This section seeks to discuss the implications of bank policies on financial performance of commercial banks in Ghana under the different eras. For the purpose of this study, the eras are

[16] Redenomination resulted in the cancellation of four zeroes from the original cedi value.

segregated into 2008 to 2012, 2013 to 2015, and 2016 to 2019. The segregation in periods is based on the either the introduction of key regulations or a change in the minimum capital requirement.

#### 2.3.3.1 *Analysis for the Period 2008 to 2012*

Following the redenomination, in 2007, the BoG increased the minimum capital requirement of universal banks from GH¢7 million[17] to GH¢60 million (US$62.51 million)[18]. Foreign banks were to meet this requirement by the end of December 2009 while domestic banks were required to increase their minimum capital by the end of December 2012.

During this period (2007–2012), the total asset base of banks improved significantly. Net loans grew by approximately 100 percent, total assets expanded by 145 percent and the deposit base of commercial banks increased from approximately GH₵7 billion (US$5.01 billion) to GH₵20 billion (US$14.29 billion)[19]. In terms of profitability, the Return on Assets (ROA) of commercial banks improved from an average of 2.5 in 2007 to 3.6 in 2012, while Return on Equity (ROE) increased from an average of 30 to 34.5 in the same period. Damankah et al. (2014) attributed the growth in profitability to introduction of innovative and non-traditional revenue avenues (such as short-term investment, fees, and charges from electronic transactions) of income generation for the banking sector. Commercial banks in this period employed the use of shared and outsourcing services which largely lowered operating expenses and improved earnings (Senyo et al., 2015).

The capital base of banks increased following the increase in minimum capital requirement to GH¢60 million, growing the Capital Adequacy Ratio (CAR) from an average of 14 in 2007 to 19 in 2012. In this period, the increased capital requirement afforded banks (specifically, the foreign banks) the opportunity to sponsor big-ticket deals such as syndicated loans for the bulk purchase of cocoa for export. Banks were also able to financially support oil transactions in Ghana as the country had just discovered oil (PricewaterhouseCoopers, 2008). Accordingly, the higher capital bases are more likely to cushion banks against possible losses from credit and liquidity risks, further enhancing the stability of the commercial banking sector (PricewaterhouseCoopers, 2008)

Irrespective of observed expansion in Ghana’s commercial banking sector, the NPL ratios observed in the period 2007 to 2010 increased from 7 percent to 17.60 percent. A stability and assessment update on Ghana’s financial system by the International Monetary Fund (2011) attributed this increase to the poor performance of state-owned banks that focused more on lending to national projects at the expense of prudential considerations and the delay by the government in paying contractors following the poor fiscal position of the country. In 2010 the fiscal deficit increased

[17] This is the redenominated value of 70,000,000.
[18] This figure is converted at US$1 to GH¢0.959 as at December 2007.
[19] These figures are converted at US$1 to GH¢1.399 (average exchange rate from 2007 to 2012).

significantly from 3.5 percent to 5.9 percent of GDP owing to the implementation of "single spine" which increased salaries for government workers (Younger, 2016). In the banking sector, the increase in fiscal deficit increased the risk of borrowings, resulting in the highest lending rates for the period under review at 31.92 (Bank of Ghana Data).

The trend of NPLs changed in 2011, reducing to 14.15 and 13.20 in 2012. This reduction was believed to have been caused by the upsurge in new loans disbursed (i.e. increase in gross new loans) and not necessarily as a result of the reduction in the stock of NPLs (Bank of Ghana, 2018).

#### 2.3.3.2 *Analysis for the Period 2013 to 2015*

The minimum capital requirement was again revised in 2013 to GH¢120 million (US$55.5 million)[20]. New entrants were mandated to have the minimum capital base while existing banks were given time to build their capital to this required level. The reason for this increase bordered on several issues.

Despite the expansive growth in total assets of the banking sector in the period, 2008–2012, the cedi depreciated against the United States Dollar by an average of 14.5 percent in 2013. There was also a marginal slowdown in deposit mobilisation owing to the influx of non-traditional banks such as savings and loans companies and microfinance institutions. Total deposits as a percentage of total assets dropped from 71.89 in 2012 to 64.51 in 2013. CAR reduced marginally from 18.56 in 2012 to 18.54 in 2013 and net loans advanced reduced from a growth of 37.5 (from 2011 to 2012) to 25 (from 2012 to 2013). The BoG therefore required the increase in minimum capital to shore up the value of the minimum capital requirement and to strengthen the capacity of banks in a keenly competitive market (Bank of Ghana, 2013).

To meet this requirement, most commercial banks were forced to merge, with some highly capitalised banks acquiring some distressed banks. Consequently, net loans in the Ghana's commercial banking sector expanded from GH¢15.43 billion (US$7.14 billion) in 2013 to GH¢27.04 billion (US$7.13 billion) in 2015. Total assets increased from GH¢36.17 billion (US$16.73 billion) to GH¢ 63.38 billion (US$16.70 billion) in the same period, and total deposits grew from GH¢23.33 billion (US$10.79 billion) to GH¢41.25 billion (US$10.87 billion).

Irrespective of the expansion in assets and deposits, Ghana's banking sector still continued to face some distress following the recapitalisation to GH¢120 million (US$55.5 million). CAR continued to decrease from 18.45 in 2013 to 17.81 in 2015. ROA reduced from 4.54 in 2013 to 3.26 in 2015, and ROE reduced from 42.53 in 2013 to 31.57 in 2015. NPLs increased from 12.00 in 2013 to 14.67 in 2015. According to the Banking Sector Report (2015), the decline in performance of the commercial banking sector for the period 2013 to 2015 can be attributed to the marginal slowdown

[20] This figure is converted at US$1 to GH¢2.162 as at December 2013.

in the pace of economic activities owing to the effect of the increase in utility tariffs which emanated from the energy sector challenges and the depreciation of the Ghana cedi. Also, during this period, the Bank of Ghana undertook an Asset Quality Review that revealed a higher exposure to government, particularly in the energy sector. This review required banks to increase their impairment classifications for government loans, increasing the stock of NPL in the sector.

#### 2.3.3.3 *Analysis for the Period 2016 to 2019*

Consequently, the period following the year 2015 (2016 to 2019) saw a further restructuring of the commercial banking sector. These moves include:

- the development and implementation of the Banks and Specialised Deposit-Taking Institutions Act, 2016,
- the liquidation and revocation of licences of seven banks,
- the consolidation of five banks,
- the issuance of the Corporate Governance Directive, 2018 detailing provisions on risk governance, internal and external controls as well as corporate culture and values,

The Banks and Specialised Deposit-Taking Institutions Act, 2016 (Act 930), is a key reform that regulates the current activities of Ghana's banking sector. This Act particularly sets out the prerequisites for granting licences, details conditions under which the licence of a financial institution may be revoked and establishes a deposit insurance scheme to protect depositors. Act 930 gives the Central Bank the power to foreclose unlicenced deposit-taking institutions or any other company carrying out unlicenced banking activity. Contrary to the earlier provisions set out in Act 673, Act 930 enhances the regulatory and legal power of the Central Bank and limits the ability of the judiciary to overturn the decisions of the Central Bank.

Based on the stipulations of Act 930, the Bank of Ghana in 2017 and 2018 restructured the banking sector to protect depositors' funds and prevent the incidence of bankruptcy in the sector. The need to restructure emanated from identified mismanagement of funds and illegal use of stated capital by executives of some commercial banks (Bank of Ghana, 2017). During the restructuring, nine banks were liquidated. The liabilities and some assets of seven of the nine banks were consolidated to set up the Consolidated Bank Ghana Limited.

During the restructuring period, the BoG per Section 28 (1) of Act 930 revised upward the minimum paid-up capital for existing banks and new entrants from GH¢120 million (US$55.5 million) to GH¢400 million (US$82.99 million)[21] (233.33 percent increase). Banks were required to comply with the increase in minimum capital by December 2018. The increase in the minimum capital

[21] This figure is converted at US$1 to GH¢4.82 as at December 2018.

requirement followed an independent assessment of the asset quality of the entire banking sector. This assessment revealed that the loan and investment portfolio of some commercial banks was significantly impaired, thus there was a need to inject more capital to provide a safety net for depositors and support the performance of the financial sector (Bank of Ghana, 2017).

The BoG enacted the Corporate Governance Directive in 2018. This directive sought to address some issues that resulted in the restructuring of the sector by tightening the initial requirements for engagement of non-executive and executive management personnel and instituting a periodic assessment of the performance of personnel.

In respect of financial performance, the commercial banking sector in Ghana has experienced significant growth in the last period under consideration, 2016–2019. Following the increase in regulatory capital to GH¢400 million in 2018, the average capital adequacy ratio (CAR) for the entire banking sector has particularly remained well above the regulatory minimum of 10 percent and the BoG stipulated ratio of 13 percent. Total assets in Ghana's banking sector have also increased significantly in the same period, showing the highest growth of approximately over 100 percent for the entire period under consideration (i.e. 2007 to 2019). Of the total assets recorded in December 2019, domestic and foreign assets made up 91 percent (at GH¢187 billion) (US$33.79 billion) and 9 percent (at GH¢19 billion) (US$3.43 billion)[22] respectively.

The significant growth in assets is largely driven by the increase in the purchase of long-term securities which is attributed to the preference of commercial banks to hold fewer assets in loans as opposed to long-term government securities and BoG bills. Particularly, following the recent increase in the minimum capital requirement, commercial banks have done little lending, holding their excess cash primarily in government and BoG securities, which are deemed to be a more remunerative and safer source of income.

Expectedly, loans and advances have increased at a much slower pace in the period 2016 to 2019. This trend could be attributed to the tightening response of banks following the increase in capital requirement and impairment allowances for NPLs. As argued by Altunbas et al. (2007), banks that incur a higher cost to build up the required capital reserve may become more risk-averse, investing in less risky ventures which may ultimately reduce loans granted to sectors deemed to be risky.

Similarly, for the period 2016 to 2019, NPLs reduced from 17.29 in 2016 to 13.94 in 2019 (Table 2.1): this reduction may be attributed to a combination of loan write-off stipulated by the BoG and improved loan recoveries in the later periods under consideration (Bank of Ghana Banking Sector Report, 2019).

[22] This figure is converted at US$1 to GH¢5.534 as at December 2019.

ROA and ROE also reduced from 2016 to 2018 (Table 2.1). This decline was partly explained by a decrease in the growth of interest and non-interest income following a general economic downturn caused by the energy crises experienced in Ghana and the liquidity challenges faced by commercial banks in these years (Bank of Ghana, 2016). ROA and ROE increased marginally in 2019. The BoG in their 2019 Annual Report (Bank of Ghana Annual Report, 2019) attributed this gain in profitability to the effects of the just ended restructuring process.

*Table 2.1: Summary Performance and Structure of the Commercial Banking Sector in Ghana (2008–2019)*

| Period | Net Loans (GH₵'000) | Total Assets (GH₵'000) | Total Deposit (GH₵'000) | Domestic Deposit (GH₵'000) | Total Borrowings (GH₵'000) | TA/GDP | Deposit/TA | CAR | NPL/TL | ROA | ROE | Liquid Assets to Total Deposits |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2008–2012** | | | | | | | | | | | | |
| **2008** | 5,593,943.54<br>$4,620,420.86 | 10,692,218.35<br>$8,831,435.00 | 6,949,005.51<br>$5,739,659.30 | 5,144,341.41<br>$4,249,063.69 | 1,359,989.92<br>$1,123,308.76 | 65.61 | 64.99 | 13.84 | 7.69 | 2.54 | 30.13 | 34.76 |
| **2009** | 6,150,123.28<br>$4,288,788.90 | 14,043,277.18<br>$9,793,080.32 | 8,970,633.10<br>$6,255,671.62 | 6,222,945.94<br>$4,339,571.79 | 1,873,138.52<br>$1,306,233.28 | 64.92 | 63.88 | 18.24 | 16.2 | 2.1 | 23.6 | 37.33 |
| **2010** | 6,973,528.21<br>$4,798,739.48 | 17,397,657.16<br>$11,971,963.36 | 11,816,736.47<br>$8,131,527.99 | 8,926,832.02<br>$6,142,879.18 | 1,870,969.34<br>$1,287,482.34 | 67.08 | 67.92 | 19.13 | 17.6 | 2.71 | 28.63 | 30.31 |
| **2011** | 8,344,008.76<br>$5,267,349.76 | 22,059,059.11<br>$13,925,294.56 | 15,990,652.55<br>$10,094,471.66 | 11,928,206.12<br>$7,529,957.78 | 1,781,712.55<br>$1,124,747.52 | 70.80 | 72.49 | 17.41 | 14.15 | 2.8 | 27.19 | 32.42 |
| **2012** | 11,682,505.00<br>$6,200,575.87 | 27,237,112.54<br>$14,456,298.78 | 19,581,050.83<br>$10,392,787.45 | 14,347,525.97<br>$7,615,055.45 | 2,262,719.76<br>$1,200,955.24 | 36.34 | 71.89 | 18.56 | 13.20 | 3.61 | 34.57 | 29.75 |
| **2013–2015** | | | | | | | | | | | | |
| **2013** | 15,426,050.42<br>$7,147,646.38 | 36,169,859.00<br>$16,759,271.15 | 23,331,708.16<br>$10,810,725.68 | 16,927,794.00<br>$7,843,477.90 | 4,858,726.20<br>$2,251,286.35 | 29.25 | 64.51 | 18.45 | 12.00 | 4.54 | 42.53 | 30.46 |
| **2014** | 22,215,714.45<br>$6,942,193.82 | 51,441,606.11<br>$16,074,999.57 | 32,428,222.60<br>$10,133,502.89 | 22,830,874.31<br>$7,134,425.27 | 8,221,640.47<br>$2,569,182.36 | 33.1 | 63.04 | 17.93 | 10.98 | 4.72 | 44.01 | 34.99 |
| **2015** | 27,039,260.41<br>$7,124,969.81 | 63,381,973.65<br>$16,701,442.33 | 41,252,295.16<br>$10,870,170.00 | 29,236,154.98<br>$7,703,861.65 | 9,509,318.57<br>$2,505,749.29 | 35.13 | 65.09 | 17.81 | 14.67 | 3.26 | 31.57 | 34.27 |
| **2016–2019** | | | | | | | | | | | | |
| **2016** | 30,960,349.77<br>$7,371,160.84 | 81,220,123.68<br>$19,337,203.87 | 51,664,357.07<br>$12,300,451.66 | 38,080,296.82<br>$9,066,305.61 | 13,636,786.25<br>$3,246,699.26 | 37.76 | 63.61 | 17.75 | 17.29 | 2.52 | 27.09 | 33.92 |
| **2017** | 31,463,908.69<br>$7,125,463.39 | 93,627,408.18<br>$21,203,299.18 | 58,209,336.71<br>$13,182,357.66 | 43,491,198.47<br>$9,849,219.48 | 16,929,324.44<br>$3,833,893.71 | 36.48 | 62.17 | 15.63 | 21.59 | 2.4 | 27.88 | 35.83 |
| **2018** | 31,790,416.73<br>$6,595,522.14 | 107,340,394.84<br>$22,269,791.46 | 68,289,676.91<br>$14,167,982.76 | 51,483,757.07<br>$10,681,277.40 | 14,827,012.95<br>$3,076,143.77 | 35.94 | 63.62 | 21.95 | 18.19 | 2.26 | 27.7 | 36.79 |
| **2019** | 39,959,564.40<br>$7,221,129.52 | 130,431,652.69<br>$23,570,423.53 | 83,459,783.81<br>$15,082,094.04 | 59,458,339.45<br>$10,744,771.03 | 20,446,901.02<br>$3,694,978.23 | 43.67 | 63.99 | 20.92 | 13.94 | 2.87 | 28.65 | 35.22 |

Note: TA* – Total Assets, CAR* – Capital Adequacy Requirement (measures solvency), NPL/TL* – Non-Performing Loans as a ratio of Total Loans (measures asset quality), ROA* – Return on Assets (measures profitability), ROE* – Return on Equity (measures profitability), GDP* - Gross Domestic Product

*Source of Data: Monthly returns by the commercial banks to the Bank of Ghana from January 2008 to December 2019*

### 2.3.4 *Interest Rate Structure of the Commercial Banking Sector in Ghana (2008–2019)*

In respect of movement in interest rates, Ghana's policy rate has changed steadily, increasing from 12.5 in March 2007 to 14.5 in December 2019. Consequently, market interest rates have also changed reflecting the trends of changes in the policy rate (Table 2.2).

Specifically, the policy rate increased significantly from 12.5 in August 2007 to 18.5 in September 2009 following the global surge in food and fuel prices in that period (Kovanen, 2011). In the same period, deposit rates increased from 4.5 percent to 9.5 percent, lending rates from 24.25 percent to 32.75 percent, and time deposit rates from 9 percent to 13.5 percent. The high lending rates according to Kovanen (2011), reduced the creditworthiness of borrowers and increased NPLs during this period. Ghana's economy picked up after September 2009, and the trend of policy rates improved on the back of reduced inflation levels. The policy rate hit a low point of 12.5 in December 2011 which resulted in reductions in deposit rates to 4.05 percent, lending rates to 25.93 percent, and time deposit rates to 7.75 percent. The favourable downward trend reversed in March 2012. In 2012, Ghana commenced electricity rationing which lasted till 2016. The rationing programme increased the operational cost of most businesses and ultimately resulted in an economic downturn. For this period, the policy rate increased systemically from 13.5 in March 2012 to 26.0 in September 2016. Deposit rates increased from 4.05 percent to 6.13 percent, lending rates from 25.93 to 27.97 percent, and time deposit rates from 7.75 to 13 percent.

In recent periods, the policy rate in Ghana has reduced: from 25.5 percent in the last quarter of 2016 to 16.0 percent in December 2019. According to the BoG's Monetary Policy Committee's releases, a reduction in policy rate generally follows an improvement in economic performance and efficiency of the banking sector.

Responses of market rates to the recent changes in policy rate are mixed. Lending rates, although reduced from 28.09 percent to 23.06 in December 2016 and 2019 respectively, stalled at levels above 20 percent. As evidence of competition, particularly for deposits for commercial banks in Ghana, time deposits dropped by only 1.5 basis points compared to the significant drop of 11 basis points in the policy rate. For the same period, despite the reduction in the policy rate, savings deposit rates differed in the direction of change of policy rate by increasing from 6.05 to 7.75.

*Table 2.2: Trend of Interest Rates in Ghana's Commercial Banking Sector (2008–2019)*

| Year | No. of Banks | No. of Foreign Banks | No. of Domestic Banks | PR* | LR* | SD* | 3-Months TD* |
|---|---|---|---|---|---|---|---|
| **2008** | 25 | 14 | 11 | 15.79 | 25.03 | 5.80 | 11.27 |
| **2009** | 26 | 15 | 11 | 18.29 | 31.92 | 9.17 | 17.06 |
| **2010** | 26 | 15 | 11 | 14.67 | 29.93 | 7.92 | 12.88 |
| **2011** | 27 | 16 | 11 | 12.92 | 27.03 | 5.18 | 8.91 |
| **2012** | 28 | 16 | 12 | 14.46 | 25.53 | 4.86 | 10.05 |
| **2013** | 26 | 15 | 11 | 15.67 | 26.60 | 5.35 | 12.35 |
| **2014** | 29 | 18 | 11 | 18.67 | 27.01 | 5.44 | 12.90 |
| **2015** | 29 | 17 | 12 | 23.00 | 28.62 | 5.24 | 13.34 |
| **2016** | 33 | 17 | 16 | 25.92 | 28.14 | 6.32 | 13.04 |
| **2017** | 33 | 16 | 17 | 22.25 | 27.13 | 7.19 | 14.06 |
| **2018** | 34 | 17 | 17 | 17.75 | 24.47 | 7.55 | 12.08 |
| **2019** | 24 | 14 | 10 | 16.00 | 23.52 | 7.55 | 11.50 |

Note: PR* – Policy Rate, LR* – Lending Rate, SD* – Savings Deposit Rate, 3-Months TD* – 3-Months' Time Deposit Rate

*Source of Data: Bank of Ghana*

### 2.3.5 *Ownership Structure and Competition of the Commercial Banking Sector in Ghana (2008–2019)*

Following the implementation of FINSAP, the ownership structure of Ghana's commercial banking sector has shifted more towards foreign ownership. Particularly, in the last decade, the number of foreign banks has consistently been higher than that of domestic banks (Table 2.3). As of December 2019, 24 commercial banks were operating in the country with 14 foreign-owned banks and 10 domestic-owned banks. Out of the 14 foreign-owned banks, five originated from Nigeria, one from Togo, one from South Africa[23], and three from the European region.

Not only has the number of foreign banks increased but the share of assets, deposits, and loans granted by the foreign banks have exceeded that of domestic banks in the past decade (from 2008 to 2019) (Table 2.3). This observation aligns with that of Ackah and Asiamah (2016) who argue that the influx of foreign banks has increased the number of offshore funds and broadened the credit base of the sector by making more funds available to promote economic growth.

Second, in respect of the degree of competitiveness in the banking sector, using the CR4 ratio[24] to measure the concentration levels, Dadzie and Ferrari (2019) found that the post-reform era brought

[23] As at the period under consideration (2007 to 2019) only one South African bank operated in Ghana. The number of South African banks increased to three following the period under consideration, i.e. from 2019.

[24] The CR4 ratio is used to estimate the market share of the four largest firms in an industry.

about a reduction in concentration levels and ultimately increased competitiveness in the banking industry. Evidence shows that deposits of the largest four banks reduced from 76 percent in 1988 to 70 percent in 1994. In December 2019, the largest four banks covered only 24 percent of total deposits and 23 percent of total assets.

Another notable trend associated with the heightened levels of competition is the increased geographical span of banks via the branch network system and the rapid adoption of e-banking systems by commercial banks. After the implementation of FINSAP, the number of commercial bank branches increased from approximately 315 in 1998 to 1,557 in 2018 (Bank of Ghana, 2018). Technological innovations contributed largely to deepening banking services in Ghana (Abor, 2005): as of December 2019, all commercial banks in Ghana had introduced ATMs, e-banking, telephone banking, SMS banking, etc.

*Table 2.3: Structure of the Commercial Banking Sector in Ghana (2008–2019)*

| | **Ownership** | | **Share of Total – Foreign Banks** | | | **Share of Total – Domestic Banks** | | |
|---|---|---|---|---|---|---|---|---|
| **Year** | **No. of Foreign Banks** | **No. of Domestic Banks** | **Total Assets** | **Net Loans Granted** | **Deposit** | **Total Assets** | **Net Loans Granted** | **Deposit** |
| **2008** | 14 | 11 | 56 | 51 | 56 | 44 | 49 | 44 |
| **2009** | 15 | 11 | 56 | 47 | 56 | 44 | 53 | 44 |
| **2010** | 15 | 12 | 55 | 46 | 53 | 45 | 54 | 47 |
| **2011** | 17 | 12 | 55 | 50 | 54 | 45 | 50 | 46 |
| **2012** | 17 | 13 | 57 | 53 | 56 | 43 | 47 | 44 |
| **2013** | 17 | 13 | 60 | 54 | 57 | 40 | 46 | 43 |
| **2014** | 18 | 12 | 65 | 62 | 60 | 35 | 38 | 40 |
| **2015** | 18 | 12 | 58 | 56 | 58 | 42 | 44 | 42 |
| **2016** | 18 | 13 | 57 | 53 | 58 | 43 | 47 | 42 |
| **2017** | 17 | 16 | 52 | 50 | 58 | 48 | 50 | 42 |
| **2018** | 17 | 17 | 54 | 51 | 53 | 46 | 49 | 47 |
| **2019** | 14 | 10 | 57 | 60 | 56 | 43 | 40 | 44 |

*Source of Data: Bank of Ghana based on monthly submissions made by commercial banks to the Bank of Ghana from January 2008 to December 2019*

### 2.3.6 *Summary of Ghana's Macroeconomic Performance*

Overall, it is instinctive to assume that Ghana's macroeconomic conditions have impacted the performance of its commercial banking sector over the years. In Table 2.4, the study compares the macroeconomic and financial soundness indicators of Ghana to that of other key countries in Africa: Nigeria, Kenya and South Africa.

Table 2.4 indicates that Ghana's economic growth over the past decade has remained the highest (when compared to Nigeria, Kenya and South Africa) with a GDP growth rate of 6.84 percent. According to Edmond (2019), this can be attributed to the discovery of oil and the recognition of Ghana as a primary exporter of commodities such as gold and cocoa worldwide.

Nevertheless, such economic growth prospects do not transcend to other key macroeconomic variables such as inflation. Irrespective of the inflation targeting goal of a single-digit inflationary rate, Ghana's inflation rate averaged 11.95 from 2008 to 2019. According to Asiama et al. (2014), the relatively high inflation rates mainly emanate from the high fiscal and structural deficits currently being faced by the country which in recent times has increased the need for external funding. The increased fiscal deficit is largely a result of the high public debt rate in Ghana which nearly tripled between 2006 and 2016, rising from 26 percent to 63 percent of GDP (Asobiela, 2020). The structural deficits have originated largely from the deterioration in the balance of trade as the import costs of the county has consistently exceeded the revenue attained from exports (Özyurt, 2019). Consequently, the increasing need for external financing has exposed the country to external shocks, particularly via the exchange rate channel, leading to a rather significant depreciation of the national currency (the cedi) (Özyurt, 2019).

These economic challenges have translated into relatively high lending rates and interest rate spreads, low broad money supply, and reduced credit by banks to the private sector (Table 2.4).

Dadzie and Ferrari (2019) argued that the comparatively high inflation and exchange rate risks experienced in Ghana over the years have resulted in negative real interest rates and increased the operational cost of banks while reducing credit to the private sector. The increase in operational cost is invariably transferred to customers via high lending rates which may ultimately result in high NPLs. Table 2.4 indicates that the lending rates offered, and the interest rate spread of commercial banks in Ghana for the period under assessment, far exceeded that of other countries. When compared to Nigeria (another West African country) the lending rates and interest rate spread in Ghana were higher by 64 and 85 percent respectively. According to Owusu-Antwi (2009), such high-interest rate spreads tend to discourage depositors and borrowers, adversely affecting the intermediation function and reducing the efficiency of commercial banks in the country. Ultimately, the increased NPLs together with the frequent increases in minimum capital requirement make banks more likely to invest in less risky and liquid projects, reducing lending to the private sector and again impairing intermediation in Ghana's commercial banking sector.

*Table 2.4: Comparison Of Selected Macroeconomic And Financial Soundness Indicators And Interest Rates Across Countries (Averaging Values From 2008 To 2019)*

| | Ghana | Nigeria | Kenya | South Africa |
|---|---|---|---|---|
| **Macroeconomic Indicators** | | | | |
| GDP (current US$) | 47,955,558,081.11 | 418,228,956,568.55 | 59,772,574,893.12 | 347,649,485,246.10 |
| GDP per capita (constant 2010 US$) | 1,555.36 | 2,365.50 | 1,053.82 | 7,447.14 |
| GDP growth rate (annual %) | 6.84 | 4.46 | 5.14 | 1.67 |
| Inflation, consumer prices (annual %) | 11.95 | 11.85 | 8.85 | 5.75 |
| **Financial Soundness Indicators** | | | | |
| Broad money (% of GDP) | 27.16 | 24.14 | 41.39 | 74.06 |
| Bank nonperforming loans to total gross loans (%) | 14.85 | 10.88 | 7.18 | 3.98 |
| Domestic credit to the private sector by banks (% of GDP) | 13.86 | 13.26 | 32.10 | 68.75 |
| **Interest Rates** | | | | |
| Central Bank Policy Rate | 18.13 | 11.46 | 9.71 | 6.31 |
| Treasury Bill Rate | 17.59 | 8.84 | 8.36 | 6.63 |
| Savings Rate | 6.46 | n/a | 2.77 | 3.82 |
| Deposit Rate | 12.46 | 8.63 | 7.62 | 6.78 |
| Lending Rate | 27.08 | 16.54 | 15.30 | 10.02 |
| Interest Rate Spread | 14.62 | 7.91 | 7.68 | 3.24 |

*Source of data: Computed based World Bank Data (World Development Indicators 2021)*

## 2.4 *Conclusion*

This chapter presented a historical account of the evolution of commercial banking in Ghana, highlighting the various financial sector reforms that have been put in place from 1970 to 2019. The chapter also presented an in-depth account of the current structure of Ghana's commercial banking sector and the performance of the sector from 2008 to 2019. Explanations were provided for the observed variations in performance indicators.

The onset of commercial banking in Ghana was characterised by extensive government control and increased intermediation cost to customers of commercial banks. In this period, commercial banks experienced sharp declines in real interest rates, and deposits. The sector also accumulated increased losses by lending to 'government preferred clients' that were unable to repay loans.

To resolve challenges in the commercial banking sector, financial sector reforms were introduced in the late 1980s to liberalise the banking sector to create a more competitive and efficient banking system. A notable reform introduced in these times was the FINSAP. This reform aimed at liberalising and restructuring the banking sector by reducing government stakes in state-owned banks, easing the entry restrictions of foreign banks, and removing NPAs from the balance sheet of banks. Further policies which included the Banking Act (1989, 2002 and 2004) were also implemented following FINSAP to improve the prudential regulation of the commercial banking sector. The minimum capital requirement of banks was regularly increased to augment the ability of the sector to absorb unexpected shocks to their capital base. In 2018, the minimum capital requirement was revised to GH¢400 million.

Given the extent of deterioration in the banking sector before FINSAP, the reforms have attained significant progress. Presently, the commercial banking sector is under less governmental control with increased foreign and private participation. The reforms have also eased and improved prudential supervision by the BoG with the Banking Supervision Department carrying out both on- and off-site supervision on regular basis. Regarding the increase in the capital requirement, as of December 2019, all banks except one have exceeded the capital adequacy ratio stipulated by the BoG.

Despite the gains brought about by the financial sector reforms, Ghana's commercial banking sector is still fraught with challenges that have significantly impaired intermediation between borrowers and savers. The relatively reduced intermediation is made evident when in the period 2008 to 2019, banks in Ghana granted the least amount of credit to the private sector compared to the performance of banks in Nigeria, Kenya and South Africa. Ghana's commercial banking sector charged the highest lending rate and reported the highest interest rate spread and NPLs when compared to Nigeria, Kenya and South Africa for the same period.

According to Dadzie and Ferrari (2019), the challenges of Ghana's commercial banking sector can be attributed to weak macroeconomic, institutional, and regulatory conditions. High inflation and exchange rates have stalled the attainment of positive real interest rates on interest-bearing instruments in the banking sector, and high capital requirements imposed on banks have caused banks to invest in more liquid and risk-free instruments rather than loans, crowding out the private sector.

In conclusion, although financial sector reforms may have liberalised the commercial banking sector, performance indices show that these reforms have probably had only a limited impact on enhancing the efficiency of intermediation in Ghana's commercial banking sector. From a policy perspective, there is a need for policymakers and management of commercial banks to measure the efficiency of banks and develop effective strategies to address identified gaps that have caused inefficiencies in Ghana's commercial banking sector.

# CHAPTER 3

# THEORY AND MEASUREMENT OF EFFICIENCY: A FOCUS ON THE DEA APPLICATION

## 3.1 *Introduction*

The concept of efficiency originally emerged from the study of productivity, a notable economic theory discussed extensively by both Classical and Keynesian theorists. In scientific papers, productivity and efficiency are often used interchangeably to depict the process by which a set of inputs are transformed into a set of ‘useful’ outputs by production units (Coelli et al., 2005; Allen et al., 2013).

Studies such as Fried et al. (2008), Cummins and Xie (2013), O’Donnell (2018) and Sickles and Zelenyuk (2019), debunked the overlapping use of efficiency and productivity in a theoretical survey, distinguishing between these two concepts. The researchers defined productivity as the ratio of outputs to inputs in a production process at a given point in time, while efficiency was based on Farrell’s (1957) definition of firm performance. In defining efficiency, Farrell did not only focus on the relationship between inputs and outputs but compared observed inputs and outputs with optimal inputs and outputs within a sector. Unlike the concept of productivity, which measures the performance of a production unit at a point in time, the fundamental idea of efficiency is to use frontiers to segregate performing firms from their non-performing counterparts.

This chapter explores the various frontiers used in defining efficiency, focusing on the theory and the different types of efficiency. It also sets the background for Chapter 4 by introducing the parametric and non-parametric measures of efficiency, and discusses DEA and the various variable selection approaches used to estimate efficiency scores under DEA. In estimating DEA, both the traditional and modern methods are introduced.

## 3.2 *The Theory of Efficiency*

### 3.2.1 *Frontiers Used in Estimating Efficiency*

In measuring efficiency, existing literature has discussed various types of economic frontiers which have informed the estimation of different types of efficiency (Farrell, 1957; Lovell, 1993; Coelli et al., 2005; Cummins and Xie, 2016). Empirically, the most common types of efficiency estimated are technical efficiency, derived from the production frontier, and allocative efficiency, which is made up of the cost efficiency from the cost frontier and revenue efficiency obtained from the revenue frontier. These frontiers and efficiency types are discussed below.

3.2.1.1 *Production Frontier and Technical Efficiency*

The most common efficiency frontier estimated in the assessment of firm performance is the production frontier, which was originally proposed by Farrell (1957). This frontier generally estimates how efficient firms are at using the minimum amount of input to produce outputs (input orientation) or how efficient firms are at maximising output with the same level of input (output orientation) (Farrell, 1957; Chen et al., 2015; Cummins and Xie, 2013, 2016).

Technical efficiency is measured with the production frontier. A firm operating on the frontier is seen as fully technically efficient, while a firm operating away from the frontier would need to reduce input or maximise output to be on the frontier.

Figures 3.1 and 3.2 (adapted from the research of Cummins and Xie, 2013) illustrate the production frontier and technical efficiency for one input–one output relationship under the input and output orientations respectively. For both illustrations, the amount of input used is shown on the x-axis, while the amount of output produced is on the y-axis. For the input orientation frontier shown in Figure 3.1, firms on the frontier at point A are described to be fully efficient since they are employing the minimum amount of input needed to produce a given level output, or they are using the optimal level of technology to produce a given level of output. Firms away from the frontier, for example at point B, are inefficient. For firms at point B to be fully efficient, the input level used would need to be reduced to point I. For example, under the input orientation, a firm with a technical efficiency score of 0.60 would need to reduce its input by 40 percent to be fully efficient and to produce the same amount of output being produced by a fully efficient firm.

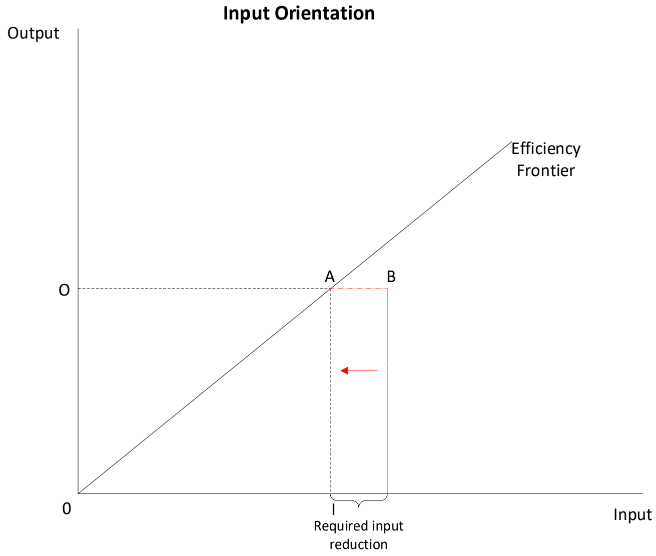



*Figure 3.1: Input Orientation to estimating Technical Efficiency (Single Input–Single Output) (Cummins and Xie, 2013)*

Similarly, under the output orientation frontier shown in Figure 3.2, firms operating at point A of the efficiency frontier are described as fully efficient since they are producing the maximum output O with a given input level of the point I. At for example, point B, firms become inefficient as they are producing a lower amount of output with the same given level of input I. For firms at point B to be fully efficient, they would need to increase output, using the same amount of input I. For example, under the output orientation, a firm with a technical efficiency score of 0.60 would need to increase its output by 40 percent (with the same level of input) to be fully efficient to be considered fully efficient.

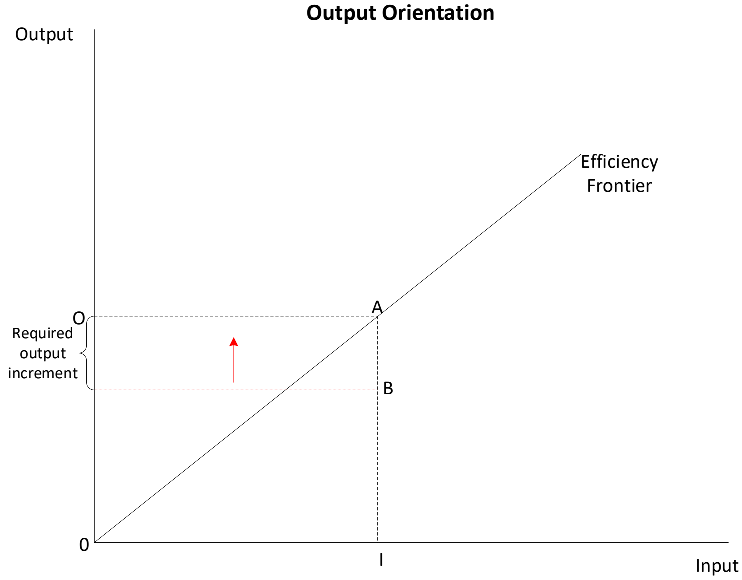



*Figure 3.2: Output Orientation to estimating Technical Efficiency (Single Input–Single Output) (Cummins and Xie, 2013)*

Thus, according to Farrell (1957), Aly et al. (1990), and in Ghana, Adjei-Frimpong et al. (2014), a firm's technical efficiency is estimated as follows:

For input orientation:

$$Technical\ Efficiency = \frac{frontier\ input\ use}{actual\ input\ use}$$

For output orientation:

$$Technical\ Efficiency = \frac{frontier\ output\ produced}{actual\ output\ produced}$$

For cases where multiple inputs are used to produce a given level of output, Farrell (1957) proposed the use of the 'efficient isoquant', which assumes that the changes in the production function of the firm are homothetic (of order O), i.e. changes in the pairwise combinations of input variables result in the same level of output along the isoquant.

As illustrated in Figure 3.3 (again illustrated by Cummins and Xie, 2013), Farrell assumes that a constant return to scale (CRS) informs the shape of the efficiency frontier, shown by the isoquant YY. This isoquant presents the combination of inputs ($X_1X_2$) that produces a given level of output when a firm is deemed fully efficient. YY therefore shows the minimum level of inputs($X_1X_2$) needed to produce a unit of output. In this respect, every combination of inputs on the isoquant is considered as technically efficient whereas points above, such as point F, are seen as technically inefficient. Point F is technically inefficient as the combination of input used is more than is required to produce a unit of output. Along the ray OF, the distance between S and F measures the technical inefficiency of the firm that uses the input combinations at point F. The distance SF, therefore, illustrates the amount by which inputs would have to be reduced with output remaining the same. The amount of technical inefficiency can therefore be provided by the ratio of $\left(\frac{SF}{OF}\right)$ while that of technical efficiency can be represented by $\left(\frac{OS}{OF}\right)$.

Overall, the scores for technical efficiency range from 0 to 1. Fully efficient firms on the production frontier have an efficiency estimation score of 1, while inefficient firms score less than 1.

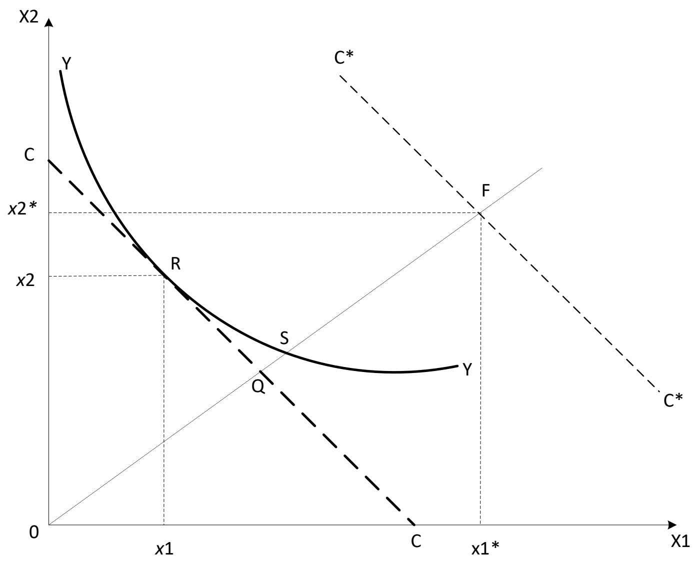



*Figure 3.3: Illustration of Technical, Cost and Allocative Efficiency (Multiple Input– Single Output) (Cummins and Xie, 2013)*

Another key subject related to the concept of technical efficiency is scale efficiency. The fundamental assumption of Figure 3.3 is the CRS, which implies that a unit increase in the input results in a proportional increase in outputs. This assumption does not hold in all cases. Some firms operate either under increasing returns to scale (IRS) or decreasing returns to scale (DRS). A firm operating under IRS needs to increase its scale or grow larger to maximise its input-output ratio, while a firm operating under DRS needs to reduce its scale or become smaller to maximise its input–output ratio.

Considering the varying scales of firms, the technical efficiency of firms is segregated into two main components: pure technical efficiency and scale efficiency. Pure technical efficiency assesses the performance of firms on a variable return to scale (VRS) frontier, while scale efficiency assesses firms only on a CRS frontier. The VRS frontier examines firms based on CRS, IRS, and DRS assumptions while the CRS frontier assesses performance based on only the CRS assumption (Cooper et al., 2000).

As confirmed by Avkiran (2004) and all researchers that have examined technical efficiency, overall technical efficiency is estimated as follows:

$$Technical\ efficiency = Scale\ Efficiency * Pure\ Technical\ Efficiency$$

Like technical efficiency, scores for pure technical and scale efficiencies range from 0 to 1. A score of less than 1 indicates inefficiency and a score of 1 is fully efficient.

#### 3.2.1.2 *Cost Frontier and Cost Efficiency*

The cost frontier is another key frontier technique commonly used to examine the performance of firms. This frontier is used to measure the cost efficiency of firms by comparing the minimum cost to be incurred in the production of firm outputs $wx$ to the actual cost incurred $wx*$ (Cummins and Xie, 2013). As the measurement of technical efficiency, firms operating on the cost frontier, CC (as shown in Figure 3.3), are fully cost-efficient while those that are above or on the right of the frontier CC, at C*C* are cost-inefficient and would need to reduce the cost to produce the same amount of output. From Figure 3.3, cost efficiency is measured as:

$$Cost\ Efficiency = \frac{frontier\ cost\ (OQ)}{actual\ cost\ (OF)}$$

Like the technical efficiency scores, cost efficiency scores also range between 0 and 1, with fully efficient firms having cost scores of 1 and cost-inefficient firms having a score of less than 1.

Farrell (1957) prescribes that for a firm to be cost-efficient, it must be both technically and allocatively efficient. Akazili et al. (2008) defined allocative efficiency as an efficiency concept that goes beyond assessing the relationship between input and output variables on the production frontier (as technical efficiency) to assessing the effects of price on the combinations of input and output variables. Similarly, Siudek (2008) described allocative efficiency as the concept that examines the mix and quantities of inputs that produce a given set of output at a minimum cost, ensuring minimisation of waste in the production process. Cummins and Xie (2013) further illustrated the notion of allocative efficiency by including in the diagram the market prices of inputs at $w_1 w_2$ (see Figure 3.3). The isocost line C*C* which runs through the point F represents the cost of $X_1^* X_2^*$ at $w_1 X_1^* + w_2 X_2^* = k_0$The cost at $k_0$ can be reduced by moving the isocost line in a parallel manner till it is tangent to the isoquant at point R. At this point, the isocost line CC represents the cost of $X_1$ and $X_2$ at $w_1 X_1 + w_2 X_2 = k_1$. The relative distance between Q and S can be obtained by $\left(\frac{OQ}{OS}\right)$. In respect of the least input cost combination at point R, the ratio $\left(\frac{OQ}{OS}\right)$would represent the cost reduction required by the producer to move from a technically but not allocatively efficient point S to both a technically and allocatively efficient point R. At point F, the allocative efficiency is measured by the ratio $\left(\frac{OQ}{OS}\right)$.

Overall, according to Farrell (1957), Cummins and Xie (2013) and recently Decker et al. (2017), allocative efficiency is measured as:

$$Allocative\ Efficiency = \frac{cost\ efficiency}{technical\ efficiency}$$

#### 3.2.1.3 *Revenue Frontier and Revenue Efficiency*

Revenue efficiency is also measured relative to a revenue frontier, which is defined as the ratio of maximum revenue to the current revenue of a DMU (Mozaffari et al., 2014). In estimating revenue efficiency scores, studies have compared the revenue of a firm to the revenues of a fully efficient firm that utilises the same amount of input quantities and output prices. A bank that is revenue-efficient has an efficiency score of 1 while an inefficient firm has a revenue efficiency score of less than 1. According to Cummins and Xie (2013), to achieve revenue efficiency, a firm will either have to adopt the best technology practice or choose an optimal mix of outputs.

For this study, only the technical efficiency (including scale and pure technical efficiencies) is estimated. Our choice is based on the availability of data which excludes data on prices of input and output variables.

### 3.2.2 *Microeconomic Theories on Firm Efficiency*

Before our discussions on the frontier estimation techniques, this section summarises the various theories on firm performance. The objective of this section is to discuss the theories of firm performance within the context of efficiency frontier analysis, ultimately providing reasons why firms may not be able to operate efficiently.

3.2.2.1 *Neoclassical Theory of the Firm*

The neoclassical theory, first developed by Cournot in 1883, treats a firm like a black box[25] that transforms inputs into outputs. According to Berthonnet (2019), this theory further assumes that firms operate in a perfectly competitive market where they seek to maximise profit and revenues by minimising cost. In a perfectly competitive market, it is presupposed that all firms earn only a normal profit, i.e. firms cannot earn more than necessary to cover economic costs. In the short run though, some firms may earn abnormal profits which may attract the entry of new players and increase competition in the industry. This competition will invariably force prices down to the point where all firms are earning normal profit in the long run.

To distinguish between efficient and inefficient firms, the neoclassical theorists believe that firms that earn below normal profit are inefficient, and over a period may be forced to exit the industry. These theorists, therefore, suggest that in a perfectly competitive market, firms that do not operate on the efficiency frontier are inefficient.

This notion has been disputed by existing empirical studies such as Demsetz (1997), Dong (2010) and Teece (2019), who observed that the neoclassical argument only holds in an environment where the price system is perfect, i.e. where resources are well allocated. These researchers argue that in the real world, where price systems are not perfect, the survival of a firm depends on the capabilities of management and the internal structure of a firm. Therefore, a firm with high management capabilities but with profits below the normal level can survive and not fail, implying that some firms may not be efficient, but still survive in the market.

To address the challenges of the neoclassical theory, studies including that of Dong (2010), Augier (2013) and Teece (2019) in describing the theory of the firm, summarised several other theories that explain the sources of firm inefficiencies. Key among these theories were the managerial theories, proposed by Williamson in 1964, behavioural theories, introduced by Cyert and March in 1963, and the X-efficiency theory suggested by Leibenstein in 1966. Overviews of these theories are presented below.

3.2.2.2 *Managerial Theories of the Firm*

According to Dong (2010) and Teece (2019), Williamson (1964) argued that executive managements of firms have divergent interests from the owners of the firms. Therefore, dissimilar to the neoclassical theories which believe that the ultimate objective of the firm is to make a profit, Williamson (1964) under the managerial theories of the firm, asserted that members of management

[25] According to Andersson and Johansson (2018), in economics, a black box is a system which can be viewed in terms of its input and output (vectors), without any knowledge of its internal workings or the possible interactions with the environment.

pursue other interests rather than optimising profit, although they work under a condition of profit constraint.

To capture and expand the managerial theories of the firm, Williamson (1964) related the theory of firm efficiency to the principal–agent hypothesis (Dong, 2010; Teece, 2019). In the principal–agent relationship, the firm is considered as a contract between the owners (principal) and subcontractors (agents/executive management) with the principal engaging the services of the subcontractors to maximise the value of the firm. Under the principal–agent hypothesis, the principal does not have complete knowledge of the operations of the firm and its performance capabilities. The agents, on the other hand, have more information relative to the principals, and they capitalise on this information gap to pursue their interests (such as paying out higher salaries, or improving working conditions). This results in the problem of 'moral hazard' which requires that principals incur additional costs to monitor the activities of the agents and motivate the agent's behaviour in the interest of the principal (Dong, 2010).

In summary, to determine the causes of firm inefficiencies, Williamson (1964) argues that the divergent behaviours of the agents and the resulting increase in monitoring cost reduce firm profitability and induce inefficiencies in firm operations (Dong, 2010).

#### 3.2.2.3 *The Behavioural Theories of the Firm*

Dong (2010) and Augier (2013) in explaining the theory of the firm, described the behavioural theory of the firm, proposed by Cyert and March in 1963 and Simon in 1995. This theory questions the optimisation objective of firms, claiming that firms cannot optimise their objectives as they do not operate in a perfect environment. Specifically Simon (1995) introduced the concept of 'satisficing'[26] and bounded rationality in the objectives of the firms, as opposed to optimisation objectives such as the revenue maximisation and cost minimisation goals. According to Simon (1995), stakeholders of a firm desire to act rationally, but face challenges owing to cognitive limitations in solving problems and also as a result of information asymmetry. These challenges cannot support the revenue maximisation goals as firms cannot always keep costs at their minimum level and this may result in some inefficiency.

Similarly, Cyert and March (1963) argued that the firm is made up of different stakeholders with varying interests (Dong, 2010; Augier, 2013). Some interests may be conflicting, requiring the continuous processes of negotiations and payments to ensure that the needs of stakeholders are satisfied. In an attempt to satisfy stakeholders, there may be disparities between the resources

[26] The word 'satisfice' was used by Simon (1995) to mean 'satisfy' or 'suffice' (Dong, 2010).

available to the firm and the payment made to keep stakeholders satisfied. These disparities could result in organisational slack which will cause inefficiencies. An example of organisational slack is the payment of wages above what is required to keep the labour satisfied. This results in unnecessary costs and inefficiencies in the firm. In a perfect environment, payments made may converge to the ideal levels resulting in zero organisational slack. In reality, firms do not operate in perfect situations. There are changing business cycles and, specifically in these times, there are rapid changes in technologies adapted. This may at every point in time require firms to strive harder to attain optimal efficiency. Given the imperfect nature of the market, firms can always be inefficient in the market.

#### 3.2.2.4 *The X-efficiency Theory of the Firm*

The "X-efficiency" theory has been extensively discussed in existing studies[27]. Proposed by Leibenstein in 1966, this theory rejects the assumptions of the neoclassical theorists that firms exist to maximise profits. Similar to the behavioural and managerial utility theories, Leibenstein (1996) claimed that firms maximise the utility or desires of management rather than maximising profit. To justify this claim, the researcher argued that most often, firms do not operate on an efficiency frontier but rather operate on a production frontier within the efficiency boundary. The production frontier not only assesses the relationship between input and output variables, but also measures how well management aligns technology, human resource management, and other resources to produce a given level of output.

### 3.2.3 *Measurement of Efficiency – Frontier Estimation Techniques*

To estimate efficiency frontiers, existing studies have proposed two key techniques: the parametric and the nonparametric approaches. The distinguishing features between these two approaches are in relation to the assumptions made in estimating the shape of the efficiency frontier and the treatment and interpretation of random error (if the random error is estimated) (Alber et al., 2019).

#### 3.2.3.1 *Parametric Approach*

The parametric techniques, also known as the econometric models, provide a detailed interpretation of the residuals in the standard Ordinary Least Square (OLS) estimates. As an advantage, the parametric approach allows for random error and is less likely to misidentify measurement errors. In effect, this approach seeks to separate random error that arises from measurement blunders and unusual financial performance from inefficiency (Bauer et al., 1998; Al-Jarrah et al., 2017). As a limitation, the parametric approach presumes the shape of the efficiency frontier by specifying the functional form for the relationship between input and output variables. Assumptions used to

[27] This includes studies such as Kirkpatrick et al. (2008), Dong (2010), Kablan (2010) and Tsiritakis (2017).

estimate the functional form may not consider all necessary variables, resulting in specification and estimation problems (Tuškan and Stojanović, 2016; Lai and Kumbhakar, 2018).

Empirically, to separate the random error from inefficiency, three key distributional assumptions are used via the application of either the Stochastic Frontier Approach (SFA) (Lovell, 1993; Dong et al., 2014; Lai and Kumbhakar, 2018; Sakouvogui, 2020), the Thick Frontier Approach (TFA) (Berger and Humphrey, 1992; Berger, 1993; Bauer et al., 1998; Chen, 2016) and the Distribution-Free Approach (DFA) (Berger, 1993; Mamatzakis, 2015; Bhatia et al., 2018; Hendrawan and Nasution, 2018).

#### 3.2.3.1.1 *Stochastic Frontier Approach (SFA)*

This application of the parametric approach uses a composed error model which assumes that inefficiencies follow an asymmetric distribution, whereas random errors follow a symmetric distribution (Lai and Kumbhakar, 2018). The error term in the function estimated by the SFA is estimated as $\varepsilon = \mu + v$ where $\mu \geq 0$ is the inefficiency under a half-normal distribution, and $v$ is the random error under the normal distribution assumption. A notable advantage of the SFA to particularly regulators and bank management is its ability to rank the efficiency of firms based on the residual term $\mu$, which represents the cost function residuals. For a given set of output quantities, firms with lower cost function residuals are ranked higher and as more efficient. The SFA treats deviations from the frontier as a "composed residual" made up of inefficiency arising from managerial incompetence and noise or random error originating from mistakes in measurement and other factors beyond the control of management.

#### 3.2.3.1.2 *Thick Frontier Approach (TFA)*

Although The TFA assumes the same functional form as the SFA, it does not use all the units in the dataset to estimate the frontier. To estimate the TFA, firms are grouped into quartiles[28] based on average output or average cost. For the grouping by output, firms in the least quartile with lower outputs are less efficient, while firms in the last quartile with higher average output are more efficient. In the context of cost, firms in the group with the least average cost are efficient while firms in the group with the highest average cost are less efficient. Various frontiers are estimated, first with the group considered to be efficient and then with the group categorised as inefficient. To differentiate between random error and inefficiency, the difference between the mean output or

[28] To segregate firms by quartiles, it is prudent and more representative to classify firms into different asset sizes. Firms in each size class with the lowest average cost or highest output form the subset of data required to estimate the thick frontier of the best performing firms, while firms with lower output and increased average costs within different asset sizes form the frontier of the less performing firms (Bauer et al., 1998).

average cost of the groups represent inefficiency while the difference in the mean output and average cost within the groups are measured as the random error. Notable studies that have employed the TFA are Bauer et al. (1998) and Chen (2016).

A disadvantage is that the TFA indicates the differences in efficiency between the best and worst quartile of firms, but not for individual firms within the groups (Berger and Humphrey, 1992). Also, owing to the varying classifications of firms, the TFA generally requires the use of a large dataset. The absence of a large dataset may make classification spurious and not representative of the industry under consideration.

Lastly, another challenge of the TFA is that it does not give precise estimates of the overall efficiency of the dataset. The price estimates attached to the multiple inputs and outputs of firms within a group cannot be measured with precise accuracy (Dong, 2010; Kumbhakar and Wang, 2010). Berger and Humphrey (1991) argue that the objective of the TFA is not to measure with precision but to provide a general overview of the possible levels of inefficiencies.

##### 3.2.3.1.3 *Distribution Free Approach (DFA)*

The DFA also distinguishes random error from inefficiency in a distinct way. A recent study that has used this estimation technique is Bhatia et al. (2018).

For the DFA, the separation of random error from inefficiency is based on the use of panel data (Bauer et al., 1998; Berger, 1993). Under the panel dataset, the DFA averages the composite error term of different cross-sectional data. The random error component in the cross-sectional data is assumed to be close to zero, thus the average error for each firm within the dataset indicates the inefficiency across firms. Irrespective of the simplicity of the assumptions made by the DFA, there is a question on whether averaging the composite error accounts for the random error in the estimated function (Bauer et al., 1998; Kumbhakar and Wang, 2010).

#### 3.2.3.2 *Non-Parametric Approach*

The non-parametric approach is a linear programming concept originally proposed by Farrell in 1957 to assess the efficiency of a single output case. This concept was further altered by Charnes et al. in 1978 to allow for the estimation of efficiency of large datasets with multiple input-output variables. Empirically, the two most popular non-parametric approaches used are the Free Disposal Hull (FDH) and the Data Envelopment Analysis (DEA) (Murillo-Zamorano, 2004; Dong, 2010).

#### 3.2.3.2.1 *Data Envelopment Analysis (DEA)*

Empirically, the DEA is the most applied efficiency estimation approach used by existing literature[29]. This technique is a mathematical programming technique proposed by Charnes et al. in 1978 to assess the efficiency of comparable units or firms known as Decision Making Units (DMUs). To estimate efficiency, the DEA forms a best practice frontier and measures the efficiency of individual firms to that of the constructed frontier. The firms shown on the frontier have an efficiency score of 1 and are those that maximise output with the given level of input or that use the minimum amount of input to produce a given level of output (Berger and Humphrey, 1997; Coelli et al., 2005; Chen, 2016).

The expansive use of the DEA is attributed to its advantages. First, unlike the econometric parametric approaches, the DEA does not require any prior assumption in estimating the frontier and allows for the efficiency evaluation of multiple input–multiple output firms (Casu et al., 2004; Titko et al., 2014). Secondly, the DEA measures the relative efficiency of DMUs by first identifying the best performers, i.e. units that give the highest efficiency scores, and comparing the efficiency scores of each unit in the dataset to that of the best performers. This analysis allows for the identification of outliers as it shows both the best and worst performers within a dataset (Avkiran, 1999). Lastly, as a strength, the DEA does not discriminate against input and output variables used: the selection is based on the availability of data and not on the importance of variables. This advantage allows for the use of the DEA in a small dataset (Ahn and Le, 2014).

Despite the above advantages, the DEA also has some drawbacks. Primarily, this technique is noted to overestimate firm inefficiencies as it does not separate statistical noise from inefficiency emanating from management behaviour (Kuosmanen and Kortelainen, 2005). This implies that the DEA does not allow for the estimation of random error arising from blunders in measurements, unusual financial performance, and misspecification or omission of input and output variables. With the DEA, the entire distance between the efficiency score of a firm and the frontier is interpreted as inefficiency. Also, according to Asmare and Begashaw (2018), the statistical inference made by the DEA assumes no knowledge about the distribution of the dataset and therefore does not utilise all the information on the dataset used. This drawback presents a less efficient representation of the dataset used.

[29] Over the past two decades, Seiford (1997) has listed over 400 papers in detailed bibliography, Cooper et al. (2007) gave over 2,000 DEA references and Liu et al. (2012) argued that over 4,500 papers in the ISI Web of Science Database have used DEA. Examples of studies include Grigorian and Manole (2006), Erasmus (2014), Othman et al. (2016) and Kumar et al. (2021)

#### 3.2.3.2.2 *Free Disposal Hull (FDH)*

Ultimately in a multiple-input, single-output situation, DEA assumes convexity which implies that in operating on the efficiency frontier, changes in the pairwise inputs result in the same level of output. Deprins et al. (1984) debunked this theory in their proposal of the FDH parametric approach. The FDH relaxes the assumption of convexity, operating under the presumption that there is no linear substitution between observed input and output variables on a pairwise linear frontier. The FDH, therefore, composes the frontier based on actual observations only. Recent studies that have employed the FDH include Da Silva et al. (2016) and Tavakoli and Mostafaee (2019).

### 3.2.4 *Selection of Frontier Method: Is there a best method?*

The above analysis on the frontier estimation techniques categorised the efficiency measurement techniques into two main groups: parametric and non-parametric approaches. The primary benefit of the parametric approach is its ability to segregate random error from the inefficiency component of the residual in the estimated function. As a disadvantage, the parametric approaches presuppose the shape of the efficiency frontier. Misspecifications of assumptions that specify the presupposed shape may result in wrong estimations and inaccurate interpretations of the performance of firms. An advantage of the non-parametric approach is that it does not presuppose the shape of the efficiency frontier, allowing for more accurate estimations. The disadvantage of non-parametric techniques, though, is the inability to separate random error from inefficiencies.

Owing to the benefits and drawbacks of both the parametric and non-parametric approaches, there is often a debate on which efficiency frontier estimation measure is most preferred. In discussing the conditions under which frontier estimation measures are used, Bauer et al. (1998) and Dong et al. (2014) argued that the empirical adoption of frontier approaches have most often depended on the efficiency concept being studied (technical efficiency and economic efficiency), the number of firms in the dataset and the availability of data in respect of input and output variables. Specifically, Bauer et al. (1998) claimed that DEA studies have commonly been used to measure technical efficiency (which uses data that is exclusive of cost) whereas parametric approaches have been used to measure economic efficiency (which uses data inclusive of cost).

As the objective of this thesis is to measure the technical efficiency of commercial banks in Ghana, this study relies on the use of the DEA non-parametric technique. The section below discusses extensively the DEA estimation measures and the evolution of the DEA technique in recent times.

### 3.3 *Estimating Technical Efficiency using the DEA Approach*

A key advantage of the DEA model is its flexibility and ability to adapt to changes to improve the accuracies of estimations (Murillo-Zamorano, 2004; Zhong et al., 2021). This has resulted in several extensions to the basic DEA models: the Charnes, Cooper, and Rhodes DEA model (CCR) and the Banker, Chames, and Cooper DEA model (BCC). This section discusses the benefits and challenges of the traditional DEA models and provides an extensive review of revisions of the traditional models that seek to improve the accuracy of estimations.

#### 3.3.1 *The Traditional Methods – Input Orientation*

##### 3.3.1.1 *CCR Model*

The first empirical application of the DEA to measure the overall technical efficiency of DMUs was modelled by Charnes et al. (1978), and is commonly referred to as the Charnes, Cooper, and Rhodes (CCR) DEA model. In estimating efficiency, the CCR model imposes three assumptions on the efficiency frontier: the assumption of constant returns to scale (CRS), the convexity of the set of input-output combinations, and high disposability of inputs and outputs.

To provide an in-depth understanding, we adopt the diagram depicted by Murillo-Zamorano (2004) to illustrate the relationships between inputs and outputs in the CCR model. Here, F, G, H, I, J and K are six DMUs that use different combinations of inputs $X_1$ and $X_2$ to produce output Y. The line KJ shows the frontier unit isoquant measured by the CCR DEA technique for all DMUs assessed. Each DMU employs different amounts of the two inputs to produce varying amounts of the same output. To determine the inefficiency of each DMU, the performance of a single DMU is compared to that of other units on the frontier that use the same combinations of inputs. The technical efficiency of DMU F will be represented by the ratio $\left(\frac{OF^*}{OF}\right)$ where F* is a linear combination of DMUs G and H. G and H are therefore peer groups of DMU F that utilise the same combinations of inputs since both F and F* are on the same ray. The efficiency of I can be directly measured to H as H is on the efficient isoquant and the same ray as I. The ratio $\left(\frac{OH}{OI}\right)$ shows the technical efficiency of I. Lastly, although unit J is on the efficiency frontier, it is not technically efficient since it is using the same amount of input $X_2$ as G but more of input $X_1$ to produce the same amount of output.

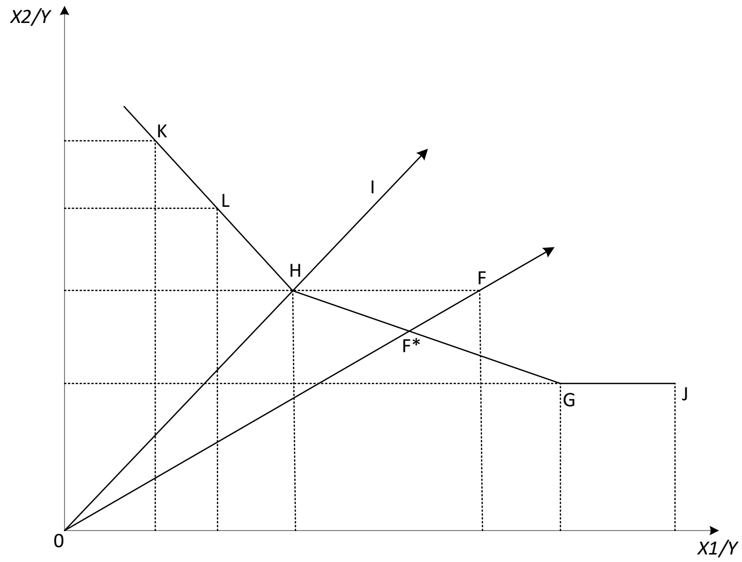



*Figure 3.4: The CCR Model (Murillo-Zamorano (2004), pg.38)*

The efficiency frontier is therefore measured by calculating the segments KH, HG, and GJ that account for the performance of all the DMUs. This frontier is not an accurate isoquant but a linear representation of all the observations of real DMUs at points K, H, G and J, while the units between them at L and F* are hypothetical points calculated as the weighted averages of inputs. The technical efficiency scores for individual DMUs will therefore be calculated by a mathematical programming technique where results will have to satisfy the inequality constraints that an increase (decrease) in a particular output (input) will not worsen other inputs (outputs).

To determine efficiency, the score of each DMU is compared to a linear combination of efficient DMUs termed the peer group. Given a set of N comparable DMUs within the peer group with m inputs and s outputs, for each DMU not located on the frontier, we can estimate a vector $\bar{\mu} = (\mu_1, \dots \dots . \mu_N)$ where $\mu_j$ indicates the weight of each DMU in the peer group. The CCR DEA model is formulated to maximise the relative efficiency score of individual DMUs, on the assumption that weights of input and output variables of each DMU must be possible for all other DMUs included in the dataset.

In effect, the CCR DEA calculations are designed to maximise the relative efficiency score of each DMU, subject to the constraint that the set of weights for each DMU must also be feasible for all the other DMUs included in the sample. The efficiency score can therefore be calculated by the following mathematical programming formulation:

$$
\begin{aligned}
& TE_{CRS} = \min_{\mu} \psi^{0} \\
& s.t. \\
& \qquad \sum_{j=1}^{n} \mu_j X_{ij} \leq \psi X_i^0 \quad i = 1,......,m \\
& \qquad \sum_{j=1}^{n} \mu_j Y_{rj} \geq Y_r^0 \qquad r = 1,......,s
\end{aligned}
\tag{3.1}
$$

The linear program illustrated in Equation (3.1) shows the peer group that yields the same amount of output as the DMU under consideration, but uses just a proportion of inputs (ψ) used by the DMU. The ultimate objective is therefore to determine the peer group that for each DMU, produces the same amount of output but minimises the amount of inputs used (ψ). The technical efficiency score is determined by the optimal value of ψ.

3.3.1.2 *BCC Model: Input Orientation*

Primarily, in estimating the CCR model, Charnes et al. (1978) put in a CRS restriction which assumes that all DMUs in the dataset are operating under optimal scale, measuring scale efficiency. In the real world, this assumption is misleading since the performance of firms is mostly affected by external factors such as financial constraints, macroeconomic conditions, and varying types of competition and market power (Murillo-Zamorano, 2004; Dellnitz et al., 2018). This gap informed the development of the BCC Model by Banker, Chames, and Cooper in 1984, who modelled the DEA estimation under a VRS function, to measure pure technical efficiency.

The VRS model is estimated by including a convexity constraint $\sum \mu_j = 1$ to equation (3.2). This constraint ensures that DMUs are compared only to other DMUs of similar size, avoiding the negative impact of scale efficiency on technical efficiency scores. Ultimately, under the VRS input orientation, the linear programming problem is solved as follows:

$$
\begin{aligned}
& TE_{VRS} = \min_{\mu} \psi^{0} \\
& s.t. \\
& \qquad \sum_{j=1}^{n} \mu_j X_{ij} \leq \psi X_i^0 \quad i = 1,......,m \\
& \qquad \sum_{j=1}^{n} \mu_j Y_{rj} \geq Y_r^0 \qquad r = 1,......,s \\
& \qquad \sum_{j=1}^{n} \mu_j = 1
\end{aligned}
\tag{3.2}
$$

A major challenge with the above equation is its inability to determine whether the firm is operating under increasing or decreasing returns to scale. This is resolved by introducing a constraint $\sum \mu_J \leq 1,$ in Equation (3.3) which depicts a situation of non-increasing returns to scale (NIRS). The inclusion of this constraint allows us to differentiate between different scales in the production structure. In situations where $TE_{NIRS} = TE_{VRS} \neq TE_{CRS}$, a firm is noted to be operating under DRS, where $TE_{NIRS} = TE_{VRS} = TE_{CRS}$, a firm is operating under CRS, and when $TE_{NIRS} \neq TE_{VRS}$, a firm is operating under IRS.

3.3.2 *Traditional Approach – Output Orientation models*

The above analysis focuses on input-orientation models which attempt to maximise the proportional decrease in input variables while in the envelopment space. As noted earlier in this chapter, the DEA model may also be output oriented. The output-oriented models seek to maximise the proportional increase in the output variables of firms in the envelopment space.

The choice of whether to estimate the frontier under input or output orientation depends on the characteristics of the dataset available. For example, for a regulated sector such as the banking sector, where outputs are normally assumed to by exogenous to the control of management (i.e. not directly under the control of management), it is preferable to use the input-orientation model to estimate the production frontier (Novickytė and Droždz, 2018; Ramanathan, 2007). Coelli and Perelman (200) and Ramanathan (2007), however argued that both input- and output-oriented frontiers do not have major influences on the reported efficiency scores of DMUs assessed as both models use the same efficiency frontier.

Following equations (3.1) and (3.2) above, the output-oriented models can be estimated as follows:

$$TE = \max_{\mu} \psi^{0} \qquad\qquad \min_{w_r Z_i} h_0 = \frac{\sum_i z_i X_{i_0}}{\sum_r w_r Y_{r_0}}$$

$$\text{s.t.} \qquad\qquad \text{s.t.}$$

$$\sum_{j=1}^{n} \mu_j X_{ij} \leq X_i^0 \qquad\qquad \frac{\sum_i z_i X_{i_0}}{\sum_r w_r Y_{r_0}} \geq 1$$

$$\sum_{j=1}^{n} \mu_j Y_{rj} \geq \psi Y_r^0 \qquad\qquad w_r, Z_i > 0$$

$$j = 1, \ldots\ldots, n \qquad i = 1, \ldots\ldots, m \qquad r = 1, \ldots\ldots, s$$

$$\sum_{j=1}^{n} \mu_j = 1 (VRS) \qquad\qquad \sum_{j=1}^{n} \mu_j \leq 1 (NIRS) \tag{3.3}$$

Similar to the input-oriented models, the output-oriented technical efficiency models can also be segregated into scale efficiency and pure technical efficiency.

### 3.3.3 *Selection of Variables – Estimation of the DEA Traditional Models in the Banking Sector*

The traditional DEA models are fraught with many challenges that have required that these models are reviewed to improve the accuracy of technical efficiency estimations. Particularly in the banking sector, a key concern is the selection of input and output variables in the estimation of technical efficiency.

In evaluating bank technical efficiency, several studies have identified challenges with respect to the variables used in the estimation of the traditional DEA models. According to Dong et al. (2014), studies such as that of Sealey and Lindley (1977) argued that variables used to estimate bank efficiency by existing studies focus solely on the intermediation function of the sector, ignoring other pertinent roles played by banks. Berger and Humphrey (1997) described the output and input variables of banks as generally intangible, further claiming that the intangible nature of bank variables over the years has resulted in disagreements over which products and services banks produce and how to identify and measure such products. Particularly, Berger and Humphrey (1997) contested the treatment of deposits: are deposits input or output variables and how do you measure deposits? The authors argued that in many cases, deposits are inputs. They explained that following the deregulation of the banking sector, the deposit side of banking underwent significant changes which informed the removal of interest rate ceilings and the creation of new account types. Such changes consequently increased the number of services offered to depositors (treating deposits as outputs) as opposed to using deposits to create value in the form of loans (treating deposits as inputs). Furthermore, Berger and Humphrey (1997) claimed that a component of deposits may become an output variable in instances where related customers tend to have lower lending rates as a result of the significant balances they hold with banking institutions (Berger and Humphrey, 1997). The treatment of deposits as solely an input variable has questioned the accuracy of estimations in existing studies.

To resolve the above challenges on the selection of input and output variables in bank efficiency studies, Berger and Humphrey (1992) proposed four main approaches: the intermediation, production, user cost, and value-added approaches. These approaches particularly sought to address the technical efficiency of banks in executing their varying roles.*The Intermediation Approach*

The intermediation approach, originally modelled by Sealey and Lindley in 1977, seeks to assess the efficiency of banks in bridging the gap between borrowers and savers. In the existing literature, the intermediation role of banks is the most studied function of banks[30]. One key reason for the widespread use of this approach is its ability to account for interest-related activities, distinguishing banks from any other firms (Ahn and Le, 2014). Also, this approach better assesses the effects of competition on a bank as a highly competitive bank would aim at minimising cost (particularly interest expense) in the provision of any given output (Ferrier and Lovell, 1990; Wheelock and Wilson, 1995). The intermediation approach is also preferred owing to the ease of accessing the data required for this approach. The monetary value of the input and output variables required is mostly readily available in published financial statements of banks (Ahn and Le, 2014).

Despite the benefits, the intermediation approach has two notable challenges. First, the treatment of deposits as an input variable only observes the role of deposits in producing loans. This disregards the relevance of services provided to depositors, including the operational costs incurred in the cash handling process. In addition, other output functions of deposits such as increasing liquidity, payments, and other safekeeping services are ignored. Finally, as mentioned earlier, the intermediation approach does not consider all the contemporary auxiliary roles played by banks. Inclusive to bridging the financing gap, banks now play significant roles in risk management by serving as insurers and monitors of credit risks (Ahn and Le, 2014). Consequently, in recent times, there have been significant reductions in interest-related activities as opposed to the non-interest-related activities of banks, demanding the evaluation of bank performance in respect of their new roles (Allen and Santomero, 2001).

Examples of recent studies that have used the intermediation approach are provided in the next chapter.

#### 3.3.3.2 *The Production Approach*

The production approach examines banks' performance in terms of operational activities and provision of auxiliary services such as transactions on deposit accounts, and preparation and maintenance of documents. Contrary to the intermediation approach, the production approach does not include interest expense in the assessment of efficiency. Rather, input variables considered under the production approach include physical factors (such as labour, materials, space, or information systems). Output variables include the number and type of transactions or documents processed over a given period (mostly represented by the number of deposits and loan accounts). Examples of studies that have used the production approach to estimate the efficiency of banks include Drake et al. (2006), Liu and Tone (2008) and Haralayya and Aithal (2021).

[30] For example, Aiello and Bonanno (2018), in reviewing approximately 120 papers published over the period 2000 to 2014, noted that over 50 percent of the papers reviewed used the intermediation approach.

Another difference between the production and intermediation approaches is observed in the measurement of variables. While the intermediation approach uses the monetary value of variables, the production approach focuses on the number of transactions or loan and deposit documents processed over a period.

Particularly, the production approach has gained credence for treating deposits as an output. According to Ahn and Le (2014), this treatment of deposits has earlier been justified by renowned researchers such as Longbrake (1974) and Hughes et al. (2001), who argued that deposits are better treated as outputs as depositors incur cost through interest spread in the bid to enjoy services such as safekeeping and liquidity. These researchers also argued that deposit-related activities utilise a significant amount of physical capital and labour which serve as inputs with the deposits being outputs. The production approach is described as a more reliable method for assessing the efficiency of banks' branches as branches have more control over customer documents other than funding and investment decisions (Berger and Humphrey, 1997). However, as a disadvantage, the production approach does not take into consideration the intermediary role played by banks between savers and borrowers. Since intermediation is seen as the primary function of a financial institution, avoidance of the assessment of this function significantly impairs the assessment of viability and efficiency of banks (Ahn and Le, 2014). Limitation in access to data on the number of transactions, accounts, etc. has negatively affected the application of the production function. In effect, this limitation heightens the need to approximate values, which in turn increases measurement error (Ahn and Le, 2014).

#### 3.3.3.3 *The User Cost Approach*

Developed by Hancook (1985, 1986, 1991), the user cost approach assesses the opportunity cost of holding a financial asset or liability over a period (Ahn and Le, 2014; Bhatia et al., 2018). Current studies that have used the user cost approach to measure the efficiency of banks are Djalilov and Piesse (2014) for banks in Central Asia and Humphrey (2020) for banks in the USA.

Specifically, to determine whether a variable is an input or output, the user cost approach examines the net contribution of a variable to bank revenue. For variables classified as assets, when the financial returns exceed the opportunity cost of funds, the variable is considered as an output. When the financial returns of the variable are lower than the opportunity cost of funds, it is an input. Similarly, for liability variables, when the financial costs are lower than their opportunity cost, the variable is output. Otherwise, when financial costs are higher than their opportunity cost, the variable is an input (Alber et al., 2019).

A key advantage of the user cost approach is the consideration of variables that look beyond interest payments. In effect, the user cost approach specifies variables that are of interest to shareholders, holistically assessing variables that are of economic benefit to the bank under consideration (Fixler and Zieschang, 1992). Variables examined, therefore, include factors such as reserve requirements, capital gains or loss, and deposit insurance rates (Ahn and Le, 2014). Despite this advantage, the calculation of the user cost is complex and requires data that is not readily available. Berger and Humphrey (1992) further argue that the complexities in the calculation of variables may result in measurement errors.

#### 3.3.3.4 *The Value-added Approach*

Like the user cost and production approach, the value-added approach is concerned with the multiplicity of roles played by banks. Particularly, the value-added approach assesses the economic value and cost of variables that contribute to the increase in the long-term competitiveness and not just the intermediation role of banks (Berger and Humphrey, 1992). This approach views deposits (time, savings, and demand) and loans as outputs owing to their contribution to value creation in the banking sector. Line items such as other earnings, including investment and government securities, are classified as outputs. Input variables include financial items such as purchased funds and non-financial items such as labour and physical capital (Ahn and Le, 2014).

An advantage of the value-added approach, as indicated earlier, is that it accommodates all the pertinent functions of the bank, be it intermediation, provision of services, profit maximisation, economic development, etc. (Grigorian and Manole, 2006). Also, the use of accounting data to estimate the value of the variables estimates the efficiency frontier more credible and valid (Ahn and Le, 2014). Recent studies that have used the value-added approach are Vidyarthi (2019) for banks in India, Samad (2018) for banks in Bangladesh.

Irrespective of the benefits of the value-added approach, it presents blurred assumptions in the selection of input and output variables. Even though all banking activities add value, the value-added approach only considers variables with significant value added as output factors. Variables identified as adding relatively less value are consequently defined as unimportant factors. The challenge, according to Ahn and Le (2014), is the ambiguity in determining the significance of the level of value added. Also, the value addition of variables differs per bank type, thus, the classification of input and output variables change per bank under consideration.

On the whole, researchers such as Berger and Humphrey (1997) and Dyson et al. (2001) argue that the different variable selection methods greatly influence the efficiency scores measured and the ranking of DMUs within a dataset. Ultimately, Cooper et al. (2007) claim that these varying selection techniques result in different interpretations of performance, complementing each other when similar results are obtained from varying selection techniques. These researchers claim that it is risky to rely on one model and more prudent and accurate for empirical research works to use more than one technique in the identification and measurement of input and output variables.

### 3.3.4 *Extensions to the Traditional DEA Models*

Despite the common use of the CCR and BCC models in the literature, there are certain limitations. In this section, we examine some limitations of traditional DEA techniques and discuss some selected modelling extensions that have attempted to mitigate these limitations.

#### 3.3.4.1 *Benchmarking – Metafrontiers*

The CCR and BCC models in estimating the efficiency scores of firms identify a group of best performers with which every inefficient DMU can be benchmarked for improvement. As a limitation, studies such as Talluri (2000) have noted that there may be differences in the operating practices and technologies between an inefficient DMU and the benchmarks identified by the traditional DEA techniques. This may be because some DMUs that form the frontier may not exist in reality, creating an inaccurate estimation of efficiencies. To overcome this limitation, researchers have instituted performance-based clustering methods for identifying the most appropriate benchmarks for comparison. In literature, these clusters are known as metafrontiers.

The metafrontier analysis is based on a DEA model that allows for comparison between varying groups of firms while considering any differences between the groups (Battese et al., 2004; Assaf and Matawie, 2010; Parsa, 2022). In effect, the metafrontier allows for the measurement of technical efficiencies of firms operating under different and comparable technologies and operational practices. Consequently, according to Assaf and Matawie (2010), this type of analysis gives rise to two efficiency measures: one that measures the distance of an input-output point of a DMU to that of a group frontier (basically known as the traditional measure of technical efficiency), and one that measures the distance between the group frontier and a meta frontier (known as the 'technology gap').

#### 3.3.4.2 *Assessment of Efficiency over time – Windows DEA Analysis*

As earlier indicated, the traditional DEA models are most appropriate for the analysis of a small sample sized dataset. To increase the discriminatory power between efficient and inefficient banks, Avkiran (2004) argues for a sample size larger than the product of the number of input and outputs. One way to increase the sample size of the dataset is by using the Windows DEA proposed by Charnes et al. in 1985.

Another challenge of the traditional DEA models is their inability to capture variations in efficiency over time (Talluri, 2000). To resolve this challenge, the window DEA is used. The windows DEA assesses the trend of efficiency scores of DMUs over varying periods by treating each DMU as a different entity in each period assessed. In effect, this method increases the discriminatory power of the DEA technique by creating sufficient observations from the dataset (Talluri, 2000; Avkiran, 2004; Halkos et al., 2014; Sengupta and De, 2020). For example, with a dataset of 20 banks and a window size of 3, the dataset will equate to 60 DMUs, increasing the discriminatory power of the dataset and creating enough observations to improve the accuracy of estimations and freedom of interpretation.

#### 3.3.4.3 *Sensitivity to Sampling Data and the Deterministic Behaviour of the Traditional Models – Bootstrap Technique*

To mitigate the impact a smaller sample dataset may have on the accuracy of efficiency estimates, Efron (1981) proposed the bootstrap technique (Murillo-Zamorano, 2004). This technique seeks to address the challenges emanating from the deterministic nature of the traditional DEA models by separating statistical noise from inefficiencies under the control of the agent (management). According to Simar and Wilson (1998), since the statistical estimation of the frontier is obtained from a fixed dataset, the corresponding results are prone to sampling variations originating either from miscalculations or omission of variables, thus the introduction of the bootstrap technique.

Bootstrap is implemented by repeatedly simulating the data-generating process to increase the dataset. This is usually done by resampling and applying the original estimator to each simulated sample so that resulting estimates mimic the sampling distribution of the original estimator (Simar and Wilson, 1998).

Notable studies that have used the bootstrap technique to assess the efficiency of banks include Ferrier and Hirschberg (1997), Sufian (2015), Alhassan and Tetteh (2017) and Khan and Gulati (2019).

#### 3.3.4.4 *The preciseness of Measurements of Variables – Stochastic DEA*

Stochastic DEA particularly seeks to solve the challenges that arise from the assumption that the values of all variables used are known with precision when applying traditional DEA models. Studies such as Cooper et al. (2000) and Khodabakhshi (2009) debunked this assumption, claiming that the data in a real application cannot be exactly measured. The researchers therefore suggested stochastic DEA as one of the measures to deal with the imprecision of data variables used in estimating the DEA efficiency scores.

In effect, stochastic DEA allows for the measurement of data and measurement error by incorporating stochastic features into the traditional DEA models (Kuah et al., 2010). In literature, the inclusion of stochastic features has been applied in various ways. Examples include the inclusion of probability or chance constraints in the traditional linear programming model (Cooper et al., 2002), the relaxation of the input combinations used in the estimation of efficiency (Khodabakhshi and Asgharian, 2009), and the incorporation of stochastic parameters to estimate the most productive scale size in DEA (Khodabakhshi, 2009). Examples of other studies that have used stochastic DEA are Tsionas (2020) and Wanke et al. (2019).

3.3.4.5 *The preciseness of Measurements of Variables – Fuzzy DEA*

Originally proposed by Cooper et al. (2000), Fuzzy DEA, like Stochastic DEA, seeks to solve the challenges associated with the imprecise nature of data used to measure efficiency. Specifically, for the banking sector, the relevance of Fuzzy DEA cannot be underestimated owing to the assumptions used in estimating the prices or values of input and output variables. For example, variables such as advances are rarely precise figures, possessing fuzzy characteristics, i.e. the price of these variables is heavily influenced by the subjective determination of risks attached to loans granted. Also, fluctuating interest rates impose fuzzy characteristics on variables such as investment incomes (Kumar et al., 2017).

To incorporate fuzzy features into the traditional DEA models, studies such as Sengupta (1992) considered fuzziness in both the objective and constraints used in the estimation of the traditional DEA models, Hougaard (2005) combined the scores of technical efficiency with other sources of information and Entani et al. (2002) proposed a model which consisted of ranges of efficiency scores obtained from the pessimistic and optimistic viewpoints.

Additional examples of studies that have used Fuzzy DEA include Kao and Liu (2000), Saati et al. (2002), Tlig and Hamed (2017), Nasseri et al. (2018) and Wanke et al. (2018, 2016).

Overall, despite the contribution of both stochastic DEA and fuzzy DEA, there are challenges with these new variations (Qin and Liu, 2010). Where data is known to be inaccurate, fuzzy or stochastic DEA may be appropriate. Should data be highly accurate, the traditional models are preferred.

3.3.4.6 *Omission of Undesirable variables – Introduction of the Slack-Based Variable*

As indicated in the earlier sections of this chapter, the most basic form of technical efficiency is computed by the ratio of inputs and outputs. When this ratio is converted into a linear program by the Charnes Cooper transformation technique (as in Model 1), the optimal objective value of $\psi$ is estimated to represent the ratio of inputs and outputs. In estimating the $\psi$, it is expected that the equation considers excesses in inputs and shortages in outputs, known as slacks or undesirable variables. For a situation where $\psi$ =1 and there is no slack, the DMU is seen as CCR efficient, otherwise a DMU with slacks is disadvantaged against the reference dataset (Tone, 2002). Unfortunately, for both the traditional CCR and BCC models, the slack variables are ignored. The absence of slack variables is noted to result in spurious estimations since, in most instances, undesirable and desirable inputs and outputs are used and produced at the same time during a production process (Tone, 2002; Yang and Pollitt, 2009). To resolve this challenge and account for all the variables used and produced in the production process, Tone (2002) proposed the Slack-Based Model (SBM), which sought to improve the accuracy of efficiency estimates and interpretation by considering both input and output excesses or shortages (slacks) in the traditional DEA models[31].

#### 3.3.4.7 *Accounting for Interlinking Activities within Firms – Network DEA, Network SBM DEA and Dynamic network DEA models*

Lastly as discussed in the introduction of this thesis, the traditional models (the CCR and BCC models) are noted to be black-box techniques that ignore the performance of interlinking activities within firms. To measure the efficiency of interlinking activities, Charnes et al. (1986) introduced the network DEA. Empirically, Charnes et al. (1986) used the network DEA to segregate and measure the performance of two key activities under the army recruitment process in the USA, with the output of the first stage treated as the input of the second stage. In effect Charnes et al. (1986) argued that the results from the network DEA were more meaningful and informative than the results obtained from the traditional black-box approach.

Following the adoption of the network DEA, Tone (2002, 2003) introduced the slack-based measure within the network DEA model, referring to this method as the network SBM model. Unlike the traditional models which assume proportional changes in input and output variables, the SBM introduces a slack variable into the equation, and allows for non-proportional changes in inputs and output variables (i.e. a non-radial method).

A disadvantage is that the basic network DEA focuses on a single period, ignoring the inter-linkages and carry-over activities between two or more consecutive periods. To address this challenge, Färe et al. (2007) introduced the dynamic DEA model which accounts for carry-over activities and enables the estimation of efficiency over a longer period. In effect, the dynamic network DEA model not only measures efficiency of individual processes or activities within a firm, but evaluates divisional efficiencies across time. Following the works of Färe et al. (2007), other researchers such as Chen (2009) and Tone and Tsutsui (2014) have used the network dynamic DEA.

[31] Detailed empirical discussions and modelling specifications of the SBM model are presented in the next chapter.

Tone and Tsutsui (2014) again used a slack-based measure in the dynamic network DEA, referring to their model as the dynamic network SBM. In this model, the authors defined linking activities as carry-overs and classified these carry-overs into desirable, undesirable, discretionary (fixed) and nondiscretionary (free)[32]. According to Tone and Tsutsui (2014), the desirable carry-overs refer to positive variables such as profit carried forward or income surplus that are transferred to the next period, while the undesirable carry-overs are the negative variables that reduce the earnings of a firm, such as loss carried forward, bad debt and dead stock.

Recent studies that have incorporated the slack-based measure within the dynamic network model are given in the next chapter.

### 3.4 *Conclusion*

Several studies have reviewed varying measurement techniques in order to estimate the efficiency of banks. Literature shows that the most common technique used is the DEA non-parametric measure which unlike the parametric measures discussed in this chapter, does not require any prior assumption in estimating efficiency frontiers, thus minimising subjectivity in estimations of performance scores. Also, the DEA, dissimilar to the parametric measures, is able to compare efficiency scores of each unit in the dataset and does not discriminate between variables used.

Therefore to mitigate errors arising from subjective analysis and allow this thesis compare efficiency on a bank-by-bank basis, this chapter selects the DEA non-parametric measure as the efficiency estimation method to be used for this thesis. We further described the basic models (CCR and BCC models) used in the estimation of efficiency scores under the DEA, and examined the methods used in selecting variables used for efficiency measurement. For the selection of variables, this chapter presented an overview of the various variable selection techniques proposed by Berger and Humphrey (1992), emphasising that the objective of a study and the data available played a significant role in the selection of variables.

Irrespective of the noted advantages of the basic DEA models, this chapter also highlighted some drawbacks which in recent times have necessitated the update of the CCR and BCC models. Key among the disadvantages is the overestimation of firm inefficiencies by the CCR and BCC models as these methods do not segregate statistical noise from actual inefficiencies. Also, it was argued that there may be statistical errors when small sample sizes are used to estimate the basic DEA efficiency scores, and additionally, the basic DEA models are criticised for not accounting for the interlinkages between activities in an operational procedure.

[32] Detailed empirical discussions and modelling specifications of the dynamic network SBM DEA model are presented in the next chapter.

Based on the observed disadvantages, the chapter further presented a concise review and justification of some extensions that have sought to resolve some identified limitations of the traditional DEA models. The extensions discussed in this chapter do not represent all the modifications of the traditional DEA models but are representative of recent and current revisions.

Given the extensions to the traditional DEA models, the next chapter, Chapter 4, uses the SBM Network Dynamic DEA model and the bootstrap black-box approach (both the CCR and BCC) to estimate the technical efficiency of 18 commercial banks in Ghana. Chapter 4 also reviews empirical studies that have used the SBM, network dynamic DEA and the bootstrap black-box approach to review the efficiency of banks.

# CHAPTER 4

# EFFICIENCY OF BANKS IN GHANA: EMPIRICAL EVIDENCE FROM THE SBM NETWORK DYNAMIC MODEL AND THE BOOTSTRAP BLACK BOX APPROACH

## 4.1 *Introduction*

Considering the nature of service provided by the banking sector, and the error that may arise from the size of the data set used in this thesis, this chapter proposed the use of the black-box bootstrap technique and the network DEA structures to measure the efficiency of 18 commercial banks in Ghana. This study is currently the only study in Ghana that estimates and compares efficiency scores of banks from both the traditional black-box approach and the dynamic network DEA. It is also the only study that uses the three-stage dynamic network DEA to measure the efficiency of banks in Ghana.

Overtime, most studies in Ghana that have researched bank efficiency have adopted only the traditional black-box approach. By using just the black box approach, the existing studies ignore the multiple functions of a bank and assumes that banks play one particular role. However, as discussed earlier, banks have a network structure, such that their services offered to customers are produced in sub-processes which have intermediate outputs that feed as inputs into other sub-processes (Liu and Tone, 2008; Huang et al., 2014). Therefore, to evaluate bank efficiency, it is necessary to move away from the black-box approach to a model that can simultaneously evaluate the efficiency of multiple roles within banks.

Two most cited studies that have attempted to examine the efficiency of the multiple roles played by banks in Ghana are Zhou et al. (2018) and Appiahene et al. (2019)[33]. This study however differs from Zhou et al. (2018) and Appiahene (2019) by extending the subprocesses examined from two to three. Whereas Zhou et al. (2018) used the two-stage network DEA to assess the efficiency of the production and profitability activities in a bank, and Appiahene (2019) focused on activities concerning the management of IT cost and conversion of deposits to loans and profits, this study assesses the efficiency of three subprocesses of commercial banks in Ghana.

First of all, we assess the efficiency of banks in collecting deposits from customers (stage 1 – production). Second, we evaluate how efficient banks are in using deposits to provide loans to clients and invest in other securities while minimising bad loans (stage 2 – intermediation), and finally, the study measures the efficiency of generating income from loans and investments in the

[33] Details of these works are provided in the literature review session of this chapter (Section 4.2).

form (stage 3 – revenue generation). Such an analysis will be of significant interest for both theoretical and practical purposes for countries in developing economies.

To estimate efficiency scores under both the black-box and dynamic network DEA approaches, efficiency is decomposed into the overall technical, scale, and pure technical efficiencies. The overall technical efficiency assesses the efficiency of transforming inputs into outputs while pure technical efficiency evaluates management efficiency and scale efficiency captures the effect of size on efficiency.

Overall, the computation of and comparison between the results obtained from the black box and the dynamic network DEA approaches and the various types of efficiencies under both approaches (technical, pure technical, and scale efficiencies) provide in-depth insight into the efficiency of banks in Ghana. Such analysis further enhances empirical evidence on the efficiency of the network structure of commercial banks, particularly in developing countries.

To attain the objectives of this chapter, Section 4.2 below presents an extensive review of empirical studies that have used the DEA approach (particularly the traditional models, bootstrap technique, and the network DEA) to evaluate the efficiency of banks. Section 4.3 describes the models used to estimation, Section 4.4 discusses the empirical results and Section 4.5 concludes the chapter with policy implications and recommendations.

## 4.2 *Literature Review*

This section discusses the methodology and findings of notable empirical studies that have used the DEA technique to measure the efficiency of banks. The section particularly focuses on studies that have used the traditional DEA approaches (i.e. the CCR and BCC), the slack-based measure, the bootstrap technique, and the dynamic network DEA to assess the efficiency of banks. The literature reviewed is further categorised into studies within and outside the African region.

### 4.2.1 *Evidence on the DEA Application on Banks outside the African Region*

#### 4.2.1.1 *Using the Traditional Black Box Approaches to Assess Technical Efficiency*

The first application of DEA in the banking sector can be traced back to the study of Sherman and Gold (1985), who used the CCR DEA model to assess the technical efficiency of 14 branches of a bank in the USA. To select the variables used in estimating the model, Sherman, and Gold (1985) used the production variable selection technique, choosing three input variables (labour, office space, and supply costs) and one output variable (number of transactions processed). The researchers measured average efficiency scores ranging from 0.78 to 1 and concluded that out of the 14 branches assessed, only six operated efficiently.

Ultimately, the claim of Sherman and Gold (1985) that the DEA model provides better insight into the performance of firms than the other methods of evaluating performance, informed the use of the DEA model by other researchers. Table 4.1 provides a summary of additional studies that have used the black-box DEA approach to study the efficiency of banks globally.

In the North American region, the DEA model has increasingly been used to assess the efficiency of bank branches and banks as a whole. Examples of some of the most cited studies in this regard include Parkan (1987), Rangan et al. (1988), Aly et al. (1990), Ferrier and Lovell (1990) and Miller and Noulas (1996).

Specifically, Parkan (1987), another early use of DEA, used the traditional DEA method (CCR) and the intermediation variable selection technique to evaluate the efficiency of 35 branches of a Canadian bank. Parkan employed six input and six output variables. Input variables were total authorised Full-Time Equivalent (FTE), annual rent, quality of customer service space ranking, telephone and stationery expenses, number of online terminals, and marketing activity ranking. Output variables were the number of transactions, commercial account openings, retail account openings, number of loan applications, customer service survey rating, and number of corrections. Efficiency scores of DMUs assessed ranged from 0.882 to 0.975. Considering the pertinent role played by deposits in the intermediation process, a distinct gap in Parkan's study is the absence of deposits as either an input or output variable.

Rangan et al. (1988) treated deposits as outputs and used the CCR and BCC DEA models to estimate the efficiency scores of 215 banks in the USA. The researchers used three inputs (capital, labour, and purchased funds) and five outputs (real estate loans, commercial and industrial loans, consumer loans, demand deposits, and time and savings deposits) to estimate technical efficiency scores. The researchers observed an average technical efficiency score of 0.70, pure technical score of 0.72, and scale efficiency of 0.97. In this study, however, the treatment of deposits solely as an output variable ignores the role deposits play in the generation of loans, largely ignoring the intermediation role of banks.

Similar to the study of Rangan et al. (1988), Aly et al. (1990) and Ferrier and Lovell (1990) also used deposits as an output variable in their assessment of bank efficiency in the USA. Aly et al. (1990) employed the intermediation approach, using the value of deposits, while Ferrier and Lovell (1990) employed the production approach, using the number of deposit accounts. In detail, Aly et al. (1990) used three input variables (labour, capital, and loanable funds) and five output variables (real estate loans, commercial and industrial loans, consumer loans, all other loans, and demand deposits) to ascertain the technical, pure technical and scale efficiencies of 322 banks in the USA for the year 1986. The researchers measured technical and pure technical efficiency scores that ranged from 0.22 to 1.00. Scale efficiency had a higher minimum value of 0.70 and a maximum score of 1. Ferrier and Lovell (1990) also used three input variables and five output variables (Table 4.1). to measure the pure technical efficiency scores of banks in the USA for the year 1984 using the BCC DEA model. The minimum efficiency scores of banks assessed were higher than those observed by Aly et al. (1990), with scores ranging from 0.75 to 0.98.

Miller and Noulas (1996) used deposits as input variables to evaluate the technical efficiency of banks in the USA. Using the intermediation variable selection technique, the authors considered four input variables (total transaction deposits, total non-transaction deposits, total interest expense, and total non-interest expense) and six output variables (commercial and industrial loans, consumer loans, real estate loans, investments, total interest income, and total non-interest income). They reported relatively lower efficiency scores than most studies that have used the black-box approach to study bank efficiency in the USA, recording a minimum technical efficiency score of 0.38, pure technical efficiency score of 0.51, and scale efficiency of 0.73. However, the treatment of deposits solely as an input variable raises doubts regarding the accuracy and completeness of efficiency estimates as services offered to depositors (which are ultimately treated as outputs) are ignored.

In Europe, notable studies that have used the black-box approach to assess the technical efficiency of banks include Giokas (1991), Berg et al. (1992), Jackson and Fethi (2000) and Casu and Molyneux (2003).

Like Parkan (1987), Giokas (1991) used the DEA model to measure the efficiency of 17 bank branches in Greece. In this study, the results of the CCR model gave indications of the overall technical and scale efficiencies, while the BCC model provided information on the pure technical efficiency of branches assessed. To select the variables used in the estimation model, Giokas (1991) employed the production approach with three input variables (labour, operating expenses, and utilised branch space) and four output variables (number of transactions performed by section of deposits and capital transfers, number of transactions performed by section of credit, number of transactions performed by section of foreign receipts, and number of transactions performed by each branch). Overall, the author noted efficiency scores ranging from 0.57 to 1.00 for the CCR model and 0.66 to 1.00 for the BCC model. Again, by using the production variable selection technique and ignoring the role deposits play as an input variable, Giokas (1991) did not cater for the intermediation role of banks.

Another notable study in Europe is that of Berg et al. (1992). This study, which is one of the few to use the value-added variable selection technique, assessed the efficiency of 152 banks in Norway from 1980 to 1988, using both CRS and VRS returns to scale. In this study, the authors used labour and materials[34] as inputs and loans[35] and deposits as outputs, again ignoring the role deposits play in the intermediation process of banks. In conclusion, Berg et al. (1992) observed efficiency scores ranging from 0.53 to 0.78 for the VRS assumption to scale and 0.50 to 0.69 under the CRS assumption to scale. Berg et al. (1992) were one of the earliest studies to include a negative variable in the estimation of bank efficiency. They introduced loan losses (or NPLs) as an output variable. They found little impact from the inclusion of this variable, observing that efficiency scores reduced only slightly when loan losses were introduced. They attributed the negligible impact of loan losses to the fact that most fully efficient banks did not have large losses in the years under consideration.

Jackson and Fethi (2000) also used the CCR and BCC models to assess the efficiency of Turkish banks in 1998. Similar to Berg et al. (1992), these researchers used the value-added approach in the selection of variables, employing two input variables (number of employees and the sum of non-labour operating expense (x), direct expenditure on buildings and amortisation expenses (x2) and three output variables (loans, demand deposit, and time deposit). Jackson and Fethi (2000) observed that under the CRS assumption, banks reported efficiency scores ranging from 0.14 to 1.00, whereas under the VRS assumption, efficiency scores ranged from 0.37 to 1.00.

Casu and Molyneux (2003) employed DEA to investigate the trend of changes in efficiency from 1993 to 1997. This study specifically assessed the performance of banks in France, Germany, Italy, Spain, and the United Kingdom. The authors concluded that over the years, the efficiency of banks assessed has been relatively low, although there was a marginal improvement over the period of analysis, except in Italy.

Effectively, the claim of the relative superiority of the DEA methodology against other methods of bank performance assessment is not restricted to only the North American and European areas: several studies that have used the DEA model to assess the efficiency of banks in the Asian and Middle Eastern regions. The most cited studies include Bhattacharyya et al. (1997), Mukherjee et al. (2002), Fukuyama et al. (1999), Rezvanian and Mehdian (2002) and Ariss et al. (2007).

Bhattacharyya et al. (1997) used the black-box CCR DEA model to assess the technical efficiency of banks in India from 1996 to 1999. The study further used the DEA black-box model to distinguish the performance of banks categorised as foreign, privately owned, and public owned. By employing the value-added variable selection technique, the researchers used two inputs (interest expense and operating expense) and three outputs (advances, deposits, and investments) in their model. As

[34] This is measured by the operating expense by the material price index.
[35] This is represented by long- and short-term loans and negative loan losses.

empirical findings, Bhattacharyya et al. (1997) observed that the mean scores of all banks assessed were 0.80 (for all banks), 0.76 (for private banks), 0.87 (for public banks), and 0.75 (for foreign banks).

Mukherjee et al. (2002) also used the CCR DEA model to assess the technical efficiency of banks in India from 1996 to 1999, again distinguishing between scores per ownership type. The authors used the intermediation variable selection technique, selecting five inputs and output variables respectively in the model used. Deposits were again treated as an output variable and not an input variable. In conclusion, this study observed average efficiency scores of 0.75 for all banks assessed, 0.85 for private banks, 0.86 for public banks, and 0.93 for foreign banks.

Fukuyama et al. (1999) also used the CCR and BCC DEA models to assess the efficiency of cooperative banks in Japan from 1992 to 1996. The authors used the intermediation variable selection technique with three inputs (labour, capital, and deposits) and two outputs (loans and security investments). This study found that the technical efficiency of the banks assessed was mainly driven by improved managerial capabilities measured by pure technical efficiency. In effect, the authors observed efficiency scores ranging from 0.36 to 0.62 for overall technical efficiency, 0.27 to 0.44 for pure technical efficiency, and 0.04 to 0.16 for scale efficiency. As a gap, the deposit variable was only treated as an input variable and not as an output.

In Singapore, Rezvanian and Mehdian (2002) used both the CCR and BCC DEA models to assess the efficiency of banks from 1991 to 1997. Employing the intermediation variable selection technique, the authors included two inputs (borrowed funds, and other inputs (labour and capital)) and three outputs (total loans, securities, and other earning assets) in their estimation model.Unlike Fukuyama et al. (1999), who found pure technical efficiency to be driving overall technical efficiency, Rezvanian and Mehdian (2002) observed that scale efficiency drives the overall technical efficiency of banks in Singapore. This study reported overall technical efficiency and pure technical scores ranging from 0.44 to 1 respectively, while scale efficiency ranged from 0.67 to 1.

For the Middle Eastern region, Ariss et al. (2007) is one of the most cited studies. This study used the CCR and BCC models and the intermediation variable selection technique to assess the efficiency of six Gulf Cooperation Council (GCC) countries. This study used borrowed funds, labour, and fixed assets as inputs and net loans, securities, and other earnings as outputs. Similar to the works of Rezvanian and Mehdian (2002), Ariss et al. (2007) observed that overall technical efficiency was mainly driven by scale efficiency. Overall technical efficiency ranged from 0.85 to 0.90, pure technical efficiency from 0.90 to 0.94, and scale efficiency from 0.93 to 0.96.

Overall, most studies outside the African region that have employed the traditional DEA approach (i.e. the CCR and BCC models) used bank data in the 1990s or early 2000s. However, in the empirical Table 4.1 below, we present examples such as Mohapatra et al. (2019) and Tamatam et al. (2019) as recent examples of studies (using data as at 2017) that have used traditional DEA to assess the efficiency of banks in the Asian region, specifically, India. These studies employed other modern methodologies of DEA and are interested in comparing the results from traditional DEA with that of the current methods under DEA.

This implies that most studies in these regions that have used recent data have evolved from the traditional approach. Also, most studies reviewed have treated deposits as either inputs or outputs and rarely as both inputs and outputs. The use of deposits in this regard rarely resolves the dispute on how to treat deposits and provides little indication of the contribution of deposits as both inputs and outputs in the bank's production process.

*Table 4.1: Summary of Studies that have used the Traditional Black-Box Approach to Estimate the Efficiency of Banks: Outside the African Region*

| **Author** | **Country** | **Time Period** | **DEA Model** | **Selection Approach (input/output)** | **Input Variable** | **Output Variable** | **Range of Efficiency Scores** |
|---|---|---|---|---|---|---|---|
| Sherman & Gold (1985) | USA | Varying time periods | CCR DEA | Production | Labour, office space and supply costs | Number of transactions processed | TE 0.782 to 1.00 |
| Parkan (1987) | Canada | Varying time periods | CCR DEA | Intermediation | Total authorised FTE, annual rent, quality of customer service space ranking, telephone/stationery expenses, number of on-line terminal and marketing activity ranking | Number of transactions, commercial account openings, retail account openings, number of loan applications, customer service survey rating and number of corrections | TE 0.882 to 0.975 |
| Rangan et al. (1988) | USA | 1986 | CCR and BCC DEA | Intermediation | Labour, capital and purchased funds | Real estate loans, commercial and industrial loans, consumer loans, time deposits, and demand deposits | Mean scores:<br>TE 0.70<br>PTE 0.72<br>SE 0.97 |
| Aly et al. (1990) | USA | 1986 | CCR and BCC DEA | Intermediation | Labour, capital and loanable funds | Real estate loans, commercial and industrial loans, consumer loans, all other loans, and demand deposits | TE 0.22 to 1.00<br>PTE 0.22 to 1.00<br>SE 0.70 to 1.00 |
| Ferrier & Lovell (1990) | USA | 1984 | BCC DEA | Production | Total number of employees, occupancy costs and expenditure on furniture and equipment, expenditure on materials. | Number of demand deposit accounts, number of time deposit accounts, number of real estate loans, number of instalment loans, number of commercial loans. | PTE 0.75 to 0.98 |
| Giokas (1991) | Greece | 1988 | CCR and BCC DEA | Production | Labour, operating expenses, utilised branch space | Number of transactions performed by section of deposits and capital transfers, number of transactions performed by section of credit, number of transactions performed by section of foreign receipts, number of transactions performed by each branch. | CCR 0.57 to 1.00<br>BCC 0.66 to 1.00 |
| Berg et al. (1992) | Norway | 1980–1989 | CCR and BCC DEA | Value added approach | Labour and capital | Deposits and loans | VRS 0.53 to 0.78<br>CRS 0.50 to 0.69 |
| Zaim (1995) | Turkey | 1981 and 1990 | CCR and BCC DEA | Intermediation | Total number of employees, total interest expenditures, depreciation | Demand deposits, time deposits, short-term loans, long-term loans | Average scores 1981:<br>CRS 0.81<br>VRS 0.83 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | | | expenditures, expenditures on materials | | NIRS 0.83<br>Average scores 1990:<br>CRS 0.91<br>VRS 0.94<br>NIRS 0.93 |
| Miller & Noulas (1996) | USA | 1984–1990 | CCR and BCC DEA | Intermediation | Total transactions deposits, total non-transactions deposits, total interest expense and total non-interest expense | Commercial and industrial loans, consumer loans, real estate loans, investments, total interest income, and total non-interest income | TE 0.38 to 1.00<br>PTE 0.51 to 1.00<br>SE 0.73 to 1.00 |
| Pastor et al. (1997) | Europe and USA | 1992 | CCR and BCC DEA | Value added | Interest and non-interest income | Loans and deposits. | CRS 0.49 (UK) to 0.72 (Spain)<br>VRS 0.54 (UK) to 0.83 (Italy)<br>SE 0.77 (Austria) to 0.99 (France) |
| Bhattacharyya et al. (1997) | India | 1986–1991 | CCR DEA | Value added | Interest expense and operating expense | Advances, deposits and investments | Mean scores:<br>0.80 (for all banks)<br>0.76 (for private banks)<br>0.87 (for public banks)<br>0.75 (for foreign banks) |
| Fukuyama et al. (1999) | Japan | 1992–1996 | CCR and BCC DEA | Intermediation (asset approach) | Labour, capital and deposits | Loans and security investment | TE 0.36 to 0.62<br>PTE 0.27 to 0.44<br>SE 0.04 to 0.16 |
| Jackson & Fethi (2000) | Turkey | 1998 | CCR and BCC DEA | Value added | Number of employees and the sum of non-labour operating expense, direct expenditure on buildings and amortisation expenses | Loans, demand deposit and time deposit | CRS 0.14 to 1.00<br>VRS 0.37 to 1.00 |
| Mukherjee et al. (2002) | India | 1996–1999 | CCR DEA | Intermediation | Net worth of the banks, borrowings of the banks, operating expenses, number of employees and number of bank branches | Deposits, net profits, advances, non-interest income and interest spread | Mean scores:<br>0.75 (for all banks)<br>0.85 (for private banks)<br>0.86 (for public banks)<br>0.93 (for foreign banks) |
| Jemric & Vujcic (2002) | Croatia | 1995–2000 | CCR and BCC DEA | Operating and intermediation approaches | Operating approach:<br>Labour-related administrative costs, capital-related administrative costs<br>Intermediation approach:<br>Fixed assets and software, number of employees, total deposits | Operating approach:<br>Output – interest and related revenues, noninterest revenue<br><br>Intermediation approach:<br>Output – total loans extended, short term securities | Operating approach:<br>CCR 0.45 to 0.79<br>BCC 0.78 to 0.87<br>Intermediation approach:<br>CCR 0.34 to 0.63<br>BCC 0.60 to 0.75 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Rezvanian et al. (2002) | Singapore | 1991–1997 | CCR and BCC DEA | Intermediation | Borrowed funds and other inputs (labour and capital) | Total loans, securities and other earning assets | TE 0.44 to 1.00<br>PTE 0.44 to 1.00<br>SE 0.67 to 1.00 |
| Grigorian & Manole (2006) | Bahrain | 1997–2003 | CCR and BCC DEA | Production | Personnel expenditure, fixed asset and interest expense | Interest and non-interest income, net loans and liquid assets | Conventional Banks:<br>TE 0.33 to 1.00<br>PTE 0.43 to 1.00<br>SE 0.50 to 1.00<br>Islamic Banks:<br>TE 0.30 to 1.00<br>PTE 0.37 to 1.00<br>SE 0.57 to 1.00 |
| Mehdian et al. (2007) | USA | 1990 and 2003 | CCR and BCC DEA | N/A | Number of full-time employees, capital, and borrowed funds | Commercial and industrial loans, real estate loans, other loans, and securities. | TE 0.58 to 1.00<br>PTE 0.62 to 1.00<br>SE 0.67 to 1.00 |
| Ariss et al. (2008) | Middle East (GCC countries) | 1999–2004 | CCR and BCC DEA | Intermediation | Borrowed funds, labour and fixed assets | Net loans, securities and other earnings | TE 0.85 to 0.90<br>PTE 0.90 to 0.94<br>SE 0.93 to 0.96 |
| Titko et al. (2014) | Latvia | 2012 | BCC DEA model | Intermediation | Deposits from customers, balances due to credit institutions and interest expense | Interest income, net interest income or interest margin | 0.060 to 1.00 |
| Řepková (2015) | Czech Republic | 2001–2012 | CCR and BCC DEA | Intermediation | Labour and deposits | Loans and net interest income | BCC model 0.85 to 0.97<br>CCR model 0.61 to 0.90 |
| Mohapatra et al. (2019) | India | 2011–2015 | CCR and BCC DEA | Intermediation and production approaches | Labour, equity capital, debt capital | Investment assets, loan assets and income | BCC model 0.99 to 0.99<br>CCR model 0.97 to 0.99 |
| Tamatam et al. (2019) | India | 2008–2017 | CCR and BCC DEA | Intermediation | Total assets and total deposits | Advances, interest income, total income and operating profit | TE 0.83 to 1.00<br>PTE 0.85 to 1.00<br>SE 0.94 to 1.00 |

Note: BCC*– Banker, Charnes and Cooper, CCR*– Charnes, Cooper and Rhodes, TE – Overall Technical Efficiency, PTE* – Pure Technical Efficiency, SE*– Scale Efficiency

#### 4.2.1.2 *Using the New DEA models to Assess Technical Efficiency*

##### 4.2.1.2.1 *The Bootstrap DEA model*

As discussed in Chapter 3 of this thesis, the traditional DEA model, although largely used for the estimation of banking sector efficiency, produces biased efficiency scores, therefore the bootstrap technique is used.

Following the first empirical application of the bootstrap technique by Simar and Wilson (1998), several other studies, particularly in more developed countries, have combined the bootstrap technique and traditional DEA models to assess the performance of banks.

Assaf et al. (2011) used the bootstrap DEA technique VRS model to assess the efficiency of nine Saudi banks. The model used three input and three output variables (Table 4.2). These researchers observed lower efficiency scores when the bootstrap technique was applied. The average bootstrap scores ranged from 0.78 to 0.92 while the traditional models without the bootstrap technique ranged from an average of 0.82 to 0.97. This discrepancy in scores indicates the sensitivity of the dataset used to sampling variations.

In Australia, Moradi-Motlagh and Saleh (2014) re-examined the technical efficiency of banks using the DEA bootstrap approach and data from 1997 to 2005. Unlike studies like Ferrier and Hirschberg (1997) who modelled only the CRS assumption (CCR model), and Assaf et al. (2011) who only estimated scores under the VRS assumption (BCC model), this study used the bootstrap technique on both the CCR and BCC models, evaluating technical, pure technical and scale efficiencies by employing two inputs (interest expense and non-interest expense), and two outputs (interest income and non-interest income). The results obtained from this study were compared to the results of Paul and Kourouche (2008) who did not use the bootstrapping technique but assessed the same banks in the same period. In effect, comparing the traditional and bootstrap results showed the sensitivity of the efficiency scores of some Australian banks to sampling variation, questioning the accuracy of estimations derived from the traditional models. For example, Moradi-Motlagh and Saleh (2014) observed lower efficiency scores when the bootstrapping technique was used. Pure technical efficiency scores averaged 0.96 (ranging from 0.88 to 1.00), which is 2 percent less than the average score derived from the traditional DEA model. Also, the scale efficiency scores ranged from 0.89 to 1.00 and overall technical efficiency scores ranged from 0.83 to 1.00.

Other key studies that have used the bootstrap technique to estimate the efficiency of banks outside the African region include Sufian (2015) for banks in Malaysia, Matthews (2010) for banks in Pakistan, and Li et al. (2020) for commercial banks in China (Table 4.2).

Overall, most studies that have compared efficiency estimates from various DEA models have observed that the traditional DEA method without the bootstrap technique overestimates efficiency scores (Li et al., 2020). The overestimation of scores presents challenges in policy development as banks may be perceived to be performing better than they actually are.

#### 4.2.1.2.2 *Network DEA / Dynamic Network DEA*

Most empirical studies in recent times have used the network DEA or the dynamic network DEA to assess the efficiency of banks. As earlier indicated, these models have been used to evaluate the linkages between processes and divisional units within banks in a period or across periods (Färe et al., 2007).

Over time, existing studies have classified the network or dynamic network DEA models into either a closed system model or an open system model. In the closed-system DEA model, all the outputs of the preceding stage are treated as inputs in the subsequent stage, whereas in the open system DEA model, the outputs of the preceding stage are partial inputs in the subsequent stage. Following this classification of models, most studies have further employed a two-stage or three-stage approach when using the network or dynamic network models.

In the banking sector, most studies that have modelled the two-stage network analysis have depended on the closed system DEA, while most that have modelled the three-stage network analysis have used the open system DEA. Particularly, the two-stage closed network DEA system has been mostly used by researchers to address the challenges perceived in the treatment of deposits, i.e., whether deposits are an input variable or an output variable.

By using the two-stage closed DEA network model, the deposit is treated as an output in the first stage and an input in the second stage (Fukuyama and Matousek, 2017; Fukuyama and Weber, 2015). Other studies that have applied the two-stage closed network DEA model, as earlier indicated, have sought to disaggregate the production model of banks into sub-processes and divisions to provide a more accurate estimation of efficiency (Seiford and Zhu, 1999; Wang et al., 1997; Fukuyama and Matousek, 2011; Matthews, 2013).

A key example of a study that used the two-stage closed network DEA model is Seiford and Zhu (1999), who used a two-stage network DEA approach to examine the marketability and profitability of 55 banks in the USA for 1995. For the profitability stages, the authors used employee costs, assets, and stockholders’ equity to generate interlinking variables such as revenue and profits. The marketability stage used the interlinking variables (i.e., revenue and profit) to generate market value, total return to investors, and earnings per share. In conclusion, Seiford and Zhu (1999) observed that the profitability stage of the banks was more efficient than the marketability stage. In the profitability stage, technical efficiency measured by the CCR model ranged from 0.60 to 1.00 while the results modelled by the BCC technique ranged from 0.62 to 1.00, while the marketability stage showed reduced technical efficiency scores ranging from 0.45 to 1.00 for the CCR model and 0.59 to 1.00 for the BCC model.

Another example of a study that used the two-stage closed network DEA is Fukuyama and Matousek (2011), who used data from 1991 to 2007 to compare the efficiency of Turkish banks obtained from both the black-box approach and the network DEA model. In this study, labour and capital were used as input variables, loans and securities as output variables, and deposits as intermediate outputs or links from the first to the second stage. The authors found that efficiency scores obtained from the black box model were significantly higher than those observed from the network DEA model. Scores derived from the traditional models ranged from 0.55 to 0.85 while those from the network DEA model ranged from 0.39 to 0.70.

Fukuyama and Weber (2010) in the evaluation of bank performance in Japan from 2000 to 2006 presented a new dimension to the use of the two-stage closed network DEA. This study included in its model a slack variable (NPLs) and compared the results of the model with and without the slack variable. To account for the two stages, the study first assessed the efficiency of banks in converting labour, physical capital, and equity into raised funds, and secondly, the efficiency of banks in using the raised funds to generate loans, securities investments, other business activities, and NPLs. Fukuyama and Weber (2010) concluded that inefficiency estimates are more when slack variables are ignored. They further observed that with the inclusion of NPLs as outputs in the second stage, performance in the first stage exceeded that of the second stage. Technical efficiency scores ranged from 0.31 to 0.73 in the first stage and from 0.24 to 0.56 in the second stage.

Several other research works have attempted to use the two-stage network analysis to evaluate the performance of banks. Some notable studies include Wang et al. (1997) who evaluated the effect of Information Technology (IT) on bank performance, and Wanke and Barros (2014), who assessed the cost and production efficiency processes of banks in Brazil (Table 4.2).

Regarding the three-stage analysis, a key research work that has used the three-stage network DEA is that of Matthews (2013), who used the three-stage open system network analysis to evaluate risk management and managerial efficiency in Chinese banks. To evaluate the performance of management, in the first stage the author used operational cost and fixed assets to generate personnel cost and other operating costs. The outputs of the first stage were used as inputs to determine the number of branches, the interest cost, and non-interest earning income. In the third stage, the outputs from the second stage – number of branches, interest cost and NPLs were used to generate the final output, i.e., interest income. Efficiency measured for the second stage was the highest at an average of 0.64, implying that banks assessed performed better at turning deposits and operational cost into an increased number of branches and non-interest earning income, although interest cost was also generated at this stage. Efficiency estimates for the first stage ranged from 0.22 to 0.90, while those for the second and third stages ranged from 0.01 to 1.00 respectively. Overall, Matthews (2013) argued that the network DEA better reveals the sources of inefficiencies.

Nevertheless, as indicated in Chapter 3 of this thesis, the network DEA model is unable to assess efficiency across periods or to measure efficiency changes over time. To resolve this challenge, several studies have used the dynamic network DEA. This model runs under the assumption that certain intermediate products used by a DMU in a current period may affect output in a future period. In the banking sector, examples of notable studies that have used the dynamic network DEA model include Akther et al. (2013), Avkiran (2015), Fukuyama and Matousek (2017) and Dia et al. (2020).

Akther et al. (2013) assessed the performance of banks in Bangladesh and developed and compared efficiency estimates from a two-stage dynamic network DEA SBM model with those of a black box SBM model. The authors considered labour, physical capital, and equity capital as inputs in the first stage which produced the intermediate product, deposits. In the second stage, deposits were used to generate loans, securities, and NPLs (which are considered bad input for the next period). To conclude, Akther et al. (2013) observed that the results from the black-box approach and the network dynamic model were not aligned. Technical efficiency estimates from the black-box model were much higher, ranging from 0.88 to 0.93, while those from the network dynamic DEA model ranged from 0.20 to 0.65.

Similarly, Avkiran (2015) developed a non-oriented two-stage dynamic network slack-based model using the BCC assumption. The authors evaluated performance under interest and non-interest-bearing operations and treated the variable (number of referrals) as an intermediate product across periods. Although averagely, efficiency estimates by foreign banks under the non-interest-bearing operation exceeded those of domestic banks, and those of domestic banks under the interest-bearing operation exceeded those of foreign banks, results obtained for both stages assessed found no significant difference between efficiency estimates produced by foreign and domestic banks in China.

Fukuyama and Matousek (2017) estimated the performance of Japanese banks across varying periods, assessing the technical efficiency of regional banks in Japan from 2001 to 2013 by disaggregating the bank processes into two stages: the fundraising and loan and investment processes. For stage 1, the fundraising stage, Fukuyama and Matousek (2017) used the input variables (labour cost and capital) to produce deposit (the intermediate product). They then used deposits in stage 2 (the loan and investment stage) to produce loans (classified as a good output) and NPLs (classified as a bad carry-over). On the whole, the researchers concluded that regional banks in Japan have not attained optimal levels in their production and revenue generation processes. The technical efficiency of the fundraising stage ranged from 0.73 to 0.83, while that for the loan and investment stage ranged from 0.74 to 0.80. The authors further juxtaposed efficiency estimates derived from models that included or excluded the variable NPLs. The authors observed that the gaps between optimal and actual performance levels reduced, even becoming positive when NPLs were included in the model. This finding confirms the positive effect of the restructuring process undertaken in the early 2000s on the performance of banks and the reduction of NPLs in Japan.

In terms of the application of the dynamic network model within a three-stage system, Dia et al. (2020) used both the bootstrap black-box DEA and bootstrap Dynamic Network DEA model to assess the efficiency of credit institutions in Canada. The authors assessed the production, intermediation, and revenue generation stages. Deposits were used as an intermediate product from the production stage to the intermediation stage, while loans, securities, and impaired loans were used as intermediate products from the intermediation stage to the revenue generation stage. The final output of the revenue generation stage included interest income and non-interest income. The authors observed that efficiency scores estimated by the black-box model were significantly higher than those of the dynamic network model. Within the network structure, the production stage was found to be more efficient, with scale efficiency being the highest (Table 4.2).

To summarise this section, Table 4.2 below summarises the findings of most studies outside the African region that have used the new DEA models, specifically the bootstrap technique and the network or dynamic network DEA.

*Table 4.2: Summary of Studies that have used the Bootstrap Technique, the Network or the Dynamic Network DEA model to Estimate the Efficiency of Banks – Outside the African Region*

| **Author** | **Country** | **Time Period** | **DEA Model** | **Input Variable** | **Output Variable** | **Efficiency Scores** |
|---|---|---|---|---|---|---|
| **Studies with Bootstrap Technique** | | | | | | |
| Ferrier & Hirschberg (1997) | Italy | 1986 | Bootstrap DEA technique and traditional DEA model – CCR model | Capital, consumer deposit accounts, commercial deposit accounts, industrial deposit accounts and number of employees. | Loans (industrial, consumer and commercial), deposits at other financial institutions and investments and the number of branches | Traditional Model:<br>TE 0.87 -1.00<br>Bootstrap Model:<br>TE 0.95 -1.00 |
| Matthews (2010) | Pakistan | 2002–2009 | Bootstrap CCR model | Labour, capital (fixed assets) and deposits | Model 1: Loans minus NPLs, Other Earning Assets, Non-interest income, NPL as bad output<br>Model 2: Loans minus NPLs, Other Earning Assets, NPL as bad output<br>Model 3: Non interest income, interest income<br>Model 4: Total Loans, Other Earning Assets, Non-interest income<br>Model 5: Total Loans, Other Earning Assets | Average Technical Efficiency<br>Model 1: 0.78<br>Model 2: 0.80<br>Model 3: 0.67<br>Model 4: 0.73<br>Model 5: 0.79 |
| Assaf et al. (2011) | Saudi | 1999–2007 | Bootstrap DEA – BCC models (VRS) | Total employees, fixed assets and total deposits | Total customer loans, securities and interbank loans. | Traditional Model:<br>PTE 0.82 to 0.97<br>Bootstrap Model:<br>PTE 0.78 to 0.92 |
| Moradi-Motlagh & Saleh (2014) | Australia | 1997–2005 | Bootstrap DEA – CCR and BCC models | Interest expense and non-interest expense | Interest income and non-interest income | TE 0.83 to 1.00<br>PTE 0.88 to 1.00<br>SE 0.89 to 1.00 |
| Sufian (2015) | Malaysia | 1999–2008 | Bootstrap DEA model – BCC model | Fixed assets, personnel expenses and deposits | Loans, investment, non-interest income | Domestic Banks:<br>TE 0.74 to 0.94<br>Foreign Banks<br>TE 0.77 to 0.97 |
| Li et al. (2020) | China | 2009–2015 | Traditional Model and Bootstrap DEA – BCC model | Number of employees, fixed assets and total deposits a | Loans (pass loan, special mention loan and NPLs) and non-interest income | Traditional Model:<br>PTE 0.61 to 1.00<br>Bootstrap Model:<br>PTE 0.60 to 0.99 |

| Author | Country | Time Period | DEA Model | Input Variable | Output Variable | Efficiency Scores |
|---|---|---|---|---|---|---|
| **Network/Dynamic Network Studies (with or without SBM, with or without bootstrap)** | | | | | | |
| Wang et al. (1997) | Across countries | 1987–1989 | Two stage network DEA – CCR model | Collection of funds – stage 1<br>Fixed assets, number of employees and IT budget<br><br>Stage 2<br>Deposits (intermediate variable) | Collection of funds – stage 1<br>Deposits (intermediate variable)<br><br>Stage 2<br>Profits, percentage of loans recovered | Overall Efficiency<br>TE 0.06 to 1.00<br><br>Stage 1<br>TE 0.52 to 1.00<br><br>Stage 2<br>TE 0.17 to 1.00 |
| Seiford & Zhu (1999) | USA | 1995 | Two Stage Network DEA – CCR and BCC models | Profitability<br>Employees, assets, stockholders' equity<br>Marketability<br>Revenue and profits | Profitability<br>Revenue and profits<br>Marketability<br>Market value, total return to investors, earnings per share | Profitability<br>CCR 0.60 to 1.00<br>BCC 0.62 to 1.00<br><br>Marketability<br>CCR 0.45 to 1.00<br>BCC 0.59 to 1.00 |
| Fukuyama & Weber (2010) | Japan | 2000–2006 | Two stage network DEA with the SBM | First Stage<br>Labour, physical capital and equity<br><br>Second stage<br>Raised funds – intermediate variable | First Stage<br>Raised funds (demand deposits, certificates of deposit, call money, bills sold, borrowed money, foreign exchange liabilities, and a miscellaneous liability) – intermediate variable<br><br>Second stage<br>Loans, securities investments, other business activities and NPLs | First Stage<br>Average efficiency – 0.31 to 0.73<br><br>Second stage<br>Average efficiency – 0.24 to 0.56 |
| Fukuyama & Matousek (2011) | Turkey | 1991–2007 | Black box DEA model and the Two stage Network DEA – BCC model | First Stage<br>Labour and capital<br><br>Second Stage<br>Deposits | First Stage<br>Deposits<br><br>Second Stage<br>Loans and securities | Traditional DEA<br>TE 0.55 to 0.85<br><br>Network DEA<br>Overall TE – 0.39 to 0.70 |
| Akther (2013) | Bangladesh | 2005–2008 | Black box model and the two-stage network SBM model | Stage 1<br>labour, physical capital, and equity capital<br><br>Stage 2<br>Deposits (intermediate product) | Stage 1<br>Deposits (intermediate product)<br><br>Stage 2<br>Loans, securities and bad loans (undesirable output) | Black box model SBM<br>TE 0.88 to 0.93<br><br>Network SBM model<br>TE 0.20 to 0.65 |

| Author | Country | Time Period | DEA Model | Input Variable | Output Variable | Efficiency Scores |
|---|---|---|---|---|---|---|
| **Network/Dynamic Network Studies (with or without SBM, with or without bootstrap)** | | | | | | |
| Matthews (2013) | China | N/A | Three stage network DEA SBM model | First Stage<br>Operational Cost, Fixed Assets<br><br>Second Stage<br>Personnel cost, other operating cost (link variables from stage 1) and deposits<br><br>Third Stage<br>Number of branches and interest cost (link variables from stage 2) and NPLs | First Stage<br>Personnel cost, other operating cost (link variables to stage 2)<br><br>Second Stage<br>Number of branches and interest cost (link variables to stage 3) and non-interest earning income<br><br>Third Stage<br>Interest earnings | Overall Efficiency<br>TE 0.02 to 0.95<br><br>First Stage<br>TE 0.22 to 0.90<br><br>Second Stage<br>TE 0.01 to 1.00<br><br>Third Stage<br>TE 0.01 to 1.00 |
| Ebrahimnejad et al. (2014) | USA – 49 branches of Peoples Bank | N/A | Three stage network DEA SBM model | First Stage<br>Operational Cost, Capital Cost<br><br>Second Stage<br>Operational Cost, Capital Cost<br><br>Third Stage<br>Consumer Checking Deposit, Consumer Savings Deposit, Business Checking Deposit, Business Savings Deposit | First Stage<br>Consumer Checking Deposit, Consumer Savings Deposit<br><br>Second Stage<br>Business Checking Deposit, Business Savings Deposit<br><br>Third Stage – Good output<br>Return on assets, user fees income and interest income<br><br>Third Stage – Bad Output<br>consumer loan delinquencies and business loan delinquencies | First Stage<br>Average efficiency-0.43<br><br>Second Stage<br>Average efficiency – 0.51<br><br>Third Stage<br>Average efficiency – 1.00 |
| Wanke & Barros (2014) | Brazil | 2012 | Two-stage network DEA approach | Cost Efficiency<br>Number of branches and employees<br><br>Production Efficiency<br>Administrative Expense<br>Personnel Expense (intermediate variables) | Cost Efficiency<br>Administrative Expense<br>Personnel Expense (intermediate variables)<br><br>Production Efficiency<br>Equity<br>Permanent Assets | Overall Efficiency<br>TE 0.29 to 0.52<br><br>Cost Efficiency<br>TE 0.35 to 0.60<br><br>Production Efficiency<br>TE 0.79 to 0.90 |
| Avkiran (2015) | China | 2008–2010 | Non oriented two-stage dynamic network slack-based measure – BCC model | Interest-bearing operations<br>Interest expense on deposit, other interest expense, personnel expense, other operating expense<br><br>Non-interest-bearing operations | Interest-bearing operations<br>Interest income on loans, other interest income, number of referrals (intermediate product) and NPLs (undesirable output)<br><br>Non-interest-bearing operations | Overall Efficiency<br>TE 0.31 to 1.00<br><br>Interest-bearing operations<br>TE for foreign banks – 0.92 to 0.97<br>TE for domestic banks – 0.99 to 1.00 |

| Author | Country | Time Period | DEA Model | Input Variable | Output Variable | Efficiency Scores |
|---|---|---|---|---|---|---|
| **Network/Dynamic Network Studies (with or without SBM, with or without bootstrap)** | | | | | | |
| | | | | Personnel expense, other operating expense, number of referrals (intermediate product) | Net fees and commission, operating income, proportion of fruitless referrals (undesirable output) | Non-interest-bearing operations<br>TE for foreign banks – 0.94 to 0.97<br><br>TE for domestic banks – 0.93 to 0.99 |
| Chao et al. (2015) | Taiwan | 2005–2011 | Three-Stage Dynamic Network DEA Model | Capability- First Stage<br>Operating costs and capital utilisation expense<br><br>Efficiency - Second Stage<br>Intellectual capital<br><br>Profitability – Third Stage<br>Loans, investments, written off bad debts (undesired input) | Capability: First Stage<br>Intellectual capital<br><br>Efficiency: Second Stage<br>Loans, investments, written off bad debts (undesired output) and NPLs (undesirable carry-over).<br><br>Profitability: Third Stage<br>Interest income, fee income and investment related income, loan loss reserve (carry-over) | Overall Efficiency<br>TE 0.26 to 1.00<br><br>Capability: First Stage<br>TE 0.31 to 1.00<br><br>Efficiency: Second Stage<br>TE 0.56 to 1.00<br><br>Profitability – Third Stage<br>TE 0.99 to 1.00 |
| Fukuyama & Weber (2015) | Japan | | Two-Stage DEA Dynamic Network Model | Stage 1<br>Labour, capital, equity<br><br>Stage 2<br>Deposits and other raised funds (intermediate products) | Stage 1<br>Deposits and other raised funds (intermediate products)<br><br>Stage 2<br>Loans and securities, carry-over assets and NPLs (undesirable output) | Overall TE – 0.79 to 0.81 |
| Fukuyama & Matousek (2017) | Japan | 2001–2013 | Two-Stage Dynamic Network DEA model | Fund Raising Process<br>Labour and capital<br><br>Loan and Investment Process<br>Deposits (intermediate product) | Fund Raising Process<br>Deposits (intermediate product)<br><br>Loan and Investment Process<br>Loans (good output)<br>NPLs (bad output) | Fund Raising Process<br>TE 0.73 to 0.83<br><br>Loan and Investment Process<br>TE 0.74 to 0.80 |
| Dia et al. (2020) | Canada | 2000–2017 | Bootstrap black – box DEA and Bootstrap Dynamic Network DEA model – CCR and BCC models | Production Stage – Stage 1<br>Total assets, number of employees and other operating cost<br><br>Intermediation Stage – Stage 2<br>Deposits (intermediate product) | Production Stage – Stage 1<br>Deposits (intermediate product)<br><br>Intermediation Stage – Stage 2<br>Loans, securities and impaired loans (undesirable output) – all intermediate products | Black-box bootstrap DEA model<br>TE 0.85 to 0.95<br>PTE 0.91 to 0.97<br>SE 0.97 to 0.99 |

| Author | Country | Time Period | DEA Model | Input Variable | Output Variable | Efficiency Scores |
|---|---|---|---|---|---|---|
| **Network/Dynamic Network Studies (with or without SBM, with or without bootstrap)** | | | | | | |
| | | | | Revenue Generation Stage – Stage 2<br>Loans, securities and impaired loans (undesirable input) – all intermediate products | Revenue Generation Stage – Stage 2<br>Interest income and non-interest income | Bootstrap Dynamic Network DEA model<br>Overall scores<br>TE 0.41 to 0.57<br>PTE 0.51 to 0.68<br>SE 0.61 to 0.90<br><br>Stage 1<br>TE 0.76 to 0.89<br>PTE 0.83 to 0.95<br>SE 0.91 to 0.96<br><br>Stage 2<br>TE 0.75 to 0.83<br>PTE 0.83 to 0.92<br>SE 0.84 to 0.96<br><br>Stage 3<br>TE 0.60 to 0.90<br>PTE 0.64 to 0.90<br>SE 0.89 to 0.98 |

Note: BCC*– Banker, Charnes and Cooper, CCR*– Charnes, Cooper and Rhodes, TE – Overall Technical Efficiency, PTE* – Pure Technical Efficiency, SE*– Scale Efficiency

### 4.2.2 *Evidence on the DEA Application on Banks in the African Region*

An empirical review on the use of the DEA model to assess the efficiency of banks reveals that most of these studies focus on developed nations, particularly in North American, European and Asian countries. In effect, relatively fewer studies have attempted to use the DEA technique to assess bank efficiency on the African continent. The studies in Africa have mostly based their results on the black-box DEA models instead of the newly developed models such as the bootstrap technique and the network DEA or dynamic network DEA models.

#### 4.2.2.1 *Using the Traditional Black Box Approaches to Assess Technical Efficiency*

Key examples of the studies that have used the black-box approach to assess bank efficiency in Africa are discussed below.

In East Africa, Hauner and Peiris (2005), Aikaeli (2006) and Raphael (2013) are some of the most cited studies that have employed the black-box DEA model to assess bank efficiency.

Hauner and Peiris (2005) analysed the impact of financial reforms on the competition and efficiency of banks in Uganda from 1999 to 2004. Overall, the authors found that efficiency scores of smaller banks were relatively lower than those of larger banks, and foreign banks were more efficient than other categories of banks. For all the banks and periods under consideration, the pure technical efficiency of banks assessed ranged from a minimum of 0.70 to a maximum of 1.00 with the improved efficiency levels indicating a positive effect of the financial sector reforms in Uganda.

Aikaeli (2006) also used the black-box DEA to evaluate the efficiency of commercial banks in Tanzania by investigating the overall technical, pure technical, scale, and cost efficiencies. This study employed the intermediation approach in the selection of variables, using labour, capital, and deposits as inputs, and loans, advances and overdrafts, and investment in securities as outputs.

Authors such as Hauner and Peiris (2005) observed that foreign banks were more efficient than their domestic counterparts. Overall technical efficiency ranged from approximately 0.93 to 0.99, pure technical efficiency from 0.95 to 1.00, and scale efficiency from 0.97 to 1.00.

In the last decade, Raphael (2013) investigated the efficiency of banks in Kenya, Tanzania, Uganda, Rwanda, and Burundi using the CCR and BCC DEA models with the intermediation variable selection technique. The results of this study indicated that Kenya had more efficient banks over the period assessed, followed by Uganda, Tanzania, Burundi, and Rwanda. Overall, the mean efficiency scores of the East African banks assessed ranged from 0.56 to 0.81 for overall technical efficiency, 0.36 to 0.86 for pure technical efficiency, and 0.83 to 0.95 for scale efficiency.

In southern Africa, studies that have used the black-box DEA models to evaluate the performance of banks include Van Heerden and Van der Westhuizen (2008) and Erasmus (2014).

Van Heerden and Van der Westhuizen (2008) used DEA under the VRS assumption to estimate the technical efficiency of branches of one of the largest banks in South Africa. This study used the intermediation approach to classify input and output variables, employing deposits, interest expense and non-interest expense as input variables, and total loans, interest income and non-interest income as output variables. The DEA model used was further categorised into the input and output orientation, assessing the efficiency of banks at minimising input resources or maximising output. The study showed that in South Africa, as in most countries, bank managers performed better at reducing input resources than in maximising output. The pure technical efficiency measured ranged from approximately 0.65 to 1.00 for the input orientation and 0.62 to 1.00 for the output orientation. The authors concluded that the higher bank fees imposed on bank customers by the South African bank reflected the increased inefficiencies in the operations of banks in the country.

Erasmus (2014) reported higher efficiency scores of South African banks before, during, and after the global financial crisis from 2007 to 2008. Using data from 2006 to 2012, Erasmus (2014) under the intermediation variable selection approach found the average efficiency scores of five big banks in South Africa ranged from 0.729 to 1 (when linear averages of output were used) and 0.985 to (when the log-linear averages of output were used).

Studies that have used the DEA to evaluate the efficiency of banks in West Africa have increased in numbers over the years.

Sobodu and Olankunle (1998) was one of the first studies that used the DEA to model the efficiency of banks in West Africa. This study assessed the impact of financial deregulation policies on the performance of banks in Nigeria, observing that intermediation efficiency of banks reduced significantly following the adoption of the deregulation policies, with improvements noticed only in the later periods assessed. On average, the DEA model based on the CRS assumption showed that the efficiency of banks prior to the implementation of the deregulation policies ranged from approximately 0.48 to 0.74, while the scores after the adoption of the deregulation policies ranged from 0.49 to 0.69. For both eras, the technical efficiency of the Nigerian banks assessed was generally low. Like Sobodu and Olankunle (1998), most studies that have used DEA to assess bank efficiency in Nigeria have reported low scores compared to banks in the Eastern African or Southern African countries. For example, in an evaluation of Nigerian banks from 1991 to 1994, Ayadi et al. (1998) reported minimum technical efficiency scores of 0.3. Zhao and Murinde (2011) observed a minimum technical efficiency score of 0.37 for the period 1993 to 2008. Omankhanlen (2013) assessed the performance of Nigerian banks post the financial sector reforms in 2004 and measured average scores ranging from 0.42 to 0.90 for technical efficiency, 0.40 to 0.90 for pure technical efficiency, and 0.80 to 0.99 for scale efficiency.

In Ivory Coast, Yannick et al. (2016) used the black-box DEA to evaluate the efficiency of 14 banks under both the CCR and BCC models. Like most studies in the African region, the researchers used the intermediation variable selection technique. They observed that most banks included in the study were inefficient in relation to the transformation of deposits into loans. They recorded an average technical efficiency score of 0.48 (ranging from 0.30 to 0.93) and an average pure technical efficiency score of 0.79 (ranging from 0.36 to 1), while scale efficiency ranged from a minimum of 0.41 to a maximum of 0.98.

For cross-border studies, Kablan (2007) was the first to use the DEA to measure the efficiency of West African Economic Monetary Union (WAEMU) banks, particularly in Benin, Burkina Faso, Ivory Coast, Mali, Senegal, and Togo. Togo reported the least intermediation efficiency scores, while banks in Senegal reported the highest efficiency scores, using both the CCR and BCC models. On average, for the total sample evaluated, technical efficiency scores averaged 0.76, while pure technical efficiency scores averaged 0.85.

Lastly, in Ghana, there have been a growing number of studies that have used the black-box DEA models to evaluate the technical efficiency of banks. The most cited studies include Korsah et al. (2001), Saka et al. (2012), Adusei (2016) and Alhassan and Ohene-Asare (2016).

Most of these studies assess the impact of the financial liberalisation policies on the efficiency of banks in Ghana and also evaluate the impact of foreign ownership on the performance of Ghana's banking sector.

Over time, a general review of empirical studies on bank efficiency in Ghana shows improvement in technical efficiency. Specifically, Korsah et al. (2001) using the dataset from 1988 to 1999, observed that efficiency increased just after the adoption of the liberalisation policies, although stalling in the later periods. In this study both the technical and pure technical efficiency scores ranged from a minimum technical and pure technical efficiency score of 0.32 to a maximum of 1.

A more recent study by Saka et al. (2012) shows higher minimum scores (at 0.76 for domestic banks and 0.67 for foreign banks). In this study, Saka et al. (2012) evaluated the effect of foreign banks on the technical efficiency of domestic banks in Ghana in the period 2000 to 2008. Using the intermediation variable selection approach, the authors confirmed that foreign ownership of banks had a positive effect on the technical efficiency of domestic banks in the period under review, supporting the liberalisation policies which promoted the entry of foreign banks into the country.

Compared to Korsah et al. (2001), Adusie (2016) measured much higher efficiency scores when a more recent dataset in 2013 was used to assess the performance of 23 universal banks in Ghana. In this study, Adusie (2016) calculated an average technical efficiency score of 0.89 with a minimum technical efficiency score of 0.45[36]. The next lowest technical efficiency score was 0.60. The pure technical efficiency score averaged 0.94 with a minimum score of 0.53, while scale efficiency also averaged 0.94 with a minimum score of 0.66.

Finally, Alhassan and Ohene-Asare (2016) also observed higher efficiency scores in the evaluation of 26 commercial banks in Ghana for the period 2004 to 2011. Using both the CCR and BCC black-box DEA models, the authors reported higher technical efficiency scores from 0.81 to 0.92, pure technical efficiency scores from 0.85 to 0.92, and scale efficiency scores from 0.89 to 0.95.

Overall, the empirical studies reviewed reveal that in the African region, specifically in Ghana, most studies have focused on evaluating the effect of management capabilities (measured by pure technical efficiency) or scale (measured by scale efficiency) on bank performance. These studies note that the inefficiencies in Ghana's banking sector are mostly caused by the reduced capabilities of management rather than the size of banks. Most studies have also focused on assessing technical efficiency in respect of intermediation, evaluating how well banks turn deposits into loans. There is a growing diversification in the operations of banks in Africa. Particularly in Ghana, most banks have evolved from the traditional income source of interest earned on loans to increased engagement in digital technology and other growing sources of non-interest income. This trend, therefore, requires an extension in efficiency measurement from just the traditional black-box approach to the more current technique, preferably the network DEA model.

As argued by Efron (1981), the seemingly smaller dataset used by most studies in Africa, such as Adusie (2016), may impair the accuracy of efficiency estimates measured for banks in the African region. This gap requires the use of the bootstrap technique which simulates the data generating process to increase the dataset. However, as stated in the introduction of Section 4.2.2, very few studies in Africa have addressed the issues pertaining to the measurement of efficiency of the diverse operations of banks in recent times. Also, studies that address the erroneous impact of the data sample size on efficiency scores are very scarce. Table 4.3 provides a summary of studies that have used the DEA model to assess the efficiency of banks in Africa, focusing on studies that have used the black-box approach, the bootstrap technique, the network DEA and the dynamic network DEA models.

[36] This score was reported for Royal Bank which had just been licensed in December 2012.

#### 4.2.2.2 *Using the New DEA models to Assess Technical Efficiency of Banks in Africa*

##### 4.2.2.2.1 *The Bootstrap DEA model*

In East Africa, Kamau (2011) used the bootstrap technique to estimate the CCR and BCC DEA efficiency scores of banks in Kenya. This study particularly sought to evaluate the performance of banks post the liberalisation era using deposits, capital, and labour as input variables, and loans and investments as output variables. The study indicated that Kenyan banks in the period 1997 to 2009 had room for improvement, that foreign banks were more efficient than their domestic peers, and that local private banks were more efficient than the local public banks. Larger banks were also found to be more efficient than medium-sized and smaller banks. More importantly, in terms of the bootstrap model adopted, the author did not find any significant difference between the scores adjusted for bias using the bootstrap and the scores which were not adjusted for bias.

Another key example of a study that applied the bootstrap technique is that of Alhassan and Tetteh (2017) who employed a bias-corrected bootstrap DEA technique to evaluate the performance of banks in Ghana from 2003 to 2011. The researchers also investigated the impact of non-interest income on the performance of banks in Ghana. They used an intermediation variable selection approach. In the first empirical model, where non-interest income was included as an output variable, the study observed technical efficiency scores ranging from 0.42 to 0.77, pure technical efficiency scores from 0.55 to 0.90, and scale efficiency scores from 0.75 to 0.94. However, with the exclusion of non-interest income as an output variable, Alhassan et al. (2017) measured lower efficiency scores. Technical efficiency ranged from 0.35 to 0.75, pure technical efficiency from 0.52 to 0.87, and scale efficiency from 0.75 to 0.86. The discrepancy in results between the first and second models used indicates the importance of non-interest income to the efficiency of banks in Ghana. Compared to studies such as Korsah et al. (2001), Saka et al. (2012) and Alhassan and Ohene-Asare (2016), the efficiency scores measured by Alhassan et al. (2017) are relatively low. This may imply that the dataset on Ghana’s banking sector is prone to sampling variation and the avoidance of the bootstrap technique may impair the accuracy of results by overestimating efficiency scores.

##### 4.2.2.2.2 *Network DEA / Dynamic Network DEA*

Wanke et al. (2019) used the network DEA model to assess the efficiency of banks in South Africa in respect of potential mergers and acquisitions for the period 2003 to 2012. This study measured efficiency in the production and intermediation stages. The production stage used employees, fixed assets, and operational expenses to generate deposits and loans, while the intermediation stage used deposits and loans to produce interest and non-interest income. Generally, the authors concluded that out of the total number of banks evaluated, 22 banks were efficient and 67 banks were inefficient. The authors also confirmed that most banks will increase technical efficiency when merged. Potential gains from mergers and acquisitions were higher in the production stage (stage 1) than the intermediation stage (stage 2), suggesting that managers are more capable of reducing operational expenses, fixed assets, and employee costs during mergers than they can reduce loans and deposits.

As mentioned in the introduction of this section, Zhou et al. (2018), used a two-stage network DEA approach to assess the efficiency of the production and profitability stages of commercial banks in Ghana. Using data from 2009 to 2014, the researchers evaluated how well bank managers turn personnel and interest expenses into deposits (stage 1) and consequently, how efficiently deposits and loans are turned into interest and non-interest income. This study also accounts for the production and effect of an undesirable variable, by including NPLs as an input variable in the second stage (i.e., the profitability stage). Overall, Zhou et al. (2018) found commercial banks in Ghana to be technically inefficient, with efficiency estimates ranging between 0.40 to 0.49. Unlike the banks in South Africa (as assessed by Wanke et al. (2019)), Ghanaian commercial banks performed better in the profitability stage (i.e., in converting deposits, loans, and NPLs into interest and non-interest income). In the production stage, banks reported efficiency scores ranging from 0.17 to 0.27, whereas in the profitability stage, efficiency scores ranged from 0.77 to 0.87.

Appiahene et al. (2019) used a two-stage DEA model to investigate the impact of Information Technology (IT) on the performance of 444 Ghanaian bank branches. In stage one, the researchers evaluated how efficiently the management of banks converted IT expenditure, fixed assets, and number of employees to deposits, while in stage two, the study assessed the capabilities of management to turn deposits into profits and performing loans. For the first stage, only 14 (3.15 percent) banks were fully efficient at a score of 1.00, however 329 bank branches (74.09 percent) had an efficiency score below 50 percent.

*Table 4.3: Summary of Studies that have used the Black-Box Approach, Bootstrap Technique, the Network or the Dynamic Network DEA model to Estimate the Efficiency of Banks – Within the African Region*

| **Author** | **Country** | **Time Period** | **DEA Model** | **Selection Approach (input / output)** | **Input Variable** | **Output Variable** | **Efficiency Score** |
|---|---|---|---|---|---|---|---|
| **Studies in Africa excluding Ghana** | | | | | | | |
| Soboddu & Akiedo (1998) | Nigeria | 1983–1993 | CCR DEA | intermediation | Interest expense, non-interest expense, transaction deposit and non-transaction deposit | Interest income, non-interest income and total loans | Pre-sap 0.48-0.74<br>Post-sap 0.49-0.69 |
| Ayadi et al. (1998) | Nigeria | 1991–1994 | CCR DEA | intermediation | Interest paid on deposits, personnel and administrative expense, total deposits | Loans, interest income, non-interest income | TE 0.03-1.00 |
| Hauner & Peiris (2005) | Uganda | 1999–2004 | BCC DEA | intermediation | deposits, loans, and contingent liabilities | Deposit holdings, securities, and loans | PTE 0.70 to 1.00 |
| Kablan (2007) | WAEMU Region (Benin, Burkina Faso, Ivory Coast, Mali, Senegal and Togo) | 1996–2004 | CCR and BCC DEA | intermediation approach | labour, physical capital, financial capital | Loans and deposits | <u>Average TE Scores:</u><br>Benin –0.80<br>Burkina Faso-0.65<br>Ivory Coast-0.72<br>Mali-0.75<br>Senegal-0.83<br>Togo-0.55<br>WAEMU-0.76<br><br>**<u>Average PTE Scores:</u>**<br>Benin – 0.84<br>Burkina Faso-0.70<br>Ivory Coast- 0.89<br>Mali-0.80<br>Senegal-0.95<br>Togo- 0.60<br>WAEMU-0.85 |
| Aikaeli (2006) | Tanzania | 1998–2004 | CCR and BCC DEA | intermediation | labour, capital, and deposits | Loans, advances and overdrafts, investment in securities. | TE 0.93 to 0.99<br>PTE 0.95 to 1.00<br>SE 0.97 to 1.00 |
| Van Heerden & Van der Westhuizen (2008) | South Africa | 2005–2007 | BCC DEA | intermediation | deposits, interest expense, non-interest expense | total loans, interest income, non-interest income | Input orientation PTE -0.65-1.00<br>Output orientation PTE -0.62-1.00 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Kamau (2011) | Kenya | 1997–2009 | BCC and CCR DEA and bootstrap DEA model | intermediation | Deposits, capital and labour | Loans and investment | CRS: 0.47 VRS: 0.56. SE:0.84 |
| Zhao & Murinde (2011) | Nigeria | 1993–2008 | CCR DEA | intermediation | Interest expense, non-interest expense and financial capital | Loans, other earning assets and deposits | Average TE 0.37 to0.84 |
| Omankhanlen (2013) | Nigeria | 2005–2009 | CCR and BCC DEA | intermediation | Total deposits, fixed assets and operating expenses | Total loans extended, net profits, and total investment | Average efficiency<br>TE 0.42 to 0.90<br>PTE 0.40 to 0.90<br>SE 0.80 to 0.99 |
| Raphael (2013) | Tanzania, Kenya, Uganda, Rwanda and Burundi | 2008–2011 | CCR and BCC DEA | intermediation | Deposit, interest expenses, operating expenses | Loan, investment, interest income and noninterest income | TE 0.56 to 0.81<br>PTE 0.69 to 0.86<br>SE 0.83 to 0.95 |
| Erasmus (2014) | South Africa | 2006–2012 | standard DEA (linear averages of output) and alternative DEA approach (log linear averages of output) | intermediation | Deposits, Other liabilities, Shareholders' equity, Staff costs, non-interest expense, Fixed assets | Loans and Overdrafts, Non-interest income | standard DEA: 0.729 to 1.00<br>alternative DEA: 0.985 to 1.00 |
| Yannick et al. (2016) | Ivory Coast | 2008–2010 | CCR and BCC DEA | Intermediation approach | deposit | Loans | TE 0.30 to 0.93<br>PTE 0.36 to 1.00<br>SE 0.41 to 0.98 |
| Bahrini (2017) | MENA Region | 2007–2012 | CCR and BCC DEA with bootstrap technique | intermediation | Labour, fixed assets and deposits | Loans and other earning assets | TE 0.67 to 0.82<br>PTE 0.71 to 0.90<br>SE 0.90 to 0.95 |
| Banya & Biekpe (2018) | 10 African countries (Morocco, Uganda, Tanzania, Ghana, Nigeria, Botswana, Kenya, Mauritius, South Africa, Tunisia) | 2008–2012 | CCR and BCC DEA | intermediation | Deposits, labour and capital | Loans and investment | TE 0.46 to 0.72<br>PTE 0.62 to 0.90<br>SE 0.66 to 0.89 |
| Wanke et al. (2019) | South Africa | 2003–2012 | Two-Stage Network DEA model | Production and intermediation approaches | <u>Production stage</u><br>employees, fixed assets, and operational expenses<br><br><u>Intermediation Stage</u><br>Deposits and loans | <u>Production stage</u><br>Deposits and loans<br><br><u>Intermediation Stage</u><br>Interest and non-interest income | 22 banks were efficient while 67 banks were inefficient. |

| Studies in Ghana | | | | | | | |
|---|---|---|---|---|---|---|---|
| Korsah et al. (2001) | Ghana | 1988–1999 | CCR and BCC DEA | production | Staff costs, non-staff operating costs, and capital (premises and fixed assets). | deposits, loans and commissions & fees | TE – 0.32-1.00<br>PTE – 0.32-1.00 |
| Saka et al. (2012) | Ghana | 2000–2008 | CCR DEA | intermediation | intermediating deposits, fixed assets, total expenses, and shareholders' equity | Loans and advances | domestic banks: 0.76 to 0.89<br>Foreign banks: 0.67 to 0.91. |
| Adusei (2016) | Ghana | 2013 | CCR and BCC DEA | intermediation | Deposits, fixed assets and shareholders' equity | Loans, investment, profit before interest and tax | TE -0.45-1.00<br>PTE – 0.53-1.00<br>SE – 0.66-1.00 |
| Alhassan et al., 2016 | Ghana | 2003–2011 | CCR and BCC DEA | intermediation | Deposits, fixed assets and personnel expenses | Loans, other earning assets, fees and commission income | TE-0.81-0.92<br>PTE-0.85-0.97<br>SE-0.89-0.95 |
| Alhassan et al. (2017) | Ghana | 2003–2011 | CCR and BCC DEA with bootstrap technique | intermediation | Fixed assets, bank deposits, and staff expenditure | Model 1<br>Gross loans and advances, book value of investments and fees and commission income.<br><br>Model 2<br>Gross loans and advances and book value of investment | Model 1<br>TE: 0.42-0.77<br>PTE: 0.55-0.90<br>SE: 0.75-0.94<br><br>Model 2<br>TE: 0.35-0.75<br>PTE: 0.52-0.87<br>SE: 0.75-0.86 |
| Zhou et al. (2018) | Ghana | 2009–2014 | Two stage network DEA, dynamic DEA and slack-based model DEA | intermediation | Production stage: personnel and interest expense<br>Profitability stage: deposits (intermediate product), loans and NPLs (undesirable output) | Production stage: deposits (intermediate product)<br>Profitability stage: interest, non-interest incomes | Overall TE – 0.40-0.49<br>Stage 1 – 0.17-0.27<br>Stage 2 – 0.77-0.87 |
| Appiahene et al. (2019) | Ghana | 2016 | Two-stage network DEA model | intermediation | First stage: fixed asset, number of employees and IT expenditure<br>Second stage: deposits (intermediate product) | First stage – Deposits (intermediate product)<br>Second stage – profits, performing loans | TE - $< 0.50 - 1.00$ |

Note: BCC*– Banker, Charnes and Cooper, CCR*– Charnes, Cooper and Rhodes, TE – Overall Technical Efficiency, PTE* – Pure Technical Efficiency, SE*– Scale Efficiency

### 4.2.3 *Conclusions on Empirical Literature Review*

A survey of the literature discussed in section 4.2 above shows that globally, most studies have adopted the traditional CCR and BCC models in estimating DEA efficiency scores.

Studies in North America, Europe and Asia have mostly employed the CCR and BCC models, with banks in North America reporting relatively higher efficiency scores than their counterparts in Europe. In terms of the type of efficiency, PTE and SE scores have also been relatively higher than CRS scores. Also, owing to the complexity of activities of banks, studies on bank efficiency in the advanced regions have adopted various variable selection methods from intermediation to value-added approaches.

In addition to the traditional models, most studies on bank efficiency in developed regions (particularly Europe and Asian regions) have also used the bootstrap technique and the two-stage dynamic network DEA. Also recently, the use of the three-stage network dynamic DEA has become more common in Asian countries. There are considerable variations in efficiency scores determined by the black-box bootstrap approach and the network DEA model. Evidenced in the literature surveyed for the advanced regions, we note that scores from the black box approach are much higher than those from the dynamic network approach. This supports the conclusion that the black-box models may overestimate efficiency scores.

Studies in Africa have predominantly used the black-box approaches with just a few using the two-stage network dynamic DEA. Also, owing to the reduced complexities of products offered by banks in Africa, and their reliance on lending as the major source of revenue, existing studies, especially works done on Ghana, have mostly used the intermediation selection approach.

Similar to the observations made in more advanced regions, we note that the overall technical efficiency scores estimated by the dynamic network DEA fall within a relatively lower range than the technical efficiency cores calculated by the black-box models, even when bootstrapped. This observation agrees with the findings of Fukuyama and Matousek (2011) and Dia et al. (2020) who argued in favour of the network DEA approach, stating that the use of the black-box, although gives a much higher efficiency score, misrepresents the true performance of institutions. The common use of the black-box approach in Ghana therefore raises concerns about the accuracy of the estimation of bank efficiency in the country.

To address this concern, this study is the first to use both the black-box and the dynamic network DEA models to assess the performance of banks. It is also the first stud in Ghana to include in the black-box model both the bootstrapping technique and a slack variable (in this case, NPL). According to Fukuyama and Weber (2010), the bootstrap technique will minimise bias estimation errors and improve on the accuracy of scores, while the slack variable generates accurate and realistic efficiency estimates and also avoid the overestimation of technical efficiency scores.

Secondly, this is the first known study on the efficiency of banks in Ghana that will attempt to use a three-stage dynamic network DEA model to measure the efficiency of commercial banks. The use of the three stages is a key distinguishing factor between studies such as Zhou et al. (2018) and Appiahene et al. (2019) who used two stages within the dynamic network DEA to ascertain the efficiency of banks in Ghana.

The detailed specification of both the black-box approach and the three-stage dynamic network DEA model are presented in the next section.

## 4.3 *Methodology*

### 4.3.1 *Modelling of the Black-Box DEA*

#### 4.3.1.1 *Black-Box DEA with the bootstrap technique*

In Ghana, the discrepancies between bank efficiency estimates derived from models with and without the bootstrap technique could be explained by the fact that models without the bootstrap technique do not effectively eliminate the negative impact of random errors, resulting in biased efficiency scores. To improve bank efficiency scores and build on their confidence interval, this study as mentioned earlier adopts the bootstrap technique proposed by Simar and Wilson (1998).

According to Simar and Wilson (1998), the crucial step in the adoption of the bootstrap technique is to properly specify the Data Generating Process (DGP) underlying the original data. The DGP applies the original estimator to each simulated sample, causing estimates to mimic the sampling distribution of the original estimator.

Similar to Dia et al. (2020), this study adopts the Monte Carlo resampling method to specify the DGP. According to Carsey and Harden (2013), Monte Carlo resampling methods are computational algorithms that repeatedly simulate data to obtain the distribution of an unknown probabilistic unit. In this study, this simulation method is preferred because it is best known for comparing competing data for small samples under realistic conditions. This advantage is in tandem with the benefit of the non-parametric measure, DEA, which is also best known for estimating efficiency estimates from a small dataset.

The DGP, $P$, used to estimate the traditional CCR and BCC models specified in equations (3.1) and (3.2), employs a random sample where $X = \left\{(\mathrm{x_{ij,}y_{rj}})\middle|\mathrm{i} = 1, \dots, \mathrm{m}; \mathrm{r} = 1, \dots, \mathrm{t}; \mathrm{j} = 1, \dots, \mathrm{n}\right\}$ is used to estimate the relative efficiency scores of $\theta_j(j = 1, \dots, n)$. To successfully implement the bootstrap technique, it is necessary to generate the bootstrapped estimator $\widehat{P}$ from the DGP.

To generate $\widehat{P}$, a new dataset $X^* = \left\{ \left( x^*_{ij}, y^*_{rj} \right) \middle| i = 1, \dots, m; r = 1, \dots, t; j = 1, \dots, n \right\}$ is produced using the data obtained from the efficiency estimates from the original dataset. Given that $\widehat{P}$ is known, $X^*$ defines the corresponding input variables $\hat{x}^*$ and output variables $\hat{y}^*$ whose distributions are also known. Where the distribution of variables is not known, a pseudo dataset is used to construct the bootstrap technique. In this case the Monte Carlo resampling method is used to repeatedly compute $\widehat{P}$. From this resampling method, a collection of B pseudo samples, $x^*_b(b = 1, \dots, B)$, is produced to estimate the pseudo relative efficiencies $\widehat{\theta}_b$. Unfortunately, as explained by Kneip et al. (2008), where the distribution of variables is unknown, the dataset used in estimating the pseudo relative efficiencies, $\widehat{\theta}_b$, contains arbitrary numbers of inputs and outputs which have several unknown quantities. According to Kneip et al. (2008), such a dataset gives a biased confidence interval for the pseudo relative efficiencies, as the confidence intervals for efficiency estimated by bootstrap sub-sampling is quite sensitive to the choice and sample size of variables used.

To improve the confidence interval of the efficiency estimates derived from the bootstrap technique, and also to ensure that the distribution of data in the bootstrap sample is representative of the original distribution, this study smoothens the bootstrap efficiency scores. In smoothening the efficiency scores, this study follows the works of Bahrini (2017) and again Dia et al. (2020) and uses the Kernel Density Estimation procedure. The Kernel Density Estimation originally proposed by Simar and Wilson (1998) seeks to “smooth’’ the bootstrap efficiency results, $\hat{\theta}^*_b(b = 1, \dots, B)$. Overall, in estimating the bootstrap DEA efficiency scores, this study runs the number of iterations proposed by Simar and Wilson (1998), which is 2,000 iterations. This number of iterations ensures adequate convergence of the confidence intervals and increases the accuracy of efficiency estimates.

The whole DEA analysis was executed using the DEA Solver Pro 12.0.

#### 4.3.1.2 *Black-Box DEA with a Slack Variable*

In addition to incorporating the bootstrap technique within the black-box DEA model, this study, as discussed in the introductory section of this thesis, includes a slack variable (NPLs) in the estimation of the overall technical, pure technical, and scale efficiency scores. Following existing studies such as Seiford and Zhu (1999) and Zhou et al. (2018), the CCR and BCC models used are further expanded to account for slack or undesirable variables.

$$\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \bar{s}_i / x_{i_0}}{1 + \frac{1}{s}\sum_{k=1}^{s_1} s_k^g / y_{k_0}^g + \sum_{k=1}^{s_2} s_k^b / s_{k_0}^b}$$

$$\begin{aligned} & s.t. \\ & \sum_{j=1}^{n} \lambda_j y_{k_j}^g - s_k^g = y_0^g, k = 1,\dots\dots\dots, K, \\ & \sum_{j=1}^{n} \lambda_j y_{k_j}^b - s_k^b = y_0^b, k = 1,\dots\dots\dots, K, \\ & \bar{s} \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0 \end{aligned} \tag{4.1}$$

.$\boldsymbol{x}$, $y^g, y^b$ represents the inputs, desirable and undesirable outputs respectively, $s^-, s^b, s^g$ indicate the excesses in inputs and undesirable output and the shortages in desirable outputs, and $\boldsymbol{\lambda}$ is the intensity vector. For interpretation, efficiency score ($\rho *$) ranges between 0 and 1, with a score of 1 indicating that a bank is efficient with no slack while a bank with 0 is inefficient.

### 4.3.2 *Variable Selection Approach*

Following the discussions in Chapter 3, this study adopts the input orientation CCR and BCC models illustrated in Equations (3.1) and (3.2) of this study. This choice is premised on the fact that management is better able to control inputs than outputs. Equations (3.1) and (3.2) therefore provide the overall technical efficiency scores (the CCR model) and the pure technical and scale efficiency scores (BCC model).

Again, as stated in Chapter 3, this thesis adopts the intermediation approach in selecting variables for the established models. The intermediation variable selection approach is selected for three main reasons. First, this study assesses banks as a whole and the entire banking sector as opposed to branches of a particular bank. Second, data available in the banking sector of most developing countries makes the intermediation approach the most reliable variable selection technique to use. There are challenges in sourcing data for other approaches such as the production, value-added, and user cost approaches (Isik and Hassan, 2003). Lastly, as argued by Sealey and Lindley (1977), the primary role played by financial institutions is to bridge the gap between savers and borrowers, serving as an effective channel for household and business funding. To fulfil this role, Sealey and Lindley (1977) suggest that banks normally use labour, physical capital, and deposits to produce loans and other earning assets. This function is basically the intermediation function, therefore making it prudent to assume the intermediation approach in the estimation of efficiency of banks. In this vein, this study follows existing studies such as Alhassan and Tetteh (2017) and Zhou et al. (2018), and the black-box model uses deposits, total assets, employee cost, and other operating expenses as input variables. For the output variables, the study employs gross loans, securities, and other shares, interest income, and non-interest income. To consider the effect of the slack variable, we also treat NPLs as an additional output.

### 4.3.3 *Three Stage Dynamic Network DEA Model*

In this DEA model, the banks' processes and activities are divided into three stages. The first and second stages address the controversial treatment of deposits by using deposits as an output variable in the first stage and as an input variable in the second stage (Akther et al., 2013; Fukuyama and Weber, 2015; Wang et al., 2019). Specifically, the first stage (the production process) models the conversion of the input variables (fixed assets, employee cost, and other operating costs) into deposits, the output variable.

The second stage (the intermediation process) utilises the input variable, (deposits) to produce good outputs (gross loans and shares and securities), and the bad output (NPLs). The inclusion of NPLs in the second stage emphasises the need for bank management to oversee and monitor impaired loans to enhance the efficiency of banks (Dia et al., 2020).

Lastly in the third stage (revenue generation process), we assess how well the banks' lending rates and securities generate revenue. This process has mostly been ignored (Akther et al., 2013; Fukuyama and Weber, 2015) or combined with the second stage by most studies that have used the network dynamic DEA model (Lin and Chiu, 2013; Ebrahimnejad et al., 2014). Dia et al. (2020) however argued that the separation of the intermediation stage from the revenue generation stage directly measures a bank's efficiency in the generation of profits which is an essential mandate.

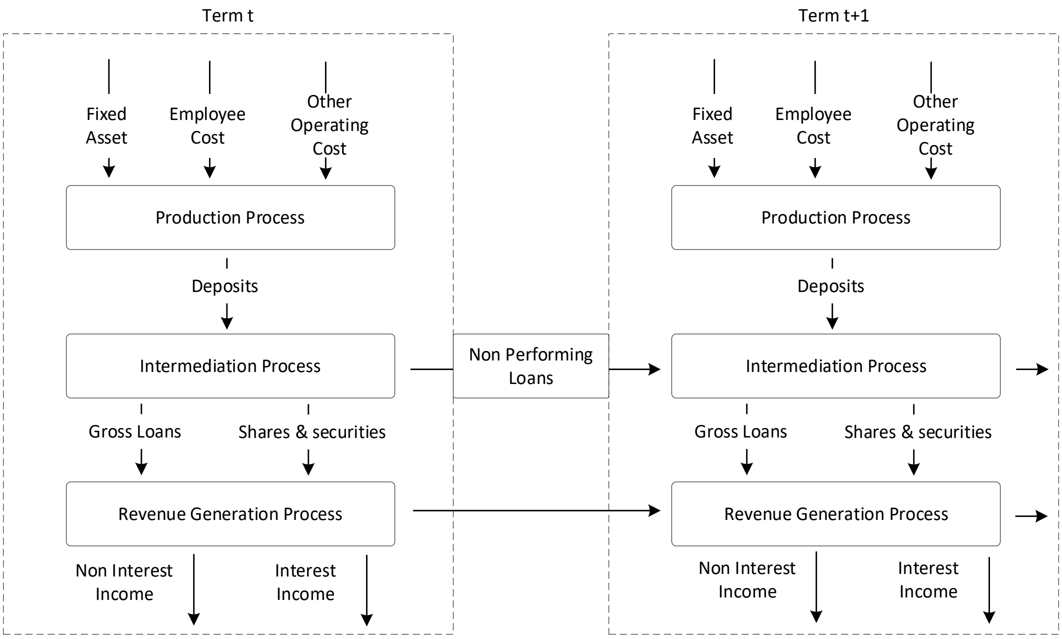



*Figure 4.1: The Research Model adopted from Dia, Golmohammadi and Takouda (2020)*

## 4.4 *Empirical Findings*

### 4.4.1 *Scope of Data*

In order to ensure a balanced panel dataset, 18 out of 24 banks (as at December 2019) were selected for the purpose of this study. This is because some banks had not been in existence, or had been liquidated during for the period January 2008 to December 2019.

The choice of period is also determined by the availability of reliable data from the Banking Supervision Department of the Bank of Ghana. The period selected also reflects the recent changes in the minimum capital requirement after the redenomination of the Ghanaian currency, which occurred in 2007. The DEA Solver Pro software[37] was used in the estimation of efficiency scores.

Table 4.4 indicates the sources and use of funds by commercial banks in Ghana for the period under consideration.

From the table, the deposit was mainly used to grant loans, rather than invest in securities and other long-term investments. Consequently, the loans granted yielded higher interest income as opposed to non-interest income. The increased amount of gross loans resulted in large amounts of impaired loans, revealed by the values of NPLs. At the maximum values, NPLs made up 23 percent of gross loans. Banks had a considerably higher asset base, exceeding total deposits and gross loans by 26 percent and 54 percent respectively at the maximum values. Also, of the total expenditure of the bank, employee cost remained the highest cost item. At the maximum values, employee cost made up 51 percent of total operating cost.

[37] This software estimates the most comprehensive DEA models and all their possible combinations. It also has no limitation on the number of DMUs and addresses the various methods (bootstrap, radial, non-radial (SBM), cost, revenue, and profit models), orientation (input-, output), and returns to scale (CRS, VRS, NIRS, NDRS, and GRS).

*Table 4.4: Descriptive Statistics of Data Used (2008–2019)*

| Descriptive | Employee Cost | Total Operating Cost (Excluding Employee Cost) | Fixed Assets | Total Deposits | Gross Loans | Securities other than Shares (Long-Term Investments) | Non-Performing Loans | Interest Received from Overdrafts, Loans and Other Advances | Non-Interest Income |
|---|---|---|---|---|---|---|---|---|---|
| **Mean** | 36,217,496 | 31,989,659 | 2,059,238,521 | 1,303,725,985 | 879,845,318 | 255,847,621 | 153,552,422 | 86,820,113 | 40,927,753 |
| **Median** | 18,091,801 | 16,927,284 | 1,341,360,804 | 828,020,664 | 586,013,509 | 41,491,607 | 81,922,155 | 46,862,328 | 23,700,801 |
| **Standard Deviation** | 50,769,097 | 42,378,260 | 2,143,061,907 | 1,410,582,594 | 873,438,374 | 559,786,711 | 191,410,175 | 114,187,224 | 51,488,719 |
| **Minimum** | 112 | 107 | 10,568,521 | 115,343 | 114,969 | 0 | 0 | 859 | 282 |
| **Maximum** | 495,039,678 | 474,822,846 | 13,019,668,536 | 9,628,761,141 | 5,944,076,834 | 4,371,483,931 | 1,337,783,474 | 1,131,457,776 | 509,432,308 |

Source: Bank of Ghana- based on monthly submissions made by commercial banks (data used is in GH¢)

### 4.4.2 *Analysis of Results*

Primarily, analysis of results in this chapter seeks to answer whether method (bootstrap SBM DEA model or network dynamic SBM DEA model) matters in the estimation of efficiency scores. This section presents the results of the two distinct methods employed and uses P-value tests (at least 10 percent significance level) to assess the significance of the differences between results estimated. Under each of the methods used, results are estimated for overall technical efficiency (OTE), pure technical efficiency (PTE), and scale efficiency (SE). P-value tests (at least 10 percent significance level) are also used to estimate the significant differences between the scores derived from the varying efficiency types. For the sake of anonymity, the banks are represented by codes.

#### 4.4.2.1 *Discussion of Results from the Bootstrap SBM DEA Model*

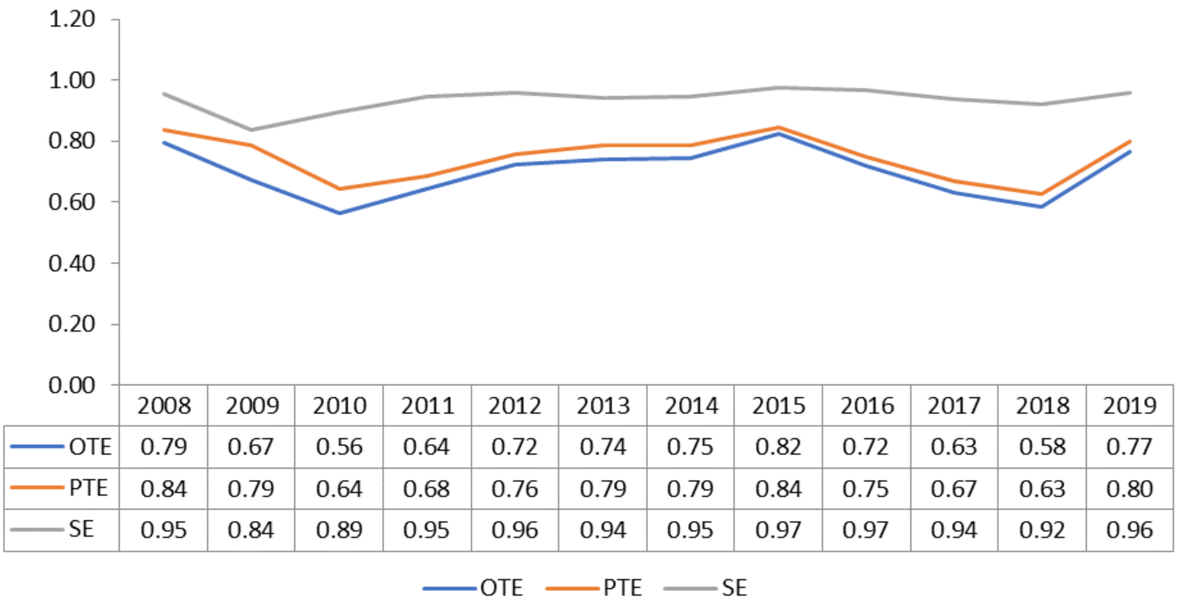
Tables 1.1 to 1.3 in the appendix reveals that in terms of the bootstrap SBM DEA model, banks examined by this study were largely technically inefficient (i.e., below the efficiency score of 1) for the period under study. The overall TE of banks in Ghana was driven by SE rather than pure TE. This implies that over the period under assessment, management performance resulted in inefficiencies in Ghana's banking sector. Average efficiency scores for the period were 0.67 for OTE, 0.73 for PTE, and 0.91 for SE. This means that management of banks in Ghana need to reduce input by 33 percent to attain full OTE, 27 percent for full PTE, and 9 percent to achieve full SE. Across the years under review, average OTE scores ranged from 0.56 to 0.82, PTE from 0.63 to 0.84, and SE from 0.83 to 0.97. These scores are higher than the observed results of Alhassan and Tetteh (2017) who recorded slightly lower efficiency scores for the period 2003 to 2011.

The differences in observations may be attributed to the expansion of the economy in the periods following the time examined by Alhassan and Tetteh (2017). In these periods, Ghana discovered oil and commenced the sale of crude oil. Banks were also allowed to engage in big-ticket transactions such as participation in syndicated lending for the bulk purchase of cocoa beans for export (PricewaterhouseCoopers, 2008). These expansions increased deposits and loans granted and ultimately resulted in increased profitability which may have enhanced the performance of management, and ultimately TE.

The recent increases in capital requirement may have also over the period enhanced shareholders' scrutiny on management's performance. This argument is in tandem with the observations of Bitar et al. (2018) who found that a rise in regulatory capital increased the incentives of shareholders to monitor the performance of management, ultimately resulting in an improvement in bank operational efficiency.

The inclusion of a slack variable (specifically NPLs) in the bootstrap model, unlike the study of Alhassan and Tetteh (2017) who did not include a slack variable, may have also increased efficiency scores observed by this thesis. In this regard, the findings of this thesis agree with the observations of Zago and Dongili (2011) who in their analysis of bank efficiency in the USA showed that ignoring NPLs significantly underestimated the efficiency of banks; once bad loans were considered, bank's efficiency improved significantly. As explained by Zago and Dongili (2011), the increase in efficiency when NPLs are included in the bootstrap model may be an indication that commercial banks in Ghana have adequate provisions.

Results between the varying efficiency types, OTE, PTE, and SE are elaborated by Figure 4.2, which shows the trend of changes in efficiency scores for the period 2008 to 2019.




| | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| OTE | 0.79 | 0.67 | 0.56 | 0.64 | 0.72 | 0.74 | 0.75 | 0.82 | 0.72 | 0.63 | 0.58 | 0.77 |
| PTE | 0.84 | 0.79 | 0.64 | 0.68 | 0.76 | 0.79 | 0.79 | 0.84 | 0.75 | 0.67 | 0.63 | 0.80 |
| SE | 0.95 | 0.84 | 0.89 | 0.95 | 0.96 | 0.94 | 0.95 | 0.97 | 0.97 | 0.94 | 0.92 | 0.96 |

*Figure 4.2: Annual bootstrap SBM Scores for OTE, PTE and SE*

The efficiency dips shown in Figure 4.2 can largely be attributed to changes in regulatory policies and the economic performance of Ghana. SE shows a relatively constant trend, although dipping in 2009 and marginally increasing in the period 2018 to 2019. PTE and OTE have a more volatile trend, dipping in 2010, peaking in 2015, and further dipping in 2018, before showing an increasing trend in the last period of review.

The dips in the years 2009 and 2010 can be attributed to the contraction in the growth of the economy caused mainly by the increased fiscal deficit in these years (discussed in Chapter 2 of this thesis). The decline in growth resulted in high default risk which may have reduced the technical efficiency of banks.

Again, as explained in Chapter 2 of this thesis, the dip in 2015 may reflect the peak of Ghana's energy crisis which culminated in the rationing of electricity supply and a build of NPLs. The banking sector was also faced with significant challenges in these times. An asset quality review carried out by the Bank of Ghana in the year 2015 and 2016 showed that most banks were faced with poor capital base, liquidity, and corporate governance practices, making them insolvent and largely inefficient (Benson, 2019).

The increase in efficiency after 2018 may indicate a positive response of banks to the recently increased capital requirement which sought to strengthen the sector. Again, as earlier mentioned, the required increase in capital in the year 2018 may have increased shareholders' scrutiny of management, improving corporate governance practices and TE.

Overall, irrespective of the variations in efficiency scores reported under each assumption (OTE, PTE and SE), the P-value tests (at least 10 percent significance level) show that the difference between the efficiency scores measured for PTE and SE, and OTE and SE under the bootstrap SBM DEA model are not statistically significant. The difference between efficiency scores measured for OTE and PTE is however statistically significant (Table 4.5).

*Table 4.5: Test of Significance between Efficiency Scores: Bootstrap SBM DEA Model*

| | **OTE -PTE** | **PTE -SE** | **OTE -SE** |
|---|---|---|---|
| P-value | 0.071 | 3.87 | 9.43 |

Source: Results estimated by author from data submitted by commercial banks in Ghana

4.4.2.2 *Discussion of Results from the Three Stage Network Dynamic SBM DEA Model*

Drawing on the discussions in section 4.3.2, the study applies the Network Dynamic SBM DEA model, using the CRS and VRS assumptions. The CRS estimates the OTE and SE, while the VRS estimates the PTE. In estimating the model, equal weights are assigned to the three stages: the production stage (PS), intermediation process (IP), and the revenue generation stage (RG). The model therefore reports four scores: the overall score and scores for the production, intermediation process, and revenue generation stages.

Averagely, the network dynamic SBM DEA model used shows the overall score for SE as the highest (Table 4.6), confirming the fact that the inefficiencies in Ghana's banking sector are mainly driven by the performance of management (measured by PTE) and not the size of the bank (measured by SE).

*Table 4.6: Summary Results for Network Dynamic SBM DEA Model*

| | CRS – OTE | | | | VRS – PTE | | | | CRS-SE | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Overall Score** | **PS** | **IP** | **RG** | **Overall Score** | **PS** | **IP** | **RG** | **Overall Score** | **PS** | **IP** | **RG** |
| **Average** | 0.37 | 0.35 | 0.43 | 0.32 | 0.48 | 0.43 | 0.59 | 0.41 | 0.77 | 0.82 | 0.72 | 0.78 |
| **Max** | 0.55 | 0.81 | 0.86 | 0.80 | 0.85 | 0.94 | 0.94 | 0.99 | 0.64 | 0.86 | 0.92 | 0.80 |
| **Min** | 0.26 | 0.20 | 0.18 | 0.03 | 0.33 | 0.23 | 0.29 | 0.06 | 0.80 | 0.86 | 0.64 | 0.55 |
| **St Dev** | 0.06 | 0.10 | 0.15 | 0.16 | 0.10 | 0.15 | 0.16 | 0.20 | 0.63 | 0.71 | 0.95 | 0.82 |

Source: Results estimated by author from data submitted by commercial banks in Ghana

In more detail, Figures 4.3 to 4.5 present a pictorial representation of scores for all three stages assessed for the OTE, PTE and SE.

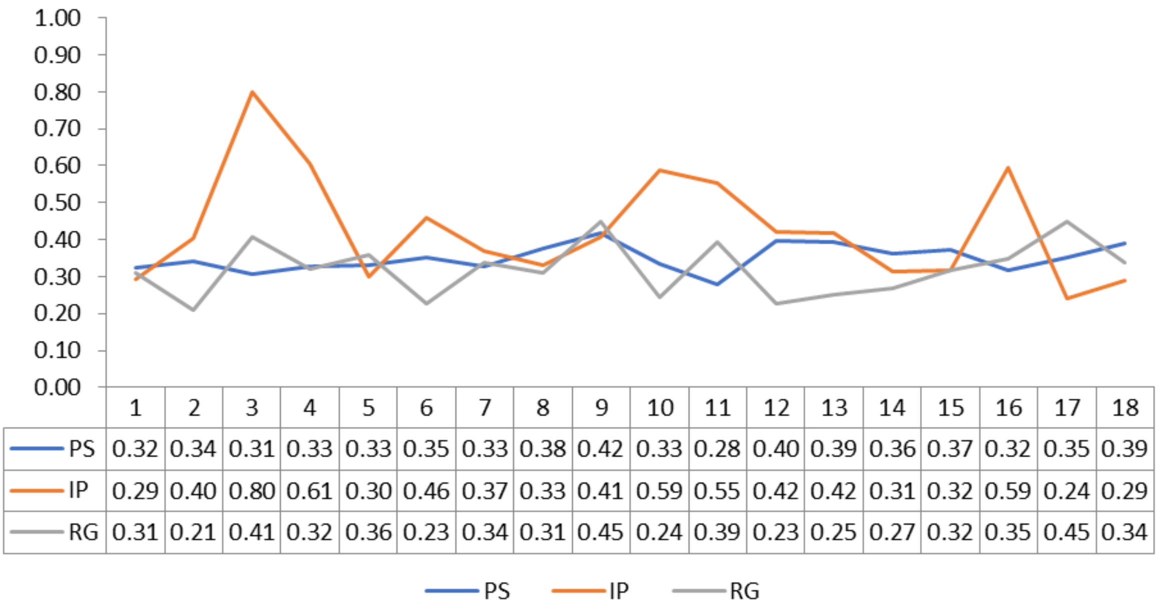
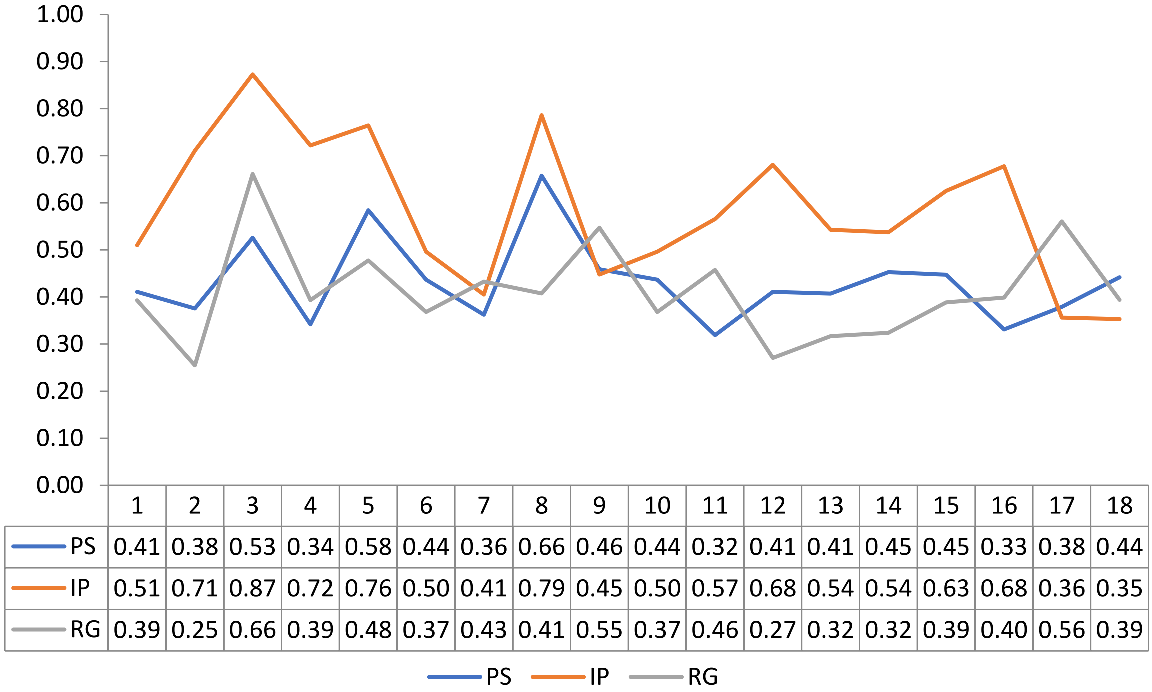



*Figure 4.3: Results for the Three Stage Network Dynamic SBM DEA model – Overall Technical Efficiency*

The average scores for the second stage (IP) exceeded that for the first (PS) and third (RG) stages for both the OTE and PTE measures, meaning, banks in Ghana were better able to convert deposits to loans.

Under the CRS OTE assumption (Figure 4:3), Bank 3, a bank classified as domestic and small with assets lower than the average asset size of the industry, had the highest efficiency score (0.80) for the second stage (IP). Bank 9 and 17 however had the highest efficiency scores for the third stage (RG) (0.45) and first stage (PS) (0.42). As at December 2019, bank 9 and 17 had total assets larger than the average assets of the banks assessed in this study. Banks 9 and 17, are also classified as a foreign bank with its parent bank in a West African country.




| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PS | 0.41 | 0.38 | 0.53 | 0.34 | 0.58 | 0.44 | 0.36 | 0.66 | 0.46 | 0.44 | 0.32 | 0.41 | 0.41 | 0.45 | 0.45 | 0.33 | 0.38 | 0.44 |
| IP | 0.51 | 0.71 | 0.87 | 0.72 | 0.76 | 0.50 | 0.41 | 0.79 | 0.45 | 0.50 | 0.57 | 0.68 | 0.54 | 0.54 | 0.63 | 0.68 | 0.36 | 0.35 |
| RG | 0.39 | 0.25 | 0.66 | 0.39 | 0.48 | 0.37 | 0.43 | 0.41 | 0.55 | 0.37 | 0.46 | 0.27 | 0.32 | 0.32 | 0.39 | 0.40 | 0.56 | 0.39 |

*Figure 4.4 Results for the Three Stage Network Dynamic SBM DEA model – Pure Technical Efficiency*

Under the VRS assumption, Bank 3 reported the most efficient score in the second (IP) and third stages (RG) at 0.87 and 0.66 respectively, while bank 8 was most efficient in the first stage (PS) (0.66). Both banks 3 and 8 are domestic banks with parent companies domiciled in Ghana. Bank 3 is however classified as a small bank while bank 8 is a big bank.

For the SE (Figure 4.5) as earlier indicated, most banks were most efficient in the first stage (PS) and least efficient in the third stage (RG). This implies that most banks were operating at their optimal level of production based on their size. This gain however did not translate proportionally into revenue generation.  Specifically, Bank 13 was most efficient in PS with a score of 0.95, Bank 11, in IP with a score of 0.94 and bank 18 in RG with a score of 0.87. Both banks 13 and 11 are domestic banks while bank 18 is a foreign owned bank.

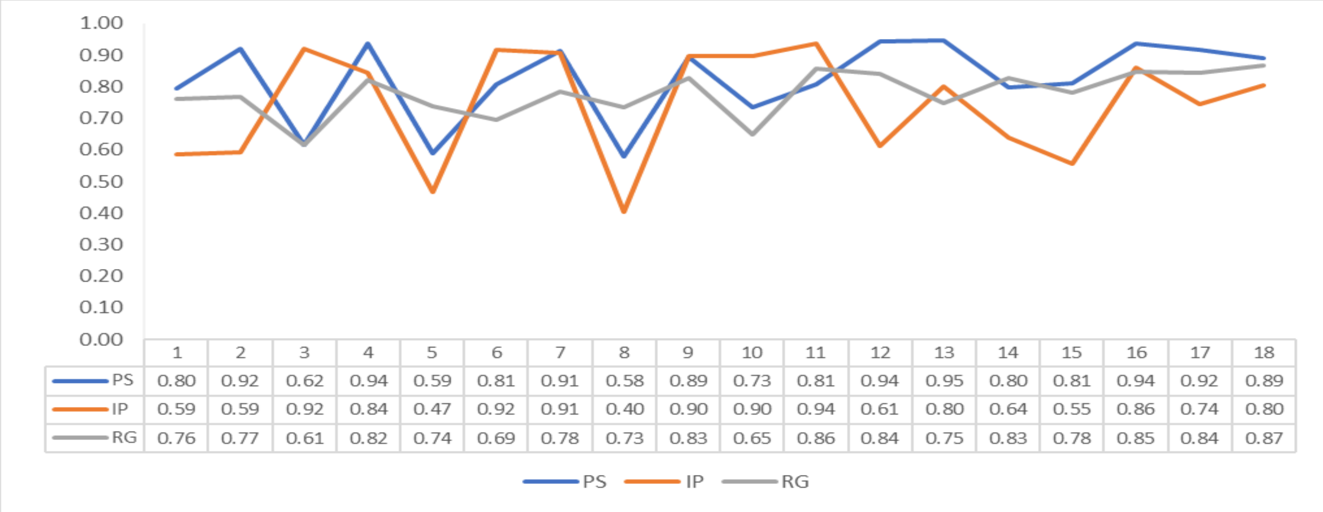



*Figure 4.5: Results for the Three Stage Network Dynamic SBM DEA model – Scale Efficiency*

Overall, the performance of banks for each stage assessed are presented in Tables 1.4 to 1.6 in the Appendix.

*Table 4.7: Results of Test of Significance between the Stages of Efficiency – Dynamic Network Model*

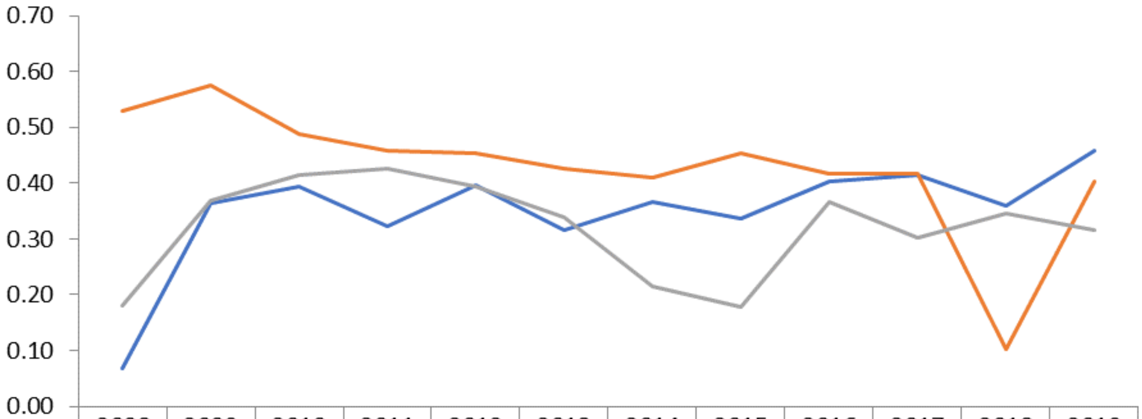
| **OTE** | | **PTE** | | **SE** | |
|---|---|---|---|---|---|
| **Stages** | **P value** | **Stages** | **P value** | **Stages** | **P value** |
| **PS-IP** | 0.02 | PS–IP | 0.00 | PS–IP | 0.05 |
| **IP–RG** | 0.01 | IP–RG | 0.00 | IP–RG | 0.18 |
| **PS–RG** | 0.07 | PS–RG | 0.26 | PS–RG | 0.10 |

Source: Results estimated by author from data submitted by commercial banks in Ghana

Largely, the efficiency scores estimated are statistically different across the activity levels assessed (Table 4.7). Under the CRS (OTE), the P-values estimated for scores between PS and IP, IP and RG, and PS and RG, rejects the null hypothesis, indicating that differences between the results of all the stages assessed are statistically significant. Similarly, for the variable return to scale (PTE), the differences in scores are all statistically significant with the exception of the scores between the first (PS) and third (RG) stages (at a P-value of 0.26). Also for SE, only differences in the scores between the second stage (IP) and third (RG) stages are not statistically significant (at a P-value of 0.18).

Regarding changes in efficiencies over the years, the efficiency of the second stage (IP), calculated under both the CRS (OTE) and VRS (PTE) assumptions, surpassed that of the other stages from 2008 to 2017 (Figures 4.6 and 4.7).

Particularly, in respect of the CRS assumption (OTE) (Figure 4.6), the study revealed a downward trend in efficiencies for stage 2 (IP) from 2009 to 2018 with the most significant drop experienced in 2018. 2019 showed an increase in intermediation efficiency. There was an upward trend in efficiency for Stage 3 (RG) from 2009 to 2012. This was followed by a downward trend, with a significant drop in the year 2015. In 2016, the Stage 3 efficiency of banks picked up, with a slight reduction in 2017 and another reduction in 2019. On the other hand, efficiency for Stage 1 (PS) has been sporadic over the years, with the most significant drop noted in the year 2018. In effect, the significant drop in intermediation and production efficiencies in the year 2018 could be attributed to the increase in minimum capital and the challenges faced by Ghana's banking sector in this year. Regarding intermediation, the increase in capital requirement may have caused banks to become more risk-averse, reducing loans advanced to the general public. In terms of the reduced production efficiency, the growing challenges caused by the liquidation of seven banks between 2017 and 2018 reduced customer confidence in the banking sector, negatively impacting management's ability to convert operational expenditure into deposits.



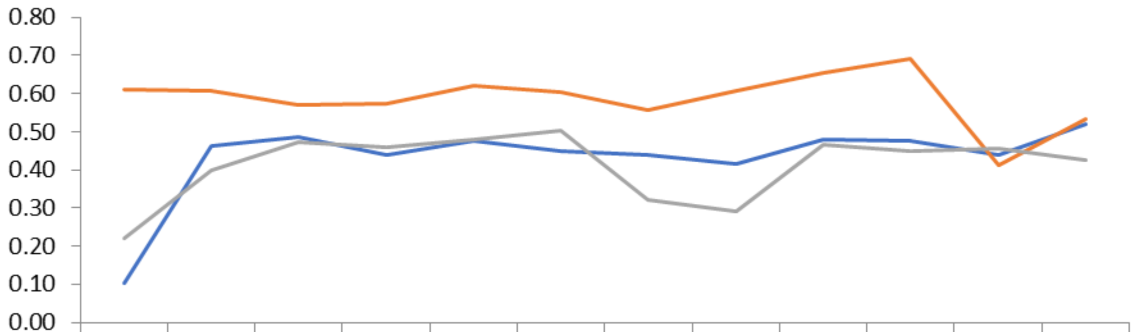

| | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PS | 0.07 | 0.36 | 0.39 | 0.32 | 0.40 | 0.32 | 0.37 | 0.34 | 0.40 | 0.41 | 0.36 | 0.46 |
| IP | 0.53 | 0.57 | 0.49 | 0.46 | 0.45 | 0.43 | 0.41 | 0.45 | 0.42 | 0.42 | 0.10 | 0.40 |
| RG | 0.18 | 0.37 | 0.41 | 0.43 | 0.39 | 0.34 | 0.21 | 0.18 | 0.37 | 0.30 | 0.35 | 0.32 |

PS IP RG

*Figure 4.6: Periodic Results for the Three Stage Network Dynamic SBM DEA model – Overall Technical Efficiency*

On the VRS assumption (PTE) (Figure 4.7), stage 2 (IP) showed an upward trend, marginally reducing in 2014 and increasing significantly in 2017. IP efficiency dropped significantly in 2018 and improved in 2019.

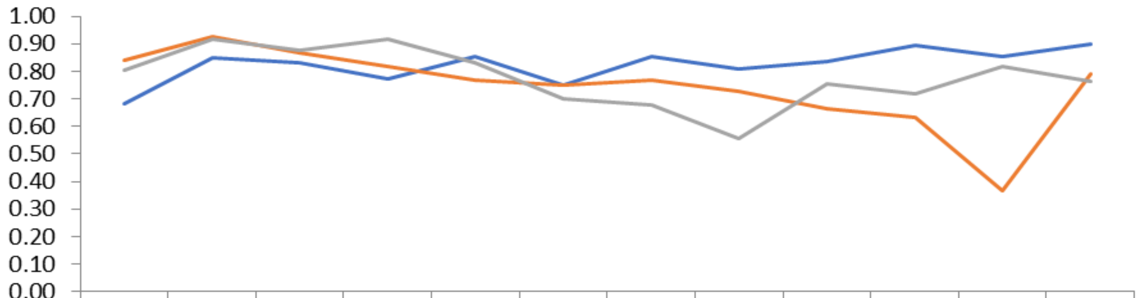
The efficiency of stage 3 (RG) reduced from 2013 to 2015, increased in 2016, with a marginal reduction in 2017 and 2019. The efficiency of Stage 1 (PS) under the VRS assumption also reduced marginally in 2010, 2014, and 2018, increasing in 2019. As earlier mentioned, the drop in IP and PS in 2018 can be attributed to the increase in the minimum capital requirement and the reduced confidence in the banking sector following the liquidation of some banks. The drop in all three stages of efficiency in the period 2013 to 2015 can be attributed to the effect of the electricity challenges faced by the country in these times. Overall, it can be noted that the recent restructuring exercise of the Central Bank has yielded adequate improvement as efficiency in the production stage and intermediation has improved. The drop-in revenue generation in 2019 can be attributed to reduced interest and non-interest income following the reduction in the price of lending (Table 2.2 in Chapter 2).




| | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PS | 0.10 | 0.46 | 0.49 | 0.44 | 0.48 | 0.45 | 0.44 | 0.41 | 0.48 | 0.48 | 0.44 | 0.52 |
| IP | 0.61 | 0.61 | 0.57 | 0.57 | 0.62 | 0.60 | 0.55 | 0.61 | 0.65 | 0.69 | 0.41 | 0.53 |
| RG | 0.22 | 0.40 | 0.47 | 0.46 | 0.48 | 0.50 | 0.32 | 0.29 | 0.47 | 0.45 | 0.46 | 0.43 |

PS IP RG

*Figure 4.7: Periodic Results for the Three Stage Network Dynamic SBM DEA model – Pure Technical Efficiency*




| | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PS | 0.68 | 0.85 | 0.83 | 0.77 | 0.85 | 0.75 | 0.85 | 0.81 | 0.84 | 0.90 | 0.85 | 0.90 |
| IP | 0.84 | 0.93 | 0.87 | 0.82 | 0.77 | 0.75 | 0.77 | 0.73 | 0.66 | 0.63 | 0.37 | 0.79 |
| RG | 0.81 | 0.92 | 0.88 | 0.92 | 0.83 | 0.70 | 0.68 | 0.55 | 0.75 | 0.72 | 0.82 | 0.76 |

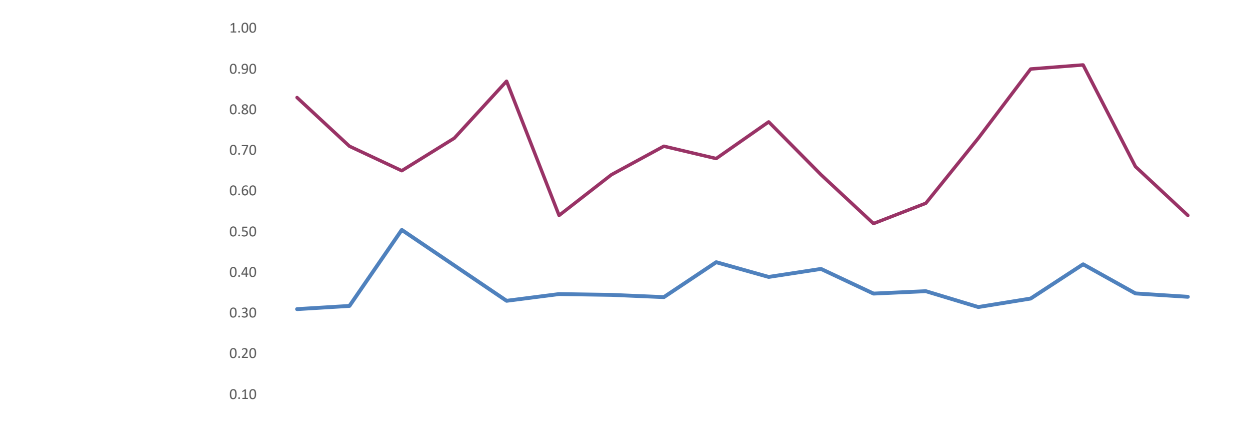
PS IP RG

*Figure 4.8: Periodic Results for the Three Stage Network Dynamic SBM DEA model – Scale Efficiency*

For SE, over the years, the production stage (stage 1) has been the most efficient, with a positive trend. Stage 3 (RG) and stage 2 (IP) efficiencies have had negative trends with the IP stage showing relatively lower efficiency scores than the RG stage. Again, similar to the CRS and VRS assumptions, the period that reported the most significant drop for stage 1 (PS) and stage 2 (IP) was 2018. This implies that irrespective of how big a bank was, its intermediation and production efficiencies were still negatively impacted by the increase in the minimum capital requirement and the liquidation exercise undertaken this year.

#### 4.4.2.3 *Comparison of results from the Three Stage Network Dynamic SBM DEA Model and the Bootstrap SBM DEA model*

Finally, having separately discussed the efficiencies reported from the black-box bootstrap SBM DEA model and the network dynamic DEA model, this study computes and discusses the statistical difference between the efficiency scores measured by these varying models. Under each scale assumption, the results obtained from the black-box approach are compared to the overall score measured under the network dynamic DEA model (Figures 4.9 to 4.11).




| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dynamic Network Model | 0.31 | 0.32 | 0.50 | 0.42 | 0.33 | 0.35 | 0.34 | 0.34 | 0.42 | 0.39 | 0.41 | 0.35 | 0.35 | 0.31 | 0.34 | 0.42 | 0.35 | 0.34 |
| Black Box Model | 0.83 | 0.71 | 0.65 | 0.73 | 0.87 | 0.54 | 0.64 | 0.71 | 0.68 | 0.77 | 0.64 | 0.52 | 0.57 | 0.73 | 0.9 | 0.91 | 0.66 | 0.54 |

*Figure 4.9: Comparison between Black-Box Bootstrap SBM DEA model and the Three Stage Network Dynamic SBM DEA model – CRS Assumption (OTE)*

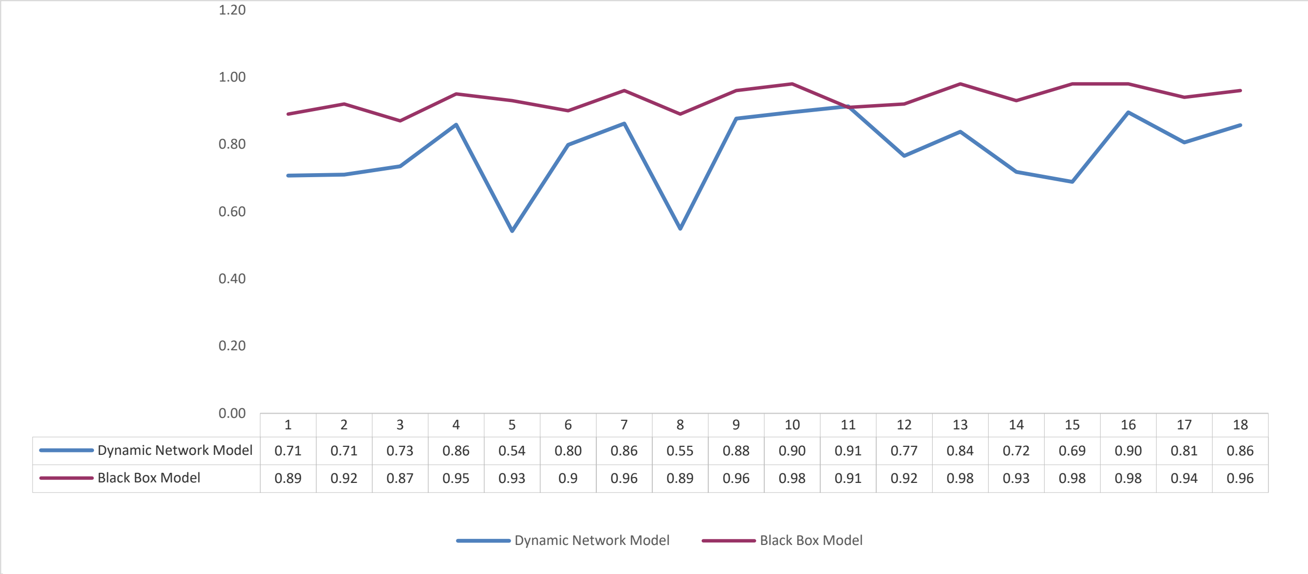



*Figure 4.10: Comparison between Black-Box Bootstrap SBM DEA model and the Three Stage Network Dynamic SBM DEA model – Scale Efficiency*

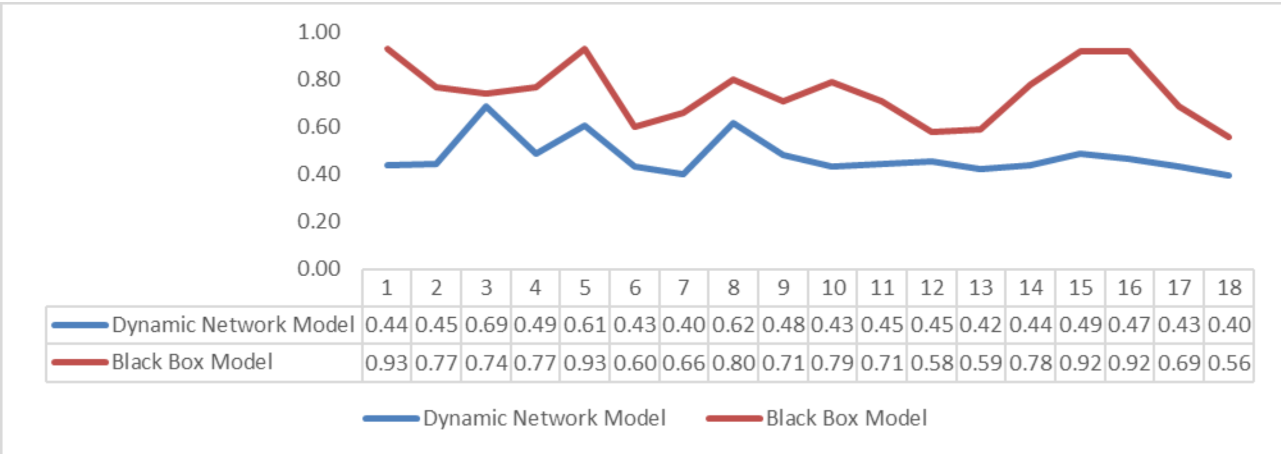



*Figure 4.11: Comparison between Black-Box Bootstrap SBM DEA model and the Three Stage Network Dynamic SBM DEA model – Pure Technical Efficiency*

In comparing the scores from the black box approach with those from the network structure, the results obtained for this study agree with the findings of Dia et al. (2020). Efficiency scores from the black-box model are relatively higher than that from the network structure for all 18 banks assessed, confirming the argument that the black-box approach may overestimate efficiency scores. Particularly, under the CRS assumption, the black-box approach averaged 0.70 while that for the network structure averaged 0.36. For the VRS assumption, the black-box approach averaged 0.74 and the network structure, 0.48, and for SE, the black-box approach averaged 0.93 and the network structure 0.78.

The efficiency scores measured does not only differ in magnitude, but are significantly different at a 10 percent significance level under all assumptions made (OTE, PTE and SE) (Table 4.8).

*Table 4.8: Statistical Differences between Efficiency Scores – Black-Box vs. Network Model*

| Stages | P value |
|---|---|
| **OTE** | 1.51E-12 |
| **PTE** | 4.49E-09 |
| **SE** | 2.6E-06 |

Source: Results estimated by author from data submitted by commercial banks in Ghana

In line with Dia et al. (2020), and following the observed statistical differences across the three stages observed (Table 4.7) and the black-box and network model (Table 4.8), this study supports the use of the network structure since it provides detailed information on disaggregated functions of banks and is less likely to overestimate the efficiency of banks in Ghana.

## 4.5 *Conclusions*

In this chapter, the study measured the efficiency of 18 commercial banks in Ghana in the period 2008 to 2019, using a bootstrap SBM DEA model and a network three-stage dynamic network SBM DEA model. The two models were used to facilitate the comparison of scores derived from the black-box approach and the network structure model and to provide enough information for assessing the core divisions and functions of commercial banks in Ghana. Under the network structure, this chapter focuses on the production, intermediation, and revenue generation stages as the core functions of banking in Ghana.

The results show that banks in Ghana were generally inefficient under both models used. For both models, the banks assessed reported the highest efficiency scores for SE, indicating that the inefficiencies in Ghana's banking sector are caused by the PTE of management rather than the size of banks. Also, for both models, there was a significant decline in efficiency in the year 2018, which was the period in which Ghana's banking sector was restructured. Finally, by comparing the results of the network structure model with the black-box model, this chapter concludes that the network structure model not only provides a more in-depth view into the performance of banks but the results between the black-box model and the network model are statistically different. The overall scores obtained from the network structure model were noticeably lower and statistically different from those obtained from the black-box model. This finding is consistent with the findings of Fukuyama and Matousek (2011) and Dia et al. (2020).

Under the network dynamic SBM DEA model for both the CRS and VRS assumptions, most banks were seen to be most efficient in stage 2 (IP). This observation suggests to the Central Bank to put in place regulatory policies to enhance the intermediation function of banks in order to improve the efficiency scores of financial institutions in the country.

Also, for the dynamic network DEA model, the results suggest that the efficiency of the third stage (RG) did not decline in 2018. The high revenue generated in 2018 to 2019 confirms the trend discussed in Chapter 2 of this thesis: in 2018 and 2019, following the recent increase in minimum capital requirement, commercial banks held more government securities relative to loans which brought in a safer source of revenue.

Overall, despite the extensive information provided by the analysis of efficiency in this chapter, there remains a gap. This gap is peculiar to the DEA methodology in the sense that the DEA model only measures efficiency scores without indicating the sources of inefficiencies observed. In effect, the sole knowledge on efficiency scores without any indication of the causes of inefficiencies does not improve policy aimed at improving the performance of banks. To bridge this gap, it is prudent for researchers to identify the sources of inefficiency.

The next chapter of this thesis, Chapter 5, therefore seeks to use regression models to determine the sources of inefficiencies by regressing both bank-specific and macro-economic factors on the efficiency scores derived from the dynamic network SBM model used in this chapter, Chapter 4.

# CHAPTER 5

# DETERMINANTS OF TECHNICAL EFFICIENCY OF COMMERCIAL BANKS IN GHANA USING THE TRUNCATED BOOTSTRAP REGRESSION MODEL AND THE TOBIT MODEL

## 5.1 *Introduction*

As earlier indicated, this chapter aims to identify and examine the determinants of efficiency in Ghana's commercial banking sector over the period 2008 to 2019. Against the background presented in Chapter 4 of this thesis, this study initially estimated bank efficiency scores of 18 commercial banks in Ghana using the three-stage dynamic network SBM DEA and observed that all banks assessed were generally inefficient. Foreign banks showed higher efficiency scores in deposit mobilisation (production stage) and revenue generation while domestic banks mostly excelled in converting deposits to loans (intermediation stage).

Albeit the uniqueness and advantages of the DEA model used, the results presented in Chapter 4 may not provide adequate information for policymaking. As a major gap, the three-stage dynamic network SBM DEA model used to estimate efficiency scores in Chapter 4, like the traditional black-box DEA model, does not identify the sources of inefficiency (Murillo-Zamorano, 2004). Also, the dynamic network SBM DEA model uses only bank-specific information, ignoring the effect of other external factors such as macroeconomic conditions, market competition, and legal and regulatory reforms, on the performance of banks in Ghana (Dietsch and Lozano-Vivas, 2000). These external factors may have statistically significant impacts on efficiency of banks (Aly et al., 1990; Favero and Papi, 1995; Goddard et al., 2004; Miller and Noulas, 1996).

To address the above gaps and improve understanding of the factors that influence efficiency of banks, most studies, particularly in Ghana, have employed a two-step model (Adjei-Frimpong et al., 2014; Alhassan and Tetteh, 2017; Karimu Tossa, 2016; Saka et al., 2012). The first stage estimates the efficiency scores using the parametric or non-parametric efficiency estimation models, and the second stage regresses the efficiency scores obtained from the first stage on various explanatory variables to identify which factors have a statistically significant impact on efficiency.

For the second stage, most studies in Ghana have used regression procedures such as the ordinary least square (OLS) (Karimu Tossa, 2016), panel regression (Tetteh, 2014), and random and fixed effects Tobit regression models (Saka et al., 2012), with the most common regression model used being the Tobit models.

The traditional regression models have been criticised, especially by Simar and Wilson (2007), who proposed the truncated bootstrap regression model. The motivation for the truncated bootstrap regression emanates from the need to improve on the statistical accuracy of the regression models used by most studies. According to Simar and Wilson (2007), the traditional two-step regression models, especially the Tobit regression model, produce inconsistent results owing to two key challenges: the presence of serial correlation in the DEA efficiency model as the scores estimated are relative to the performance of DMUs in the dataset used, and the challenge of correlation between the input and outputs used to estimate the efficiency scores and the explanatory variables used in the regression model.

Thus, in line with research works such as Simar and Wilson (2007) and (Singh and Thaker, 2020), the truncated bootstrap regression model is preferred in this study owing to its ability to address the challenge of correlation between the explanatory variables and the error term in the equation, as input and output variables used in the estimation of the DEA efficiency scores are correlated with the explanatory variables. The truncated bootstrap regression is employed as it is able to estimate bias-corrected efficiency scores, minimising the serial correlation and improving on the validity of inferences made from the regression model.

In Ghana, only Alhassan and Tetteh (2017) have used the truncated bootstrapped regression to examine the effect of external factors on bank efficiency scores. These authors used data from 2003 to 2011 to establish the effect of non-interest income on efficiency of 26 Ghanaian banks. This current study follows a pattern similar to that of Alhassan and Tetteh (2017) although it differs in the objective of the model, the type of DEA model used, the explanatory variables used and the period assessed.

To the best of our knowledge, this study is the first to apply the truncated bootstrap regression to three production processes of banks in Africa, particularly Ghana. Whereas Alhassan and Tetteh (2017) estimated the bootstrapped DEA model for one production process, this chapter will adopt the input and output variables used in the estimation of the three-stage network SBM DEA in Chapter 4 to estimate the bias corrected efficiency scores for three production processes: deposit mobilisation, intermediation, and revenue generation.

Alhassan and Tetteh (2017) focused on bank-specific determinants (more information is provided in the literature review section of this chapter), whereas this study includes in the explanatory variable, a measure of competition and macro-economic variables. In terms of data coverage, this study extends the study period to 2019, compared to Alhassan and Tetteh's (2017) study.

To estimate competition of Ghana's banking sector, this study uses the Boone indicator, which has rarely been estimated for Ghana's banking sector. To the best of our knowledge, with the exception of Alhassan and Ohene-Asare (2016) and Dadzie and Ferrari (2019), most studies such as as Saka et al. (2012) and Aboagye (2012) have used the HHI to measure competition of banks. The HHI has been criticised for failing to consider the complexities of banking operations in a way that allows for an accurate assessment of the relationship between competition and efficiency (Cobbinah et al., 2020).

Finally, to test for the robustness of the inferences made from the truncated bootstrap regression model, this study also employs the Tobit regression model to explain the determinants of inefficiency in the deposit mobilisation, intermediation and revenue generation processes of banks in Ghana. Such detailed adoption of the Tobit regression model is the first in Ghana.

The rest of this chapter proceeds as follows. Section 5.2 discusses the theoretical and empirical literature on the determinants of efficiency, also focusing on the theory behind the measure of competition in the banking sector. Section 5.3 presents the model specification and the econometric techniques used to estimate the relationship between efficiency scores and the determinants chosen. It also provides information on the source of the dataset used. Section 5.4 presents and discusses the empirical results and Section 5.5 concludes the paper with policy implications and recommendations.

## 5.2 *Literature Review*

Theoretically, literature has most often expressed bank efficiency as a function of internal and external factors (Altunbas et al., 2007; Casu and Molyneux, 2003). Internal factors originate from bank-specific variables mostly recorded by the balance sheet and profit and loss accounts, while the external factors refer to variables within the macroeconomic and regulatory environment, exclusive of the control of bank management.

Following the trend set by existing studies, this section is discussed under three broad headings. The first part provides the effect of internal factors on bank efficiency, presenting both the theoretical arguments on the direction of the effect of the factors and empirical evidence supporting the theories provided. The second part dwells on the impact of external factors on bank efficiency and again discusses both the theoretical and empirical underpinnings. The third part focuses on theoretical discussions on competition and efficiency in the banking sector, elaborating on the chosen methodology for estimating efficiency. An extensive summary of the empirical evidence is presented in Table 5.3.

### 5.2.1 *Theoretical Literature Review*

#### 5.2.1.1 *Determinants of Bank Efficiency – Internal Factors*

In determining bank efficiency, the most common variables categorised as internal factors include size, ownership, profitability, capital and risk management environment (which assesses the asset quality and liquidity risk) (Athanasoglou et al., 2006) (Table 5.3).

Regarding the impact of size on bank efficiency, economic theory suggests conflicting effects. Agency theorists have argued that as bank size increases, particularly within an unstructured market system, the decisions of managers conflict with that of shareholders resulting in the misallocation of resources and reduced efficiency (Mester, 1992), while stewardship theorists claim that as bank size increases, managers become less likely to misuse the firm's resources, resulting in increased efficiency (Hughes et al., 2001). Other researchers such as Eichengreen and Gibson (2001) claim that the impact of size on bank efficiency takes a bell shape (non-linear). These researchers argue that size positively impacts bank efficiency to a certain degree, after which an increase in size results in bureaucracies and misuse of resources, leading to reduced efficiency.

In the same vein, studies on the effect of foreign or domestic ownership on bank efficiency have not arrived at any consensus. In the pioneering work of Berger and DeYoung (2001), authors who assessed the effect of geographic expansion on the efficiency of US banks for the period 1993 to 1998, concluded on two main theories: the home-field advantage and global advantage hypotheses. The home-field advantage hypothesis suggests that domestic banks outperform their foreign counterparts owing to their extensive knowledge and experience within their environment which includes the benefit of language and cultural adaptation. The global advantage theory on the other hand claims that the benefits of sophisticated technology and skilled personnel make foreign banks more efficient than their domestic counterparts. Hence, from a theoretical point of view, the effect of ownership (foreign or domestic) on efficiency is not conclusive.

In terms of the impact of profitability on bank efficiency, most studies have measured profitability as Return on Assets (ROA) and return on equity. Theoretically, the Efficiency Structure theory (ES) is used to describe this relationship, proposing that an increase in either ROA or ROE, most often arising from a reduction in operational cost, could improve technical efficiency (Athanasoglou et al., 2006; Altunbas et al., 2007). This observation can however be disputed in an oligopolistic market where an increase in profitability could impair efficiency levels (Ayoola, 2022).

Also, as earlier indicated, the next most common internal factor that has been treated as a determinant of bank performance and efficiency is the risk environment. This internal factor has mostly been measured in terms of liquidity risk, asset quality, and capital risk. Liquidity risk examines the ratio of loans to deposits, asset quality measures the amount of NPL within a bank and capital risk assesses the level of solvency of banks (Athanasoglou et al., 2006).

To measure the impact of liquidity risk on bank efficiency, two conflicting theories have been used: the portfolio theory of investment and the trade-off theories. The Portfolio theory of investment, originally proposed by Markowitz in 1952, suggests that for an institution to maximise efficiency, an investor would have to choose a portfolio that maximises return for a given level of risk (Pfiffelmann et al., 2016). This portfolio decision therefore hinges on whether to invest all available funds in long-term securities or loans, or keep some funds in cash and/or invest in short-term investments such as treasury bills (Byers et al., 2015; Pfiffelmann et al., 2016). The trade-off theories argue that when banks hold a greater amount of liquid assets, cash or deposits, they lose out on the gains of investing or lending the funds, and ultimately reduce the efficiency and performance of the bank (Athanasoglou et al., 2006; Abbas et al., 2019).

Studies on the relationship between asset quality (measured by NPLs) and bank efficiency are mostly founded on (i) information asymmetry, (ii) adverse selection, and (iii) moral hazard theories (Manz, 2019). The information asymmetry and adverse selection theories argue that banks are more likely to lend to high-risk borrowers as adequate information on borrowers is not available, resulting in reduced efficiencies (Ezeoha, 2011). Also, the moral hazard theory explains the likelihood of borrowers engaging in activities external to the purpose for which loans were granted. Such actions increase credit default, reducing the efficiency of banks (Stiglitz, 1990).

Lastly, both theoretical and empirical literature identify capital as a key determinant of the solvency and efficiency of banks. In examining this relationship, the most common measure used for capital has been the capital adequacy ratio, which is measured as the ratio of the bank’s capital to its risk-weighted assets (Kosmidou et al., 2017). Like most internal factors, the theoretical literature on the effect of capital on bank efficiency gives conflicting results, implying that there is no clear answer on whether a capital increase improves bank efficiency or vice versa. The trade-off theory postulates that as the cost of regulatory capital increases, banks take higher risks to attain higher returns, reducing their operational efficiency (Altunbas et al., 2007). The agency theory presents two conflicting outcomes. First, the agency theory proposes that shareholders increase supervision of management, which improves efficiency when capital increases (Staub et al., 2010). The second view claims that an increase in capital buffer activates excessive risk-taking behaviour which results in reduced efficiency (Hellmann et al., 2000). The stewardship theory is similar to the first argument of the agency theory, arguing that an increase in capital heightens the scrutiny of shareholders and invariably improves the efficiency of banks. Negating the direct relationships proposed by the trade-off, agency, and stewardship theories, Berger (1995) proposed a bell shape relationship. By examining the impact of capital on the efficiency of banks in the USA, Berger asserted that although regulatory capital had a positive relationship with bank efficiency, efficiency reduced over time as capital increased above a certain threshold.

#### 5.2.1.2 *Determinants of Bank Efficiency – External Factors*

For the external factors, this chapter focuses on the most discussed macroeconomic determinants of bank efficiency: inflation and Gross Domestic Product (GDP) per capita.

Revell (1970), using the Economic Growth theory, was the first to explain the relationship between inflation and bank efficiency (Revell, 2018). He argued that a rise in inflation may increase salaries and operating costs above the rate of increase in inflation, which may decrease the profitability and efficiency of banks. Following the argument of Revell (1970), other studies found that timely and accurate forecasting of the inflation rate by bank management allowed for adequate adjustment of interest rates which resulted in higher revenue relative to the cost increase associated with inflation, resulting in improved performance as inflation rises (Trujillo-Ponce, 2013).

The Economic Growth theory (Endogenous Growth Theory) is used to describe the relationship between GDP per capita and bank performance and efficiency. The Endogenous Growth theory suggests that GDP per capita affects the performance of banks via its impact on net interest income, operational costs, and NPLs. Firstly, authors such as Bolt et al. (2012) explained that the expected increase in deposits and disposable income of banks during periods of growth in GDP per capita may provide adequate room for management to diversify products, resulting in reduced operational cost, and increased net interest income, which ultimately improves the efficiency of banks (Bolt et al., 2012). Secondly, in respect of the impact of GDP per capita on NPLs, Koju et al. (2018) also claim that an increase in GDP per capita may reduce the unemployment rate in the country, creating more creditworthy customers and ultimately reducing NPLs while increasing bank profitability and efficiency.

#### 5.2.1.3 *Competition and Efficiency*

Several hypotheses have been used to explain the relationship between efficiency and competition. The most common hypothesis used in existing literature are the ‘structure–conduct–performance hypothesis’ and ‘relative market power’ hypotheses. Following from the relative market power is the ‘quiet life hypothesis’ which has also been extensively used in past literature.

*<u>Structure–Conduct–Performance Hypothesis</u>*

Proposed by Mason in 1939 and later by Bain in 1956, the Structure–Conduct–Performance (SCP) paradigm explains the relationship between the conduct of firms and the structure of the market they operate in, further suggesting that the conduct of the market, influenced by structure, determines efficiency of banks (Lelissa and Kuhil, 2018). The term 'structure' relates to the number and size of firms in the industry and also refers to the pertaining exit and entry conditions of the market. 'Conduct' relates to the behaviour of the market in respect of the quantity and quality of products and services produced and the pricing and the cost of these products and services.

Theoretically, the SCP paradigm is explained by two hypotheses: the traditional SCP hypothesis and the Efficient Structure Hypothesis (ESH).

The traditional SCP hypothesis postulates that where there are fewer, larger banks, the banking sector is more likely to engage in more collusive and anticompetitive behaviours, which may result in higher profits irrespective of the levels of efficiency. Thus, under this hypothesis, there is no established relationship between competition and efficiency (Molyneux et al., 1994; Lelissa and Kuhil, 2018).

The ESH goes beyond the Traditional SCP hypothesis to argue for a direct relationship between firm's profits, market structure and efficiency. Per this the positive gain in profit is attributed to an increase in market share by more efficient firms and not necessarily because of collusive powers as argued by the Traditional SCP hypothesis (Molyneux and Forbes, 1995; Lelissa and Kuhil, 2018).

*Relative Market Power Hypothesis and the Quiet Life Hypothesis*

Under the relative market power hypothesis, the market share of a firm, similar to the ESH, is used as a proxy for competition, where increased market share implies improved competitiveness, and vice versa (Blankson et al., 2022).

The 'quiet life hypothesis', which is derived from the relative market hypothesis, argues for a negative relationship between efficiency and market share, claiming that increased market power reduces managers' motivation to improve profitability and increase efficiency (Rahim, 2017).

*Measures of Competition*

To test the above hypothesis, literature has used two distinct measures of competition: structural and non-structural measures.

The structural measures, which are primarily keen on assessing the impact of the market structure on bank efficiency, include estimation methods such as the number of firms, the concentration ratios and the HHI, each with distinct advantages and disadvantages as shown in Table 5.1 below.

*Table 5.1: Structural Measures of Competition*

| Measure | Advantages | Disadvantages |
|---|---|---|
| **Number of firms (Kedia, 2006; Leon, 2015)** | Simple, limited data. | Not the most reliable measure. Level of concentration using this measure differs significantly if the market is dominated by one firm as opposed to if the market is made up of firms of the same size. |
| **Concentration Ratios (Leon, 2015; Radojičić et al., 2021)** | Simple, limited data although requires more information than the number of firms measured, takes into consideration the market share of top firms. | Focuses only on the market share of a selected number of firms, does not take into consideration the size distribution of the remaining firms in the industry. |
| **Herfindahl–Hirschman Index (HHI) (proposed by Hirschman, 1964) (Cobbinah et al., 2020; Ergungor, 2004)** | Most frequently used measure, goes beyond the market share of top firms, uses information on the market share of each firm in the industry. | Fails to consider the complexities of banking operations in a way that allows for an accurate assessment of the relationship between competition and efficiency. |

Ultimately, the structural methods discussed above are preferred for the minimal data required for their estimations. The key challenge is the perceived simplicity of these structural measures: it is argued that these measures ignore the known complexities of the banking sector such as the effect of information asymmetry, size of banks, product and service variations etc. (Ergungor, 2004; Leon, 2015; Cobbinah et al., 2020).

Unlike the structural methodologies, the non-structural measures of competition focus on the competitiveness of individual firms rather than the behaviour of the market. Key methodologies under this measure include the Lerner Index, the Conjectural Variation Model, Panzar and Rosse Model, and Boone Indicator (Leon, 2015). Each of these methods have varied objectives and derive their measures from different assumptions. The Lerner Index examines the level of pricing power of a firm in a market, the Conjectural Variation Model assesses competitor reaction should a firm increase its output by one percent, the Panzar Rosse Model (also known as the H-Statistics) looks at the transmission of input price to firm's revenue, and the Boone Indicator examines whether efficient firms in a market are more profitable in a competitive market. Consequently, each measure has its advantages and disadvantages, which are presented in Table 5.2 below.

*Table 5.2: Non-Structural Measures of Competition*

| Measure | Characteristics | Advantages | Disadvantages |
|---|---|---|---|
| Lerner Index | Described as the difference between a firm's price and its marginal cost.<br>An index of 0 represents perfect competition and a great divergence signifies a greater monopoly power | Simple to use and straightforward to interpret.<br>Requires minimal data, calculated with a minimum number of observations.<br>Good measure for measuring the market power of an individual firm over a period. | Requires firm level data on prices and other variables.<br>Difficult to determine marginal cost, especially in the banking industry.<br>Similar to the SCP, has theoretical and empirical limitations; market power |

| Measure | Characteristics | Advantages | Disadvantages |
|---|---|---|---|
| | (Bulow and Klemperer, 2002; Amir et al., 2010). | | cannot be equated to competition, so not a good measure for competition.<br>There are instances where increased variation in price and marginal costs results in increased competition.<br>Assumes perfect technical and allocative efficiency which rarely occurs. |
| Conjectural Variation Model (Iwata model and Bresnahan-Lau model) | Assesses the reaction of competitors if a firm in a market increases its output by one percent (Zhou et al., 2021). | Directly estimates firm's conduct over a continuous period of time. | Uses a large number of observations.<br>Has similar limitations to the Lerner Index. |
| Panzar and Rosse (PR) | Most widely used method for assessing competition in the banking sector.<br>Shows how changes in input prices are transmitted to firm's revenue.<br>Weak transmission signifies monopolistic powers while strong transmission signifies perfect competition (Claessens and Laeven, 2004; Mustafa and Toçi, 2017) | Simple to use and employs few numbers of observations.<br>Most appropriate for studies on less matured banking industries.<br>Beneficial for cross-country studies as data on market is not needed in the revenue equation. Only data from firms is used to estimate the revenue equation specified by the PR model. | Static in nature.<br>Sometimes difficult to identify the transmission process.<br>Makes use of varying assumptions which have to be verified.<br>Uses detailed information on pricing. |
| Boone Indicator | Examines whether efficient firms gain higher market shares and profit in competitive markets.<br>The more probable it is that efficient firms gain higher market share and profit, the more competitive the market is (Kar and Swain, 2014; Dadzie and Ferrari, 2019). | Founded on strong theoretical foundations.<br>Simple to use and estimate.<br>Requires limited number of observations.<br>It is not necessarily a price measure, considers non-price strategies.<br>Gives a continuous measure of competition.<br>Is able to measure competition of bank market segments whereas other measures can only assess the entire banking industry. | Different forms of competitive situation cannot be distinguished; ignores variation in product quality, design and other innovative actions by the firm.<br>Requires firm-level variables and information on prices<br>This method may give incorrect results in the short term as efficient gains may not be translated into lower prices or higher profits in the short term. |

Based on data available and the characteristics of the various methodologies explained in Table 5.2 above, this study examines competition with the Boone indicator.

### 5.2.2 *Empirical Literature Review*

#### 5.2.2.1 *Determinants of Bank Efficiency*

There have been a growing number of empirical studies on determinants of bank efficiency. In the past, such studies have been extensively conducted on banks in developed regions such as the USA (Kwan and Eisenbeis, 1995; Mester, 1993, 1996), and the Europe area (Altunbas et al. (2007), for banks in 15 European countries, Girardone et al. (2004) for banks in Italy and Pasiouras et al. (2007) for banks in Greece) (Table 5.3). To identify the relationship between efficiency scores and the determinants, these research works have employed regression models which include the panel data estimations, fixed-effect regression models, Tobit regression, and GMM estimations, OLS panel corrected standard error models, and the truncated bootstrap regression.

Within the last decade however, the growth in the number of studies on determinants of bank efficiency has extended from the advanced economies to more developing or transitioning countries across the globe.

For example, Weill (2003) assessed the determinants of the efficiency of banks in Poland and the Czech Republic for the year 1997. In his first stage analysis, Weill (2003) used SFA to estimate the cost-efficiency frontier of banks and the Tobit regression model to estimate the effect of factors such as ownership type (foreign or domestic), ratio of loans to investment assets, the share of deposits in total balance sheet, and size (total balance sheet assets) on the efficiency score estimated. The author found a positive relationship between bank efficiency and foreign ownership, total assets, and the ratio of loans to investment assets. There was an inverse relationship between cost efficiency and share of deposit in the total balance sheet. Sufian (2009) also examined the determinants of bank efficiency in MENA and the Asian region by using DEA to estimate the technical, pure, and scale efficiencies of banks in the period 2001 to 2006. Sufian (2009) also used the Tobit regression model but assessed the impact of more factors by focusing on internal factors such as loans (total loans divided by total assets), size (logarithm of total assets), deposits (logarithm of total deposits), NPL (ratio of loan loss provisions to total loans), expense (non-interest expense divided by total assets), capital (total equity divided by total assets) and profitability (ROA). The external factor considered was GDP (measured as the logarithm of GDP). Sufian (2009) observed a positive relationship between bank efficiency, loans, size, capital, profitability, and GDP, but a negative impact on deposits and NPLs on the efficiency of banks measured.

Recently, Jiménez-Hernández et al. (2019) and Singh et al. (2020) both used the truncated bootstrap regression technique and the DEA efficiency model to estimate the efficiency scores of banks in Latin American countries and India respectively. Jiménez-Hernández (2019) for the period 2014 to

2016, assessed the impact of internal factors such as size (total assets), foreign or domestic ownership, private or public ownership, loan to asset ratio, and loan loss reserve to total asset ratio. External factors considered included GDP per capita, market concentration (measured by the HHI), domestic credit as a percent of GDP, inflation rate, and population density. Jiménez-Hernández (2019) observed a positive relationship between technical efficiency and size, loan to asset ratio, GDP per capita, and domestic credit as a percent of GDP. There was a negative relationship between technical efficiency and foreign ownership, private ownership, loan loss reserve, concentration, and inflation. Singh et al. (2020) ascertained the robustness of the truncated bootstrap regression model by comparing the estimated regression results to that of a Tobit regression model. Using data from 2008 to 2012, the authors examined the effect of internal factors such as size, return on assets, concentration, equity to asset ratio, ownership type, capital adequacy, and the number of branches, and the external factor, GDP growth. Under the truncated bootstrap technique, Singh (2020) found a positive effect of the number of branches, foreign ownership type, and capital adequacy on bank efficiency. The Tobit regression model showed that return on asset, concentration, number of branches, foreign ownership type, and GDP growth had a positive impact on bank efficiency. Discrepancies in these regression models are introduced in the subsequent section of this chapter, which discusses the regression model to be used for this study.

Other key studies that have extensively discussed the determinants of bank efficiency in developing countries outside the African region are Hasan and Marton (2003) for banks in Hungary, Grigorian and Manole (2006) for banks in 17 transitioning countries in Europe, Havranek et al. (2016) for banks in Poland, Andrieş and Căpraru (2014) for banks in Central and Eastern European countries, and Batir et al. (2017) for banks in Turkey. In the Asian region, a key study is that of Ariff and Luc (2008) for banks in China. A summary of these studies is provided in Table 5.3.

In Africa, particularly in Ghana, studies on determinants of bank efficiency have grown over the years. Aikaeli (2006) assessed the determinants of banks in Tanzania, Kirkpatrick et al. (2008) looked at banks in nine sub-Saharan African countries, Kablan (2007) 35 banks in the WAEMU zone, Kiyota (2011) banks in 29 sub-Saharan countries, and Banya and Biekpe (2018) banks in ten African countries (Botswana, Ghana, Kenya, Mauritius, Nigeria, Tanzania, South Africa, Tunisia, and Uganda).

In Ghana, Saka et al. (2012) used data from 2000–2008 to assess the determinants of the efficiency of commercial banks in Ghana, Alhassan and Ohene-Asare (2016) used data from 2004–2006, Frimpong (2014) 2001 to 2010, Alhassan and Tetteh (2017) 2003 to 2011, Banya and Biekpe (2018) 2008 to 2012, and more recently, Antwi et al. (2021) used data from 2009 to 2018 to assess the determinants of the efficiency of banks in Ghana.

Saka et al. (2012) found a positive and significant relationship between the entry of foreign banks, return on asset and inflation, and technical efficiency, and a negative but significant effect of loan ratio and capital adequacy ratio. The effect of the foreign ownership type on technical efficiency is in line with the global advantage theory, as in the author's view, the advanced technological products such as ATMs, and electronic banking introduced by foreign banks have been replicated by the domestic banks which have invariably increased the efficiency of the entire banking sector. Foreign banks are noted to hire skilled employees which has also contributed to increased efficiency levels. The relationship between inflation and efficiency of banks as measured by Saka et al. however contradicts the Revell (1970) theory (which proposes a negative impact). According to the authors, the positive sign may arise from the fact that deposit rates in Ghana are generally noted to be very low and rarely changing, while lending rates change frequently to reflect the rate of change in inflation. The significant spread between deposit and lending rates would normally imply an increase in profitability during periods of increased inflation, which may ultimately result in improved technical efficiencies.

The trend identified for the inflation variable is similar to the findings of Adjei-Frimpong et al. (2014) who found that the effect of inflation on pure technical efficiency was significant and positive. In this respect Adjei-Frimpong et al. (2014) argued that the cost of inflation is passed on to customers via the high interest rates charged by commercial banks. In terms of the impact of capital on efficiency, the negative relationship observed is in line with the second hypothesis of the trade-off theory which implies that excess equity results in excess risk-taking activities which may reduce efficiency.

Like Saka et al. (2012), Alhassan and Ohene Asare (2016), using OLS panel corrected standard errors, fixed effects, and system GMM regression models also found a negative relationship between loans (leverage) and technical efficiency of banks and a positive impact of return on asset on technical efficiency. The authors also found a negative relationship between bank size and technical efficiency for all the regression models used. This agrees with the observations of Sufian and Habibullah (2010) and Coleman and Feler (2015), who found that larger banks in Ghana may misallocate resources resulting in reduced efficiency.

In more recent studies Alhassan and Tetteh (2016) used the truncated bootstrap regression model and found conflicting results when non-interest income was either included or excluded in the computation of technical and pure technical efficiency scores of commercial banks in Ghana for the period 2003 to 2011. With the inclusion of non-interest income, the authors found a negative relationship between size, leverage, loan loss provision, and the efficiency scores measured. When non-interest income is excluded, the authors found that technical efficiency had a positive relationship with bank size and loan loss provision but a negative relationship with leverage. Pure technical efficiency also had an inverse relationship with loan loss provision and leverage. The negative relationship between loan performance and efficiency reflects the quality of banking assets in Ghana. The consistent growth in NPLs arising from increased default of borrowers impairs the asset quality of banks in Ghana and ultimately results in reduced efficiency scores.

Ofori-Sasu et al. (2019) used the DEA to estimate overall technical and pure technical efficiency scores of commercial banks in Ghana and the random-effect and truncated panel data model to estimate the relationship between technical efficiency and liquidity plus other pertinent factors such as capital adequacy ratio and bank size. These authors observed that bank size and capital adequacy ratio were positively and significantly related to efficiency scores measured under the CCR assumption when the random effect model was used. For the truncated panel data model, capital adequacy ratio and bank size had no significant impact on efficiency under the CCR assumption but had a positive and significant impact on efficiency measured by the BCC assumption. Also, both deposit (ratio of deposit to total assets) and non-deposit funding (ratio of non-deposit to total assets) were noted to be positive and significantly linked to efficiency under the CCR assumption, although the coefficient that represents the relationship between non-deposit funding and efficiency is lower than the coefficient that depicts the relationship between deposits and technical efficiency. Ofori-Sasu et al. (2019) also identified an inverse but significant link between internal funds (sum of net profit before extraordinary items and loan loss provisions relative to total loans) and efficiency under the CCR assumption. This implies that internal funds are being used for less efficient transactions.

The bootstrap truncated model was particularly used for the most recent studies which are Banya and Biekpe (2018) and Antwi et al. (2021).

#### 5.2.2.2 *Conclusions on Empirical Literature Review on Determinants of Bank Efficiency*

Overall, studies on determinants of bank efficiency globally have shown discrepancies when various factors are regressed on technical efficiency scores (Table 5.3). These discrepancies may originate from the use of different countries (either developed or developing country, region of country), time periods assessed, efficiency estimation models (whether traditional DEA or an updated version of the DEA model), assumptions (CCR or BCC), or regression models (OLS, Tobit, truncated regression etc.).

For studies in Africa, especially Ghana, the discrepancies in findings can be directly related to the type of DEA estimation and regression models used, since determinants used mostly remain same across the studies reviewed. These determinants reflect the modus operandi (shown by the ownership structure and interest in increased profitability), regulatory requirements of banks (relating to the CAMEL indices), and the macroeconomic performance of countries in the African region. Thus, the factors commonly regressed on the efficiency scores include ownership type of banks (specifically foreign or domestic ownership structure), capital adequacy, profitability, liquidity, total asset size, asset quality, GDP, and inflation.

A key gap in the studies reviewed on determinants of bank efficiency in Ghana however pertains to the type of model used to estimate the dependant variable, the efficiency score. Primarily, all studies that have attempted to identify the determinants of technical efficiency in Ghana have used the black-box approach to measure technical efficiency. The segregation of technical efficiency has therefore only been in respect of either the CCR assumption (overall TE) or the BCC assumption (PTE) or scale efficiency.

To address the identified gap, this study uses as its dependent variable, the efficiency scores estimated by the three-stage network DEA model, as described and estimated in Chapter 4, to identify determinants of production, intermediation, and revenue efficiencies under both the CCR and BCC assumptions.

Also, this study further compares regression results derived from the Tobit regression model and the truncated bootstrap regression model. In Ghana, although studies such as Ofori-Sasu et al. (2019), Alhassan and Ohene Asare (2016), and Adjei-Frimpong et al. (2014) have used multiple regression models to arrive at their findings, no research has compared results from the Tobit and truncated bootstrap regression models. The benefits of such comparison are discussed in the next section of this chapter.

#### 5.2.2.3 *Empirical Literature Review on the Relationship between Competition and Efficiency*

Just as the growing number of studies on determinants of bank efficiency, several empirical studies have attempted to investigate the relationship between competition and bank efficiency. These studies have yielded ambiguous results, with some supporting a positive or negative relationship or no relationship at all.

A notable example of a study that has supported a positive relationship between efficiency and competition is Hannan and Berger (1997). These authors argued that lack of competition or ‘quiet life’ in a monopolistic banking sector induces incompetent behaviours of bank management, allowing them to pass on cost to customers and distorting their levels of efficiency.

Studies such as Maudos and De Guevara (2007) and Weill (2004) found a negative relationship between efficiency and competition, claiming that managers in a competitive market may not necessarily be efficient.

Casu and Girardone (2006) found no clear relationship between competition and efficiency in their analysis of banks in EU countries. They concluded that although increased competition has forced banks to be more efficient, increased efficiency is not necessarily a result of increased competition in the EU banking system.

In Africa, relatively fewer studies have attempted to examine the relationship between competition and efficiency. Hauner and Peiris (2005) use the HHI as the measure of competition in their analysis of the relationship between efficiency and competition, and concluded that competition introduced by foreign owned banks and larger banks increased the efficiency of Ugandan banking sector. Mlambo and Ncube (2011), using the Panzar-Rosse model as a measure of competition of banks in South Africa, concluded that competition increased efficiency of banks in South Africa although the number of efficient banks decreased over the period examined (1999 to 2008).

In Ghana, Aboagye (2012) used SFA to estimate efficiency, the HHI for competition, and the Tobit regression model, concluded that an increase in competition improved efficiency of the banking sector in both the deposit and loans markets. A similar finding was made by Saka et al. (2012) who used Tobit regression model and the HHI to estimate competition, but estimated bank efficiency under the black-box DEA model. Alhassan and Ohene-Asare (2016), using the fixed effect panel regression model, the Boone indicator to estimate the level of competitiveness of Ghana's banking sector and DEA to estimate efficiency, found a positive relationship between efficiency and competition of Ghana's commercial banking sector. These researchers argued that an increase in competition translates into lower interest rate spreads which ultimately increases cost efficiency of banks.

#### 5.2.2.4 *Conclusions on Empirical Literature Review on the Relationship between Competition and Efficiency*

Overall, existing studies on the competition–efficiency nexus in Ghana's banking sector has either used SFA or the black-box DEA model, yielding ambiguous results, by either supporting a positive or negative relationship or no relationship at all.

However, to the best of our knowledge, there has been no study that has employed the network DEA to estimate efficiency scores for assessing the effect of competition on the three critical areas of banking: deposit mobilisation, intermediation, and revenue generation. This study seeks to bridge this gap.

Table 5.3: Summary of Literature on Determinants of Bank Efficiency

| **Author** | **Country** | **Period** | **Efficiency Estimation Method** | **Regression Method** | **Determinants Assessed** | **Findings** |
|---|---|---|---|---|---|---|
| **Studies on Countries Outside the African Continent** | | | | | | |
| **Kwan & Eisenbeis (1995)** | USA | 1986–1991 | SFA | Least-squares estimation of equations | • Bad loans (past due loans+ non-accruals)/total loans)<br>• Capital (book value capital divided by total assets)<br>• Loan growth (average loan growth over the past five years) | Negative relationship between bank efficiency and bad loans and capital and a non-linear relationship between loan growth and bank efficiency. |
| **Altunbas et al. (2001)** | 15 European countries | 1992–2000 | SFA (cost efficiency) | Seemingly Unrelated Regression (SUR) approach | • Equity to total assets<br>• Loan loss reserve<br>• Log of assets<br>• Interest rate spread over 3-year government bonds<br>• Liquid assets to total assets<br>• Expense to total asset<br>• Net loans to total assets<br>• Liquid assets to deposits<br>• Current assets to current liabilities<br>• Cost to income ratio<br>• Loan loss provision | Positive relationship between cost efficiency and:<br>• Equity to total assets<br>• Loan loss reserve<br>• Log of assets<br>• Interest rate spread over 3-year government bonds<br>• Liquid assets to total assets<br>• Expenses to total assets<br><br>Negative relationship between cost efficiency and:<br>• Net loans to total assets<br>• Liquid assets to deposits<br>• Current assets to current liabilities<br>• Cost to income ratio<br>• Loan loss provision |
| **Hasan & Marton (2003)** | Hungary | 1993–1998 | SFA (cost and profit efficiency) | OLS | • Liquid asset ratio<br>• Short-term loan ratio<br>• Financial investment ratio<br>• Retail deposit ratio<br>• Retail loan ratio<br>• Equity ratio | Cost Efficiency<br>Positive relationship between bank efficiency and:<br>• Short-term loan ratio<br>• Financial investment ratio<br>• Retail deposit ratio |

| Author | Country | Period | Efficiency Estimation Method | Regression Method | Determinants Assessed | Findings |
|---|---|---|---|---|---|---|
| | | | | | • Log of assets<br>• Years in business<br>• Log of hours service available<br>• Acquisition dummy<br>• Foreign ownership share | • Equity ratio<br>• Years in business<br><br>Negative relationship between bank efficiency and:<br>• Liquid asset ratio<br>• Retail loan ratio<br>• Log of assets<br>• Log of hours service available<br>• Acquisition dummy<br>• Foreign ownership share<br><br>Profit Efficiency<br>Positive relationship between bank efficiency and:<br>• Liquid assets<br>• Short term loan ratio<br>• Equity ratio<br>• Years in business<br><br>Negative relationship between bank efficiency and:<br>• Financial investment ratio<br>• Retail loan ratio<br>• Retail deposit ratio<br>• Log of assets<br>• Log of hours service available<br>• Acquisition<br>• Foreign ownership share |
| **Weill (2003)** | Poland and the Czech Republic | 1997 | SFA (cost efficiency) | Tobit Regression | • Ownership type (foreign or domestic)<br>• Ratio of loans to investment assets | Positive relationship between bank efficiency and:<br>• Foreign ownership<br>• Total balance sheet asset<br>• Ratio of loans to investment assets |

| Author | Country | Period | Efficiency Estimation Method | Regression Method | Determinants Assessed | Findings |
|---|---|---|---|---|---|---|
| | | | | | • Share of deposits in total balance sheet<br>• Size (total balance sheet assets) | Negative relationship between bank efficiency and share of deposits in total balance sheet |
| **Girardone et al. (2004)** | Italy | 1993–1996 | SFA (X-inefficiency) | Logistic regression model | • Total assets<br>• Interest margin/total assets<br>• Number of branches<br>• Customer loans and customer deposits/total assets<br>• Dummies for private and public banks<br>• NPLs/total loans<br>• Net income/equity<br>• Capital (equity/total assets)<br>• Dummies for quoted banks and unquoted banks<br>• Dummies for north-western banks and north-eastern banks<br>• Dummies for banks located in the centre<br>• Commercial banks<br>• Savings banks<br>• Popularity of banks | X –inefficiency is negatively correlated to capital and positively related to the level of NPLs in the balance sheet.<br>There is also no clear relationship between x-inefficiency and bank size measured by total assets. |
| **Hauner (2005)** | German and Austria | 1995–1999 | DEA (cost and scale efficiency) | Tobit Regression | <u>Internal Factors</u><br>• Size (total assets)<br>• Concentration (HHI)<br>• Ownership (state-owned, cooperative, and independent banks)<br>• Risk (standard deviation of return on assets)<br>• Deposit (interbank deposit as a ratio of total assets and | Positive relationship between bank efficiency and:<br>• Size<br>• Concentration<br>• State-owned banks<br>• Cooperative banks<br>• Deposits<br>• Liabilities<br>• Expenses<br>• Branch assets |

| Author | Country | Period | Efficiency Estimation Method | Regression Method | Determinants Assessed | Findings |
|---|---|---|---|---|---|---|
| | | | | | customer deposit as a ratio of total assets)<br>• Expense (personnel expense per employee)<br>• Liability (securitised liability as a ratio of total assets)<br>• Branch assets (in monetary value)<br><br><u>External Factors</u><br>• GDP (GDP growth) | Negative relationship between bank efficiency and:<br>• GDP<br>• Savings bank<br>• Risk<br>• Origination from Austria |
| **Grigorian & Manole (2006)** | 17 transition economies (mostly in Europe) | 1995–1998 | DEA (revenue-generating efficiency) | Censored Tobit regression analysis | <u>Internal factors</u><br>Equity shares of total assets<br>Bank assets as a share of total assets (concentration)<br>Dummy variable for foreign ownership<br>Dummy variable for new or old bank<br><br><u>Macroeconomic factors</u><br>GDP per capita<br>Inflation<br>Monetary depth and size of the financial sector (ratio of broad money to GDP)<br><br><u>Regulatory factors</u><br>Capital adequacy<br>Maximum exposure to single borrower<br>Limit on foreign exchange open position | Positive relationship between efficiency and:<br>• Capital adequacy<br>• Equity shares of total assets<br>• Foreign ownership<br>• New banks<br>• Concentration<br>• Foreign exposure limit |

| Author | Country | Period | Efficiency Estimation Method | Regression Method | Determinants Assessed | Findings |
|---|---|---|---|---|---|---|
| **Havrylchyk (2006)** | Poland | 1997–2001 | DEA (cost, technical and allocative efficiency) | Tobit Regression | • Loan loss provision over loan<br>• Growth of assets<br>• Capital<br>• Loan over total assets<br>• Variance of return on assets<br>• Log of total assets<br>• Country dummies (Germany, USA, The Netherlands, and France)<br>• Ownership type (State and Public Listing) | <u>Technical Efficiency</u><br>Positive relationship between bank efficiency and:<br>• State-owned bank<br>• Public owned bank<br>• Germany<br>• The Netherlands<br>• Capitalisation<br>• Variance of ROA<br>• Log of total assets<br><br>Negative relationship between bank efficiency and:<br>• USA<br>• France<br>• Growth of Assets<br>• Loan loss provision over loan<br>• Loan over total assets |
| **Pasiouras et al. (2007)** | Greece | 200–2005 | DEA (technical, pure technical, and scale efficiency) | Fixed Effect Panel Regression | <u>Internal Factors</u><br>• Stock performance (cumulative annual stock returns) | • Positive relationship between stock returns and bank efficiency |
| **Ariff & Luc (2008)** | China | 1995–2004 | DEA (cost and profit efficiency) | Tobit regression | • Ownership structure<br>• Total assets<br>• Gross loans to total assets<br>• Provision to gross loans<br>• Equity to total asset<br>• Loan to deposit<br>• Return to asset<br>• Noninterest income to total income | Positive relationship between cost and profit efficiency and:<br>• Loan to deposit<br>• Return to asset<br>• Noninterest income to total income<br><br>Negative relationship between cost and profit efficiency and:<br>• Total assets<br>• Gross loans to total assets<br>• Provision to gross loans |

| Author | Country | Period | Efficiency Estimation Method | Regression Method | Determinants Assessed | Findings |
|---|---|---|---|---|---|---|
| | | | | | • Operational cost to operating income | • Equity to total asset<br>• Operational cost to operating income |
| **Delis (2009)** | EU countries | 1994–2005 | DEA | Double bootstrap regression and Tobit regression | • EBRD index of banking sector reform<br>• Concentration<br>• Loan loss provision to loans<br>• Short term interest rate<br>• Log of total assets<br>• Ratio of total investment to GDP<br>• Share of bank assets owned by foreign investors as a percent of total assets in the industry;<br>• Share of bank assets owned by the public sector as a percent of total assets in the industry | Positive relationship between bank efficiency and:<br>• EBRD index of the banking sector<br>• Size<br>• Short term interest rate<br>• Ratio of total investment to GDP<br>• Share of bank assets owned by foreign investors as a percent of total assets in the industry<br><br>Negative relationship between bank efficiency and:<br>• Concentration<br>• Loan loss provision to loans<br>• Share of bank assets owned by the public sector as a percent of total assets in the industry |
| **Sufian (2009)** | 16 MENA and Asian countries | 2001–2006 | DEA (technical, pure technical, and scale efficiency) | Tobit Regression | Internal Factors<br>• Loan (total loans divided by total assets)<br>• Size (logarithm of total assets)<br>• Deposits (logarithm of total deposits)<br>• NPL (ratio of loan loss provisions to total loans)<br>• Expense (non-interest expense divided by total assets)<br>• Capital (Total equity divided by total assets)<br>• Profitability (ROA)<br><br>External Factors | Positive relationship between bank efficiency and:<br>• Loans<br>• Size<br>• Capital<br>• Profitability<br>• GDP<br><br>Negative relationship between bank efficiency and:<br>• Deposits<br>• NPL |

| Author | Country | Period | Efficiency Estimation Method | Regression Method | Determinants Assessed | Findings |
|---|---|---|---|---|---|---|
| | | | | | • GDP (logarithm of GDP) | |
| **Andries (2014)** | Central and Eastern European countries | 2004–2008 | SFA and DEA | Ordinary Least Square (OLS) | • Bank capital structure (equity/total assets)<br>• Size of the bank (total assets)<br>• Total asset banking system<br>• Return on average equity<br>• Return on assets<br>• GDP increase rate (percent)<br>• Annual inflation rate (percent)<br>• Asset share of state-owned banks (percent)<br>• Asset share of foreign-owned banks (percent)<br>• Bank NPLs to total gross loans percentage<br>• Domestic credit to private sector ownership form of the bank<br>• Level of concentration in banking system (HHI)<br>• Percentage of assets owned by the five largest banks in the system<br>• Banking reform and interest rate liberalisation indicator<br>• Refinancing rate<br>• Interbank market rate<br>• Deposit rate<br>• Lending rate | Positive relationship between bank efficiency and:<br>• Asset share of state-owned banks (percent)<br>• Asset share of foreign-owned banks (percent)<br>• Banking reform and interest rate liberalisation indicator<br>• Bank capital structure (equity/total assets)<br>• Level of concentration in banking system (HHI)<br>• Annual inflation rate (percent)<br>• Lending rate<br>• Refinancing rate<br>• Size of the bank (total assets)<br>• Total asset banking system<br><br>Negative relationship between bank efficiency and:<br>• Return on average equity<br>• Return on assets<br>• GDP increase rate (percent)<br>• Bank NPLs to total gross loans percentage (NPL)<br>• Domestic credit to private sector<br>• Ownership form of the bank<br>• Percentage of assets owned by the five largest banks in the system<br>• Deposit rate<br>• Interbank market rate |

| Author | Country | Period | Efficiency Estimation Method | Regression Method | Determinants Assessed | Findings |
|---|---|---|---|---|---|---|
| **Batir et al. (2017)** | Turkey (conventional and Islamic banks) | 2005–2013 | DEA (technical, cost, and allocative efficiency) | Tobit Regression | Internal Factors<br>• Return on Assets<br>• Capital Adequacy (Total equity divided by total assets)<br>• Expense (Personnel and non-interest expense divided by total assets)<br>• Deposits (total deposits divided by total assets)<br>• Loans (total loans divided by total assets)<br>• NPL ratio (NPL divided by total loans)<br>• Size (logarithm of total assets)<br><br>External Factors<br>• GDP per growth (yearly growth of GDP %)<br>• Inflation (yearly increase of Consumer Price Index %) | Islamic Banks<br>• Cost efficiency is negatively associated with profitability.<br>• Positive impact of expense on allocative and cost-efficiency.<br>• No significant relationship between capital and technical efficiency<br>• Positive relationship between loans and bank efficiency<br>• Negative relationship between NPL and bank efficiency<br>• Negative relationship between bank size and technical efficiency<br>• Negative relationship between GDP growth and inflation, and bank efficiency<br><br>Conventional Banks<br>• No significant relationship between efficiency and profitability<br>• Negative impact of expense on technical and cost-efficiency<br>• Negative relationship between capital and technical efficiency<br>• Negative relationship between technical and cost efficiency, and deposit<br>• Positive relationship between loans and bank efficiency<br>• Negative relationship between NPL and bank efficiency<br>• Negative relationship between bank size and allocative and cost efficiency |

| Author | Country | Period | Efficiency Estimation Method | Regression Method | Determinants Assessed | Findings |
|---|---|---|---|---|---|---|
| | | | | | | • Negative relationship between GDP growth and inflation, and bank efficiency |
| **Jiménez-Hernández (2019)** | 17 countries in Latin America | 2014–2016 | DEA | Truncated bootstrap regression | Internal Factors<br>• Size (total assets)<br>• Foreign or domestic ownership<br>• Private or public ownership<br>• Loans to assets<br>• Loan loss reserve to total assets<br><br>External Factors<br>• GDP per capita<br>• Concentration (HHI)<br>• Domestic credit as a % of GDP<br>• Inflation rate<br>• Population density | Positive relationship between technical efficiency and:<br>• Size<br>• Loans to assets<br>• GDP per capita<br>• Domestic credit as a % of GDP<br><br>Negative relationship between technical efficiency and:<br>• Foreign ownership<br>• Private ownership<br>• Loan loss reserve<br>• Concentration<br>• inflation |
| **Singh et al. (2020)** | India | 2008–2012 | DEA (profit efficiency) | Tobit Regression and Truncated bootstrap regression | Internal Factors<br>• Size<br>• Return on assets<br>• Concentration (HHI)<br>• Equity to asset ratio<br>• Ownership type (foreign, domestic, state, private)<br>• Capital adequacy<br>• Number of branches<br><br>External Factors<br>• GDP growth | Tobit Regression<br>Positive relationship between profit efficiency and:<br>• Return on assets<br>• Concentration<br>• Number of branches<br>• Foreign ownership type<br>• GDP growth<br><br>Negative relationship between profit efficiency and:<br>• Size<br>• Equity to asset ratio<br>• Capital adequacy |

| **Author** | **Country** | **Period** | **Efficiency Estimation Method** | **Regression Method** | **Determinants Assessed** | **Findings** |
|---|---|---|---|---|---|---|
| | | | | | | Truncated Bootstrap Regression<br>Positive relationship between profit efficiency and:<br>• Number of branches<br>• Foreign ownership type<br>• Capital adequacy<br><br>Negative relationship between profit efficiency and:<br>• Size<br>• Equity to asset ratio<br>• Return on asset<br>• Concentration<br>• GDP growth |
| **Studies on Countries Within the African Continent (excluding Ghana)** | | | | | | |
| **Aikaeli (2007)** | Tanzania | 1998–2004 | DEA (technical and scale) multi trans log function (x-efficiency) | Tobit regression | • Capital adequacy<br>• Labour cost<br>• Liquidity<br>• Asset quality<br>• size | Positive relationship between x-inefficiency and:<br>• Size<br>• Liquidity<br><br>Negative relationship between x-inefficiency and:<br>• Capital adequacy<br>• Labour cost<br>• Asset quality |
| **Kirkpatrick et al. (2008)** | Nine sub-Saharan African countries | 1992–1999 | SFA and DFA (cost and profit efficiency) | Seemingly unrelated regression models | • Concentration (%, measured by the HHI)<br>• Market shares (%, measured by loans and deposits equally weighted)<br>• Asset quality (problem loans to total loans, %) | Positive relationship between profit efficiency and:<br>• Concentration asset quality<br>• Capital ratio (equity to net loans)<br>• Liquidity<br>• Cost of loans<br>• Average income of bank customers |

| Author | Country | Period | Efficiency Estimation Method | Regression Method | Determinants Assessed | Findings |
|---|---|---|---|---|---|---|
| | | | | | • Capital ratio (measured by the ratio of equity to net loans)<br>• Capital ratio, (alternatively measured by the ratio of equity to total assets, %)<br>• Liquidity (measured by the ratio of the bank's liquid assets to customer and short-term funds, %)<br>• Profitability (measured by profit in US Dollars)<br>• Profitability (alternatively measured by return on assets, %)<br>• Bank size (the ratio of bank assets to total banking sector assets, %)<br>• Bank size (alternatively measured by the bank's total assets in US Dollars)<br>• Ownership status (measured as 0 for domestic banks and 1 for foreign banks)<br>• Degree of foreign penetration, (measured as the ratio of the foreign banks' assets to total banking sector assets, %)<br>• Average income of bank customers (measured by per capita GDP)<br>• Economic growth (measured by GDP growth rate)<br>• Average cost of loans adjusted for inflation (measured by the real loan rate, %) | Negative relationship between profit efficiency and:<br>• Size<br>• Foreign penetration of banks<br><br>Positive relationship between cost efficiency and:<br>• Concentration asset quality<br>• Capital ratio (equity to total assets)<br>• Liquidity<br>• Profitability<br>• Cost of loans<br>• Average income of bank customers<br><br>Negative relationship between profit efficiency and:<br>• Size<br>• Foreign penetration of banks |

| **Author** | **Country** | **Period** | **Efficiency Estimation Method** | **Regression Method** | **Determinants Assessed** | **Findings** |
|---|---|---|---|---|---|---|
| **Kablan (2007)** | 35 banks in the WAEMU zone | 1996–2004 | DEA (technical efficiency and pure technical efficiency), SFA (cost efficiency) | Tobit regression | <u>Internal Factors</u><br>• Ratio of stockholders' equity to total assets<br>• Ratio of economic profitability defined as net income out of total assets<br>• Share of loans granted to the customers in the total assets<br>• The share of deposits of each bank in their total assets<br><br><u>External Factors</u><br>• Population density<br>• Concentration (measured by the HHI)<br>• Income per capita<br>• Share of stockholders' equity held by the foreign investors<br>• Ratio of bad loans in each country to total loans | Positive relationship between cost efficiency and:<br>• Stockholders' equity to total assets<br>• Share of deposit to total assets<br>• Concentration<br>• Income per capita<br>• Share of stockholders' equity held by foreign investors<br><br>Negative relationship between cost efficiency and:<br>• Net income out of total assets<br>• Bad loans<br>• Population density<br><br>Positive relationship between technical efficiency and:<br>• Net income out of total assets<br>• Concentration<br>• Income per capita<br>• Equity held by foreign investors<br><br>Negative relationship between technical efficiency and:<br>• Equity to total assets;<br>• Deposit to total assets<br>• Bad loans<br>• Population density<br><br>Positive relationship between pure technical efficiency and:<br>• Net income out of total assets,<br>• Share of deposit to total asset<br>• Concentration<br>• Income per capita |

| Author | Country | Period | Efficiency Estimation Method | Regression Method | Determinants Assessed | Findings |
|---|---|---|---|---|---|---|
| | | | | | | • Equity held by foreign investors<br><br>Negative relationship between pure technical efficiency and:<br>• Bad loans<br>• Population density |
| **Kiyota (2011)** | 29 sub-Saharan countries | 2000–2007 | SFA (cost and profit efficiency) | Tobit regression | <u>Internal Factors</u><br>• customer deposits/loans + other earning assets<br>• fixed assets divided by total assets deposits and short-term funding divided by equity of bank<br>• lending rates (interest revenue divided by average loan amount)<br>• deposit rates (interest expenses divided by average deposit amount)<br>• natural logarithm of total assets<br>• net interest margin (difference between interest income (loans, securities, etc) and interest expense (deposits, borrowed funds, etc)<br>• loan loss provisions divided by net interest revenue<br>• equity divided by total assets<br>• net loans divided by total assets<br>• net interest expenses divided by total assets | Positive relationship between profit efficiency and:<br>• customer deposits/loans + other earning assets<br>• net loans divided by total assets (for SSA foreign banks)<br>• loan loss provisions divided by net interest revenue<br>• net loans divided by total assets<br>• inflation rate<br>• real GDP growth rate<br><br>Negative relationship between profit efficiency and:<br>• net loans divided by total assets (for non SSA foreign banks)<br>• fixed assets divided by total assets<br>• natural logarithm of total assets<br>• net interest margin (difference between interest income (loans, securities, etc) and interest expense (deposits, borrowed funds, etc)<br>• loan loss provisions divided by net interest revenue (for domestic banks)<br>• equity divided by total assets<br>• overhead cost divided by total assets<br>• deposit rates (domestic and non SSA foreign banks) |

| Author | Country | Period | Efficiency Estimation Method | Regression Method | Determinants Assessed | Findings |
|---|---|---|---|---|---|---|
| | | | | | • overhead cost divided by total assets<br><br><u>External Factors</u><br>• inflation rate<br>• governance indicator ranging from -2.5 to 2.5<br>• real GDP per capita growth rate domestic credit to private sector (percentage of GDP)<br>• real GDP growth rate<br>• money and quasi money (M2) as percentage of GDP at count | • real GDP per capita growth rate<br>• domestic credit to private sector (percentage of GDP)<br>• money and quasi money (M2) as percentage of GDP at count<br><br>Positive relationship between cost efficiency and:<br>• net loans divided by total assets (non-SSA foreign banks)<br>• natural logarithm of total assets<br>• net interest margin (difference between interest income (loans, securities, etc) and interest expense (deposits, borrowed funds, etc)<br>• overhead cost divided by total assets<br>• deposit rates (domestic banks)<br>• real GDP per capita growth rate<br>• deposits and short-term funding divided by equity of bank (non SSA foreign banks)<br>• domestic credit to private sector (percentage of GDP)<br><br>Negative relationship between cost efficiency and:<br>• deposits and short-term funding divided by equity of bank (SSA foreign banks)<br>• net loans divided by total assets (domestic banks)<br>• equity divided by total assets<br>• deposit rate (foreign banks and non SSA foreign banks)<br>• inflation rate |

| Author | Country | Period | Efficiency Estimation Method | Regression Method | Determinants Assessed | Findings |
|---|---|---|---|---|---|---|
| | | | | | | • governance indicator ranging from -2.5 to 2.5<br>• real GDP per capita growth rate domestic credit to private sector (percentage of GDP)<br>• real GDP growth rate<br>• money and quasi money (M2) as percentage of GDP at count<br>• inflation rate |
| **Banya & Biekpe (2018)** | Ten African countries (Botswana, Ghana, Kenya, Mauritius, Nigeria, Tanzania, South Africa, Tunisia, and Uganda) | 2008–2012 | DEA (technical, pure technical, and scale efficiencies) | Truncated Bootstrap Regression | • Size<br>• Loan loss provision to total loans<br>• Total loans to total assets<br>• Noninterest expenses to total assets<br>• Ratio of debt to total assets<br>• Fixed assets to total assets | Positive relationship between technical efficiency and:<br>• Loan loss provision to total loans<br>• Noninterest expenses to total assets<br>• Fixed assets to total assets<br><br>Negative relationship between technical efficiency and:<br>• Size<br>• Total loans to total assets<br>• Ratio of debt to total assets |
| **Studies on Ghana** | | | | | | |
| **Bopkin (2012)** | Ghana | 1999–2007 | SFA (cost and profit efficiency) | Panel data estimations | • Loan loss provision over total loans and advances<br>• Return on asset<br>• Ownership type (foreign and domestic)<br>• Board size (number of persons onboard)<br>• Board composition (ratio of executive members to non-executive members)<br>• Size (total assets)<br>• Capital adequacy ratio | Positive relationship between profit and cost efficiency and:<br>• Size<br>• Board size<br>• Foreign ownership<br><br>Positive relationship between profit efficiency and:<br>• Capital adequacy ratio<br>• Board composition |

| Author | Country | Period | Efficiency Estimation Method | Regression Method | Determinants Assessed | Findings |
|---|---|---|---|---|---|---|
| | | | | | | Negative relationship between cost efficiency and:<br>• Capital adequacy ratio<br>• Board composition |
| **Saka et al., 2012** | Ghana | 2000–2008 | DEA | Tobit regression | • Foreign share of total banking assets<br>• Concentration (HHI)<br>• Return on asset<br>• Capital adequacy ratio<br>• Inflation<br>• Loan ratio | Positive relationship between technical efficiency and:<br>• Foreign share of total assets<br>• Return on assets<br>• Inflation<br><br>Negative relationship between technical efficiency and:<br>• Concentration<br>• Capital adequacy ratio<br>• Loan ratio |
| **Adjei-Frimpong (2014)** | Ghana | 2001–2010 | DEA (cost efficiency) | fixed effects estimator and two-step system GMM estimator | • Size<br>• Capitalisation<br>• loan loss provision<br>• inflation rate<br>• GDP growth rate | Positive relationship between cost efficiency and:<br>• Size<br>• Capital<br>• Loan loss provision<br>• Inflation capital<br><br>Negative relationship between cost efficiency and GDP growth rate |
| **Alhassan & Ohene-Asare (2016)** | Ghana | 2004–2006 | DEA | OLS panel corrected standard errors; fixed effects; system GMM | • Competition (Boone indicator)<br>• Bank size (logarithm of total assets)<br>• Intermediation (loans to total assets)<br>• Income diversification (non-interest income to total income) | Positive relationship between technical efficiency and:<br>• Intermediation<br>• Income diversification<br>• Return on asset<br><br>Negative relationship between technical efficiency and:<br>• Competition |

| Author | Country | Period | Efficiency Estimation Method | Regression Method | Determinants Assessed | Findings |
|---|---|---|---|---|---|---|
| | | | | | • Asset tangibility (fixed asset to total asset)<br>• Leverage (total liabilities to total assets)<br>• Return on assets | • Asset tangibility<br>• Leverage<br>• Bank size |
| **Alhassan & Tetteh (2016)** | Ghana | 2003–2011 | DEA (TE and PTE computed with or without non-interest income as an output variable) | Truncated bootstrap regression | • Size (logarithm of total assets)<br>• Bank concentration<br>• Leverage (ratio of total bank debt to total assets)<br>• Loan loss provisions to gross loans return of assets<br>• Ratio of gross loans to total assets | • When non-interest income is included as output in the computation of TE, TE has a negative relationship with all variables assessed.<br>• Except for bank concentration, PTE also has a negative relationship with all the variables assessed.<br>• When non-interest income is excluded as an output in the computation of TE, TE except for the measure of leverage has a positive relationship with all the variables assessed. PTE has a negative relationship with leverage, loan loss provision, and the ratio of gross loans to total assets. |
| **Dadzie & Ferrari (2019)** | Ghana | 2000–2014 | SFA (cost efficiency) | GMM estimator | • Competition (Boone Indicator)<br>• Ownership type (domestic, foreign, regional ownership) | • Increased levels of competition have not had any significant impact on bank efficiency. |
| **Antwi et al. (2021)** | Ghana | 2009–2018 | SFA (cost and profit efficiency) | Panel least square | • Liquidity<br>• Capital<br>• Concentration (HHI)<br>• Size (log of total assets) | • Except for the concentration measure, all variables assessed had a positive relationship with cost-efficiency.<br>• Except for size, all variables assessed had a positive relationship with profit efficiency. |

*Note: TE – Overall Technical Efficiency, PTE* – Pure Technical Efficiency, SUR – Seemingly Unrelated Regression, HHI* –Herfindahl–Hirschman index*

## 5.3 *Scope of Data and Model Specification*

### 5.3.1 *Scope of Data Used*

Similar to all the empirical analyses in this thesis, this chapter uses information sourced from the BoG. Data is extracted from the financial statements (income statement and balance sheet) submitted by 18 commercial banks licensed by the Bank of Ghana for the period January 2008 to December 2019.

### 5.3.2 *Measuring Competition – the Boone indicator*

Originally proposed by Boone (2001; 2008), the Boone indicator is a measure of competition which assesses the extent to which efficient firms are able to attain higher market shares in order to increase profitability (Dadzie and Ferrari, 2019). The Boone indicator is premised on the assumptions of the ESH which assumes that firms become more efficient when competition increases through lower production cost and increased market share (Alhassan and Ohene-Asare, 2016).

To estimate the Boone indicator, the study follows the two-step estimation model of Van Leuvensteijn et al. (2013) and Dadzie and Ferrari (2019). For the first step, the study adopts a trans log flexible functional form to estimate the total cost which is needed for the estimation of the marginal cost used in the second step[38]. The trans log cost function has two output variables: gross loans (y1) and shares and securities (y2), and two input variables: interest paid on deposits (w1) (price of funds) and ratio of operating cost to total assets (w2) (price of capital). Total Cost (TC*), calculated as the sum of interest and operating costs, represents the total cost of bank i at time t. Similar to the work of Dadzie and Ferrari (2019), the study imposes a symmetric condition and restriction of linear homogeneity on the input prices, meaning, an increase (or decrease) in cost is proportional to the increase (or decrease) in input prices. Effectively, the ratios TC*=TC/w2 and w1*=(w1/w2) are used to impose linear homogeneity in input prices.

To estimate the cost function several studies such as that of Van Leuvensteijn et al. (2011) have used the OLS to estimate the parameters of the cost function. The OLS models have been criticised for producing bias parameter estimates owing to issues of multicollinearity as the total cost function includes a number of explanatory variables (Lin and Ahmad, 2016). To resolve this issue, recent studies such as that of Dadzie and Ferrari (2019) have used the stochastic frontier model to estimate the translog cost function. This study follows a similar trend and uses a parametric SF model to estimate the translog cost function. Consequently, the study specifies the model in a logarithm form

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[38] The marginal cost (MCit) for each year in the database is estimated using a separate trans log cost function (TCF) as marginal costs are not observed directly.

as it allows the interpretation of first-order coefficients as cost elasticities. The following model specification is therefore used to estimate the TC:

$$\ln(TC_{it}^{*}) = \alpha + \beta_1 \ln w_{1it}^{*} + \beta_{11}(\ln w_{1it}^{*})^2 + \sum_r \gamma_r \ln y_{rit} + \sum_r \sum_s \gamma_{rs} \ln y_r \ln y_s + \sum_r \psi_r \ln y_{rit} \ln w_{it}^{*} + \ + \varepsilon_{it} \quad (5.1)$$

Having estimated the TC, the first step analysis ends with the computation of marginal cost (MC) which is estimated from the first derivative of Equation (5.1) as follows:

$$MC_{it} = \frac{\partial TC_{it}}{\partial q_{it}} = \frac{TC_{it}}{q_{it}}(\delta_0 + \delta_1 \ln q_{it} + \sum\nolimits_{j=1}^{3} \delta_{j+1} \ln W_{j,it}) \quad (5.2)$$

In equation 5.2, the study focuses on the marginal cost of the gross loans component as it investigates competition in terms of loan share.

To estimate the second step of the model, the study again follows the model specification used by Dadzie and Ferrari (2019) and specifies the Boone indicator model as follows:

$$\ln MS_{it} = \alpha + \sum_{t-1}^{T} \beta_t D_t \ln MC_{it} + \varepsilon_{it}. \quad (5.3)$$

where $MS_{it}$ is the market share of loans of bank i in year t and $MC_{it}$ is the marginal cost of loans as estimated from Equation 5.2. $D_t$ is a vector of T year-specific dummy variables that allows the Boone indicator to vary over time, β is the Boone indicator which measures the level of competition and $\varepsilon_i$ the unobserved error term.

To estimate Equation 5.3, the study uses the two-step GMM estimator[39], using lagged values of MC as instruments. The GMM estimator is used to accounted for the issues of endogeneity suggested by Van Leuvensteijn et al. (2011) and Schaeck and Čihák (2010) in their estimation of the Boone indicator. In this study, the possibility of endogeneity of MC is supported by a Hausman test carried out between the fixed effects model and the alternative two-step GMM model, where lagged values of MC are used as instruments.

### 5.3.3 *Model Specification*

As earlier described, the DEA, as a non-parametric approach, has been criticised for its inability to explain reasons behind the inefficiencies measured. To overcome this challenge, the two-step model discussed in the introduction of this chapter is used. This model first of all estimates the DEA

[39] Dadzie and Ferrari (2019) and Kar and Swain (2014) used the two-step GMM to estimate Equation 5.3.

efficiency score, and secondly establishes the relationship between the independent variables and efficiency scores, providing a set of explanatory variables for the inefficiencies recorded.

To estimate the two-step model, this study uses both the truncated bootstrap regression and the Tobit regression models.

5.3.3.1 *Simar and Wilson Approach – Truncated Bootstrap Regression Model*

The truncated bootstrap regression model used in this chapter follows the Simar–Wilson regression syntax in Stata proposed by Simar and Wilson (2007) and also used by recent studies such as that of Fernandes et al. (2018), Jiménez-Hernández et al. (2019) and Singh and Thaker (2020).

Unlike the Tobit regression model, Simar and Wilson (2007) argued that the truncated bootstrap regression does not recognise efficiency scores as censored data, it rather truncates data at a certain threshold. To truncate the data, the following assumptions are made by Simar and Wilson (2007):

- Primarily, the dependent variable to be truncated is assumed to fall within a specified range. In the case of this study, the efficiency scores estimated are expected to range from zero to one. This allows the study to truncate observations at the lower limit of zero, meaning observations with efficiency scores below zero will not be considered in the proposed regression analysis or at an upper limit of 1, implying that observations above 1 would not be considered. Statistically, for this study, zero observations are truncated since the sample did not contain any efficiency score with values less than zero.
- The efficiency scores estimated are assumed to be relative, not absolute figures. This assumption is met since on the frontier efficiency scores represent the ratio between input used to output produced.

Following the motivation for the use of the truncated bootstrap regression model in the introduction of this chapter, it was earlier mentioned that as the efficiency scores estimated are not directly observed (they are relative to the scores of other DMUs in the dataset), and so there may be instances of serial correlation. Also, there may be cases of correlation between the input and outputs used to estimate the efficiency scores and the explanatory variables used in the regression model. To resolve the concern of correlation and serial correlation, the truncated bootstrap regression model used in this study adopts algorithm 2 of the Simar–Wilson model. This model estimates bias-corrected efficiency scores which are then regressed on the set of environmental variables (Simar and Wilson, 2007; Singh and Thaker, 2020). The bias corrected efficiency scores estimated by algorithm 2 is preferred over the uncorrected efficiency score employed by algorithm 1 which is unable to address the concerns of correlation and serial correlation. According to Fernandes et al. (2018), although algorithm 1 strives to improve the inferences of the regression results, it does not take into consideration the biasness of the score measured.

#### 5.3.3.1.1 *First Stage Analysis: Estimation of Efficiency Scores*

To estimate the algorithm 2, the following steps are undertaken:

- Use the data employed in Chapter 4 to measure the three-stage dynamic network DEA to estimate the efficiency scores ($\hat{\theta}$) for the production, intermediation and revenue generation efficiencies. To estimate the efficiency scores, the variable return to scale and input-oriented assumptions are selected. The choice for the VRS assumption is founded on the argument of Burger and Moormann (2009) and Othman et al. (2016), who argued that in the real world, profit-driven institutions such as banks are more likely to produce under increasing or decreasing returns to scale than under the constant returns to scale assumed by the CCR model.
- As shown in Figure 4.5 in Chapter 4, production efficiency is estimated with three inputs (employee cost, fixed assets, and other operating costs) and one output (total deposits). Intermediation efficiency is also estimated with one input (total deposits) and two outputs (gross loans, and shares and securities) and the revenue generation efficiency is estimated with three inputs (gross loans, shares and securities and NPLs) and two outputs (interest and non-interest income).
- Generate a truncated bootstrap regression to estimate the coefficients $\hat{\beta}$ and $\hat{\sigma}$.
- Repeat the following steps 2,000 times (bootstrap replication) to compute bootstrap estimates of $\hat{\beta}^* \; and \; \hat{\sigma}^*$ and use the maximum likelihood method to measure the truncated regression of $\theta$ on $Z_{it}$, yielding estimates $\hat{\beta}^* \; and \; \hat{\sigma}^*$
- Use the bootstrapped values and the original estimates $\hat{\beta}^* \; and \; \hat{\sigma}^*$ to construct estimated confidence intervals for each element of $\beta$ and $\sigma$.

#### 5.3.3.1.2 *Second Stage Analysis – Regression Analysis*

The end of the first stage analysis provides a set of bias-corrected estimates of efficiency estimates $\hat{\theta}_{it}$ which are used as the dependent variable in the equation below:

$$\hat{\theta}_{it} = \beta Z_{it} + \varepsilon_{it} \quad \text{i=1, 2, n t= 1,..., T} \tag{5.4}$$

Where $\hat{\theta}_{it}$ is the bootstrapped bias-corrected efficiency scores (dependent variable) for production, intermediation, and revenue generation efficiencies under the BCC assumptions, $Z_{it}$ is is the vector of a specific explanatory variable for a bank at a certain time, $\beta$ is the parameter that establishes the relationship between the explanatory (independent) variables and efficiency scores, and $\varepsilon_{it}$ is an independent error term.

The truncated bootstrap equation is therefore estimated as follows:

$$\widehat{TEFF}_{1,t} = \alpha_0 + \beta_1 CAR_{it} + \beta_2 ROA_{it} + \beta_3 \left(\frac{TL}{TD_{it}}\right) + \beta_4 \left(\frac{NPL}{TL_{it}}\right) + \beta_5 \left(\frac{OC}{OI_{it}}\right) + \beta_6 \log TA_{it} + \beta_7 IFR_t + \beta_8\, GDP_t + \beta_9 BI_t + \beta_{10} DUMOWN_{it} + \varepsilon_{it} \tag{5.5}$$

Where $\widehat{TEFF}_{1,t}$ is the biased-corrected bootstrapped efficiency scores measured for each stage for either the CCR or BCC assumption, i is the DMU under observation, t is the period, α is the constant term, β is the coefficient of each explanatory variable, and ε is the error term. Overall, the size of the confidence interval for the bias-corrected DEA score in our case is 0.10.

#### 5.3.3.2 *Tobit Regression*

Based on the fact that efficiency scores are bounded between zero and unity, it is expected that the estimates will be biased unless censored (Fernandes et al., 2018). The Tobit regression, as earlier mentioned, therefore uses the efficiency scores estimated (without bootstrap) and treats observations as censored data, with the dependent variable (in this case, the efficiency scores) restricted within 0 and 1.

The standard Tobit regression model is therefore shown as follows:

$$\begin{aligned} & y_i^* = \beta x_i + \varepsilon_i \\ & y_i = y_i^* \quad if \;\; y_i^* \geq 0 \quad and \\ & y_i = 0, \; otherwise \end{aligned} \tag{5.6}$$

Where $\varepsilon_i \sim N(O, \sigma^2)$, $x$ and $\beta$ are the vectors of the independent variables and coefficient respectively, $y *_i$ is the latent variable, and $y_i$ is the efficiency scores measured from the DEA model.

Mathematically, the Tobit model for this study is modelled in Stata as follows:

$$TEff_{it} = \alpha_0 + \beta_1 CAR_{it} + \beta_2 ROA_{it} + \beta_3 \left(\frac{TL}{TD_{it}}\right) + \beta_4 \left(\frac{NPL}{TL_{it}}\right) + \beta_5 \left(\frac{OC}{OI_{it}}\right) + \beta_6 \log TA_{it} + \beta_7 IFR_t + \beta_8 GDP_t + \beta_9 BI_t + \beta_{10} DUMOWN_{it} + \varepsilon_{it} \tag{5.7}$$

Where TEff is the efficiency scores measured for each stage for either the CCR or BCC assumption, i is the DMU under observation, t is the period, $\alpha$ is the constant term, $\beta$ is the coefficient of each explanatory variable, and $\varepsilon$ is the error term. The explanatory variables are described in Table 5.4.

As described in the introduction of this chapter, key gaps with the Tobit regression relate to the idea of data censoring and the Data Generating Process (DGP) of the efficiency scores. In relation to the censoring of data, researchers such as McDonald (2009) have argued that the DEA efficiency scores are not generated by censoring data but rather by a particular kind of fractional or proportional data. McDonald (2009) in this regard, argued that the DEA score is rather generated by a normalisation process where the production frontier is estimated by the ratio of input to output and the exact value of the dependent variable is known, instead of the restricted range imposed by the censored model, which in this case is the Tobit regression.

Another issue with the Tobit regression relates to the DGP. As indicated by Singh et al. (2020) and Simar and Wilson (2007), the Tobit regression model ignores serial correlation and the correlation between the factors used to estimate efficiency scores in the first stage and the explanatory variables used in the second stage. This, according to the authors, results in inconsistencies and biases as the efficiency score is estimated from variables dependent on each other.

Overall, to validate the authenticity of the above challenges of the Tobit regression, and also to test the robustness of the truncated bootstrap regression, this study uses both the Tobit regression and truncated bootstrap regression, seeking to identify whether there are significant differences in the results obtained.

### 5.3.4 *Second Stage Analysis – Explanatory Variables*

Based on the literature discussed in Section 5.2 and the data available on the banking sector and macroeconomic performance of Ghana, this study, similar to most research works on banking sector efficiency, will employ both internal and external variables as determinants of bank efficiency in Ghana. Internal factors considered are total assets, capital adequacy ratio, return on assets, bad loans, liquidity ratio, and operational costs. The external factor used is inflation rate. Also included are dummy variables for ownership type (foreign or domestic banks). Table 5.4 below provides an in-depth description of the variables used and indicates the method of calculation of variables.

*Table 5.4: Summary of Variables and Corresponding Hypotheses – Second Stage Analysis*

| Variable | Measure | Hypothesis |
|---|---|---|
| **Capital adequacy ratio – CAR** | Percentage of the ratio of regulatory capital to the risk-weighted assets of banks (Kishore, 2018; Abbas et al., 2019) | Increase in CAR results in high technical efficiency – Stewardship theory<br>Increase in CAR results in higher risk-taking activities reducing efficiency – Trade Off theory |
| **Return on assets – ROA** | Percentage of the ratio of Net Profit before Tax to Average Total Assets (Utami, 2017; Kurniawan, 2021) | Increase in ROA increases technical efficiency – Efficiency Structure theory<br>In an oligopolistic market, increase in ROA can reduce technical efficiency -Market Structure Hypothesis |
| **Asset Quality – NPL/TL** | Percentage of the ratio of NPLs to Total Loans (Tanasković & Jandrić, 2015; Umar and Sun, 2018) | Increase in NPL/TL causes a reduction in technical efficiency – Information asymmetry, moral hazard and adverse selection theories |
| **Liquidity – TL/TD** | Percentage of the ratio of Total Loans to Total Deposits (Disalvo & Johnston, 2017; El-Chaarani, 2019) | Increase in liquidity beyond an idea threshold reduces technical efficiency – portfolio investment theory<br>Increase in liquidity increases technical efficiency- portfolio investment theory |
| **Operational Efficiency – OC/OI** | Percentage of the ratio of Operating Cost to Operating Income (Dewi & Badjra, 2020) | Reduction in operating cost results in an increase in technical efficiency – Efficiency Market Hypothesis |
| **Total Assets – Log TA** | Total of foreign and domestic assets including loans, overdraft, and fixed assets. This variable is logged (Dang et al., 2018) | Increase in asset results in reduction in technical efficiency – Agency theory<br>Increase in asset results in improved technical efficiency – Stewardship theory |
| **Inflation rate – IFR** | Consumer prices (percentage annual) (Trujillo-Ponce, 2013; Merin, 2016) | Increase in inflation reduces technical efficiency – Economic Growth theory |
| **GDP per Capita** | This variable is logged (Jiménez-Hernández, 2019; Singh et al., 2020) | Increase in GDP per Capita increases technical efficiency - Economic Growth theory (Endogenous Growth Theory) |
| **Boone indicator – BI** | Measure of competition (Alhassan & Ohene-Asare, 2016) | Increase in competition results in high technical efficiency scores – Efficiency Structure Hypothesis |
| **Dum Own (Dummy for ownership type)** | 1 is used to represent foreign banks; 0 for domestic banks (Sufian et al., 2016) | Foreign banks are more technically efficient – Global Advantage theory<br>Domestic banks are more technically efficient – home field advantage theory |

## 5.4 *Empirical Results*

### 5.4.1 *Descriptive Statistics*

Table 5.5 shows a descriptive analysis of the explanatory variables used in the second stage regression across the ownership type of banks (i.e., domestic and foreign banks) for the period 2008 to 2019. The analysis is made up of 216 observations.

Overall, all banks assessed were well capitalised above the stipulated minimum capital requirement of 13 percent and also reported high profitability ratios measured by ROA. NPLs were high for the period under consideration.

Particularly, foreign banks show high profitability in terms of average ROA and hold significantly higher capital adequacy requirement (CAR) when compared to their counterpart domestic banks, averaging 4.66 for ROA and 22.43 for CAR. Also, foreign banks appear to be more liquid (TL/TD) (with an average liquidity ratio of 66.90 compared to that of domestic banks at 75.09) and are better able to control operational expenditure (OC/OI) with relatively higher operating income compared to cost. There are no significant differences between the average NPL ratio of domestic and foreign banks. For the period under consideration, the average NPL ratio for domestic banks was 16.76 compared to 16.57 for foreign banks. A foreign bank reported the highest NPL ratio of 102.8, which is significantly above the industry average of 16.67. There was no significant difference between the value of total assets of foreign and domestic banks: the log of total assets averaged 9.11 for domestic banks and 9.21 for foreign banks.

Average inflation was recorded as of 12.62 (above the inflation target of +/- 8) for the period under consideration, with a minimum of 7.13 and a maximum of 19.25. GDP per capita exhibited an average value of 5,390.17 (measured in local currency), with a minimum value of 1,273.91 and a maximum value of 11,489.24.

*Table 5.5: Descriptive Statistics of Data used in the Second Stage Regression*

| | ROA | | CAR | | NPL/TL | | TL/TD | | ln (TA) | | OC/OI | | INFRate | GDP per Capita |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Domestic** | **Foreign** | **Domestic** | **Foreign** | **Domestic** | **Foreign** | **Domestic** | **Foreign** | **Domestic** | **Foreign** | **Domestic** | **Foreign** | **Domestic** | **Domestic** |
| **Mean** | 2.12 | 4.66 | 17.22 | 22.43 | 16.76 | 16.57 | 75.09 | 66.90 | 9.11 | 9.21 | 66.11 | 47.34 | 12.62 | 5,390.17 |
| **Median** | 2.34 | 4.71 | 14.55 | 19.92 | 12.39 | 14.45 | 71.56 | 64.71 | 9.15 | 9.25 | 60.80 | 46.02 | 12.02 | 5,178.15 |
| **Standard Deviation** | 2.93 | 2.62 | 22.84 | 10.55 | 12.98 | 14.58 | 25.30 | 26.24 | 0.53 | 0.46 | 44.92 | 14.96 | 4.25 | 3,399.10 |
| **Minimum** | (9.53) | 2.99 | 112.34 | 10.03 | - | 1.02 | 24.55 | 15.98 | 7.18 | 8.20 | 6.55 | 3.09 | 7.13 | 1,273.91 |
| **Maximum** | 10.16 | 11.29 | 165.18 | 77.68 | 68.18 | 102.08 | 143.20 | 177.41 | 10.09 | 10.11 | 361.73 | 113.86 | 19.25 | 11,489.24 |
| **Count** | 96 | 120 | 96 | 120 | 96 | 120 | 96 | 120 | 96 | 120 | 96 | 120 | 96 | 120 |

*Note: ROA* – Return on assets, CAR* – Capital adequacy ratio, NPL/TL* – Non-Performing Loans to Total Loans (Asset quality), TL/TD* – Total Loans to Total Deposit (Liquidity), ln (TA)* – Log of Total Assets, OC/OI* – Operating Cost to Operating Income (Operational Efficiency), INFRate* – Inflation Rate, GDP* – GDP Per Capita*

Source: Computed by author based on data from the Bank of Ghana

### 5.4.2 *Empirical Findings*

#### 5.4.2.1 *Level of Competition in Ghana's Banking Sector*

As argued by Dadzie and Ferrari (2019), the model estimated for the Boone Indicator expects a negative relationship between marginal cost and the market share of loans for the commercial banks assessed, whereas an increase in the negative coefficient for marginal cost signifies an increase in the competitiveness of Ghana's commercial banking sector. For ease of interpretation, the study uses the absolute values of the estimates obtained.

In detail, for the years under review, Ghana's banking sector, although competitive, experienced sporadic levels of competition. The commercial banking sector was most competitive in the years 2008 to 2009, and 2016 to 2019, and least competitive in the period 2010 to 2015 with the year 2010 showing the least competitiveness.

The increase in the level of competitiveness in the prior years 2008 to 2009 can be explained by the significant growth in total assets, particularly loans, which followed the expansion of the economy after the redenomination of the Ghana cedi and discovery of oil. The period 2010 to 2015 was plagued with significant macroeconomic and infrastructural challenges, particularly the significant depreciation of the local currency and the energy crisis which peaked in the years 2014 to 2015. The challenges in these periods caused a significant hike in NPLs, impairing the asset quality and competitiveness of banks in terms of loan share. Lastly, although the commercial banking sector experienced significant restructuring in the years 2016 to 2019, there was a sporadic growth in gross loans and government securities[40]. This growth was particularly seen in the year 2019 and could be explained by the availability of excess capital following the recapitalisation at the end of 2018.

Overall, the increased levels of competition in Ghana's banking sector is in tandem with that of Alhassan and Ohene-Asare (2016) and Dadzie and Ferrari (2019), who also found that the post-reform era brought about a reduction in concentration levels and ultimately increased competitiveness in the banking industry.

*Table 5.6: Boone Indicator Values for Competition*

| Year | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BI Value | -0.62 | -0.10 | -0.14 | -0.19 | -0.29 | -0.39 | -0.53 | -0.56 | -0.65 | -0.63 | -0.72 | -0.79 |

Source: Computed by author based on data from BoG

[40] Although for the period 2016 to 2019 investment in government securities increased by approximately 83 percent and that of loans by 35 percent, the absolute value for gross loans exceeded that of government securities.

#### 5.4.2.2 *Results of Diagnostic Test: Overall Performance of the Truncated Bootstrap and the Tobit regression models*

Prior to running the regression models, a diagnostic test was carried out to identify cases of multicollinearity and heteroscedasticity. The F-test was also estimated to evaluate the validity of the explanatory variables used.

The pairwise correlation was estimated to identify cases of linear dependencies or multicollinearity between the variables used. Largely, the results showed a low correlation among variables, reducing the issues of multicollinearity.

For the test on heteroscedasticity, we observed that the explanatory variables showed equal variances (homoscedasticity) for the models that define intermediation, production and revenue generation efficiency scores.

The significance of the independent variables used is confirmed by the F-test when a simple OLS regression is run. The F-test showed that all explanatory variables used are statistically significant at a 1 percent level, implying that that all the explanatory variables used are relevant in explaining production, intermediation, and revenue generation efficiencies in Ghana's banking sector.

Overall, the results of the Wald and the likelihood ratio chi-square tests suggest a rejection of the null hypothesis under both the truncated bootstrap and Tobit regression models. This indicates that under both models, the explanatory variables chosen play significant roles in determining the efficiency of production efficiency of banks in Ghana.

#### 5.4.2.3 *Determinants of Efficiency*

Table 5.7 presents the estimation results of the truncated bootstrap and Tobit regression models for the determinants of production, intermediation, and revenue generation efficiencies. To identify the significance of the results obtained, the truncated bootstrap regression uses the z-score while the Tobit regression employs the t-test. The z-statistic is a statistical test used in cases where the standard deviation is known to determine whether the means of two different datasets vary from each other while the t-statistics is used to analyse the variance between two datasets when the standard deviation is not known (Nazeer et al., 2020).

On the whole, for all the three processes of banks assessed, the results derived from both regression models remain largely similar, although there are some discrepancies (Table 5.7).

##### 5.4.2.3.1 *Determinants of Production Efficiency*

For this stage, the study assesses factors that influence production efficiency of banks in Ghana, meaning that we seek to identify factors that affect how efficiently banks convert physical assets, employee costs and other operating costs into total deposits. Table 5.7 shows the most significant determinants of production efficiency (i.e. deposit mobilisation) under both the bootstrap truncated and Tobit regression models. Although the results for both regressions are similar, we find that there are more statistically significant determinants under the truncated bootstrap regression than the Tobit model. The truncated bootstrap regression model found ROA, CAR, NPL/TL, TL/TD, LogTA, OC/OI, inflation rate and competition to be statistically significant determinants of production efficiency, while the Tobit regression concluded that CAR, NPL/TL, TL/TD, LogTA, inflation rate, and GDP per Capita were the most statistically significant determinants of production efficiency.

In respect of the impact of ROA on production efficiency, this study does not fulfil the positive assumption stated by the Efficiency Structure Hypothesis (as depicted in Table 5.4). The coefficients of ROA observed in Table 5.7 shows a significant negative impact, implying that an increase in the ROA of banks results in a reduction in production efficiency. Referring to the methodology for the estimation of ROA, a decrease in ROA is resultant from an increase in total assets (largely loans and government securities) relative to that of profit before tax, while an increase in ROA is estimated by an improvement in profit before tax (largely estimated by the difference between interest and non-interest income and total operational costs) relative to total assets. Thus, an increase in profit before tax, relative to total assets, is expected to reduce production efficiency.

To relate the negative impact of ROA on production efficiency, the study in line with the argument of Michael et al. (2014) and Li et al. (2020)[41], observes a positive relationship between loans (representing total assets) and deposits from the dataset used. This means, as loans increase, deposits also increase. There is however a conflicting relationship between profitability and deposit, which in the case of this study, a negative observation is made, thus the reduction in production efficiency. This observation is further explained by Dietrich and Wanzeried (2009) who argues that banks that have increased deposits are less profitable (lower ROAs) as more cost is incurred in mobilizing the deposits by way of increased branch networks and interest expense. In Ghana, banks with increased

[41] Michael et al. (2014) and Li et al. (2020) in their analysis of the relationship between loans and deposits, argued that an increase in lending by banks stimulates economic growth which invariably increases the funds available to households and corporates, including government, resulting in increases in disposable funds and in savings and deposits.

deposits have more branch networks which increase their operational costs and reduces expected profitability.

Similarly, the negative coefficient of the variable CAR does not agree with the traditional positive impact assumed by the Stewardship theorists. Commercial banks in Ghana increased their capital base owing to the upward review of the minimum capital requirement over the periods studied, and also increased their lending, which is factored in their risk-weighted assets (largely loans). Largely, analysis of the data set used shows that an increase in lending resulted in a reduction in CAR as the absolute values for lending far exceeded that for adjusted capital. Again, similar to the reasons provided for the relationship between ROA and deposit mobilisation, an increase in lending esults in increase in deposit mobilisation. Thus, a rise in CAR, which will mainly be driven by a reduction in the risk-weighted assets (largely loans), will reduce the efficiency of banks in deposit mobilisation, requiring banks to spend more to generate deposits and further reducing the production efficiency of banks.

Asset quality measured by NPL/TL follows the expected hypothesis as it has a negative coefficient and is statistically significant at a 10 percent level. Changes in NPL are determined by either a change in the NPL stock or total loans, where an increase in loans with a less proportional increase in NPL stock is most likely to reduce NPLs, and vice versa. For the dataset used, the study observed that the increase in loans far exceeded that of NPL stock. Thus, based on the argument of the direct relationship between loans and total deposit, it is not surprising that an increase in NPLs, informed by the reduction in loans granted, will reduce banks' deposits, increasing bank costs to be incurred to generate more deposits, and thus a reduction in production efficiency.

The coefficient of the loans to deposit (TL/TD) ratio, which is used to measure the liquidity risk of banks, shows a significant negative impact. This finding agrees with that of the trade-off theory which implies that an increase in liquidity beyond a certain threshold (measured by an increase in deposits relative to total loans and ultimately a decrease in the TL/TD ratio) has a higher chance of reducing efficiency (evidence stated in Table 5.4).

Total assets, which largely includes loans, overdrafts and government securities including fixed assets, is found to have a significant positive impact on efficiency in deposit mobilisation. This observation is contrary to the agency theory stated in Table 5.4, i.e. growth in total assets reduces technical efficiency. As explained for the other explanatory variables, growth in total assets for the period under consideration was mainly driven by growth in total loans, which was found to have a positive relationship with the ability of banks to mobilise deposits.

OC/OI, the measure of operational efficiency, has a positive significant impact on efficiency in deposit mobilization as shown by the results derived from the truncated bootstrap model. A cursory view of the dataset used shows that banks spend more on operational and staff costs when lending is increasing. Such increases in cost may be attributed to increased provisions charged to the income statement as per the International Financial Reporting Standards (IFRS)[42] and increases in the cost invested in staff assigned to build the loan portfolio of banks. As established, an increase in lending results in an increase in deposits and the data shows that deposits increase at a faster rate relative to cost, thus there is an improvement in production efficiency.

The negative sign on the coefficient of the inflation rate is to be expected. According to the Economic Growth theory, high inflation may reduce the rate of return and ultimately reduce deposits, causing a decline in production efficiency.

Also, the significant positive sign on the coefficient of the GDP per capita variable (according to the truncated bootstrap model) is in line with the Economic growth theory which proposes that increase in GDP per capita of a country enhances the technical efficiency, in this case, efficiency in deposit mobilization of banks in Ghana.

Lastly, the Boone Indicator measure of competition, which is found not to be significant under the Tobit regression model, has a significant positive impact on efficiency in production (deposit mobilisation) under the truncated regression model. This observation agrees with the Efficiency Structure Hypothesis which states that an increase in competition results in higher technical efficiency scores.

#### 5.4.2.3.2 *Determinants of Intermediation Efficiency*

Table 5.7 also summaries the determinants of intermediation efficiency as estimated by both the truncated bootstrap and Tobit regressions. This section assesses the variables that determine how efficient banks are in converting total deposits to gross loans and government shares and securities. Per the results estimated, explanatory variables identified to be statistically significant under the truncated bootstrap regression model are CAR, NPL/TL, TL/TD, logTA and foreign ownership, while the Tobit regression found CAR, NPL/TL, TL/TD, logTA, OC/OI, inflation rate, GDP per capita, competition and foreign ownership as the most statistically significant determinant of intermediation efficiency.

[42] Per IFRS 9, banks are required to recognise ECLs at all times, taking into account past events, current conditions and forecast information, and to update the amount of ECLs recognised at each reporting date to reflect changes in an asset's credit risk.

Similar to the impact of CAR on production efficiency, CAR, has a significant negative impact on intermediation efficiency under both regression models used, negating the assumptions under the stewardship theory. This presupposes that increase in capital activates an increase in lending for commercial banks in Ghana

NPL/TL also, has a statistically negative impact on intermediation efficiency for both the truncated bootstrap and Tobit regressions. As explained under the production efficiency, to reduce NPL, banks in Ghana mostly increase their lending activities, creating more intermediation, and vice versa. It is therefore not surprising that a decrease in NPL stemming from an increase in loans will ultimately increase the intermediation efficiency of commercial banks in Ghana.

TL/TD on the other hand has a positive significant impact on intermediation efficiency. As discussed under the determinants of production efficiency, increase in liquidity is associated with a reduction in the ratio TL/TD which presupposes a reduction in lending as opposed to total deposits. The positive coefficient observed therefore implies that banks with excess liquidity (i.e. lower TL/TD ratio) become less efficient in intermediation, as increased levels of deposits are required to be used for lending activities.

With the positive coefficient for total assets, the study observes that banks with increased total assets are better able to maximise the amount of loans granted with the given level of deposits, enhancing their intermediation efficiency. To explain this trend, studies such as Wheelock and Wilson (2018) argue that banks with higher asset base in terms of physical assets, loans and securities, benefit from scale economies and are better at moderating the interest charged on loans as such banks lend to larger borrowers. Effectively, the premiums charged to smaller borrowers are mostly more than that of larger borrowers (Biswas et al., 2017). Also, according to Wheelock and Wilson (2018), the cost incurred by banks when lending to the larger borrowers do not vary significantly than that incurred when lending to smaller borrowers, giving the larger sized banks enough room to maximise their lending capabilities, thus, the increase in intermediation efficiency.

Similar to the significant positive effect of the ratio OC/OI on production efficiency under the truncated bootstrap regression, the OC/OI ratio has a significant positive impact on intermediation efficiency under both the truncated bootstrap and Tobit regression models. This again confirms the finding that increase in cost in the banks is largely associated with the intention to increase their loan portfolio, thus, the improvement in intermediation efficiency. Under the Tobit regression model, the variables, GDP per capita and inflation rate again follow the Economic Growth theory, with increased inflation having a significant negative impact on intermediation efficiency and increased GDP per capita having a significant positive impact.

Also, under the Tobit model, the Boone indicator measure of competition has a significant positive effect on intermediation efficiency. This is in tandem with the findings of the Efficiency Structure Hypothesis.

Lastly, foreign ownership of banks, had a significant positive impact on intermediation efficiency. For the period assessed (2008 to 2019), intermediation for foreign banks exceeded that of domestic banks by 42 percent with total deposits for banks with parent companies outside Ghana exceeding that of their domestic counterparts by approximately 45 percent. Of the foreign banks assessed, banks originating from the West African region lent out the most (five banks), closely followed by banks originating from the European region (four banks) and then the South African region (one bank). Approximately loans from banks with parent companies within the West African region exceeded those with parent companies in the European region by 3 percent. This marginal increase translated into deposits of over 30 percent (for banks with parent companies in West Africa) when compared to banks with parent companies outside Africa.

The increased intermediation can also be attributed to the large loan transactions carried out by most corporate institutions. Thus, with a higher number of corporate clients, foreign banks are more likely to grant more loans.

#### 5.4.2.3.3 *Determinants of Revenue Generation Efficiency*

The explanatory variables – ROA, CAR, TL/TD, OC/OI, inflation rate, GDP per capita and foreign ownership of banks – are found to be statistically significant in the determination of revenue generation (i.e. the conversion of gross loans and government securities into interest and non-interest income, and profit after tax). ROA, CAR, OC/OI, inflation rate and GDP per capita and foreign ownership are significant under the Tobit regression model while ROA, TL/TD, OC/OI, inflation rate and foreign ownership significant under the Simar Wilson model.

The observed positive coefficient of ROA implies that a rise in ROA results in an increase in the revenue generation efficiency of banks. This means that an increase in profit before tax relative to that of total assets, particularly loans, increases the revenue generated by banks. A reduction in total assets, particularly loans relative to profit before tax, would increase ROA and the banks' ability to generate revenue. The channel for transmission for this impact can be explained by the effect of NPLs on revenue generation. Considering the high stock of NPLs associated with increased lending, an increase in loans will ultimately increase the provisions charged to the income statement, reducing revenue and ROA. Over the period assessed, stock NPLs increased by 34 percent as opposed to the growth in loans of 22 percent and that of interest and non-interest income of 22 percent. Thus, to increase revenue (measured as interest, on-interest income and profit after tax), banks are likely to reduce lending, resulting in higher ROA. This explains the significant positive impact of ROA on revenue generation, and also supports the notion that banks with less lending are more likely to increase their revenue as the effect brought about by the increasing stock of NPLs is moderated.

The positive impact of CAR on the revenue generation efficiency of banks can be explained by the changes in lending. To increase CAR, most banks will reduce their higher risk weighted asset, specifically loans, as the higher the risk weighted asset, the lower the CAR. In this regard, a reduction in loans will moderate the effect of NPLs, ultimately reducing provisions for credit losses charged against the capital of banks and increasing CAR. A reduction in the provisions following a decrease in lending is most likely to reduce cost, increasing profit after tax, and informing the positive effect of CAR on revenue generation efficiency of banks in Ghana.

Table 5.7 further shows that under the truncated bootstrap methodology, an increase in the ratio TL/TD, implying a reduction in liquidity, has a significant negative impact on revenue generation. This means that banks with higher lending as opposed to deposits are more likely to generate less revenue. As mentioned earlier, an increase in lending, although it will provide increased income interest, results in increases in NPL stock which are charged against the income of banks, reducing their ability to increase their revenues, measured as profit.

The ratio OC/OI has a significant positive effect on revenue efficiency. Having established that this ratio also has a significant positive effect on intermediation, it can be implied that the higher the ratio of OC/OI, the more loans granted and the higher the income interest received from the loans granted. It is prudent to note that the NPL ratio increases with an increase in intermediation and an increase of the NPL ratio beyond a certain threshold may reduce the revenue gains made from increasing cost for the sake of higher intermediation.

There is a positive impact of inflation on the revenue generation efficiency of banks in Ghana. This trend agrees with the proposed theory of Trujillo-Ponce (2013) who stated that timely and accurate forecasting of the inflation rate by bank management may allow for adequate adjustment of interest rates which will ultimately increase income interest. The study therefore deduces that the relative higher interest rates charged by banks reflect management’s expectations for increases in inflation, which allows for a prompt adjustment of interest rates, ultimately increasing their income and efficiency in revenue generation.

The impact of GDP per capita on revenue generation efficiency aligns with its impact on production and intermediation efficiencies. Using the truncated bootstrap model, GDP per capita has a significant positive impact on revenue efficiency, again, agreeing with the Economic Growth Theory.

Lastly, foreign ownership is found to have a statistically negative impact on revenue generation efficiency. Although the study found foreign banks to have a positive impact on deposit mobilisation and intermediation, interest income as a percentage of total assets was significantly lower at 39 percent than that of domestic banks at 47 percent. This implies that foreign banks would have to give out more loans to increase their income. This observation could be attributed to the risk profile of domestic and foreign banks and their associated credit risk premium. The increased ability of domestic banks to generate more income from a relatively lower level of loans can be explained by the higher risk profile of their customer base which demands a higher risk premium resulting in higher loan rates. Foreign banks in Ghana grant loans to relatively lower risk profile clients, particularly corporates. According to Dietrich (2012) and Bonfim et al. (2018), most of these corporates are able to negotiate for favourable loan rates, owing to their larger deposit base, and this may ultimately result in lower interest income compared to that of domestic banks.

#### 5.4.2.3.4 *Impact of Competition of Bank Efficiency in Ghana*

In addition to the above discussions, the various efficiency scores were regressed on the Boone Indicator measure of competition.

The results showed a significant positive association between the competition measure and production efficiency under the truncated bootstrap regression model and also significant positive association between competition and intermediation efficiency under the Tobit regression model. However, the relationship between competition and revenue generation efficiency, although showed a positive relationship, was not significant for any of the models used. The observed positive relationship is an indication of the absence of monopolistic powers of banks in Ghana, which according to the quiet life and relative power hypotheses, induces incompetent behaviours of bank management, allowing them to pass on cost to customers and distorting their levels of efficiency. It is therefore safe to assume that increased competition may have forced banks in Ghana to be more efficient in all three types of efficiencies estimated, particularly the deposit mobilisation and intermediation efficiencies, agreeing with the Efficiency Structure Hypothesis (ESH).

This finding agrees to that of Aboagye (2012), Saka et al. (2012) and Alhassan and Ohene-Asare (2016). These researchers argued that an increase in competition translates into lower interest rate spreads which ultimately increases efficiency of banks.

#### 5.4.2.3.5 *Summary of Findings*

Overall, the significance of the direction of coefficient of variables used to examine the determinants of efficiency varies with the efficiency type being assessed.

For production efficiency, the significant variables noted for both the truncated bootstrap and Tobit regressions are CAR, NPL ratio, liquidity ratio (TL/TD), total assets and inflation rate. With the exception of total assets, all the identified variables have a significant negative impact on the banks' ability to mobilise deposits.

Similarly, CAR, NPL/TL, TL/TD and size, measured as the log of total assets also have a significant impact on intermediation efficiency for both models used. Unlike all other variables that maintain the direction of impact observed under production efficiency, TL/TD shows a positive direction in its effect on intermediation efficiency.

For revenue efficiency, the study found that the variables ROA, OC/OI, inflation rate and foreign ownership have significant impact for both models used.

The negative effect of CAR observed for both production and intermediation efficiency agrees with the agency theory and assumes that banks in Ghana engage in high risk activities when capital increases. In Africa, this observation agrees with the works of Aikaeli (2007) and Saka et al. (2012).

The negative observed impact of NPL/TL ratio on production and intermediation efficiencies also aligns with most studies on determinants of bank efficiency. In the developed regions, examples of studies that have made such observations include Kwan and Eisenbeis (1995), Girardone et al. (2004), Sufian and Noor (2009) and Andries and Billon (2016). In Africa, research works such as Aikaeli (2006) and Kablan (2007) also found a negative relationship between technical efficiency and NPLs.

The effect of size on production and intermediation efficiencies contrasts the agency theory and rather agrees with the stewardship theory. In this case, managers of commercials banks in Ghana are less likely to misuse the firm's resources when assets expand, resulting in increased efficiency. Also, bigger banks are found to attract more deposits, which increases funds available for lending, or to have a larger labour force which is tasked to increase their loan portfolios and efficiency in intermediation. This finding is similar to that noted for Aikaeli (2006), Adjei-Frimpong et al. (2014) and Jiménez-Hernández et al. (2019).

The study of the impact of the ratio TL/TD has however been rarely undertaken in Ghana or Africa as a whole. This study therefore provides new evidence that suggests that increase in the ratio TL/TD, increases intermediation efficiency, i.e. lending, but reduces the deposit base and liquidity.

Lastly, direction of the coefficient for inflation rate on production efficiency aligns with the conclusions of the Economic Growth theory stated in Table 5.4. Comparable conclusions were made by Batir et al. (2017) and Jiménez-Hernández et al.( 2019).

For revenue generation efficiency, the effect of ROA followed the Efficiency Structure hypothesis, showing a significant positive impact. The observed positive impact of ROA on revenue efficiency agrees with the conclusions of researchers such as Saka et al. (2012) and Alhassan and Ohene-Asare (2016).

The direction of the coefficients of OC/OI and inflation and foreign ownership contradict the Efficiency Market, Economic Growth and Global Advantage hypotheses stated in Table 5.4. OC/OI and inflation rate have a positive effect on revenue generation, while banks with foreign ownership are found to have a significant negative impact on revenue efficiency.

Lastly, the study observed increased levels of competition in Ghana's banking sector in recent years. The efficiency scores were also regressed on the level of competition estimated by the truncated bootstrap approach and the Tobit regression model. Similar to the observations of research works such as Alhassan and Ohene-Asare (2016), the study observed a positive association between competition and all the types of efficiencies measured although the positive relationship between revenue generation efficiency and competition did not yield a significant observation, therefore confirming the fact that increased competition ensures improvement of efficiency of commercial banks in Ghana.

*Table 5.7: Determinants of Efficiency Scores*

| | **Production Efficiency** | | **Intermediation Efficiency** | | **Revenue Generating Efficiency** | |
|---|---|---|---|---|---|---|
| | SW–TBR | TR | SW–TBR | TR | SW–TBR | TR |
| **Variables** | Coefficient (p-value) | Coefficient (p-value) | Coefficient (p-value) | Coefficient (p-value) | Coefficient (p-value) | Coefficient (p-value) |
| **ROA** | -0.005 (0.0805) | -0.005 (0.139) | -0.000 (0.974) | -0.000 (0.912) | 0.014 (0.001) | 0.021 (0.002) |
| **CAR** | -0.002 (0.002) | -0.002 (0.016) | -0.002 (0.004) | -0.003 (0.001) | 0.001 (0.134) | 0.004 (0.001) |
| **NPL/TL** | -0.001 (0.003) | -0.000 (0.003) | -0.001 (0.001) | -0.002 (0.007) | 0.002 (0.215) | 0.001 (0.313) |
| **TL/TD** | -0.002 (0.000) | -0.002 (0.000) | 0.006 (0.000) | 0.006 (0.000) | -0.001 (0.079) | -0.000 (0.569) |
| **Log TA** | 0.040 (0.073) | 0.090 (0.004) | 0.170 (0.000) | 0.169 (0.000) | 0.099 (0.421) | 0.025 (0.635) |
| **OC/IO** | 0.001 (0.029) | 0.000 (0.812) | 0.001 (0.006) | 0.001 (0.006) | 0.001 (0.042) | 0.002 (0.027) |

| | | | | | | |
|---|---|---|---|---|---|---|
| **INFRATE** | -0.005<br>(0.002) | -0.005<br>(0.013) | -0.002<br>(0.119) | -0.004<br>(0.055) | 0.010<br>(0.000) | 0.013<br>(0.000) |
| **GDP per Capita** | 0.059<br>(0.115) | 0.101<br>(0.058) | 0.026<br>(0.502) | 0.141<br>(0.016) | 0.920<br>(0.131) | 0.215<br>(0.017) |
| **BI** | 0.096<br>(0.018) | 0.072<br>(0.201) | 0.027<br>(0.476) | 0.204<br>(0.001) | 0.064<br>(0.326) | 0.008<br>(0.933) |
| **DumOwn** | 0.010<br>(0.443) | 0.025<br>(0.162) | 0.016<br>(0.190) | 0.040<br>(0.031) | -0.085<br>(0.000) | -0.119<br>(0.000) |
| | | | | | | |
| Number of obs | 216 | 216 | 216 | 216 | 216 | 216 |
| Wald chi2(10) | 136.93 | | 711.53 | | 103.83 | |
| Prob > chi2(10) | 0.000 | | 0.000 | | 0.000 | |
| LR chi2(10) | | 66.85 | | 187.36 | | 61.79 |
| Prob > chi2 | | 0.000 | | 0.000 | | 0.000 |
| Pseudo R2 | | -0.278 | | -1.7700 | | -2.596 |

Notes: Values in parenthesis are the estimated p-values, indicating significance at 10%. SW-TBR refers to the Simar–Wilson truncated bootstrap regression and TR, the Tobit regression model.

## 5.5 *Conclusions*

Unlike most studies in Ghana that have estimated overall efficiency scores and investigated the determinants of such scores, this chapter, is the first study in Ghana to estimate the efficiency scores of three distinct activities of commercial banks in the country, namely, production (deposit mobilisation), intermediation and revenue generation. It is also the first study to use a two-step model to identify the factors (both bank-specific and macroeconomic variables) that determine the efficiency of Ghanaian commercial banks in deposit mobilisation, intermediation and revenue generation.

To establish the regression relationships between the efficiency scores of the three activities (i.e. deposit mobilisation, intermediation and revenue generation), and their determinants, the study adopted the Simar–Wilson truncated bootstrap and the Tobit regression models.

In line with Delis and Papanikolaou (2009) and Singh and Thaker (2020), who used both the truncated bootstrap and Tobit regression models to assess the determinants of bank efficiency in European countries and India respectively, the observed relationship between dependent and independent variables (at the significance level of 10 percent) did not vary significantly across the regression models used.

The uniqueness of the results of this study however pertains to the varying impact observed between the different types of efficiency and the independent factors considered.

For example, the NPL ratio and CAR had a statistically significant negative impact on production and efficiency due to the adverse effect of increased lending, but a positive impact on revenue generation (although not significant). Foreign ownership on the other hand, had a positive impact on deposit mobilisation and intermediation, but a negative impact on revenue generation. In this case, the study observed that although foreign owned commercial banks in Ghana were better able to mobilise more deposits and grant loans, the reduced risk levels of their borrowers did not give them the advantage of higher profits, compared to domestic owned banks which dealt with riskier clientele, thus their ability to charge higher interests and make more revenue. Finally, ROA and inflation rate also had negative impacts on production and intermediation efficiencies but a positive impact on revenue generation efficiency.

Of the independent variables used in the regression models, the impact of ROA has drawn the most attention by existing studies (Bopkin, 2012; Saka et al., 2012; Alhassan and Ohene Asare, 2016; Alhassan and Tetteh, 2016). The interest in the effect of ROA on efficiency can be linked to its association with profitability. ROA is one of the most common financial accounting ratios used to estimate the profitability of firms. It is therefore not surprising that, with the positive effect of this profitability ratio on efficiency, most policy makers especially in Ghana have generally used the term efficiency and profitability interchangeably. This implies that a profitable firm is also an efficient firm.

Existing studies have shown that the direct relationship between profitability and efficiency does not hold in all cases (see Chapter 6). Based on data availability, other studies have used different ratios such as ROE, Net Interest Margin (NIM) etc. to capture the performance of banks. While these other financial ratios, or even ROA, provide a snapshot of profitability, they have been criticised for failing to capture the dynamic roles played by banks in current times (Kumar, 2008; Frimpong, 2010). In this sense, the profitability ratios cannot be comparable to efficiency scores as the efficiency estimation measures used in this thesis, particularly the DEA, employ multiple inputs and outputs to account for the multi-dimensionality nature of banks (Arbelo et al., 2021; Chen et al., 2015).

Comparatively, the measure or profitability has been of more interest to stakeholders than the study on efficiency (Neves et al., 2020). With a keen interest to make returns on amounts invested in businesses, shareholders, executive and non-executive management of banks are increasingly becoming more interested in enhancing the profitability of their banks. The focus on efficiency in this thesis therefore does not provide adequate information to these classes of stakeholders if the impact of efficiency on profitability is not established. From the standpoint of a shareholder who is interested in increasing returns measured as profits, the efficiency scores measured in Chapter 4 and the corresponding discussions on the determinants of efficiency will only be relevant if the impact of efficiency on profitability is established. The next chapter, which is the final empirical study of this thesis, therefore attempts to complement this study by exploring the determinants of bank profitability but with focus on the impact of bank efficiency.

# CHAPTER 6

# PROFITABILITY OF COMMERCIAL BANKS IN GHANA: DOES EFFICIENCY MATTER?

## 6.1 *Introduction*

As stated earlier, the general assumption of a positive linear relationship between profitability and efficiency has been disputed, with researchers having a mixed view on the proposed direction of the relationship. Efficiency as defined and measured by this thesis (by parametric and non-parametric models) refers to the bank's ability to attain the maximum output using the minimum possible input, while profitability, mostly measured by financial ratios such as ROA and ROE, is globally used to assess a bank's ability to stay in business and preserve ongoing activities during a period in time (Stavárek and Polouček, 2004; Alomari et al., 2020).

Empirically, studies such as Košak et al. (2009) observed a positive relationship between efficiency and profitability for banks in the EU region, while Pasiouras et al. (2007) and Kosmidou (2008) confirm an inverse relationship for Malaysia, Greece and Australia. These inconsistencies in findings establish the need to determine the impact of efficiency on profitability, especially for stakeholders who are particularly interest in enhancing the profitability of their businesses.

In Africa, particularly Ghana, growing research on bank performance has largely neglected the relationship between efficiency and profitability. The few studies which have estimated the relationship between efficiency and profitability have reported contradictory evidence, finding either a positive (Alhassan et al., 2016) or a negative relationship between efficiency and profitability (Mawutor and Fred, 2015). In Ghana, these inconsistencies in findings are particularly challenging as the term efficiency has often been used as a proxy for profitability. With an inverse relationship, such approximation may be spurious.

This study therefore seeks to establish the relationship between efficiency and probability of commercial banks in Ghana using an efficiency–probability matrix that juxtaposes their profitability ratios, ROA and ROE, against their efficiency scores estimated in Chapter 4. Additionally, the study uses the GMM estimation to establish the impact of efficiency on profitability of commercial banks in Ghana.

As far as is known, although the efficiency–profitability matrix has been used by Frimpong (2010), this study is the first to examine the relationship between profitability and efficiency scores measured by the three stage DEA dynamic network SBM model in Ghana's commercial banking sector. It is therefore expected that the derived results will deepen understanding on determinants of bank performance in Ghana and provide more empirical evidence on bank efficiency studies in Ghana and Africa as a whole.

The remainder of this chapter is organised as follows: Section 6.2 reviews the literature on the relationship between profitability and efficiency in the banking sector, Section 6.3 describes the data and methodology, Section 6.4 provides the empirical results and Section 6.5 concludes the chapter.

## 6.2 *Literature Review*

### 6.2.1 *Theoretical background*

The earlier chapters have already focused on the theory, measurement and determinants of efficiency. In this section, the study first delves into the theory, measurement and determinants of profitability, and secondly addresses the theory supporting the relationship between efficiency and profitability.

#### 6.2.1.1 *Theoretical Literature Review on the Profitability of Banks*

##### 6.2.1.1.1 *Definition and Measurement of Profitability*

Traditionally, a bank’s profitability is assessed by its ability to generate profit and stay in business, (Hofstrand, 2009). To measure profitability, existing studies have adopted either the economic or accounting measures (Marwa and Aziakpono, 2014).

The accounting measures define profitability as the excess of revenue over cost, and is mostly represented by ROA, ROE and NIM (Maher et al., 2008; Marwa and Aziakpono, 2014). ROA is defined as the ratio of net income to total assets and measures the profitability of a bank relative to its assets. ROE is measured as the ratio of net income to total equity and it is used to indicate the profit generated by using the capital invested by shareholders of the bank. NIM is calculated as the ratio of the difference between interest income and interest expense to total productive assets. NIM is therefore used to evaluate the difference between interest paid by a bank to investors and the interest the bank receives from borrowers.

The economic measures of profitability calculate profit as net income after transaction, plus the opportunity cost of the factors used to generate income (Marwa and Aziakpono, 2014). In the banking sector, this profitability measure is rarely used as it is challenging to quantify the opportunity cost associated with generating profit. For this reason, and in line with most research works (as illustrated in the empirical summary, Table 6.1), this study employs accounting measures of profitability, specifically ROA and ROE.

#### 6.2.1.1.2 *Determinants of Profitability*

Like the efficiency theory, factors that determine the profitability of banks can be generally classified into two broad categories: internal and external factors, which can be further subdivided into industry-specific factors and macroeconomic factors (Djalilov and Piesse, 2016). These factors largely align to the definitions used in the determinants of efficiency and assume a similar relationship with profitability as they do to efficiency. In detail, the internal factors focus on variables that are under the control of management such as bank asset structure, bank asset quality, bank capital, revenue diversification, deposit growth and size (Neves et al., 2020; Djalilov and Piesse 2016), while external factors refer to variables relating to the country's economic and legal environment such as inflation, GDP per capita or economic growth (Neves et al., 2020).

Ultimately, considering the similarities in the determinants of profitability and efficiency, it is no surprise that the terms profitability and efficiency are used simultaneously in banking literature. It is therefore necessary at this point to delve into the theoretical assumptions supporting the perceived relationship between efficiency and profitability.

#### 6.2.1.1.3 *Theoretical Literature Review on the Relationship between Profitability and Efficiency of Banks*

As a continuation from the introduction of this chapter, the concepts 'profitability' and 'efficiency' differ in several ways in terms of definition and methodology. Primarily, profitability is known to measure the ability of firms to generate profit from their factors of production focusing on the relationship between revenues and expenditure (Tan et al., 2017), while efficiency looks at the relationship between input and output.

Regarding the issue of methodology, Stavárek and Polouček (2004) argued that profitability is most often seen as a single performance indicator that can be calculated without any reference to an existing threshold or benchmark, while efficiency is measured relative to a reference point.

Based on the above differences, empirical findings assessing efficiency and profitability of banks may differ, even providing contradictory results and trends. Irrespective of such differences, there has been very little theoretical discussion on the expected relationship of these two key concepts. For the purpose of this study, the traditional structure conduct performance hypothesis and the efficiency structure hypothesis are used to explain the relationship between efficiency and profitability of banks.

Similar to the theoretical discussions on the relationship between efficiency and competition, the SCP theories have also been used by existing literature to explain the relationship between efficiency and profitability (Hannan and Berger, 1997; Athanasoglou et al., 2008; Dietrich and Wanzenried, 2014; Bolarinwa et al., 2019).

Following the discussions on SCP in Chapter 5 of this study, the traditional SCP hypothesis postulates that banks in a highly concentrated environment are more likely to engage in anticompetitive behaviours, ultimately reducing efficiency but increasing profit. The traditional SCP hypothesis assumes that increased collusion resulting from increased barriers to entry and exit of firms in a market translates into higher profits irrespective of the efficiency levels of the banks in question (Molyneux et al., 1994). Thus, with the traditional SCP hypothesis, there is necessarily not a direct positive relationship between efficiency and profitability.

The ESH argues for a direct positive relationship between efficiency and profitability, postulating that the competitive attitude of efficient firms results in increased market share and firm size, resulting in lower costs which causes an increase in profitability. Such behaviour of an efficient firm implies that a firm makes more profit not necessarily because of their engagement in collusive activities in the market as explained by the SCP, but because the firm is operating at a relatively greater efficiency level (Hannan and Berger, 1997; Molyneux and Forbes, 1995).

### 6.2.2 *Empirical Literature Review*

Historically, efficiency has been recognised by most studies to have a positive impact on the profitability of banks. Studies in this regard assume that an improvement in efficiency scores implies an increase in managerial control over cost which ultimately reduces the operational expenses of banks, causing an increase in profitability (Bolarinwa et al., 2019). In view of the positive perception between efficiency and profitability, different measures of efficiency have been adopted by existing studies. Such measures include the cost to income ratio ( Trujillo-Ponce, 2013; Garcia and Guerreiro, 2016), cost of funds represented by the ratio of interest expense to average total deposits (Dietrich and Wanzenried, 2012), ratio of operating expense to net income (Tregenna, 2009), ratio of non-interest expense to operating revenue (Mawutor and Fred, 2015), and the econometric models represented by either the SFA, DEA or DFA (Berger, 1995 (DFA); Maredza, 2014 (DEA); Paleckova, 2015 (DEA SBM); Alhassan et al., 2016 (DEA); Tan et al., 2017 (SFA)).

Empirical results from existing studies are mixed. While some have found a positive and significant relationship, others have found a significant negative relationship or no significant relationship. Largely, most studies have found a positive relationship between profitability and efficiency.

In the North American region, Berger (1995) found evidence in support of the ESH theory when evaluating the relationship between efficiency and profitability for large banks in the USA. Using the DFA to measure x-efficiency, and ROA and ROE to evaluate profitability of banks in the period

1980 to 1989, Berger found that the x-efficiency of banks had a positive effect on profitability measured. Similarly, in the European area, Pasiouras et al. (2007), Kosmidou (2008), García-Herrero et al. (2009), Dietrich and Wanzenried (2011), Tan and Floros (2012), Trujillo-Ponce (2013) and Garcia and Guerreiro (2016) found a positive and significant impact of efficiency on profitability on banks, agreeing with the ESH theory. In the Latin American region, Chortareas et al. (2011) also in support of the ESH theory found a positive impact of efficiency on the profitability of banks in the period 1997 to 2005. The study discounted the effect of collusion on the behaviour and profitability of banks.

On the other hand, studies such as Stavárek and Polouček (2004), and Tan et al. (2017) found that banks with higher efficiency levels in Asia and Europe respectively had lower ROA. In this case, the negative impact of efficiency on profitability can be considered as evidence of market power as inefficient banks are able to transfer higher cost to product prices in order to earn more profit. This finding is in support of the structure–conduct performance hypothesis.

The inconclusive nature of the relationship between efficiency and profitability is accentuated by Tregenna (2009) and Palečková (2015) who found that efficiency did not have any significant impact on profitability of banks in the USA and Czech Republic respectively. Unlike Berger (1995) who found that x-efficiencies of banks in the USA had a positive impact on efficiency for the period 1980 to 1989, Tregenna (2009), using a data sample of banks in Ghana from 1995 to 2005 and a linear regression model, found evidence that supported the fact that profitability of banks in the USA before the global financial crisis in 2007/2008 was not attained via efficient processes, but by the increase in market power.

Consequently, as a gap in existing literature, the number of studies that have studied the impact of efficiency on the profitability of banks in developing nations are limited. Only few studies such as Oberholzer et al. (2004), Frimpong (2010), Maredza (2014), Mawutor and Fred (2015), Alhassan et al. (2016) and Bolarinwa et al. (2019), have attempted to examine the relationship between efficiency and profitability of banks in the African region.

Oberholzer et al. (2004) used data of banks from South Africa to assess the impact of efficiency on profitability. In this study, the authors used ROA, Profit Margin, No Residual Loss to Income Ratio, Income to Staff Cost ratio and Income to Assets ratio as measures of profitability, and used the DEA to measure technical, allocative, cost and scale efficiencies. Employing the Pearson correlation coefficient, the authors found no significant relationship between technical efficiency and profitability, although they observed significant impact of allocative and cost efficiency on the profitability of banks assessed. Maredza (2014) also assessed the impact of technical efficiency (measured DEA) on profitability indices (ROA, ROE and NIM) of banks in South Africa for the period 2005 to 2011. In this case, the author used the Generalised Least Squares Fixed Effects Model and found a positive and significant impact of efficiency on ROA and NIM, but no significant impact on ROE. Bolarinwa et al. (2019) evaluated the impact of efficiency (in this case scores obtained from the SFA) on the profitability (ROA and ROE) of Nigerian banks for the period 2005 to 2015. Using OLS, two-step difference GMM and two-step system GMM, the researchers largely observed a positive relationship between efficiency and profitability of banks in Nigeria.

In Ghana, Mawutor and Fred (2015) studied the impact of efficiency (measured as the ratio of non-interest expense to operating revenue) on profitability (ROA) using a basic regression model. The authors observed that, the higher the ratio of non-interest expense to operating revenue, the lower the efficiency and consequently profitability, implying a positive impact of efficiency on profitability for the period 2006 to 2011. Similarly, Alhassan et al. (2016) using the system GMM regression model and DEA, found that technical efficiency has a positive impact on profitability (at 10 percent significance level for ROA and ROE and 5 percent significance level for NIM), while scale efficiency has a negative impact on efficiency on banks in Ghana for the period 2003 to 2011. The relationship between technical efficiency and profitability is a reflection of the ESH supporting the notion that the bank's ability to maximise inputs, such as labour to reduce unit cost, which ultimately results in more profits. The negative impact of scale efficiency suggests that larger banks are less able to monitor costs, resulting in high operational costs and reduced profitability, agreeing with Ye et al. (2012) who made similar findings for banks in China.

#### 6.2.2.1 *Conclusions on Empirical Literature Review on the Relationship between Profitability and Efficiency of Commercial Banks in Ghana*

Literature reviewed in the above section shows how inconclusive findings on the relationship between efficiency and profitability are. In Africa, the inconclusiveness of findings is further accentuated by the limited number of studies on the subject.

Additionally, another key gap pertains to how efficiency has been decomposed and modeled by most studies that have attempted to investigate the relationship between profitability and efficiency of banks. Particularly in Ghana, studies that have studied bank efficiency and profitability (examples being Mawutor and Fred (2015) and Alhassan et al. (2016)) have decomposed the efficiency measure into OTE, PTE and SE, cost, revenue or profit efficiency, and not at the activity level.

To bridge the above gap, this study goes beyond these decompositions to assess the relationship with efficiency scores that pertain to deposit mobilisation (production), conversion of deposits into loans (intermediation) and revenue generation. This approach, although it allows for a detailed analysis of value and risk drivers in Ghana’s banking sector, is particularly rare in empirical literature.

Table 6.1 below presents a summary of the literature that has assessed the relationship between efficiency and profitability in various jurisdictions.

*Table 6.1: Summary Empirical Literature Review – Relationship between Efficiency and Profitability*

| **Author** | **Country** | **Period** | **Efficiency Estimation Model** | **Profitability Indicators** | **Regression Model** | **Findings** |
|---|---|---|---|---|---|---|
| **Studies Outside the African Region** | | | | | | |
| Berger (1995) | USA | 1980–1989 | DFA | ROA and ROE | Structural models | x-efficiency has a positive relationship with profitability of banks studied |
| Pasiouras et al. (2007) | Greece | 2000–2005 | DEA | Annual share price | Two-way fixed effect panel regression | Positive relationship between efficiency and share price |
| Kosmidou (2008) | United Kingdom | 1990–2002 | cost to income ratio (CIR) | ROA and ROE | Fixed effect regression | Positive impact of efficiency on profitability of banks |
| García-Herrero et al. (2009) | China | 1997–2004 | X-efficiency | ROAA, ROAE and NIM | Generalised Method of Movement | Banks with higher efficiency have higher profitability |
| Tregenna (2009) | USA | 1994–2005 | ratio of operating expense to net income | ROA and ROE | OLS with two-way fixed effect; Generalised Method of Moments (GMM) | No direct positive relationship between efficiency and profitability |
| Werner & Moormann (2009) | 5 countries in European Union | 1998–2005 | DEA | Net ROE | Static and dynamic regression models | Efficiency has a positive impact on profitability |
| Trujillo-Ponce (2013) | Spain | 1999–2009 | CIR | ROA and ROE | Generalised method of moments (GMM) estimator | Positive impact of operational efficiency on profitability |
| Maredza (2014) | South Africa | 2005–2011 | DEA | ROA, ROE and NIM | Generalised Least Squares Fixed Effects Model | Positive relationship between: (1) Efficiency and ROAA = 0.17 (2) Efficiency and NIM = 0.07 |
| Palečková (2015) | Czech Republic | 2004–2014 | DEA SBM | ROA and ROE | Granger causality and correlation coefficient | No significant impact of efficiency on profitability |
| Garcia & Guerreiro (2016) | Portugal | 2002–2011 | CIR | ROAA, ROAE and NIM | OLS estimations | Operational efficiency has a positive relationship with profitability |

| | | | | | | |
|---|---|---|---|---|---|---|
| Tan et al. (2017) | China | 2003–2013 | SFA | ROA, ROE and NIM | Two-step Generalised Method of Moments (GMM) | Increase in cost efficiency reduces ROA, ROE and NIM |
| **Studies in Africa including Ghana** | | | | | | |
| Oberholzer et al. (2004) | South Africa | 36 consecutive months | DEA (Technical, allocative, cost and scale efficiencies) | ROA, Profit Margin, No Residual Loss to Income Ratio, Income to Staff Cost ratio, Income to Assets ratio | Pearson correlation coefficient | There is no relationship between technical efficiency and profitability, there is a significant relationship between allocative and cost efficiencies and income to staff cost ratio |
| Bolarinwa et al. (2018) | Nigeria | 2005–2015 | SFA | ROA and ROE | OLS, two step difference GMM, two step system GMM | Largely, there is a positive impact of cost efficiency on the profitability ratios |
| Mawutor & Fred (2015) | Ghana (7 listed banks) | 2006–2011 | Measured as productivity ratio of non-interest expense to operating revenue | ROA | Basic regression model using the R square | Negative relationship between efficiency and profitability |
| Alhassan et al. (2016) | Ghana | 2003–2011 | DEA | ROA, ROE and NIM | System GMM | Technical efficiency has a positive impact on profitability while scale efficiency has a negative impact |

Note: ROAA*– Return on Average Asset, ROAE*– Return on Average Equity, NIM*– Net Interest Margin, SFA*– Stochastic Frontier Analysis, DEA*– Data Envelopment Analysis, GMM*– Generalised Method of Moments, OLS*– Ordinary Least Square, CIR*– Cost Income Ratio, SBM*– Slack Based Model

### 6.2.3 *The Efficiency–Profitability Matrix*

Another theory used to explain the complex relationship between efficiency and profitability of banks is the efficiency–profitability matrix developed by Boussofiane et al. (1991), which has been used by studies such as Dyson et al. (2001) in Portugal, Kumar (2008) in India, Frimpong (2010) in Ghana, and Marwa and Aziakpono (2014) for Saving and Credit Cooperatives (SACCOs) in Tanzania. Unlike the SCP, this theory goes beyond establishing a single level of association or impact to categorising units in various segments with multifaceted relationships between efficiency and profitability.

In detail, the efficiency–profitability matrix classifies banks into four distinct quadrants. The north-west quadrant, named Lucky or Sleeper, contains units which have higher profitability ratios but lower efficiency scores. Higher profitability is attributed to favourable macroeconomic conditions and less competitive behaviours of firms in the industry, while low efficiencies are as a result of the misallocation of resources by management. To improve performance, units in this category are encouraged to control the allocation of resources. The south-west quadrant is made up of Underdogs. These are firms that experience both low efficiency and low profitability and are most prone to liquidation or merger with better performing firms. To move out of this category, firms are encouraged to improve their operating environment and adopt some best practices of the Stars. The Stars or Aces are found in the north-east quadrant. They are the best performers in the industry and are characterised by high efficiency scores and profitability. Lastly, the south-east quadrant is made up of units described as Unlucky or Dogs. Firms in this quadrant exhibit high levels of efficiency but reduced profitability. The reduction in profitability may be attributed to factors beyond the control of management, particularly, the economic challenges of the unit's external environment. To improve profitability, units classified as Unlucky or Dogs are expected to migrate to environments with more favourable economic conditions or to undertake significant strategic moves that will significantly alter the business model and their operations.

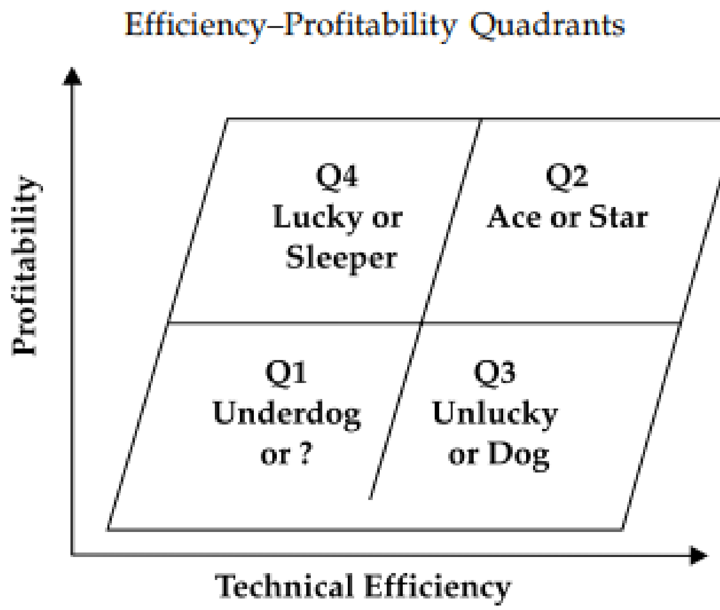


*Figure 6.1: Efficiency Probability Matrix (Kumar, 2008)*

The studies that have employed the efficiency–profitability matrix acknowledge that the fundamental challenge with this matrix is the selection of the cut-off point that establishes the limits for the four different quadrants. Marwa and Aziakpono (2014) described this task as subjective and use the top 25 percent as the cut-off point for both efficiency and profitability. Dyson et al. (2001) also used the top 25 percent cut off for the profitability score but employed a 10 percent cut-off point for efficiency scores. Kumar (2008) and Frimpong (2010), used the arithmetic average of the efficiency and profitability scores. This current study follows the works of Kumar (2008) and Frimpong (2010) and uses the arithmetic average efficiency and profitability scores as the threshold for segregation in the four quadrants of the matrix. This choice was made owing to the normal distribution of efficiency and profitability scores with no significant outliers. Figures 6.2 to 6.6 of this chapter provide the efficiency–profitability quadrants for each efficiency type measured for all 18 commercial banks.

## 6.3 *Data Sources, Efficiency–Profitability Matrix and the Regression Model*

### 6.3.1 *Data Source*

Like the sources of data used for the earlier empirical chapters, the profitability indices (ROA and ROE) used by this paper are sourced from the monthly bank level data submitted by 18 commercial banks to the Bank of Ghana. Similar to the analysis in the prior chapter (for the Tobit regression model), the efficiency scores used are based on the PTE efficiency measured in Chapter 4 of this thesis using the three-stage dynamic network SBM DEA model: this includes efficiency scores for the production, intermediation, and revenue generation stages. Again, the choice of the PTE scores is founded on the argument of Burger and Moormann (2009) and Othman (2016), who argued that in the real world, profit-driven institutions such as banks are more likely to produce under increasing or decreasing returns to scale than the constant returns to scale assumed by the CCR model. The period of assessment spans January 2008 to December 2018.

### 6.3.2 *Regression Model: Two-Step System GMM*

Specifically, in line with Alhassan et al. (2016) and Adjei-Frimpong et al. *(*2014), this study adopts the dynamic two-step GMM model to assess the relationship between efficiency and profitability indices of commercial banks in Ghana. According to Baltagi et al. (2003) and Alhassan et al. (2016), the use of the OLS in this case produces inconsistent and bias coefficients.

Thus, to deal with the challenges of reverse causality biasness and possible endogeneity, the dynamic two-step GMM is employed (Staub et al., 2010; Lee et al., 2014; Adjei-Frimpong et al., 2014). In effect, the dynamic two-step GMM model addresses the challenges of the OLS by using the lagged differences of the explanatory variables as instruments rather than the variables at level, which in this case are the efficiency scores.

Particularly for the purpose of this study, the dynamic model is adopted mainly because the independent variables used are not strictly exogeneous. Owing to the linkages in the three-stage dynamic network SBM DEA model used, the efficiency scores used as independent variables in the model may be affected by each other.

This study prefers the two-step system GMM estimator to the difference GMM estimator owing to the relatively smaller sample size. According to Arellano and Bond (1991), Blundell and Bond (1998) and Adjei-Frimpong et al. (2014), the two-step system GMM significantly reduces the potential biases and inaccuracies recorded by the first difference GMM, especially for a small and unbalanced panel dataset.

This study uses the two-step system GMM estimator to reflect the persistence in the variables employed in the analysis. According to Adjei-Frimpong et al. (2014) and originally, Staub et al. (2010), the static models mostly ignore the inter-period effect of movements in variables, taking a one-time view of the variable in question. Thus, especially in the banking sector, the static model provides spurious results since banks that are more profitable and efficient in a current year tend to be profitable and efficient in the following year. The dynamic nature of the DEA model used to estimate the efficiency scores also makes the two-step GMM regression the most preferred for this chapter.

Primarily, the OLS proposes a static equation represented as:

$$y_{it} = \beta_0 + x_{it}\grave{\beta} + \eta_i + \mu_{i,t} \tag{6.1}$$

where $i$ is the individual bank, $t$ is the time period under consideration, $y_{it}$ is the dependent variable (ROA or ROE), $x_{it}$ is the independent variable (production, intermediation or revenue generation efficiency), $\eta_i$ is the unobserved effect (such as technical abilities of management, historical factors etc.), and $\mu_{i,t}$ is the error term.

To mitigate the above discussed challenges of the OLS, this study employed the system GMM estimation technique proposed by Arellano and Bond (1991) and Blundell and Bond (1998) and used by Adjei-Frimpong et al. (2014) and Alhassan et al. (2016). As discussed, this model, estimated as follows, employs the lagged differences of the explanatory variables as instruments instead of the level variables as the instruments:

$$y_{it} = \propto y_{i,t-1} + \beta\grave{x}_{\iota t} + \varepsilon_{i,t} \text{ i= 1, 2…N and t= 1,2…. T} \tag{6.2}$$

$$\varepsilon_{it} = \eta_i + \mu_{i,t} \tag{6.3}$$

$$E(\eta_i) = 0, E\left(\mu_{i,t}\right) = 0, E\left(\eta_i\mu_{i,t}\right) = 0 \tag{6.4}$$

where $E\left(\eta_i\mu_{i,t}\right)$ is the fixed effect breakdown of the error term.

For the purpose of this study, Equation (6.2) is expanded into Equations (6.5) and (6.6) by including some control variables noted to have had a significant impact on efficiency (as discussed in Chapter 5 of this thesis). These are a dummy for ownership structure (foreign or domestic, DUMOWN), asset quality (measured by the NPL ratio NPL/TL), liquidity (ratio of total loans to total deposits, TL/TD) and the Boone Indicator measure of competition (BI). Table 6.2 below gives the expected hypothesis of the independent variables considered in the estimation models to be used.

The dynamic panel model specifications in this regard are therefore given as follows:

$$ROA_{i,t} = \beta_1 ROA_{i,t-1} + \beta_2 Ef\grave{f}Ps_{\iota,t} + \beta_3 EffIP_{i,t} + \beta_4 EffRG_{i,t} + \beta_5 DUMOWN + \beta_6 NPL/TL + \beta_7 TL/TD + \beta_8 BI + \varepsilon_{i,t} \tag{6.5}$$

$$ROE_{i,t} = \beta_1 ROA_{i,t-1} + \beta_2 Ef\grave{f}Ps_{\iota,t} + \beta_3 EffIP_{i,t} + \beta_4 Ef\grave{f}RG_{\iota,t} + \beta_5 DUMOWN + \beta_6 NPL/TL + \beta_7 TL/TD + \beta_8 BI + \varepsilon_{i,t} \tag{6.6}$$

Where the dependent variables are the profitability indices ROA and ROE, $EffPs$ is the efficiency score for the deposit mobilisation, $EffIP$ is the efficiency score for intermediation, and $EffRG$ is the efficiency score for revenue generation.

Arellano and Bond (1991) raised issues with the model estimated in Equation (6.2), stating that the presence of the lagged dependent variable as a lagged independent factor in Equation (6.2) may result in unobserved heterogeneities (i.e., may ignore some bank specific factors) as it does not allow for the conventional estimation of $\alpha$ and $\beta$. To resolve this challenge, Arellano and Bond (1991) proposed first-differencing the variables (both dependent and independent variables) as in equation (6.7) to remove any inaccuracies that may arise from unobserved heterogeneities measured by the error term.

$$y_{i,t} - y_{i,t-1} = \propto y_{i,t-1} - y_{i,t-2} + \beta \grave{x}_{i,t} - x_{i,t-1} + \varepsilon_{i,t} - \varepsilon_{i,t-1} \tag{6.7}$$

The proposal for first differencing was still seen to be inconclusive since using the first difference to remove the bias in the equation is only valid under the assumption that the error term is not correlated with the lagged explanatory variables set out by the first differenced equation proposed by Arellano and Bond (1991). Particularly, according to Adjei-Frimpong (2014), the lagged dependent variable is still potentially endogenous as the $y_{i,t-1}$ term in $y_{i,t-1} - y_{i,t-2}$ still correlates with $\varepsilon_{i,t-1}$ in $\varepsilon_{i,t} - \varepsilon_{i,t-1}$. Independent variables (x) that are weakly exogenous may also be potentially correlated with $\varepsilon_{i,t-1}$.

To resolve the challenges of the correlation with the error term, Arellano and Bover (1995) and Blundell and Bond (1998) combined the equation in level (6.2) and the first difference equation (6.7) to develop the system GMM estimator. According to Adjei-Frimpong (2014), such combination reduces the potential inaccuracies associated with the first difference equation, particularly for a small dataset with persistent data, which is the case of this study.

This work follows the estimation model of Adjei-Frimpong (2014) and estimates the Arellano–Bond system GMM estimator by using the xtabond2 command in STATA12.

*Table 6.2: Hypothesis for Independent Variables*

| Variable | Hypothesis |
|---|---|
| **Efficiency** | Increase in efficiency causes an increase in profitability – Efficiency Structure Hypothesis – Alhassan et al. (2016) |
| **Foreign Ownership** | From Chapter 5 of this thesis, foreign banks are more likely to generate lower revenues which may negatively impact profitability. This study however relies on the Global Advantage Theory which presupposes that a foreign bank might benefit from more advanced technologies, skilled labour, improved risk management etc. which can increase profitability – Claessens et al. (2001), Osei-Assibey & Dikgang (2020). |
| **Asset Quality (NPL/TL)** | Increase in NPL ratio will reduce the profitability of banks in Ghana – Alhassan et al. (2014; 2016). |
| **Liquidity (TL/TD)** | High levels of loans results in increased profitability as interest income on loans form a larger portion of revenue of banks in Ghana – TrujilloPonce (2013), Tetteh (2014), Samad (2015). |

| | |
|---|---|
| **Boone Indicator (BI)** | Direct relationship between competition and profitability - Efficiency Structure Hypothesis (ESH) |

## 6.4 *Empirical Findings*

### 6.4.1 *Descriptive Statistics*

This section reports the descriptive statistics and correlation analysis of the variables used in determining the relationship between efficiency and profitability of commercial banks in Ghana for the period 2008 to 2019. Table 6.3 shows a large variation in the minimum and maximum values of the variables used in the study period. The largest variation is apparent in the profitability ratios, i.e. ROE and ROA, suggesting that profitability of banks in Ghana are widely dispersed. ROE ranged from a minimum of approximately -57 to 38.85 while ROA ranged from -7.02 to 6.23. The negative ROE value of -57 was reported by a domestic bank while the positive value of 38.85 was reported for a foreign bank, and the negative ROA value of -7.02 was reported by a domestic bank while a foreign bank reported the positive ROA value of 6.23.

Banks assessed have moderately lower variations for efficiency scores estimated with the least variation observed for the deposit mobilisation stage (PS efficiency scores). Efficiency scores reported for intermediation show the largest variance with the maximum efficiency score of 1 and a minimum score of 0.05 as shown in Table 6.3 below.

*Table 6.3: Summary Statistics of Profitability Indicators and Efficiency Scores of Commercial Banks in Ghana (2008–2019)*

| PTE | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **ROE** | 216 | 7.277 | 10.820 | -57.020 | 38.850 |
| **ROA** | 216 | 1.978 | 1.840 | -7.020 | 6.230 |
| **PS** | 216 | 0.432 | 0.162 | 0.030 | 0.910 |
| **IP** | 216 | 0.586 | 0.256 | 0.050 | 1.000 |
| **RG** | 216 | 0.412 | 0.192 | 0.020 | 0.980 |

Source: Author’s estimation using data submitted by commercial banks to the Bank of Ghana

### 6.4.2 *Efficiency–Profitability Matrix*

To have a holistic view of the performance of commercial banks in Ghana, the DEA efficiency scores are plotted against ROE and ROA to construct the efficiency–profitability matrix. Using the efficiency scores obtained from the three-stage dynamic network SBM DEA model, the efficiency–profitability matrix is constructed three times with the ROA and ROE as the profitability indicators respectively. For both profitability indices, the first matrix shows the relationship between production efficiency (PS) (ability to mobilise deposits) and profitability, the second, the relationship between intermediation efficiency (IP) (advancement of loans) and profitability, and the last matrix, the revenue generation efficiency (RG) and profitability. Units or banks represented on the matrices are differentiated in colour to represent the different ownership type, i.e., foreign or domestic ownership. The matrices are shown in Figures 6.2 to 6.7.

The north-west quadrant represents the Lucky banks: although these banks have profitability exceeding the average, they have efficiency scores below average. According to Kumar (2008) and Marwa and Aziakpono (2014), the high profitability of these banks may be attributed to their ability to benefit from the external environment rather than their capabilities at better resource management. In the Ghanaian banking sector, some favourable external conditions that could contribute to higher profits may be the appreciation of foreign currencies or even the increase in general prices of goods and services, represented by the rate of inflation. Banks that have a higher asset base in foreign currencies or can better set their prices to account for the consistent rise in prices, stand a better chance of increasing profitability, with efficiency remaining unchanged. To increase the performance of banks under this category, banks are encouraged to minimise wastage in resources to increase efficiency and garner greater profits than what was earned.

Generally, more foreign banks are classified as Lucky than the domestic banks.

Four banks fall under this category when considering the relationship between both ROA and the PS efficiency. Of these four banks, three are classified as foreign while one is domestic. On average, the foreign banks under this category show relatively higher profits. Six banks are classified as lucky in this quadrant when ROE is taken as the profitability indicator with PS efficiency. Of these six banks, three are foreign and three domestic.

When the relationship between ROA and IP efficiency is considered, five banks are classified as Lucky (with all being foreign banks), while six banks are classified as Lucky when ROE is measured against IP efficiency. Of the six banks considered, five are foreign banks and one is domestic.

For the relationship between profit and RG efficiency, six banks are put under the Lucky category when ROA is used and seven banks when ROE is used. Of the six banks, four are foreign and two are domestic, while of the seven banks, five are foreign and two are domestic.

The south-west quadrant of the matrices constructed shows the banks classified as the Underdogs. These banks have both profitability and efficiency falling below average and are generally described as distressed or weak banks that have significant wastage of resources. Banks in this category are therefore targets for liquidation or potential mergers with stronger banks.

Generally, more domestic banks are classified as Underdogs than their foreign counterparts.

Five banks, all domestic banks, are classified as Underdogs when the relationship between ROA and PS efficiency is considered, and three banks, again all domestic banks, are seen to be Underdogs when ROE is juxtaposed against PS efficiency.

Five banks are categorised as Underdogs when the relationship between ROA and IP efficiency is evaluated: of these five banks, three are domestic and two foreign. When ROE is considered with IP efficiency, four banks are classified as Underdogs (two are domestic and two foreign).

Five banks are again classified as Underdogs, under the last efficiency estimation, i.e., RG efficiency for both ROA and ROE. Of these five banks, three are domestic while two are foreign owned banks.

Thirdly, the south-east quadrant represents the Unlucky banks that operate under higher efficiency but attain profits lower than average. In contrast to the banks classified as Lucky, banks described as Unlucky may be so due to an unfavourable environment, which again may be attributed to high inflation or the local currency depreciation in the Ghanaian economy. Thus, most banks categorised as Unlucky may not have planned adequately for the consistent increases in price and may have experienced increases in operational expenditure such as salaries which would ultimately reduce profitability over time. Most banks under this category may have been negatively impacted by the depreciation of the local currency as they may have sourced funds in foreign currency. This will ultimately reduce profitability.

Generally, most banks classified as Unlucky in the dataset used were domestic banks.

Three banks are classified as Unlucky when the relationship between PS efficiency and ROA or ROE are considered. Of these three banks, two are foreign and one domestic. In this case, although their PS efficiency may be high, these foreign banks are disadvantaged by external conditions such as high inflation and currency depreciation.

For the relationship between IP efficiency and ROA, three banks, all domestic, are classified as Unlucky, and two banks, both domestic, are categorised as Unlucky when ROE and IP efficiency are considered.

Similarly, three banks, all domestic, are described as Unlucky when the relationship between RG efficiency and ROA is assessed, and two banks, both domestic, are Unlucky when the relationship between RG efficiency and ROA is studied.

Overall, the reasons for low profitability in these domestic banks should be studied to ascertain if there needs to be a change in business strategy or adoption of different product or cost mix to improve on profitability.

Lastly, the north-east quadrant labelled as the Stars is made up of banks that have both efficiency scores and profitability above average. These banks are the most suitable to be used as benchmarks for the inefficient and unprofitable banks.

Generally, this study observes that most banks in this category are foreign banks.

Approximately 33 percent of banks can be categorised as Stars when the relationship between PS efficiency and the profitability indices (ROA or ROE) is assessed. For both ROA and ROE, six banks are categorised as Stars, with five out of these six banks being foreign banks.

Foreign banks also dominate the dataset categorised as Stars when the relationship between IP efficiency and profitability is studied. In this case, five banks are classified as Stars when ROA is used and six banks classified as Stars when ROE is used.

Finally, the study finds that three banks, all foreign owned, are classified as Stars when the relationship between RG efficiency and ROA is assessed. Three foreign banks and one domestic bank are classified as Stars when RG efficiency is compared to ROE.

Ultimately, these banks, classified as Stars, have learnt to capitalise on the opportunities presented by their environments and may probably be operating under favourable conditions.

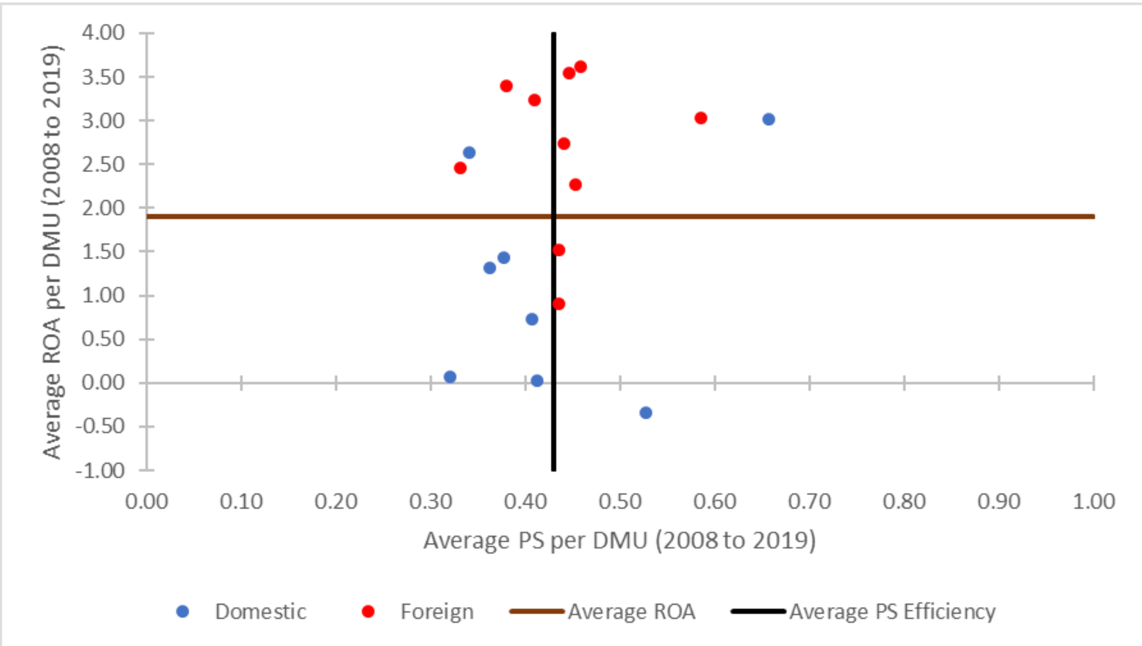


*Figure 6.2: ROA/PS Efficiency–Probability Matrix*

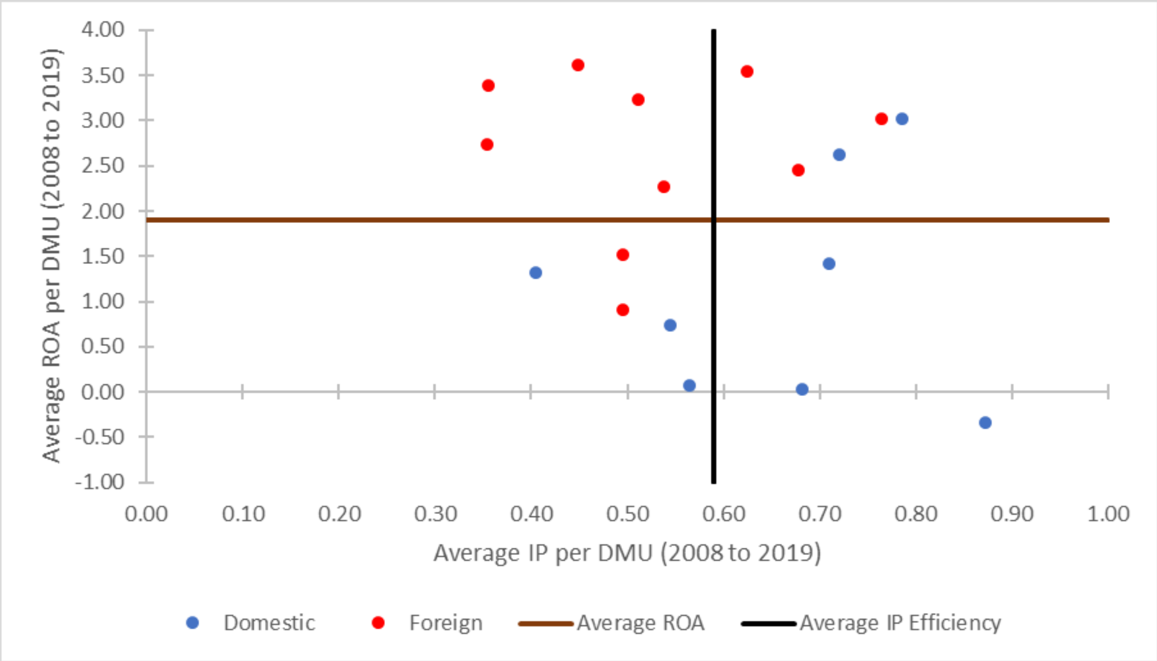


*Figure 6.3: ROA/IP Efficiency–Probability Matrix*

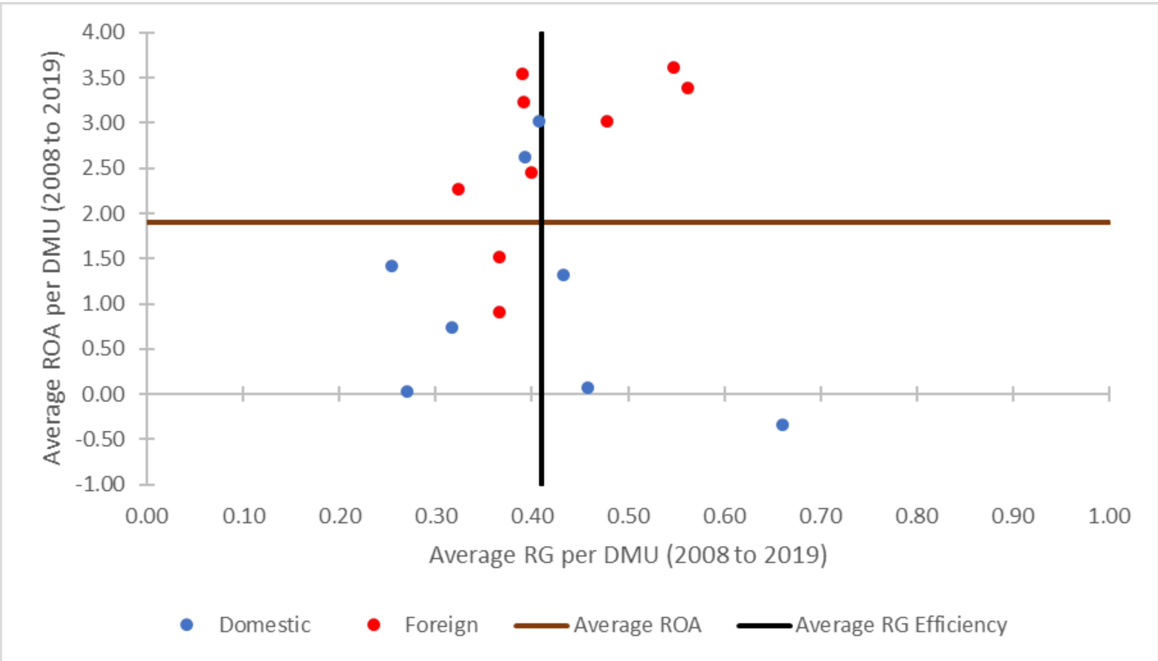


*Figure 6.4 ROA/RG Efficiency-Probability Matrix*

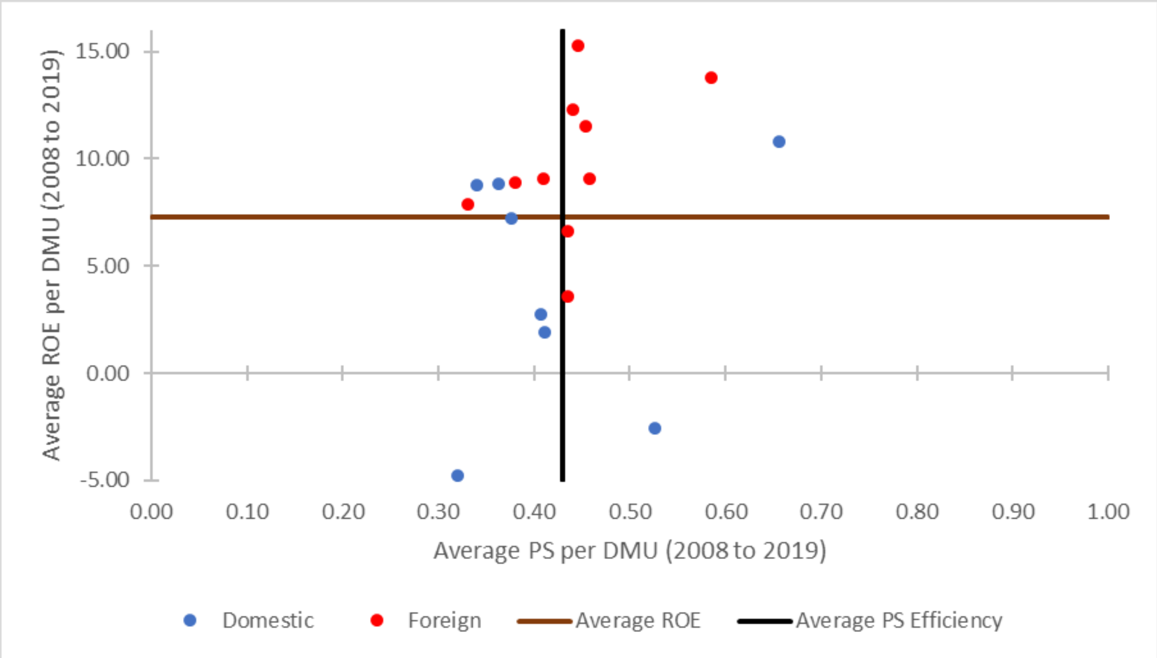


*Figure 6.5: ROE/PS Efficiency–Probability Matrix*

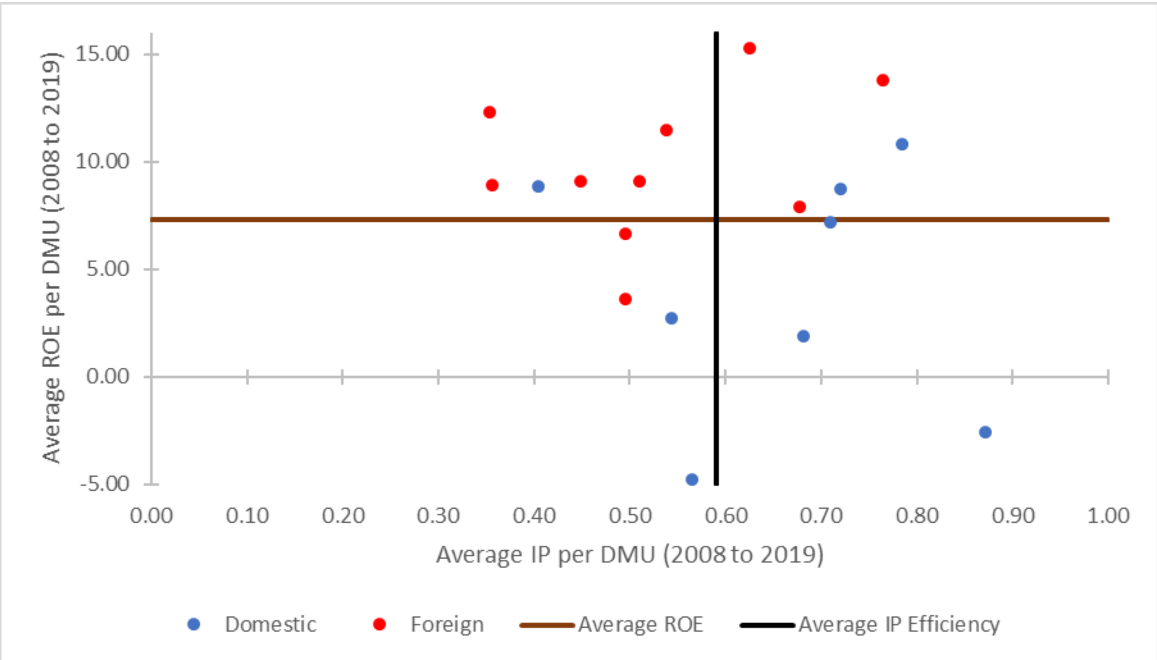


*Figure 6.6: ROE/IP Efficiency-Probability Matrix*

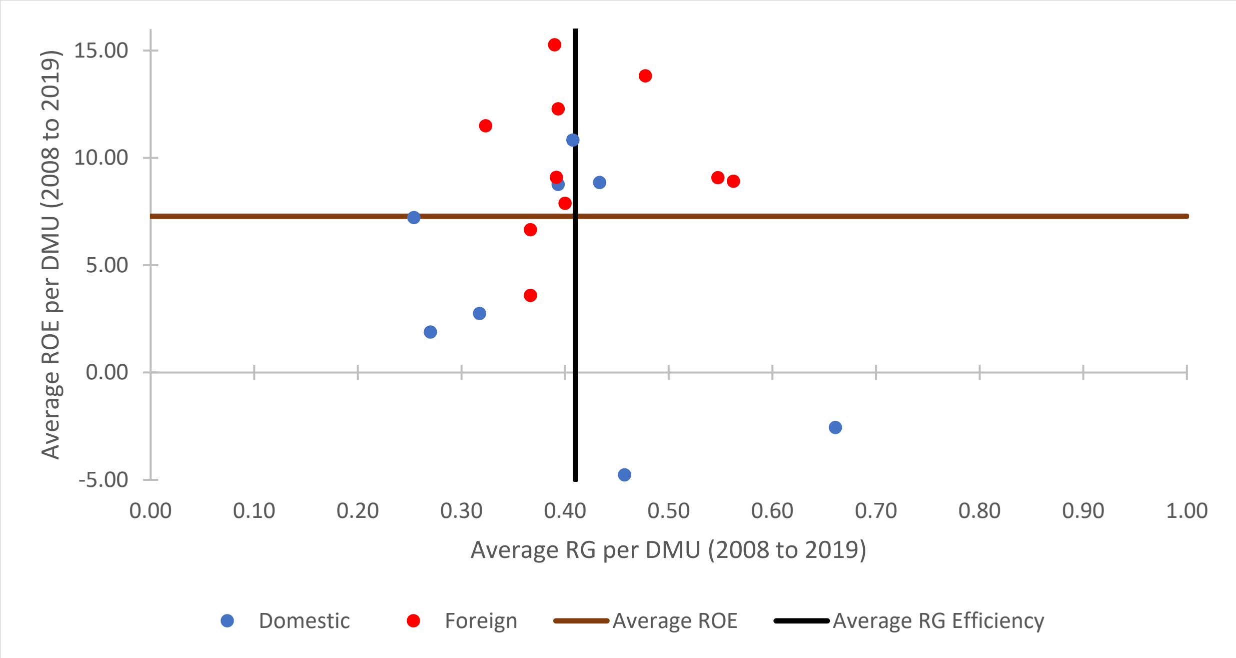


*Figure 6.7: ROE/RG Efficiency-Probability Matrix*

### 6.4.3 *Impact of Efficiency on Bank Profitability – GMM Regression Analysis*

#### 6.4.3.1 *Evaluation of the GMM Estimation Model*

To assess the strength of the model used, the study first of all tests for multicollinearity problems between the determinants of bank profitability. The results suggest low correlation between the explanatory variables.

Secondly, the study uses the Hansen J-test to evaluate the validity of the instruments used. The choice of the Hansen J-test is founded on its appropriateness when there is heteroscedasticity and autocorrelation (Adjei-Frimpong, 2014). Failure to reject the null hypothesis that the instruments used are exogenous, gives support to the model and validates the instruments used.

Similar to the works of Adjei-Frimpong et al. (2014), this study uses the difference-in Hansen test of exogeneity to establish whether any identified correlation between endogenous variables and the unobserved fixed effect stays constant over time. This assumption allows for the inclusion of the levels equation in the GMM estimation and also permits the use of lagged differences as instruments in the levels equation. Again, the null hypothesis of the difference-in Hansen test of exogeneity is that the instruments used in the equation at levels are exogenous. Failure to reject the null hypothesis supports the use of the levels equation in the GMM estimation.

In order to accept the null hypothesis of the Hansen and the difference-in Hansen tests the p-values should exceed the conventional 0.05 or the 0.10 significance levels, but not be equal to 1 or significantly closer to 1 (Roodman, 2007; Adjei-Frimpong et al., 2014). A p-value of 1 indicates misspecification.

It is also important for the null hypothesis of no second order autocorrelation not to be rejected. According to Adjei-Frimpong et al. *(*2014), rejection of the null hypothesis of no second order correlation implies misspecification of the equation as it implies that the original error term is serially correlated.

In Table 6.4, the study observes the model used is largely valid. With ROA as the dependent variable, the Arellano-Bond test statistics AR (2) of the residuals does not reject the specification of the error term, since the p-values of AR (2) is 0.435 which are more than 10 percent level of significance (Table 6.4). There is therefore no serial correlation in the error term. At 0.717, the p-values of the Hansen test also fails to reject the null hypothesis of over-identification of validity of instruments. This shows that the instruments used in the model are valid. The difference-in Hansen test of exogeneity, with p-values of 0.523 also strengthens the validity of instruments used in the level equation included in the model. The p-values of the difference-in Hansen test of exogeneity imply that the instruments used in the equation at level are exogenous and valid.

#### 6.4.3.2 *Regression Results*

Table 6.4 presents the results for the two-step system GMM estimation models for the period 2008 to 2019. A positive coefficient implies an increase in profitability should the independent variables used increase, while a negative coefficient shows a decrease in profitability should the independent variables increase.

For the independent variables, L1 represents the lag variable for the dependent variable (ROE or ROA), EFFPS represents production efficiency, EFFIP represents intermediation efficiency, EFFRG represents revenue generation efficiency, Dum Own represents ownership structure (foreign or domestic), NPL_TL represents asset quality, TL_TD is a proxy of liquidity, and BI, the bone indicator measure of competition.

The coefficient of L1 assesses the persistence of profitability over the period. According to Alhassan et al. (2016), a value between 0 and 1 shows low persistence of profitability and increased convergence to normal profits owing to heightened competition in the market. A coefficient value closer to 1 shows high persistence in profitability and lower convergence to normal profits. In Table 6.4, the coefficients of the lagged dependent variable ROE, was highly significant with a coefficient of 0.450 while the coefficients of the lagged dependent variable, ROA was 0.474 at a p-value of 0.011. These values, which are lower than 1, show low persistence in profitability and heightened competition, agreeing with the BI estimates measured in Chapter 5 which indicates increased competition in Ghana's banking sector. This finding is similar to that of Alhassan et al. (2016), who also found lower persistence in profitability for commercial banks in Ghana in the period 2003 to 2011.

Also for the period 2008 to 2019, Table 6.4 shows a significant positive impact of intermediation and revenue generation efficiencies on ROE, and a negative non-significant impact of production efficiency on ROE of banks assessed. The same trend is seen in the impact of the coefficients of efficiency types on ROA, although the results in this case, are not significant. The largely positive coefficient of the efficiency types on ROE and ROA is an indication of the ESH, which presupposes that banks that are able to minimise inputs (fixed assets, operational cost, employee cost, deposits, gross loans) to produce the expected outputs (i.e. deposits, gross loans and income) may be likely to earn more return on their shareholders' contributions and assets. In Ghana, this finding again aligns with that of Mawutor and Fred (2015) and Alhassan et al. (2016) who found that technical efficiency of commercial banks had a significant positive impact on profitability in the periods 2006 to 2011 and 2003 to 2011 respectively.

Table 6.4 also shows varying results in respect of the control variables used in the estimation of the GMM model. For ROE, TL/TD (the measure of liquidity) and the Boone Indicator (BI) measure of competition, showed significant impacts. Alternatively, only the variable representing foreign ownership had a significant impact on ROA. TL_TD had a negative impact on ROE while and BI and foreign ownership had a positive impact on ROE and ROA respectively.

The positive coefficient of foreign banks on ROA agrees with the direction of the coefficient of foreign ownership observed in Chapter 5 of this thesis. This again confirms the hypothesis stipulated by the Global Advantage Theory which presupposes that foreign banks might benefit from more advanced technologies, skilled labour, improved risk management etc. which reduce cost and ultimately increase profitability. This finding is in line with works such as Claessens et al. (2001) and Osei-Assibey et al. (2020)

Also, the significant and positive relationship observed between competition and profitability aligns with the observations for competition and efficiency and the Efficiency Structure Hypothesis (ESH). The ESH postulates that the competitive attitude of efficient firms results in increased market share and firm size, resulting in lower costs which causes an increase in profitability.

*Table 6.4: Dynamic panel-data estimation, two-step system GMM 2008–2019*

| | **2008–2013** | |
|---|---|---|
| | **ROE** | **ROA** |
| **Variables** | **Coefficient (t-stats)** | **Coefficient (t-stats)** |
| **L1** | 0.450 (0.001) | 0.473 (0.011) |
| **EFFPS** | -0.696 (0.213) | -0.162 (0.0.311) |
| **EFFIP** | 0.367 (0.082) | 0.133 (0.439) |
| **EFFRG** | 1.610 (0.005) | 0.130(0.165) |
| **Dum_Own** | 0.0285 (0.933) | 0.353 (0.019) |
| **NPL_TL** | -0.384(0.120) | -0.114 (0.151) |
| **TL_LD** | -1.252 (0.063) | -0.136 (0.725) |
| **BI** | 0.794 (0.002) | 0.045 (0.330) |
| **Constant** | 5.267 (0.107) | 1.141 (0.569) |
| **Number of instruments** | 17 | 17 |
| **Number of groups** | 18 | 18 |
| **Arellano-Bond test for AR (2) in first differences: Pr > z** | 0.639 | 0.435 |
| **Hansen test of overiding restrictions: Prob > chi2** | 0.299 | 0.717 |
| **Difference (null H = exogenous): Prob > chi2** | 0.843 | 0.523 |

Source: Author's estimation using data submitted by commercial banks to the Bank of Ghana

## 6.5 *Conclusions*

This chapter evaluated the relationship between efficiency and profitability using the efficiency–profitability matrix, and also assessed the impact of efficiency on profitability using the two-step system GMM regression model.

Using the efficiency–profitability matrix for the period 2008 to 2019, this study found foreign owned banks to be largely classified as Lucky and Stars while domestic banks were mostly categorised under the Unlucky and Underdogs quadrants.

Under the regression model used, the study observes a positive impact of efficiency on the profitability of commercial banks in Ghana. Although the effects of efficiency on profitability measured as ROA were not significant, the positive coefficients agree with the Efficiency Structure Hypothesis, indicating that banks that are able to minimise inputs (fixed assets, operational costs, employee costs, deposits, gross loans) to produce the expected outputs (i.e. deposits, gross loans and income) are likely to be profitable.

In the regression model, four control variables were used: dummy variables indicating ownership type, NPL ratio, liquidity ratio (TL/TD) and the Boone Indicator competition measure (BI). Of these variables, only the dummy variable for ownership had a significant impact on ROA, while TL/TD had a negative impact and competition, a positive impact on ROE. The direction of the coefficient of foreign ownership agrees with the Global Advantage Theory, while that for the competition measure in in tandem with the ESH.

# CHAPTER 7

# CONCLUSIONS AND POLICY IMPLICATIONS

## 7.1 *Introduction*

The consistent banking sector reforms have increased the bank efficiency of banks in Ghana.

Studies that have sought to measure the efficiency of banks globally have used various estimation methodologies. In recent times, the most prevailing methodologies in literature are the frontier models which are used to measure technical and allocative efficiencies (Cummins and Xie, 2013). Technical efficiency measures how efficient firms are in using the minimum input to attain the maximum output, whereas allocative efficiency estimates the cost and revenue efficiencies obtained from the frontier.

Different economies of scale have been adopted to estimate technical efficiency, with the key scales being the constant returns to scale and variable returns to scale. CRS estimates the scale efficiency of banks, while VRS measures pure technical efficiency. Both types of efficiencies culminate in the overall technical efficiency of a decision-making unit.

Literature has used two distinct techniques to estimate the efficiency frontiers: parametric and non-parametric measures. These techniques are basically distinguished by the assumptions made in estimating the shape of the efficiency frontier and the treatment of random error in the estimation model. The parametric measure presumes the shape of the efficiency frontier by specifying the functional form for the relationship between input and output variables, and separates random error that arises from measurement blunders and unusual financial performance from inefficiency. The non-parametric measure does not require any prior assumption in estimating the frontier and allows for the efficiency evaluation of multiple input–multiple output firms. This measure is more likely to overestimate firm inefficiencies as it does not separate statistical noise from inefficiency. This implies that the non-parametric measure does not allow for the estimation of random error arising from blunders in measurements, unusual financial performance, and misspecification or omission of input and output variables.

The weakness of the non- Ghana's banking sector has gone through significant transformations since the early 1980s with one of the most significant challenges occurring in recent years, between 2017 and 2019. Most of these transformations aimed at improving the efficiency of banks in order to stimulate growth in both the public and private sectors.

Prior to the 1990s, commercial banking in Ghana was characterised by extensive government control which increased the intermediation cost of banks and had destructive consequences on the growth and development of the sector. This period was particularly marked by inadequate capital, poor asset quality, and high operational costs. The early 1990s and beyond experienced consistent but gradual progress as the sector became more liberalised, enhancing its competitiveness and efficiency. A notable reform in this era was FINSAP which sought to reduce the political influence on bank activities and improved prudential regulation by the Supervisor.

Given the challenges of the Ghana's commercial banking sector prior to FINSAP, it is without doubt that FINSAP and several other reforms that have followed FINSAP have improved the capacity and performance of commercial banks in Ghana. Presently, with less governmental control and increased foreign and private participation, banks have far exceeded their minimum capital requirement, with most banks reporting profits at the end of their financial year. As of December 2019, 24 commercial banks were operating in the country with 14 foreign-owned banks and 10 domestic-owned banks. Of the 14 foreign-owned banks, five originated from Nigeria, one from Togo, one from South Africa, and three from the European region.

Despite the gains brought about by the financial sector reforms, Ghana's commercial banking sector is still fraught with challenges that have significantly impaired intermediation between borrowers and savers. According to Dadzie and Ferrari (2019), the weak macroeconomic performance of Ghana's economy resulted in high inflation and exchange rates that have stalled the attainment of positive real interest rates on interest-bearing instruments in the banking sector. The high capital requirements imposed on banks over the years have also caused banks to invest in government securities, crowding out the private sector. These challenges cast doubts on whether the consistent banking sector reforms have increased efficiency of banks in Ghana, therefore requiring a continuous and updated assessment of bank efficiency in Ghana.

Most studies, particularly in the African region, have adopted the non-parametric measure to estimate the efficiency of banks. The most common technique used under this measure is the Data Envelopment Analysis (DEA) which adopts either CRS or VRS to estimate the technical and scale efficiencies of firms. Estimation of the DEA model is categorised into two broad measures: input- and output-oriented models. For the input-oriented model, firms seek to minimise input to attain a certain amount of output, and for the output-oriented model, firms seek to maximise their output with a given level of input. In the banking industry, it is argued that managers have minimal control over outputs but are able to monitor and control inputs. This argument results in the preference of the input-oriented model as opposed to the output-oriented model.

Another area of concern regarding the DEA is the selection of variables used in the efficiency score estimation. Owing to the diverse functions of banks, especially in these current times, Sealey and Lindley (1977) have argued that the accurate estimation of bank efficiency goes beyond just assessing the bank's traditional function, which is intermediation, to evaluating efficiency in terms of their production, value addition and cost user. Berger and Humphrey (1997) therefore proposed various ways of selecting input and output variables for the estimation of the DEA model. These variable selection methods are the intermediation, production, user cost and value-added approaches.

By estimating the DEA efficiency model, existing studies have used either the black-box traditional model or recent extensions to the black-box DEA model. The black-box traditional model, although it assumes both the CCR and BCC assumptions, has been criticised for several reasons. First of all, the black-box model benchmarks an inefficient DMU against a group of best performers in order to improve the performance of the inefficient unit. There are differences in the operating practices and technologies between the benchmark group and the inefficient DMU, making the juxtaposition incoherent. To resolve this challenge, researchers have proposed the DEA metafrontiers which accounts for the measurement and comparison of technical efficiencies of firms operating under comparable technologies and operational practices. The use of the metafrontiers therefore results in two efficiency scores: one that measures the distance of an input-output point of a DMU to that of a group frontier (basically known as the traditional measure of technical efficiency), and the second that measures the distance between the group frontier and a meta frontier (known as the 'technology gap'). As a second gap, the black-box model is mostly appropriate for small sample size data, losing discriminatory power of the model. In this respect, the Window DEA model is used to increase the data size and reduce the discriminatory power of the model. Again, to mitigate the impact of the smaller dataset, most recent studies have used the bootstrap technique. This technique according to Simar and Wilson (1998), is a statistical estimation model that repeatedly simulates the data generating process to increase the data size.

Thirdly, the traditional black-box model assumes that all variables used in estimating the DEA efficiency score are known with precision, which is unrealistic. To curb this challenge, researchers have suggested the Stochastic DEA and the Fuzzy DEA. The Stochastic DEA incorporates stochastic features into the traditional models and deals with the imprecision of data used, while the Fuzzy DEA deals with variables possessing fuzzy characteristics and seeks to remove the imprecision associated with such variables.

Fourthly, the traditional CCR and BCC models includes slack variables which represent excesses in inputs and shortages in outputs. The absence of these variables results in spurious estimations, as both desirable and undesirable inputs and outputs are included in the model. To resolve this challenge, Tone (2002) proposed the SBM which seeks to improve the accuracy of estimates by considering both input and output shortages.

Finally, the black-box DEA model ignores interlinkages of activities within firms, treating the DMU as one black box. To account for such interlinkages, Charnes et al. (1986) introduced the network DEA, which treats the input of the prior stage as the output of the subsequent stage. This technique focuses on the interlinkages in a single period, ignoring interlinkages and carry-overs between periods. The dynamic network DEA was therefore introduced to by Färe et al. (2007) to account for carry-over activities and enable the estimation of efficiency over a longer period.

In the African region, most studies have used the DEA black-box technique to estimate the efficiency scores of banks, ignoring the challenges encountered in its use (Sobodu and Olankunle, 1998; Hauner and Peiris, 2005; Aikaeli, 2006; Van Heerden and Van der Westhuizen, 2008; Raphael, 2013; Erasmus, 2014; Yannick et al., 2016). Particularly in Ghana, studies that have used the traditional black-box model far outnumber those that have employed the current DEA trends (Korsah et al, 2001; Saka et al., 2012; Adusei, 2016; and Alhassan and Ohene-Asare, 2016). Although generally, these studies on bank efficiency in Ghana have seen gradual improvements in efficiency, the efficiency estimates derived still stand to be questioned owing to the rampant use of the black-box DEA and its associated challenges.

Specifically, with growing diversification in the functions of banks, the sole outlook of intermediation (conversion of deposits into loans) adopted by most black-box DEA models undermines the accurate representation of banks in Ghana. The first empirical paper of this thesis therefore goes beyond evaluating the efficiency of commercial banks in Ghana with the traditional black-box DEA model to comparing the results obtained from the black-box analysis with that from the dynamic network DEA model. The dynamic network DEA model, which examines the interlinkages between periods and activities of banks in this study, is used to measure the efficiency of the production (mobilisation of deposit), intermediation (conversion of deposits to loans) and revenue generation activities of commercial banks in Ghana. Such detailed three-stage efficiency analysis serves as the first of such studies in Ghana and is expected to enhance the understanding of Africa's banking sector to inform policy aimed at improving the performance of banks specifically in Ghana.

The study attempts to enhance the accuracy of efficiency score estimated by employing the bootstrap technique and including a slack variable (in this case the NPL), in both the black-box and dynamic network DEA estimations.

Overall, for each DEA model used, the thesis calculates the efficiency scores based on both the CCR and BCC models, estimating OTE, PTE and SE. In this case, irrespective of the frequent use of both models in the banking sector, the study based on the argument of Burger and Moormann (2009) and

Othman (2016) notes that the BCC models are preferred, particularly for the banking sector. Based on the variable return to scale assumption, Burger and Moormann (2009) and Othman (2016) claimed that in the real world, profit-driven institutions such as banks are more likely to produce under increasing or decreasing returns to scale than the constant returns to scale assumed by the CCR model.

Following the estimation of efficiency scores, the thesis goes further to identify the causes of inefficiencies for all three stages estimated by the dynamic network DEA model, by using both the Tobit and truncated bootstrap regression models to estimate the relationship between the efficiency scores observed under the VRS assumption and some internal and external factors. At this point, the thesis juxtaposes these two regression models, arguing for the truncated bootstrap regression model. The preference for the truncated bootstrap regression is first of all based on use of the Tobit regression model for solely censored data. McDonald (2009) argued that the DEA efficiency scores are not generated by censoring data but rather by a particular kind of fractional or proportional data which requires a normalisation process where the production frontier is estimated by the ratio of input to output and the exact value of the dependent variable is known, instead of the restricted range imposed by the censored model. Another factor discussed in favour of the truncated bootstrap model is its ability to account for serial correlation and correlation between the variables used. The Tobit regression model ignores serial correlation and the correlation between the factors used to estimate efficiency scores in the first stage and the explanatory variables used in the second stage, resulting in inconsistencies and biases of results obtained.

The internal factors pertain to variables under the control of management, which in the case of this thesis are total assets, capital adequacy ratio return on assets, bad loans, liquidity ratio, and operational cost. The external factors relate to the variables determined by the macroeconomic environment, including GDP per capita and inflation. Also included as independent variables in the regression models are the indicators for ownership type (domestic and foreign ownership) and competition (estimated using the Boone indicator).

Lastly, having measured the efficiency scores of banks and identified the causes of inefficiencies in Ghana's commercial banking sector, this thesis attempts to juxtapose the profitability with efficiency of banks. This is achieved by placing banks into the efficiency–profitability matrix to ascertain whether banks that are profitable are equally efficient and vice versa. Having estimated efficiency scores for the production, intermediation and revenue generation stages, the thesis further ascertains which efficiency type has the most significant effect on profitability. Are banks that are best in mobilising deposits more profitable than those that are better at intermediation or revenue generation? To answer this question, the study adopted a two-step system GMM regression model to estimate the effect of the efficiency scores estimated in the three-stage network dynamic SBM DEA model (PTE) on profitability measured by ROA and ROE.

The annual sample data used for this study is a balanced panel data with 216 observations covering 18 commercial banks in Ghana. The rest of this chapter summarises the findings of the study in Section 7.2 and discusses the policy implications in Section 7.3. Limitations of the study and future research recommendations are discussed in Section 7.4.

## 7.2 *Summary of the Findings*

### 7.2.1 *Estimating Bank Efficiency Scores*

Overall, commercial banks in Ghana for the period assessed were generally inefficient, with banks reporting the highest efficiency scores for scale efficiency and the least efficient scores for pure technical efficiency. The study also observed that overall efficiency scores measured by the network model were noticeably lower than the scores estimated by the black-box model. This finding is consistent with that of Fukuyama and Matousek (2011) and Dia et al. (2020) who argued in favour of the network DEA approach for a more correct representation of bank performance.

Generally, for both the BCC and CCR assumptions, banks assessed were noted to be most efficient in intermediation (stage 2) and least efficient in revenue generation (stage 3) under the network dynamic DEA model.

### 7.2.2 *Determinants of Bank Efficiency*

In identifying the determinants of bank efficiency, the observed direction of the chosen variables (positive or negative and the significance level at 10 percent) did not vary across the regression models used. This means that for the dataset used, results from the truncated bootstrap regression model provided nearly similar results as the Tobit regression model.

Regarding the determinants of efficiency, the impact of the variables used differed by the type of efficiency being assessed.

For production efficiency, CAR, NPL ratio, liquidity ratio (TL/TD) and inflation rate had a significant negative impact while total assets had a significant positive effect.

CAR, NPL/TL also showed a negative impact while TL/TD and size had a significant positive effect on intermediation efficiency.

For revenue efficiency, study found that the variables ROA, OC/OI, inflation rate and foreign ownership have significant impacts for both models used.

The negative effect of CAR on both production and intermediation efficiencies is seen in the calculation of CAR. In this case, when capital increases, the risky activities of banks may heighten in the form of loans (postulated by the agency theory). The increase in lending reduces the CAR, but at the same time increases intermediation efficiency, which is directly associated with deposit mobilization (production efficiency), thus the inverse relationship between CAR and the two efficiency types.

The negative coefficient observed for the NPL ratio implies that an increase in the ratio invariably reduces production and intermediation efficiencies. In this case, the thesis argues that for banks to reduce the NPL ratio, they should increase their total loans. Evidence from data used further suggested that an increase in loans also improves the deposit mobilisation efficiency of banks in Ghana.

Similarly, asset size of banks in Ghana is largely driven by loans. Thus with the significant positive relationship between asset size and production and intermediation efficiencies, it is assumed that larger banks are better able to mobilise more deposits and also give out a higher amount of loans. This observation is in tandem with the stewardship theory which states that management is less likely to misuse the firm’s resources when assets expand, resulting in increased efficiency.

In terms of liquidity (TL/TD), the study proposes that an increase in the liquidity ratio attracts less deposits (reduction in production efficiency). However, an increase in liquidity gives the banks enough room to grant more loans (increase in intermediation efficiency). Nevertheless, consistent accumulation of liquidity may impair the revenue generation process of banks, reducing efficiencies in the third stage of the network DEA.

For macroeconomic factors, inflation reduced banks’ efficiency in deposit mobilisation and lending as rates of returns on investment reduced and customers probably moved to more fixed assets.

For revenue generation efficiency, ROA, OC/OI and inflation rate are noted to have a positive effect, while foreign banks are found to have a significant negative impact.

The positive impact of ROA on revenue generation efficiency is reflective of the Efficiency Structure hypothesis, which implies that profitable banks in Ghana are more efficient.

On the other hand, the direction of the coefficients of OC/OI and inflation and foreign ownership observed under the revenue generation efficiency contradict the Efficiency Market, Economic Growth and Global Advantage hypotheses respectively.

The ratio OC/OI has a positive significant impact on all efficiency types measured. The study notes that in the dataset used, banks spend more on operational and staff costs when lending is increasing. Such increases in cost may be attributed to increased provisions charged to the income statement as per the IFRS and increases in the cost invested in staff assigned to build the loan portfolio of banks.

As established, an increase in lending results in an increase in deposits and intermediation. The increase in loans is expected to yield more interest income relative to costs incurred, thus the positive impact of the ratio OC/OI on revenue generation.

The positive effect of inflation on revenue generation efficiency although contrasts the Economic Growth theory, agrees with the proposed theory of Trujillo-Ponce (2013). This means that banks in Ghana are better able to timely and accurately forecast inflation rates thus allowing for adequate adjustment of interest rates which will ultimately increase interest income.

Lastly, foreign ownership of banks has a non-significant positive impact on production and intermediation efficiencies but a significant negative impact on revenue generation efficiency. Having established a direct positive relationship between total assets (specifically loans), and deposits, the study observed that foreign banks owing to availability of funds from increased sources, granted more loans than their domestic counterparts, resulting in improved production and intermediation efficiencies. However, irrespective of their higher deposit and loan base, the interest income as a percentage of total assets was significantly lower at 39% compared to that of domestic banks at 47% percent. This trend is explained by the clientele base of foreign banks, who are noted to have higher bargaining powers to beat down the interest rates charged, thus a reduction in interest income in relation to the loans granted.

### 7.2.3 *Estimation of Competition and the Relationship between Competition and Efficiency of Banks*

Estimation of the Boone Indicator measure of competition revealed that Ghana’s banking sector is largely competitive, although the level of competition varied across the period under assessment. The commercial banking sector was most competitive in the years 2008 to 2009, and 2016 to 2019, and least competitive in the period 2010 to 2015 with the year 2010 showing the least competitiveness. The variations in the level of competition are mainly driven by the macroeconomic and structural changes in Ghana’s banking sector such as the redenomination of the Ghana cedi, discovery of oil, significant depreciation of the local currency and energy crisis.

The level of competition observed by this study agrees with the findings of Alhassan and Ohene-Asare (2016) and Dadzie and Ferrari (2019), who also found that the post-reform era brought about a reduction in concentration levels and ultimately increased competitiveness in the banking industry.

Consequently, using the Boone Indicator measure of competition as an independent variable in both the truncated bootstrap and Tobit regression models, the study observed a significant positive association between the competition measure and production efficiency under the truncated bootstrap regression model and also significant positive association between competition and intermediation efficiency under the Tobit regression model. The relationship between competition and revenue generation efficiency was however not significant, although it also showed a positive coefficient. Our observation agrees with the Efficiency Structure Hypothesis which presumes that increase in competition drives efficiency owing to the absence of monopolistic powers of industry players. This finding agrees to that of Aboagye (2012), Saka et al. (2012) and Alhassan and Ohene-Asare (2016).

#### 7.2.4 *Relationship between Efficiency and Profitability of Banks*

Overall, the observed relationship between efficiency and profitability were inconclusive.

Employing the efficiency–profitability matrix, most foreign banks in Ghana were noted to be classified as either Lucky or Stars. Lucky banks are defined as firms with high profitability but low efficiency, while Stars are firms with both high profitability and efficiency. The fortune of banks classified as Lucky could be attributed to macroeconomic conditions such as the appreciation of foreign currencies and increases in inflation. Thus, foreign banks that had higher assets in foreign currencies and were able to accurately project and account for inflation were seen to yield more profit although they were not necessarily efficient.

Most domestic banks were classified as either Unlucky and Underdogs. Banks classified as Unlucky had higher efficiencies but lower profitability, while the Underdogs had both low efficiency scores and profitability levels. The fortune of banks classified as Unlucky could be attributed to increases in inflation. Thus, banks that were not able to accurately project movement in inflation may experience sporadic increases in operational expenditure which may reduce profitability.

Using the GMM estimator to measure the impact of the three stages of efficiency measured (deposit mobilisation, intermediation and revenue generation) on the profitability indicators (ROA and ROE), this study observed low persistence in profitability as the increased competition in Ghana’s banking sector does not allow all banks to earn abnormal profits. Additionally, although the results obtained for ROA as a dependent variable were not significant, the study found that all three types of efficiency largely had a positive impact on profitability measured by ROA and ROE, agreeing with the Efficiency Structure Hypothesis. This postulates that banks in Ghana earn more profit not necessarily because of market power but improved efficiencies. Thus banks that are able to minimise inputs (fixed assets, operational costs, employee costs, deposits, gross loans) to produce the expected outputs (i.e. deposits, gross loans and income) are likely to earn a better return on their shareholders’ contributions and assets.

For the other variables included in the GMM regression model, the study found that only the dummy variable for ownership had a significant impact on ROA, while TL/TD and competition had a negative and positive impact on ROE respectively. The direction of the coefficient of foreign ownership agrees with the Global Advantage Theory, while that for the competition measure is in tandem with the ESH.

## 7.3 *Policy Implications of the Study*

As Ghana's banking sector undergoes significant shifts to improve its performance, the findings of this study offer pertinent contributions to policy makers, the Bank of Ghana, executive and non-executive management of commercial banks, to formulate policies and guidelines that will enhance bank efficiency and ultimately promote the economic growth of the country.

Considering the relatively lower levels of revenue generation efficiency and the negative impact of NPLs on bank performance in Ghana, the study recommends that commercial banks in Ghana build on their monitoring tools and strong relationships with their borrowers to control the challenges of adverse selection and moral hazards and ultimately increase profits and revenue. Particularly, having reported the least efficiency in revenue generation, domestic banks are encouraged to practice more caution in advancing loans and credit in order to mitigate credit risks and ultimately improve their revenue generation efficiency. Considering the clientele base of domestic banks, which are mostly in the informal sector, domestic banks are encouraged to have a more creative collateral system which may include the guarantee of loans by government and other credible institutions: such guarantee systems may increase lending to the informal sector, boosting private sector development.

Having reported lower pure technical efficiency scores as opposed to overall technical and scale efficiency scores, this study also encourages commercial banks in Ghana to make a conscious effort to improve the skill set of managers and staff. The study therefore agrees with Adjei-Frimpong (2014) who urged policy makers to compel commercial banks to improve their training of staff within a realistic budget. Improved training will increase the skill set of staff, increase productivity, reduce bureaucracy and ultimately increase the efficiency of the commercial banking sector in Ghana: this is particularly urgent for domestic banks.

To control for the adverse effect of foreign ownership on revenue generation efficiency of commercial banks in Ghana, the study proposes that the Bank of Ghana and the Ghana Association of Bankers, together with other pertinent stakeholders, encourage foreign banks to design their loan request and approval conditions to suit expansion in their lending activities to the informal sector, particularly to the SME sector, but not neglecting the monitoring processes required to reduce NPLs. Such expansion in credit will allow the foreign banks to earn more interest income relative to loans granted following the high-risk premiums charged to the informal sector. According to Ampah et al. (2017), expansion of loans to the SME sector in Ghana is likely to create more jobs and promote economic growth as these institutions employ over 70 percent of the working population in the country.

Regarding the negative impact of TL/TD on revenue, this study again proposes adequate monitoring of credit granted by commercial banks in the country, as a reduction in liquidity, represented by an increase in TL/TD which presupposes increase in lending and consequently NPLs.

Finally, to encourage the transition of domestic banks from the Unlucky classification to Stars or Lucky quadrants in the efficiency–profitability matrix, this study recommends that domestic banks diversify their income earning portfolio and adopt strategies that would result in increased revenues and improved profitability. Such strategies include moving away from the traditional servicing of loans to more advanced banking services such ATM transactions, and advisory and safe-keeping services. Irrespective of the high bargaining power of corporate customers, they have a larger deposit base than most clients in the informal sector. Thus, to increase their deposit base, and consequently lending and profitability, domestic banks are encouraged to market to the larger clientele base and also the informal sector. Ultimately, banks that are classified as Underdogs are encouraged to be either liquidated or merged with more successful banks.

## 7.4 *Limitations of the Study and Future Research*

This section provides some limitations of the study and makes recommendations for future research.

First of all, the study applies only the DEA methodology to assess the efficiency of commercial banks in Ghana. This methodology has some drawbacks, with the most significant challenge being its inability to separate statistical error and noise from inefficiencies. Although with the sample size assessed, DEA was the most preferred option, it is recommended that future studies to assess bank efficiency in Ghana widen the scope to include both non-parametric and parametric measures such as SFA and DFA. These parametric measures are better able than DEA to separate inefficiency from random errors. Also, the use of both measures would test the robustness of the efficiency scores estimated for commercial banks in Ghana.

Secondly, this study assesses and uses only technical efficiency to represent the overall performance of commercial banks in Ghana. This is inadequate as there are other efficiency types such as cost and profit efficiencies which may provide additional information on bank performance in Ghana. Whereas technical efficiency evaluates the effectiveness of management in using the minimum input to produce the maximum output, it does not take into consideration the cost and price of both input and output variables. Cost efficiency, on the other hand, measures how well banks minimise their costs with given input prices and technology, and profit efficiency evaluates how effective banks are at maximising their revenues. To measure cost and profit efficiency, the study would require the price of factors such as loanable funds, loans, labour and other operational costs. Although the data on the cost of loans (interest income) were available, the study did not have access to data on cost of loanable funds (interest paid) and cost of employees (mostly estimated as the ratio of labour cost and number of employees). Considering the crucial role played by cost and prices in the activities of a financial institution, the study suggests that future studies on bank efficiency in Ghana account for cost by estimating cost and profit efficiency and technical efficiency.

Next, according to Wanke et al. (2016), the truncated bootstrap and Tobit regression models do not provide predictive analysis. However, the prediction of bank performance is extremely crucial as decline in efficiency without any prior indication may result in the collapse of an economy. Thus, future studies in line with the suggestions of Wanke et al. (2016) should employ regression models that use the artificial neural network models instead of the usual linear regression to predict bank efficiency.

Finally, this study focuses only on commercial banks in Ghana. We suggest that future studies go beyond Ghana’s commercial banking sector to the rural banking sector or other savings and deposit institutions such as savings and loans companies or microfinance institutions. Future studies could also take a cross-country approach and include other African countries such as Nigeria, Kenya and South Africa in the analysis. Widening the scope of studies in this regard will provide useful information on bank efficiency in the African region. Additionally, another possible area of research concerning this thesis maybe an assessment of the effectiveness of regulatory policies on the efficiencies of commercial banks in Ghana, which the scope of this study did not addressed.

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# APPENDIX

*Table 1.1 of Appendix: Overall Technical Efficiency: Bootstrap SBM DEA Model*

| Bank Code | MEAN | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 16 | 0.91 | 0.73 | 0.99 | 0.86 | 0.93 | 0.90 | 0.97 | 0.79 | 0.98 | 0.94 | 0.90 | 0.90 | 0.99 |
| 15 | 0.90 | 1.00 | 0.94 | 0.88 | 0.94 | 0.86 | 0.99 | 0.73 | 0.80 | 0.95 | 0.91 | 0.89 | 0.91 |
| 5 | 0.87 | 0.84 | 0.85 | 0.54 | 0.76 | 0.85 | 0.76 | 0.99 | 1.00 | 0.97 | 0.97 | 0.98 | 0.92 |
| 1 | 0.83 | 0.63 | 0.40 | 0.55 | 0.74 | 0.98 | 0.98 | 0.88 | 0.93 | 0.97 | 0.96 | 0.99 | 0.99 |
| 10 | 0.77 | 1.00 | 1.00 | 0.75 | 0.65 | 0.73 | 0.97 | 0.94 | 0.96 | 0.71 | 0.48 | 0.38 | 0.73 |
| 14 | 0.73 | 0.79 | 0.25 | 0.50 | 0.83 | 0.74 | 0.87 | 0.64 | 0.77 | 0.67 | 0.85 | 0.96 | 0.94 |
| 4 | 0.73 | 0.74 | 0.56 | 0.47 | 0.48 | 0.69 | 0.89 | 0.95 | 0.95 | 0.94 | 0.64 | 0.61 | 0.84 |
| 8 | 0.71 | 0.89 | 0.96 | 0.75 | 0.77 | 0.67 | 0.60 | 0.61 | 0.71 | 0.83 | 0.51 | 0.59 | 0.56 |
| 2 | 0.71 | 0.91 | 0.54 | 0.68 | 0.96 | 0.98 | 0.80 | 0.77 | 0.82 | 0.59 | 0.47 | 0.36 | 0.63 |
| 9 | 0.68 | 0.53 | 0.87 | 0.45 | 0.57 | 0.63 | 0.66 | 0.73 | 0.74 | 0.69 | 0.63 | 0.71 | 0.98 |
| 17 | 0.66 | 0.50 | 0.13 | 0.37 | 0.87 | 0.97 | 0.99 | 0.92 | 0.94 | 0.42 | 0.77 | 0.38 | 0.70 |
| 3 | 0.65 | 0.99 | 0.79 | 0.32 | 0.68 | 0.76 | 0.56 | 0.69 | 0.68 | 0.55 | 0.59 | 0.39 | 0.83 |
| 11 | 0.64 | 1.00 | 0.62 | 0.60 | 0.32 | 0.66 | 0.46 | 0.57 | 0.93 | 0.91 | 0.46 | 0.38 | 0.74 |
| 7 | 0.64 | 1.00 | 0.97 | 0.33 | 0.32 | 0.62 | 0.55 | 0.67 | 0.98 | 0.57 | 0.48 | 0.58 | 0.56 |
| 13 | 0.57 | 0.60 | 0.62 | 0.39 | 0.37 | 0.57 | 0.56 | 0.68 | 0.77 | 0.64 | 0.51 | 0.39 | 0.79 |
| 18 | 0.54 | 0.83 | 0.61 | 0.41 | 0.43 | 0.47 | 0.58 | 0.58 | 0.69 | 0.58 | 0.44 | 0.37 | 0.51 |
| 6 | 0.54 | 0.70 | 0.45 | 0.64 | 0.51 | 0.50 | 0.55 | 0.54 | 0.60 | 0.53 | 0.40 | 0.45 | 0.60 |
| 12 | 0.52 | 0.60 | 0.57 | 0.67 | 0.43 | 0.46 | 0.58 | 0.73 | 0.57 | 0.49 | 0.39 | 0.21 | 0.55 |

Source: Results estimated by author from data submitted monthly by commercial banks to the Bank of Ghana (data used is in GH¢)

*Table 1.2 of Appendix: Pure Technical Efficiency: Bootstrap SBM DEA Model*

| Bank Code | MEAN | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | 0.93 | 0.85 | 0.87 | 0.72 | 0.84 | 0.99 | 0.94 | 1 | 1 | 0.98 | 1 | 0.99 | 0.97 |
| 1 | 0.93 | 0.97 | 0.75 | 0.77 | 0.93 | 0.98 | 0.99 | 0.9 | 0.93 | 0.97 | 0.96 | 0.99 | 0.99 |
| 16 | 0.92 | 0.76 | 0.99 | 0.87 | 0.95 | 0.91 | 0.98 | 0.83 | 0.98 | 0.97 | 0.92 | 0.92 | 0.99 |
| 15 | 0.92 | 1 | 1 | 0.91 | 0.96 | 0.87 | 1 | 0.78 | 0.81 | 0.97 | 0.91 | 0.89 | 0.91 |
| 8 | 0.8 | 1 | 0.98 | 0.99 | 0.99 | 0.78 | 0.78 | 0.67 | 0.74 | 0.85 | 0.54 | 0.62 | 0.69 |
| 10 | 0.79 | 1 | 1 | 0.75 | 0.68 | 0.75 | 0.98 | 0.95 | 0.97 | 0.72 | 0.51 | 0.41 | 0.76 |
| 14 | 0.78 | 0.8 | 0.53 | 0.53 | 0.88 | 0.77 | 0.89 | 0.71 | 0.78 | 0.69 | 0.85 | 0.96 | 0.96 |
| 2 | 0.77 | 0.94 | 0.84 | 0.82 | 0.98 | 0.98 | 0.89 | 0.86 | 0.85 | 0.62 | 0.48 | 0.37 | 0.64 |
| 4 | 0.77 | 0.79 | 0.65 | 0.48 | 0.52 | 0.72 | 0.97 | 0.98 | 0.95 | 0.99 | 0.68 | 0.65 | 0.84 |
| 3 | 0.74 | 1 | 0.82 | 0.47 | 0.69 | 0.85 | 0.62 | 0.75 | 0.77 | 0.6 | 0.86 | 0.52 | 0.98 |
| 11 | 0.71 | 1 | 0.97 | 0.85 | 0.35 | 0.68 | 0.5 | 0.59 | 0.98 | 0.91 | 0.5 | 0.4 | 0.81 |
| 9 | 0.71 | 0.53 | 0.88 | 0.48 | 0.58 | 0.65 | 0.68 | 0.75 | 0.76 | 0.7 | 0.69 | 0.82 | 0.99 |
| 17 | 0.69 | 0.51 | 0.2 | 0.45 | 0.87 | 0.98 | 0.99 | 0.94 | 0.95 | 0.44 | 0.77 | 0.41 | 0.71 |
| 7 | 0.66 | 1 | 0.97 | 0.34 | 0.33 | 0.64 | 0.64 | 0.71 | 0.99 | 0.66 | 0.49 | 0.61 | 0.58 |
| 6 | 0.6 | 0.75 | 0.53 | 0.64 | 0.51 | 0.53 | 0.57 | 0.7 | 0.62 | 0.54 | 0.5 | 0.69 | 0.63 |
| 13 | 0.59 | 0.63 | 0.62 | 0.39 | 0.38 | 0.57 | 0.59 | 0.68 | 0.8 | 0.65 | 0.54 | 0.4 | 0.82 |
| 12 | 0.58 | 0.67 | 0.95 | 0.7 | 0.43 | 0.47 | 0.58 | 0.73 | 0.61 | 0.59 | 0.41 | 0.27 | 0.56 |
| 18 | 0.56 | 0.84 | 0.63 | 0.43 | 0.45 | 0.49 | 0.59 | 0.63 | 0.69 | 0.59 | 0.46 | 0.4 | 0.52 |

Source: Results estimated by author from data submitted monthly by commercial banks to the Bank of Ghana (data used is in GH¢)

*Table 1.3 of Appendix: Scale Efficiency – Bootstrap SBM DEA Model*

| Bank Code | MEAN | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 16 | 0.98 | 0.95 | 0.99 | 0.98 | 0.96 | 0.99 | 1.00 | 0.95 | 1.00 | 0.98 | 0.98 | 0.99 | 1.00 |
| 15 | 0.98 | 1.00 | 0.94 | 0.97 | 0.98 | 0.99 | 0.99 | 0.94 | 0.98 | 0.98 | 0.99 | 1.00 | 1.00 |
| 10 | 0.98 | 1.00 | 1.00 | 1.00 | 0.95 | 0.97 | 1.00 | 1.00 | 0.99 | 0.98 | 0.94 | 0.95 | 0.97 |
| 13 | 0.98 | 0.96 | 1.00 | 1.00 | 0.99 | 1.00 | 0.96 | 0.99 | 0.97 | 0.98 | 0.95 | 0.96 | 0.97 |
| 18 | 0.96 | 0.99 | 0.98 | 0.96 | 0.96 | 0.95 | 0.98 | 0.93 | 0.99 | 0.99 | 0.96 | 0.92 | 0.99 |
| 7 | 0.96 | 1.00 | 1.00 | 0.99 | 0.96 | 0.97 | 0.88 | 0.95 | 0.99 | 0.88 | 0.99 | 0.97 | 0.96 |
| 9 | 0.96 | 0.99 | 0.98 | 0.94 | 0.98 | 0.96 | 0.97 | 0.97 | 0.97 | 0.99 | 0.89 | 0.84 | 0.99 |
| 4 | 0.95 | 0.95 | 0.87 | 0.99 | 0.93 | 0.95 | 0.92 | 0.97 | 1.00 | 0.95 | 0.94 | 0.95 | 0.99 |
| 17 | 0.94 | 0.99 | 0.64 | 0.87 | 0.99 | 0.98 | 1.00 | 0.98 | 0.98 | 0.96 | 0.99 | 0.93 | 0.98 |
| 5 | 0.93 | 0.99 | 0.97 | 0.78 | 0.91 | 0.85 | 0.80 | 0.99 | 1.00 | 0.99 | 0.97 | 1.00 | 0.95 |
| 14 | 0.93 | 0.99 | 0.48 | 0.94 | 0.94 | 0.96 | 0.98 | 0.91 | 0.98 | 0.97 | 1.00 | 1.00 | 0.98 |
| 2 | 0.92 | 0.97 | 0.65 | 0.83 | 0.98 | 1.00 | 0.90 | 0.90 | 0.96 | 0.95 | 0.97 | 0.96 | 0.99 |
| 12 | 0.92 | 0.90 | 0.60 | 0.97 | 0.98 | 0.97 | 0.99 | 1.00 | 0.95 | 0.89 | 0.97 | 0.80 | 0.98 |
| 11 | 0.91 | 1.00 | 0.64 | 0.71 | 0.95 | 0.97 | 0.94 | 0.96 | 0.95 | 1.00 | 0.92 | 0.94 | 0.92 |
| 6 | 0.90 | 0.94 | 0.83 | 1.00 | 1.00 | 0.96 | 0.97 | 0.79 | 0.96 | 0.99 | 0.76 | 0.66 | 0.96 |
| 8 | 0.89 | 0.89 | 0.98 | 0.76 | 0.78 | 0.88 | 0.79 | 0.93 | 0.97 | 0.98 | 0.96 | 0.96 | 0.81 |
| 1 | 0.89 | 0.65 | 0.52 | 0.72 | 0.79 | 1.00 | 0.99 | 0.98 | 0.99 | 1.00 | 1.00 | 1.00 | 1.00 |
| 3 | 0.87 | 1.00 | 0.96 | 0.69 | 0.99 | 0.90 | 0.91 | 0.93 | 0.90 | 0.92 | 0.68 | 0.76 | 0.84 |

Source: Results estimated by author from data submitted monthly by commercial banks to the Bank of Ghana (data used is in G

*Table 1.4 of Appendix - First Stage: Network Dynamic DEA Model*

| Ranking of DMU | Average OTE | Ranking of DMU | Average PTE | Ranking of DMU | Average SE |
|---|---|---|---|---|---|
| 9 | 0.42 | 8 | 0.66 | 13 | 0.95 |
| 12 | 0.40 | 5 | 0.58 | 12 | 0.94 |
| 13 | 0.39 | 3 | 0.53 | 4 | 0.94 |
| 18 | 0.39 | 9 | 0.46 | 16 | 0.94 |
| 8 | 0.38 | 14 | 0.45 | 2 | 0.92 |
| 15 | 0.37 | 15 | 0.45 | 17 | 0.92 |
| 14 | 0.36 | 18 | 0.44 | 7 | 0.91 |
| 6 | 0.35 | 6 | 0.44 | 9 | 0.89 |
| 17 | 0.35 | 10 | 0.44 | 18 | 0.89 |
| 2 | 0.34 | 1 | 0.41 | 6 | 0.81 |
| 10 | 0.33 | 12 | 0.41 | 11 | 0.81 |
| 5 | 0.33 | 13 | 0.41 | 15 | 0.81 |
| 7 | 0.33 | 17 | 0.38 | 1 | 0.80 |
| 4 | 0.33 | 2 | 0.38 | 14 | 0.80 |
| 1 | 0.32 | 7 | 0.36 | 10 | 0.73 |
| 16 | 0.32 | 4 | 0.34 | 3 | 0.62 |
| 3 | 0.31 | 16 | 0.33 | 5 | 0.59 |
| 11 | 0.28 | 11 | 0.32 | 8 | 0.58 |
| **Average** | **0.35** | | **0.43** | | **0.83** |

Source: Results estimated by author from data submitted by commercial banks in Ghana

*Table 1.5 of Appendix: Second Stage: Network Dynamic DEA Model*

| Ranking of DMU | Average OTE | Ranking of DMU | Average PTE | Ranking of DMU | Average SE |
|---|---|---|---|---|---|
| 3 | 0.80 | 3 | 0.87 | 11 | 0.94 |
| 4 | 0.61 | 8 | 0.79 | 3 | 0.92 |
| 16 | 0.59 | 5 | 0.76 | 6 | 0.92 |
| 10 | 0.59 | 4 | 0.72 | 7 | 0.91 |
| 11 | 0.55 | 2 | 0.71 | 9 | 0.90 |
| 6 | 0.46 | 12 | 0.68 | 10 | 0.90 |
| 12 | 0.42 | 16 | 0.68 | 16 | 0.86 |
| 13 | 0.42 | 15 | 0.63 | 4 | 0.84 |
| 9 | 0.41 | 11 | 0.57 | 13 | 0.80 |
| 2 | 0.40 | 13 | 0.54 | 18 | 0.80 |
| 7 | 0.37 | 14 | 0.54 | 17 | 0.74 |
| 8 | 0.33 | 1 | 0.51 | 14 | 0.64 |

| | | | | | |
|---|---|---|---|---|---|
| 15 | 0.32 | 6 | 0.50 | 12 | 0.61 |
| 14 | 0.31 | 10 | 0.50 | 1 | 0.59 |
| 5 | 0.30 | 9 | 0.45 | 2 | 0.59 |
| 1 | 0.29 | 7 | 0.41 | 15 | 0.55 |
| 18 | 0.29 | 17 | 0.36 | 5 | 0.47 |
| 17 | 0.24 | 18 | 0.35 | 8 | 0.40 |
| **Average** | **0.43** | | **0.59** | | **0.74** |

Source: Results estimated by author from data submitted by commercial banks in Ghana

*Table 1.6 of Appendix: Third Stage: Network Dynamic DEA Model*

| Ranking of DMU | Average OTE | Ranking of DMU | Average PTE | Ranking of DMU | Average SE |
|---|---|---|---|---|---|
| 17 | 0.45 | 3 | 0.66 | 18 | 0.87 |
| 9 | 0.45 | 17 | 0.56 | 11 | 0.86 |
| 3 | 0.41 | 9 | 0.55 | 16 | 0.85 |
| 11 | 0.39 | 5 | 0.48 | 12 | 0.84 |
| 5 | 0.36 | 11 | 0.46 | 17 | 0.84 |
| 16 | 0.35 | 7 | 0.43 | 9 | 0.83 |
| 18 | 0.34 | 8 | 0.41 | 14 | 0.83 |
| 7 | 0.34 | 16 | 0.40 | 4 | 0.82 |
| 4 | 0.32 | 18 | 0.39 | 7 | 0.78 |
| 15 | 0.32 | 4 | 0.39 | 15 | 0.78 |
| 1 | 0.31 | 1 | 0.39 | 2 | 0.77 |
| 8 | 0.31 | 15 | 0.39 | 1 | 0.76 |
| 14 | 0.27 | 6 | 0.37 | 13 | 0.75 |
| 13 | 0.25 | 10 | 0.37 | 5 | 0.74 |
| 10 | 0.24 | 14 | 0.32 | 8 | 0.73 |
| 6 | 0.23 | 13 | 0.32 | 6 | 0.69 |
| 12 | 0.23 | 12 | 0.27 | 10 | 0.65 |
| 2 | 0.21 | 2 | 0.25 | 3 | 0.61 |
| **Average** | **0.32** | | **0.41** | | **0.78** |

Source: Results estimated by author from data submitted by commercial banks in Ghana