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Assessment of the Efficiency and the Productivity Changes of Banks in Ghana Using Data Envelopment Analysis Approach

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Abstract: *Due to the unstable nature of the banking sector in recent years in Ghana and the complex environment of the banking system, there is a need to assess the efficiency and productivity of the sector and its environment to minimize management waste and improve business practices. Traditional methods of evaluating performance using a single ratio such as Return on Equity (ROE) do not provide reliable results; hence, the use of the Data Envelopment Analysis model. Panel data was collected from nineteen (19) banks for the period from 2015 to 2023 for this study. In terms of the banking operation model, the input- oriented intermediation approach model was used. Data Envelopment Analysis was also used to analyze efficiency and productivity using the CCR and BCC models, as well as the Malmquist index, respectively. DEAP Software, version 2. 0, was used to measure overall technical efficiency, pure technical efficiency, and scale efficiency. The DEA-Malmquist index was also employed to measure and assess changes in total factor productivity, technical efficiency, and efficiency changes. Most of the banks recorded an improvement in efficiency levels, with mean scores of 80. 9 per cent and 87 per cent using the CCR and BCC models, respectively, but pure technical inefficiency significantly impacted inefficiency compared to scale efficiency, with a mean score of 92. 9 percent. The overall results from the Malmquist index on productivity factor change showed that the total factor productivity change index regressed by 12. 1 percent. Technical change was found to be the most important source of productivity decline, with a regression of 9. 9.6 percent. Efficiency change regressed by 2 percent, with its decomposition showing pure technical change and scale efficiency change regressed by 0. 80 percent and 1. 1.2 percent, respectively. The regression in total factor productivity change, due to technical and efficiency changes, indicates great potential for the industry to increase productivity through investment in technology and its utilization, by constantly equipping personnel with relevant technological advancements.*

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I. Introduction

Through the mobilization of surplus funds and their distribution to those in need, the financial sector and banks in particular, play a key role in the economy of a country; the supply of credit, and the facilitation of efficient payment systems for economic development and progress. Globalization, deregulation, liberalization and technological changes have significantly changed the banking operating environment. Banks are competing among themselves to survive and thrive in this ever increasing volatile and fierce economic environment. Efficiency and productivity evaluation is an essential tool for the success of banks because it helps to facilitate comparison across similar banks and reveals variations in performance thereby showing factors necessary for improvements. The aim of the research is to use this tool to highlight operational waste and risk associated with banking business for management to adopt good business practices to minimize such inefficiencies and increase productivity (Kumar, 2019).

The economy of Ghana has seen some financial crises for some time now, therefore, during the early years of independence the government undertook a structural adjustment programme (SAP) in 1983. Included in the reforms was the Financial Institutions Adjustment Programme (FINSAP) formerly known as the Financial Sector Adjustment Programme (Gockel and Akoena, 2002). This was done to address issues in the banking sector brought on by economic mismanagement that resulted in high inflation, subpar economic development, and problems with the balance of payments. Ghana experienced worse banking crises in 2017 due to poor banking practices. The Bank of Ghana, the country's regulator and supervisory body, provided inadequate oversight and regulation, which had a negative impact on the economy. In every economy, the growth of the financial and development is influenced by the regulatory and supervisory structure in place. This calls for regular assessment of productivity and efficiency using a range of methods (Airyar et al., 2015).

The objective of most financial sector reforms is to increase the banking industry's effectiveness, since inefficiencies will lead to economic deterioration, which in the long run, negatively affect the very foundation of the economy. Regulatory crackdown and poor business practices experienced in the year 2017 made the government of Ghana incur a huge cost of Gh¢11.7b as stated in the 2020 budget statement, which is just over

3% of National Gross Product (GNP) in 2019 (Kumar, 2019). The clean-up exercise or reforms brought about job losses, and loss of businesses' capital, as well as individual savings. Even though the government was making great effort to pay depositors, many have not received their funds yet. This led to the revoke of the licenses 8 financial companies, 15 savings and loans companies, and 347 micro institutions. Distressed financial sector, especially the banking sector, led to misallocations in the economy, returns on capital decreases, transaction cost rises and the overall result is a detrimental impact on the economy's growth and development (Kumar, 2019).

The fragile nature of Ghana's financial sector, especially the banking industry necessitated constant measurement and evaluation of efficiency and productivity to enable stakeholders to take quick and decisive decisions to avoid further financial crunch in the economy. Modern banking development priority is on performance measurement and evaluation hence the study used Data Envelopment Analysis to gauge the changes in productivity and efficiency of Ghanaian banks. In terms of empirical research, the body of knowledge about the effectiveness and productivity of banks is growing. Ghanaians have performed a large number of research on banking productivity and efficiency. However, none had applied DEA efficiency and collaborated with the DEA Malmquist productivity index as it is in this study. Under Data Envelopment (DEA) investigation, non-parametric method was used by (Adusei, 2016; Akoena et al., 2013; Blankson et al., 2022) to give an empirical investigation of the technical efficiency of banks in Ghana.

Further investigations by Alhassan and Biekpe (2016), and Beatson et al., (2011) delved into productivity change among Ghanaian banks using Malmquist productivity index. Saka et al. (2012), Bokpin, (2013), Isshaq, and Bokpin (2012), Ohene-Asare and Asmild, (2012), Danquah et al. (2013), and Oteng Abayie et al. (2011) provided an empirical analysis of the technical and financial effectiveness of Ghanaian banks using a stochastic under parametric technique. The study on efficiency and productivity change in Ghanaian banking sector from 2015 to 2023 was inspired by the fact that no prior study has explicitly analysed technical efficiency and combined it with the Malmquist productivity index. Therefore, this study used these principles and techniques to evaluate Ghana's universal banking productivity and efficiency during the period of 2015 to 2023.

II. Research Methodology

The research methodology outlined in this study is the DEA methodology that is used to project Ghanaian banks' changes in productivity and efficiency between 2015 and 2023. The study design and strategy, data source, model specification, variable definition, a priori expectations about efficiency drivers, data analysis process, and ethical concerns are all covered.

2.1 Design of the study

The whole design is given to portray the procedures and methods used to collect data that are appropriate for the subject being studied and exploratory methodologies were used. The Exploratory method was employed for monitoring, evaluating, and analysing the productivity change of banks in Ghana. Exploratory investigation is a useful method of learning what is happening to seek fresh understanding, to pose questions, and to evaluate phenomena in a novel setting, according to Robson (2002), referenced in Saunders et al., (2007).

The analysis of the data in the study was done in two stages. Using DEAP software, the relative technical efficiency was measured in the first step. In the first stage, the technique employs both the CCR and BCC models to evaluate overall technical efficiency under the CCR model and technical efficiency under the BCC model, which separates the efficiency into pure technical and scale efficiencies. In the second stage, the Total Factor Productivity Index is calculated using the DEA-Malmquist index, a component of the Deap software. Efficiency Change, which is divided into Technical Change, Scale Change, and Technological Change.

To depict the process behaviour of the banks, a range of approaches were utilised, such as the intermediate approach, the user value approach, the production strategy, and the value-added approach. They were all used to provide different efficiency measurements. The production approach and the intermediate approach were the two most important methods. The study adopted the intermediation method, according to which banks act as financial intermediaries, collecting deposits and other loanable money from depositors and disbursing them to others in the form of loans and other assets for profit. This concurs with a study by Berger and Humphrey, (1997), which asserts that the intermediation technique is more suited for assessing financial institutions as a whole.

The data collected covers Ghana's universal banks from 2015 through 2023. The information that was available for each bank used in this investigation determined the data that were used. Banks with data less than three years in existence during the course of the full research period are excluded from the data. The analysis of the data looked for anomalies, reporting mistakes, and discrepancies. With these limitations, the panel data used as the sample for this study consists of 19 universal banks. Nineteen (19) banks operate each year. Information is gathered from reports that have been made public by various banks on their official websites. All 19 banks complied with the same accounting requirements. Table 1 shows the Ghanaian banks under study and their ownership structure.

Table 1: Banks and Their Ownership Structure

BANK	CODE	MAJORITY OWNERSHIP
Ecobank Ghana Limited	EBG	Foreign
Ghana Commercial Bank	GCB	Local
Absa Ghana Limited	ABSA	Foreign
Stanbic Bank Ghana Limited	SBG	Foreign
Fidelity Bank Ghana Limited	FBL	Local
Standard Chartered Bank Ghana Limited	SCB	Foreign
Zenith Bank Ghana Limited	ZBL	Foreign
CAL Bank Ghana Limited	CAL	Local
Agriculture Development Bank Ghana Limited	ADB	Local
Access Bank Ghana Limited	ABG	Foreign
United Bank of Africa (GH) Limited	UBA	Foreign
Societie Generale Ghana Limited	SG-GH	Foreign
Universal Merchant Bank Ghana Limited	UMB	Local
Republic Bank Ghana Limited	RBL	Foreign
Guranty Trust Bank Ghana Limited	GTB	Foreign
Prudential Bank Ghana Limited	PBL	Local
Bank of Africa Ghana Limited	BOA	Foreign
FBN Ghana Limited	FBN	Foreign
First National Bank Ghana Limited	FNB	Foreign

The efficiency score of the banks under scrutiny was calculated using the DEA constant return to scale (CCR) and variable return to scale (BCC) models under the intermediation strategy, productivity changes were evaluated using the DEA Malmquist productivity index model.

2.2 Measurement of Bank efficiency

In measuring and assessing bank efficiency two main approaches are used: structure and non- structure approach.

In the non-structure approach, performance measures such as return on equity (ROE) and return on assets (ROA) to estimate and forecast the efficiency of firms and evaluate management actions were used. This helped in the evaluation of the firms' performance by this efficiency method and was grouped into activity, profitability, liquidity and financial structure ratios. Structure approach was based on the assessment of banking behaviour such as efficient or profit frontiers. It much depends on the idea of optimisation. The structure approach was also classified into two: parametric and non-parametric method. Parametric method used the production possibility frontier method which measureed the economic efficiencies. This is based on market prices which are used to decide on a specific volume, structure and production to save costs or increase profit. This method specified a particular functional form, it also took into account of random errors. The parametric technique is also categorised into three (3).

Stochastic Frontier Approach (SFA), which is a parametric method and like all other types of this method is a functional form for the cost, profit or production relationship among inputs, outputs and environmental factors and also allows for error term. It requires a big sample size to make estimation reliable. It has two (2) component of error term: random errors (statistical noise) and inefficiency. Distribution Free Approach depends on average variations of a cost function that are generated on a data set to determine a cost efficiency threshold. It imposes no assumption about the distribution of the efficiency and the random errors, because inefficiency is considered as constant over time while random error tends to average out over time.

Thick Frontier Approach used assumption that deviation in predicted performance, values between the highest and the lowest quartiles represent inefficiencies while the random error is the deviation within the lowest and highest performance quartile of observations. It measures and uses the highest and the lowest performance quartile observation and requires a functional form. The main disadvantage is if functional form is incorrectly given the efficiency estimate will be skewed (Delis et al., 2009). The non-parametric model is a frontier approach model used to assess efficiency. The level of inputs or outputs is the focus of technical efficiency and it refers to increasing output at a specific input level or reducing inputs to an output level. It exploits the efficiency frontiers of decision- making units to provide efficiency measures.

Two main non-parametric frontier methodologies are free disposable hull (FDH) and DEA. FDH is a form of DEA model in which the points on the lines connecting the DEA vertices are excluded from the frontier. It is based on a representation of the production technology given by observed production plans imposing strong disposability of input and output but without the convexity assumption. DEA is a deterministic non parametric method used to compare relative efficacy of comparable decision- making units while accounting for similar work technology and job performance. It does not specify any functional form and does not take into account random errors. It uses linear programming method to estimate efficiency.

2.3 Data Envelopment Analysis

A non-parametric method called Data Envelopment Analysis (DEA) is used to examine the efficiency and compare each observed decision-making unit (DMU)'s efficiency to the sample's greatest degree of efficiency. DEA constructs the empirical efficiency frontier, sometimes referred to as the frontier or margin of production possibilities, and uses this information to determine the relative efficiency of the examined units. The efficiency frontier is established by the most effective units (best practice units), which are graded as "1," and the technical inefficiency of all other units is quantified by how distant from the efficiency frontier their input-output ratio is. Each unit included in the study has a unique linear programming problem that must be solved to determine that unit's maximum efficiency in comparison to other units in the reference set. The weight of outputs and inputs for each unit is chosen to maximise its measure of efficiency, with the restriction that the result of the relative efficiency cannot be greater than one ('1'). This ratio is then used to calculate the unit's relative efficiency. A model defined in such a way maximises the result of the relative efficiency of each unit provided that the gained set of weights must be feasible and attainable for any other unit in the observed group. This means that DEA defines the best possible achievable efficiency frontier i.e., production possibilities, and sets the maximum output for each unit at a given level of its inputs.

Each DMU is only compared to the best units in DEA, which is based on extreme values. The underlying presumption is that if one unit, using X resources as inputs, can create Y outputs (products), then all other similarly functioning units should be able to do so as well. Finding the "best" virtual production unit for each actual/real unit is at the heart of the study. If the virtual unit performs better than it does, whether it generates more outputs with the same inputs or the same outputs with less inputs, the actual unit is inefficient. In their study using a two-stage DEA model to assess the tourism potentials of Western Balkan and European Union nations, Radovanov et al. (2020) claimed that the relative efficiency measures produced by the DEA model are highly dependent on the variables and sample choices made. The following prerequisites must be satisfied, according to the literature, for the proper application of DEA.

i. Various decision-making units and the data they generate as input and output are the objects of efficiency assessment.
ii. DMUs operate within similar business conditions but often the initial data for different units are significantly different. In this research, the business in consideration is banks in Ghana which are in similar business conditions.
iii. DMUs, when precisely defined, are always of the same type of institutions (in this research banks in Ghana).
iv. The number of decision-making units should be at least two or three times higher than the sum of diverse inputs and outputs (Beasley, 1996). In this study, the decision-making units are nineteen (19) and the sum of input and output is four (4), which is four times higher than the sum of the diverse input and output.

2.3.1 DEA Input and Output Orientation

The production unit's goal is expressed in terms of input/cost reduction or output/revenue maximisation, according to management and production restrictions, while building the DEA frontier and estimating efficiency.

The two primary orientations that DEA offers are input orientation and output orientation. Efficiency is measured by the input orientation, which seeks to minimise input without sacrificing output. Input waste or surplus capacity in the manufacturing process is identified using the input-oriented approach. The output expansion is measured in terms of output orientation, supposing that the input is constant. According to Coelli et al. (2005), selecting the right orientation is crucial when employing econometric techniques since they may have issues with statistics, in contrast to the linear programming approach, which is not susceptible to statistical testing and hence has no such issues. The choice of orientation has ramifications for both theory and practice. The relevant alternative measuring orientation has not been determined by the theoretical literature (Casu and Molyneux, 2003). Practically speaking, the choice of orientation is obvious in some companies, especially those where cost control techniques are valued highly.

Since banking output is correlated with local demand, many in the banking literature have chosen input-oriented models as their foundation (Erbetta and Rapouli, 2006). As a result, cost savings seem to be a sensible managerial goal. Saving money entails using the fewest possible inputs rather than focusing on the output, which is dependent on the consumers. Many also made their decisions based on the quantities (inputs and outputs) that the managers had the most influence over. The output-oriented model is the one that should be used when a bank has limited resources and must generate as much output as possible (Coelli et al., 1998).

2.3.2 Choice between CRS and VRS DEA Model

The option between constant return to scale (CRS) and variable return to scale (VRS) is another model specification in DEA. The constant return to scale presupposes that there is no discernible correlation between efficiency and operation scale. That is, when it comes to translating inputs into outputs, huge banks can be just as effective as tiny banks. According to Drake et al. (1994), variable return to scale presupposes that an increase in inputs would inevitably lead to an excessive increase in output. Several DEA approaches include CCR and BCC, which are called after Charnes et al. (1978) and Banker et al. (1984), respectively, to quantify efficiency. To assess the technical efficiency (TE), the CCR model is employed. The scale efficiency (SE), which is calculated as the difference between the CCR and BCC efficiency scores, and the pure technical efficiency (PTE), are both examined using the BCC model.

Both constant return to scale (CCR) and variable return to scale (VRS) are used in this study. The use of both methods is necessary since the premise of a constant return to scale can only be accepted if all production units are functioning at their optimal size. Since this is not practical, we compute the variable return to scale to find a solution.

DEA input-oriented model with constant returns to scale

Model (1) is hence the mathematical formulation, as seen in Equations (1) to (4), of the CCR model in an input-oriented manner.

Model (1)

$$Z_p = \min\ \theta p \qquad (1)$$

s. t. $$\sum_{j=1}^{n} \lambda_i y_{ij} - y_{rp},\ \theta p X_{ip} \text{xip} \leq 0\ , \quad i = 1,2,\ldots m\ (1.2) \qquad (2)$$

$$\sum_{j=1}^{n} \lambda_i y_{rj} \geq y_{rp}, \quad r = 1,2,\ldots s \quad (1.3) \qquad (3)$$

$$\lambda_j \geq 0\ , \quad j = 1,2\ldots n \quad (1.4) \qquad (4)$$

Where, λj represents the weight associated DMUj. Z_p establishes the DMUp's DEA efficiency score. We must solve the aforementioned model n times in order to determine the relative efficiency score for each DMU. A DMU that achieves an efficiency score of 1 will be regarded as efficient, whereas a DMU that achieves an efficiency score below "1" will be regarded as inefficient, as shown in Figure 1.

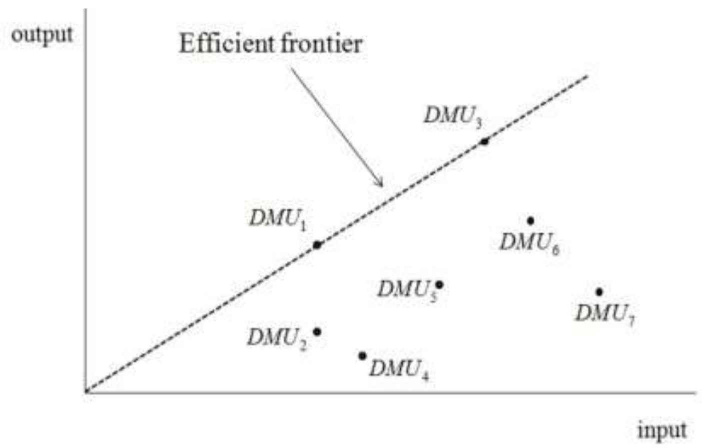

Figure 1: Efficient Frontier - CCR Model

The efficient frontier for the CCR model in the case of seven DMU is shown in Figure 1 for single input, single output cases. DMU 1 and DMU 3 are demonstrated as being effective in Figure 1.

DEA output-oriented model with constant return to scale

We use the ratio of input to output to reduce inefficiency and create the CCR output-oriented model. The following is the mathematical formulation as in Equations (5) to (8):

Model (2)

$$Hp = \max \varphi \qquad (5)$$

$$\text{s.t.} \quad \sum_{j}^{n} = 1\lambda i\, x_{ij} \geq x_{ip}, \qquad i = 1,2,\dots m \quad (2.2) \qquad (6)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \leq \varphi y_{rp} \qquad r = 1,2,\dots s \quad (2.3) \qquad (7)$$

$$\lambda_j \geq 0 \qquad j = 1,2, \dots n \quad (2.4) \qquad (8)$$

DEA input-oriented model with variable return to scale

The efficient boundaries specified in the BCC model, which is the first extension of the CCR model, reflect a convex curve that passes across effective DMUs. Convexity restrictions are an important component of the fundamental distinction between CCR and BCC models.

$\sum_{j}^{n} = 1\lambda \text{j} = 1,$ in the BCC model.

BCC model in input-oriented form given as in model (3) as shown in Equations (9) to (13):

Model (3)

$$Z_p = \min \theta p \qquad (9)$$

$$\text{s.t.} \quad \sum_{j=1}^{n} \lambda_j x_{ij} - \theta_p x_{ip} \leq 0, \quad i = 1,2 \dots m \qquad (3.2) \qquad (10)$$

$$\sum_{j=1}^{n} \lambda_j y_{ij} \geq y_{rp}, \qquad r = 1,2 \dots s \qquad (3.3) \qquad (11)$$

$$\sum_{j=1}^{n} \lambda_j = 1, \qquad (3.4) \qquad (12)$$

$$\lambda_j \geq 0 \qquad j = 1,2 \dots n \qquad (3.5) \qquad (13)$$

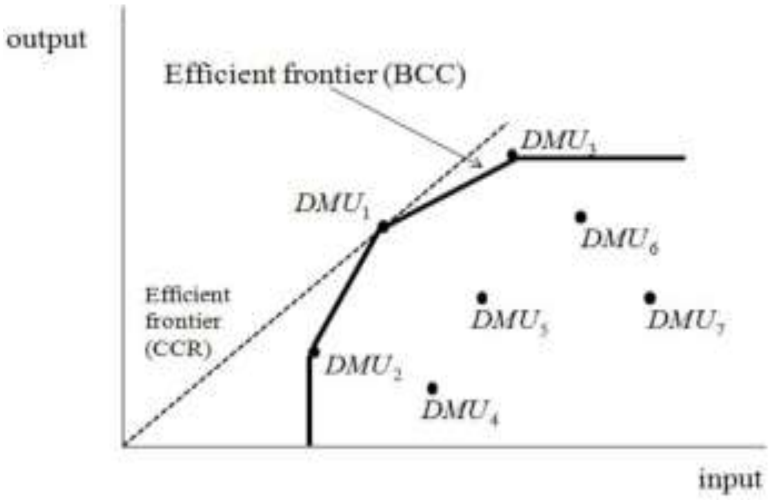

Figure 2: Efficient frontier – BCC model.

Figure 2 described the BCC efficient frontier for seven DMUs**.**

Output-oriented model with variable return to scale

BCC model in output-oriented form given in model (4) this contains four equations, ie Equation (14) to (18):

Hp = max φp (14)

s.t. $\sum_{j=1}^{n} \lambda_j x_{ij} \geq x_{ip}$ $\quad i = 1,2 \ldots m$ $\quad (4.2)$ (15)

$$\sum_{j=1}^{n} \lambda_j y_{rj} \leq \varphi y_{rp}, \quad r = 1,2 \ldots s \quad (4.3) \tag{16}$$

$$\sum_{j=1}^{n} \lambda_j = 1, \quad (4.4) \tag{17}$$

$$\lambda_j \geq 0 \quad j = 1,2 \ldots n \quad (4.5) \tag{18}$$

2.4 Measurement of Malmquist index

The Malmquist index measures the evolution of efficiency. One of the well-known indices for determining how relative productivity change in DMUs over time is measured is the Malmquist index, which is based on DEA models. This index breaks down this change into its component pieces. The index provides a useful approach to distinguish between changes in technical efficiency, pure technical efficiency, total factor productivity (TFPC), and other parameters from movements in the efficiency frontier (technological advancement) across time. The geometric mean of two TFPC indexes makes up this index. The Malmquist index's original concept was put forth by Malmquist in 1953, who suggested comparing a firm's input at comparing two separate times of time in terms of the biggest element that might be used to cut the input in one period while still enabling the company to create the same level of output in the other. After Caves et al., (1982) enlarged the original MI index and introduced the first MI type, Fare et al. (1992) showed that the Malmquist index may be computed using a non-parametric DEA-like method if suitable panel data are available. The researchers used DEA to determine the Malmquist index.

The researchers made the assumption that returns to scale are constant and separated the two elements of productivity changes over time—technological progress and change in technical efficiency. Fare et al. (1994), also gave an enlarged decomposition of the Malmquist index with a critical factor that reflected variations in scale efficiency, then took the variable return to scale into account. Using DEA, under Fare et al. (1994), we establish an input-based MI between period t (the base period) and periods as in Equation (19):

$$M_I(y^s, x^s, y^t, x^t) = \left[\frac{D^t_{I(y^s\ x^s)}}{D^t_I(y^t, (y^t\ x^t))} * \frac{D^t_I\ (y^s, x^s)}{D^t_I\ (y^t, (y^t, x^t))}\right]^{1/2} \tag{19}$$

Where $M_I(.)$ *is the input − oriented MI*, $D^t_{I(y^s\ x^s)}$ is the distance function depicting the maximum proportionate decrease of the observed period s inputs under the period t technology The definition of the distance function in Equations (20) to (23) as follows:

$D^t_{i(y^s\ x^s)}$ = min θ, (20)

subject to $y_{is} \leq \lambda Y^t,$ (21)

$\theta x_{is} \geq \lambda Y^t,$ (22)

$\lambda_i \geq 0, i = 1, \ldots n,$ (23)

Where, λ is a constant vector and θ is a scalar. The component score of the i-th company is represented by the value achieved; X and Y are input and output vectors, respectively, and x and y stand for the quantities of the i-th input consumed and output produced by the DMU_0. In actuality, the aforementioned indicator is the geometric mean of two Malmquist productivity indices. According to Fare et al. (1992), M_I > 1 denotes a rise in production; M_I < 1 indicates a productivity loss; and M_I = 1 means no change in productivity from time t to s. Relaxing the Caves et al., (1982) assume that $D^t_I\ (y^t, x^t)$ and $D^t_I\ (y^t, x^t)$should equal one and allow for technical inefficiency, Fare et al. (1992) decompose their Malmquist productivity index into two components as in Equations (24) to (25):

$$M_I = \left[\frac{D_I^t\ (y^s, x^s)}{D_I^t\ (y^t, x^t)} * \frac{D_I^S\ (y^s, x^s)}{D_I^s (y^t, x^t)}\right]^{1/2} \quad (24)$$

$$= \left[\frac{D_I^S\ (y^S, x^S)}{D_I^t (y^t, x^t)} \left[\frac{D_I^t\ (y^S, x^S)}{D_I^S\ (y^S, x^S)} * \frac{D_I^t\ (y^t, x^t)}{D_I^S (y^t, x^t)}\right]\right]^{1/2} \quad (25)$$

The first component measures the TEC = $\frac{D_I^t\ (y^S, x^S)}{D_I^t\ (y^t, x^t)}$ means the change in_technical efficiency (technical efficiency change – TEC). The second component TCC =

$$\left[\frac{D_I^t\ (y^s, x^s)}{D_I^t\ (y^t, x^t)} * \frac{D_I^S\ (y^s, x^s)}{D_I^s (y^t, x^t)}\right]^{1/2} \quad (26)$$

Measures the technical change (TCC) between the periods t and s, which assesses the movement in the technological frontier. TCC may be thought of as the average total change in a DMU's technology from time period t to time period s. According to Fare et al. (1992; 1994), a value of TCC > 1 denotes a positive shift or advancement in technology, a value of TCC < 1 denotes a reverse shift or regression in technology, and a value of TCC = 1 denotes no change in the technological frontier. In this study, we employed a catch-up effect called the Malmquist index split into two components: technical change and efficiency change (EC).

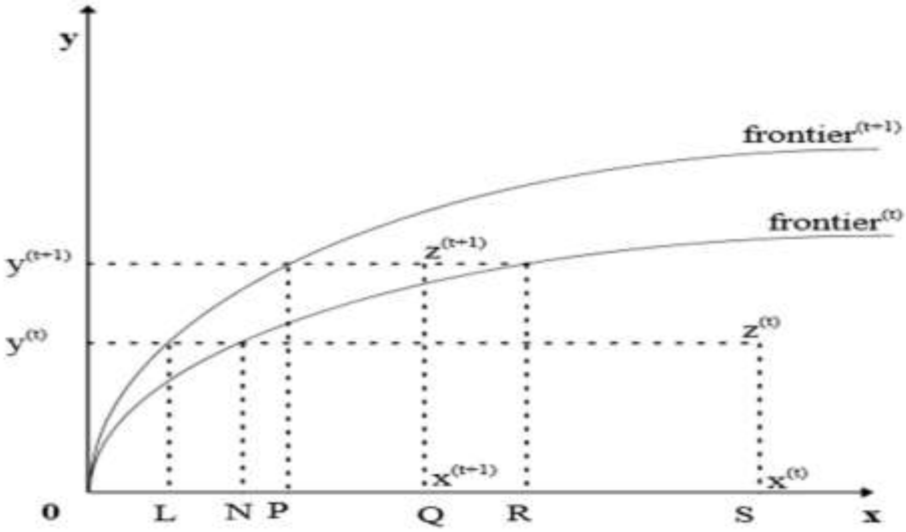

Figure 3: Malmquist index and efficiency change over time

Source: Worthington (1999)

Figure 3 provides a visual representation of this concept by creating a production frontier that shows the level of output (y) that can be generated efficiently from a specific quantity of input (x). We examine DMU A's efficiency throughout two time periods, t and t + 1, as well as the technological transition from t to t + 1, to calculate the efficiency change. The borders in the present (t) and future (t + 1) time periods that are so acquired are labelled appropriately. Particularly the assumption of inefficiency, every particular financial institution's relative mobility over time will be influenced by both its position in relation to the associated frontier (technical efficiency) and the location of the border itself (technical change).

If inefficiency is disregarded, productivity growth over time won't be able to tell the difference between advancements brought about by a financial institution catching up to its frontier and advancements brought about by the frontier itself moving up over time. The horizontal distance ratio 180 now provides an input-based metric of efficiency for every financial institution in period t, represented by the input/output bundle z(t). In other words, lowering inputs can help production become technically efficient in period t, or move closer to the efficient frontier. The horizontal distance ratio 0R/0Q should be multiplied by inputs in period t + 1 in contrast to attain technical efficiency that is similar to that observed in period t. The boundary has changed, so despite being technically less efficient than the period t + 1 frontier, 0R/0Q reaches unity.

2.5 Definition of variables

This section explains the measurements of the variables used in the measurement of efficiency and productivity change.

2.5.1 Variables selection

Intermediation, production, user cost, and value-added are the four basic methodologies that have been established in the empirical literature to characterise the input and output connection in financial institution behaviour.

Selection of input and output variables

Researchers agree that DEA has to be defined since the choice of input and output variables affects it. According to Cooper et al. (2000), to distinguish between efficient and inefficient banks, the sample size should be at least three (3) times the total number of input and output variables. According to Smith et al. (1997), the capacity of DEA to discriminate between the efficient and inefficient units reduces as the number of variables rises.

As intermediation approach has been adopted which assumes that the bank's main aim is to transform liabilities (deposits) into loans (assets). Consistent with this approach, the researcher assumed that banks collect deposits which include physical capital or fixed assets to transform them into loans & advances and investments. The most important source of input for Ghanaian banks is deposits, which may be used to carry out activities like lending and investment. Loans and other earning assets, which are a key source of revenue and it is about two-thirds (2/3) of the assets held by banks. Loans, advances, and investments were the researcher's two outputs, and fixed assets and total deposits were the researcher's two inputs, as shown in Table 2.

Table 2: Description of Input and Output

	Variables	Definition	Description	Reference
Inputs:	X1	Deposits	Total deposits from customers	Erasmus and Makina (2014) and Alhassan and Ohene-Asare (2016)
	X2	Physical capital	Fixed assets (PPE) from the Balance sheet	Alhassan and Ohene-Asare (2016)
Output:	Y1	Loans and advances	Total loans and advances offered to customers	Murillo-Melchor et al. (2009) and Maredza and Ikhide (2013)
	Y2	Other earning assets	Securities Investment	Murillo-Melchor et al. (2009)

Notes: This table lists the inputs and outputs selected for the study; they are all measured in Ghana cedis (GH¢).

2.5.2 A Priori expectation

Data Envelopment Analysis (DEA) is a non-parametric method which measures productivity change and efficiency. It evaluates and compares each DMU's efficiency with the sample's greatest degree of efficiency. A priori assumptions regarding the analytical form of the chosen variables are not necessary for DEA.

2.6 Data Analysis Technique

The statistical tools that were utilised to examine the data are described in this section. Two sections make up the analysis. Using the DEA approach, technical efficiency, pure technical efficiency, and scale efficiency are measured in the first portion. The DEA-Malmquist productivity index is used in the second section to calculate the overall productivity change index, efficiency, technical change, pure technical change, and scale change. Data was gathered from the financial statements on the websites of Ghanaian banks, and it was examined for consistency issues, reporting mistakes, and outliers. For DEA efficiency measurement, the DEAP software version 2.0 was utilised to analyse the data, while SPSS was used for descriptive analysis. The inputs and outputs used to assess efficiency were described using descriptive statistics. Banks were divided between those with foreign and domestic majority ownership to facilitate further examination of the banking sector.

2.6.1 Correlation Analysis

The intensity and direction of the association between two or more variables are measured by correlation. It was employed to examine how closely related the various variables were. The data must undergo an isotonicity test as part of the technical efficiency analysis (TE) to determine the accuracy of the DEA specification. The isotonicity test looks at the correlations between inputs and outputs to see if more inputs should lead to more output, which would show a statistically significant positive correlation between inputs and outputs.

III. Results And Discussion

Before performing a DEA analysis, the input and output must be determined. Depository and Fixed Assets are the two inputs, and Loans & Advances and Investments are the two outputs, making up the data.

Based on a review of the literature indicated in the preceding section, input and output parameters were chosen. In Table 3, the statistical findings were displayed.

Table 3: Inputs and Outputs

Variable	Deposits (X1)	Physical Capital (X2)	Loans & Advances (Y1)	Securities Investments (Y2)
Mean	5.3002E6	1.7632E5	1.9444E6	1.9435E6
Std Dev	5.74557E6	1.77602E5	1.64258E6	2.07124E6
Variance	3.301E13	3.154E10	2.698E12	4.290E12
Max	3.88E7	1.26E6	9.44E6	1.19E7
Min	1464	7135	1365	8884
Sum	9.06E8	3.02E7	3.32E8	3.32E8
Number	171	171	171	171

3.1 Isotonicity test

Technical efficiency analysis, as previously noted, calls for an isotonicity test to ascertain the inter-correlation between input and output variables. The results of the isotonicity test are displayed below using the SPSS software's Spearman correlation coefficient as shown in Table 4. The result of the isotonicity tests the results shows that an increasing amount of input results in greater output, implying a positive statistically significant correlation.

Table 4: Results of Correlation Coefficient

Variables	X1	X2	Y1	Y2
X1	1.00			
X2	0.621	1.000		
Y1	0.864	0.749	1.00	
Y2	0.491	0.235	0.390	1.000

3.2 Descriptive Statistics for Timeframe for the Total Technical Efficiency Scores

Descriptive data for the efficiency score calculated using DEA are shown in Table 5. The table indicates that there will be a noticeable decrease in efficiency in 2023. The average OTE score was determined to be 0.803 in 2015, and it decreased to 0.615 in 2023, thus showing a decrease in the banks' overall technical efficacy. The minimum score for the years is: 0.462, 0.350, 0.534, 0.556, 0.398, 0.324 0.508, 0.341 and 0.261 the standard deviation is 0.182, 0.161, 0.157, 0.143, 0.191, 0.210, 0.159, 0.254, 0.265 for the years 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022 and 2023 respectively.

Table 5: Results of Overall technical efficiency scores

Year	2015	2016	2017	2018	2019	2020	2021	2022	2023
Min	0.462	0.35	0.534	0.556	0.398	0.324	0.508	0.341	0.261
Max	1	1	1	1	1	1	1	1	1
Mean	0.803	0.855	0.885	0.879	0.845	0.829	0.819	0.751	0.615
St Dev	0.182	0.161	0.157	0.143	0.191	0.21	0.159	0.254	0.265
N	19	19	19	19	19	19	19	19	19
OTE<1	14	13	13	11	13	12	14	13	15
OTE=1	5	6	6	8	6	7	5	6	4

3.3 Descriptive Statistics of Pure Technical Efficiency Score for The Period 2015-2023

Table 6, the efficiency score calculated by DEA under pure technical efficiency is shown here with descriptive statistics. The average PTE score in 2015 was determined to be 0.896, while the score in 2023 was 0.723, plainly demonstrating a decline in the banks' purely technical efficiency. The minimum score for the years is 0.647, 0.350, 0.534, 0.570, 0.477, 0.532 0.554, 0.363 0.309 and the standard deviation is 0.137, 0.160, 0.135, 0.141, 0.183, 0.175, 0.145 0.260, 0.271 for the year 2015, 2016, 2017, 2018, 2019, 2020 2021, 2022 and 2023 respectively. PTE equals “1” which is regarded as locally efficient banks are as follows in terms of years. PTE = 1; 2015 (10), 2016 (9), 2017 (9), 2018 (13), 2019 (12), 2020 (11), 2021 (9), 2022 (10), 2023 (5). PTE less than which is regarded as inefficient banks in terms of years are as follows: PTE<1; 2015 (9), 2016 (10), 2017 (6), 2019 (7), 2020 (8), 2021 (10), .2022 (9), 2023 (14).

Table 6: Results of Pure technical efficiency score

Year	2015	2016	2017	2018	2019	2020	2021	2022	2023
Min	0.647	0.35	0.543	0.57	0.477	0.532	0.554	0.363	0.309
Max	1	1	1	1	1	1	1	1	1
Mean	0.896	0.908	0.92	0.918	0.886	0.888	0.893	0.798	0.723
St Dev	0.137	0.16	0.135	0.141	0.183	0.175	0.145	0.260	0.271
N	19	19	19	19	19	19	19	19	19
PTE<1	9	10	10	6	7	8	10	9	14
PTE=1	10	9	9	13	12	11	9	10	5

3.4 Descriptive Statistics of Scale Efficiency Score for The Period 2015-2023

Table 7, displays descriptive statistics of the scale efficiency score calculated by DEA. The average SE score was determined to be 0.898 in 2015 while it was 0.860 in 2023, thus demonstrating a decrease in the scale efficiency of the institutions. The minimum score for the years is 0.496, 0.717, 0.571, 0.781, 0.803, 0.608 0.634, 0.734 and 0.360 and the standard deviation is 0.154, 0.087, 0.098, 0.071, 0.067, 0.118, 0.101, 0.074, 0.171 for the year 2015, 2016, 2017, 2018, 2019, 2020 2021, 2022 and 2023 respectively. SE equals to "1" which is regarded as a constant return to scale and the most efficient scale of operations of banks are as follows in terms of years. SE = 1; 2015 (6), 2016 (6), 2017 (7), 2018 (8), 2019 (8), 2020 (7), 2021 (6), 2022 (6), 2023 (4). SE less than which is regarded as banks not operating at the appropriate scale in terms of years are as follows: SE<1; 2015 (13), 2016 (13), 2017 (12), 2019 (11), 2020 (12), 2021 (13), 2022 (13), 2023 (15). However, of the thirteen (13) banks operating at inappropriate scale in 2015, nine (9) were operating at DRS and four (4) at IRS. In 2016 six (6) banks were operating at DRS and 7 IRS. In the year 2017, two (2) banks were operating at DRS and 10 inefficient scale banks were operating at IRS. In 2018, ten (10) banks were operating at DRS and one (1) bank operating at IRS. The year 2019 also shows nine (9) banks operating at DRS and two (2) operating at IRS. Also, in the year 2020 eleven (11) banks were operating at DRS and one (1) bank operating at IRS. In the year 2021, twelve (12) banks were operating at DRS and one (1) bank at IRS. The predominant scale of the operation was decreasing return-to-scale (DRS). The year 2022, eight (8) were operating at IRS and five (5) banks operating at DRS. Also in the year 2023, ten (10) banks were operating at IRS and five (5) operating at DRS.

Table 7: Results of Scale Efficiency Score

Year	2015	2016	2017	2018	2019	2020	2021	2022	2023
Min	0.496	0.717	0.571	0.781	0.803	0.608	0.634	0.734	0.360
Max	1	1	1	1	1	1	1	1	1
Mean	0.898	0.946	0.963	0.959	0.951	0.925	0.918	0.943	0.860
St Dev.	0.154	0.087	0.098	0.071	0.067	0.118	0.101	0.074	0.171
N	19	19	19	19	19	19	19	19	19
SE<1	13	13	12	11	11	12	13	13	15
SE=1	6	6	7	8	8	7	6	6	4

3.5 Descriptive Statistics of Malmquist Index Scores for The Period 2015-2023

Table 8, Shows descriptive statistics for the DEA-estimated Malmquist index score. Although some average means are better than others, the average MPI score for efficiency change is 0.975, which for technical change is 0.896, pure technical change is 0.989, scale efficiency change is 0.986, and the total resultant of total factor productivity change is 0.874. These scores are all below 1, indicating retrogression. The minimal scores were 0.897, 0.642, 0.904, 0.90, and 0.595 for efficiency change, technical change, pure technical change, scale efficiency change, and total factor productivity change, respectively. The standard deviations are 0.049, 0.102, 0.046, 0.034, and 0.117 for efficiency change, technical change, pure technical change, scale efficiency change, and total factor productivity change, respectively as shown in Table 8.

Table 8: Results of Malmquist index scores

Variable	EFFCH	TECCH	PTECH	SECH	TFPCH
Min	0.897	0.642	0.904	0.90	0.595
Max	1.069	1.257	1.328	1.056	1.257
Mean	0.975	0.896	0.989	0.986	0.874
St Dev.	0.049	0.102	0.046	0.034	0.117
N	19	19	19	19	19
	effch< 1 =10	techch<1=18	pech<1 =9	sech<1 =13	tfpch<1 =18
	effch>1=7	techch>1 =1	pech>1 =6	sech>1 =3	tfpch>1 =1
	effch=1=2	techch=1=0	pech=1=7	sech=1 =3	tfpch=1 =0

3.6 Interpretation of Results

3.6.1 Measure and Assess the Ghanaian Universal Banks' Relative Technical Efficiency

All of the banks in the sample demonstrated higher technical efficiency under variable returns to scale (VRSTE) than they do under constant return to scale (CRSTE), per the DEA trend analysis results for the individual banks in the sample (Appendix 1). This suggests that the cause of inefficiency is a combination of managerial inefficiency, scale inefficiency, and size-related concerns. Nine out of the nineteen banks under examination exhibited pure technical efficiency that was higher than scale efficiency when the technical efficiency was divided into pure technical and scale efficiency. UMB, ABSA, SCB, EBG, GTB, ZBL, UBA. BOA and RBL are these banks. According to the CRSTE rating, the first six banks of the specified banks were likewise placed first through sixth. This indicates that scale efficiency is more of a challenge than management ones when it comes to their efficiency.

The remaining ten banks had their scale efficiency higher than their pure technical efficiency. These banks are ABG, ADB, FBN, FNB, FBL, GCB, PBL, SG-GH, SBG and CAL. These banks' inefficiencies are more of managerial issues than scale operation issues, which means for the banks to increase their efficiency they should tackle their manpower problems, business processes and technology. The average mean for the banks under study is 0.809 under overall technical efficiency (CRSTE). UMB(0.922), UBA(0.922), SCB(0.865), SG-GH(0.902), RBL(0.967), PBL(0.844), GTB(0.877), GCB(0.833), ADB(0.838) and ABSA(0.928) had their mean average above the industry average. The remaining nine banks, SBG, FBL, FNB, FBN, EBL, CAL, BOA, EBL and ABL had their respective averages below that of the industry.

Exclusively pure technical efficiency (VRSTE), which exclusively considers managerial efficiency, may reveal the banks' actual efficiency, and ineffective processes which are not able to fully utilise their manpower and technological resources. EBG only were fully efficient throughout the period and the rest had various degrees of inefficiency, even though some banks were efficient in some years for example ADB was efficient during the year 2015 and from the year 2018 to 2021. Analysing the average pure technical efficiency for the nine-year period the scores range from 72.3 percent in the year 2023 to 92 percent in the year 2017. The year 2015 PTE was 89.6 percent increased to 90.8 percent in the year 2016, increased to 92 percent in 2017, experienced a marginal decrease to 91.8 percent in 2018, and then continued the decrease to 88.6 percent in 2019 increased marginally to 88.8 percent in 2020 then 89.3 percent in 2021 then had a downward average of 79.8 percent and 72.3 percent in the years 2022 and 2023 respectively. The average PTE for the entire period of study was 87 percent. Under scale efficiency no bank was averagely efficient, each having various degrees of inefficiency. Analysing it year by year some banks were efficient in some years for instance ABSA was scale efficient from 2017 to 2021, whilst BOA was efficient from 2015 to 2018 and 2020.

The average score ranges from 86 percent in the year 2023 to 96.3 percent in the year 2017 over the study period 2015-2023. In year 2015 average SE was 89.8 percent increased to 94.6 percent in 2016 then to 96.3 percent in 2017 then had a continuous decrease from the year 2018 to 2023 where the banks recorded 95.9 percent, 95.1 percent, 92.5 percent, 91.8 percent, 94.3 percent and 86 percent respectively. The average score for the period under scale efficiency was 92.9 percent.

3.6.2 To Examine Technical Efficiency in The Context of Frontier Operational Efficiency

Efficient banks discrimination

By employing the reference sets of inefficient banks, Kumar and Gulati's (2008) methods of discriminating were used to exclude efficient banks from benchmarking, as shown in Table 9.

Table 9: Peers referenced by each individual bank and peer count 2015-2023

YEAR	2015	2016	2017	2018	2019	2020	2021	2022	2023	TOTAL
GTB	0	0	0	8	9	9	5	0	0	31
BOA	3	2	1	5	0	0	0	0	0	11
SCB	0	0	0	0	0	1	0	0	0	1
GCB	2	4	6	0	0	0	4	0	0	16
EBL	0	0	0	0	0	0	0	1	10	11
RBL	11	0	0	2	9	8	12	1	5	48
UMB	0	0	0	1	1	0	5	12	13	32
SG-GH	11	5	8	1	3	0	0	0	0	28
SBG	9	0	0	0	0	0	0	0	0	9
CAL	0	5	6	0	0	0	0	0	0	11
FBN	0	2	0	0	0	0	0	0	0	2
FBL	0	11	0	10	0	0	0	11	0	32
ABSA	0	0	5	4	6	3	1	0	0	19
FNB	0	0	0	0	0	3	0	0	0	3
FNB	0	0	0	0	0	3	0	0	0	3

The number of frequencies that exist in the reference set of inefficient banks influence how resilient the efficient banks are. As demonstrated in Table 4.7, an efficient bank that is strong and resilient is more likely to be effective than an inefficient bank until there is a dramatic shift in how business is conducted.

Benchmarking of peers

On analysing benchmarking of peers, no bank was consistently referenced over the entire years of the study but each bank has a different peer count over the years. Banks which are on the frontier are referred to as a peer in the peer count. This means those banks have the best practices which should be benched marked by the other banks (inefficient ones). RBL, UMB, FBL, GTB, and SG-GH are considered the most referenced banks by their peers, coincidently these banks with exception of FBL are regarded as small banks in terms of asset size. From the analysis, RBL was referenced forty-eight times in the years 2015, 2018, 2019, 2020, 2021, 2022 and 2023. UMB and FBL was the next referenced bank with thirty-two times, which in terms of UMB occurred more in the latter years of the study period 2022 and 2023. The next referenced was GTB referenced thirty-one times followed by SG-GH which was referenced twenty-eight times but all of it occurred at the early period of the study period from 2015 to 2019.

Ownership identification impact on efficiency

Table 1, displays the ownership structure of Banks. Six local banks and thirteen international banks out of the nineteen banks under scrutiny. The local banks are; ADB, CAL, FBL, GCB, PBL and UMB. The foreign banks are ABSA, ABL, BOA, EBL, FBN, FNB, GTB, RBL, SG-GH, SBG, SCB, UBA and ZBL. Table 10, depicts overall technical score estimates for banks in Ghana categorised into domestic banks and foreign banks for the years 2015 to 2023. The difference between the mean efficiency scores for domestic and foreign banks, 0.832 for domestic banks and 0.798 for foreign banks, shows that domestic banks are more effective than international banks. Except for 2015, 2019, 2020, 2022 and 2023 almost all domestic banks' average means are greater than those of international banks.

Table 10: Categorization of banks' mean efficiency according to Domestic and foreign over the years 2015-2023

Year	Domestic Banks Average Mean	Foreign Banks' Average Mean
2015	0.795	0.807
2016	0.935	0.818
2017	0.950	0.855
2018	0.942	0.850
2019	0.833	0.850
2020	0.826	0.830
2021	0.890	0.786
2022	0.718	0.767
2023	0.601	0.621
Average score	0.832	0.798

Market share categorization of banks

Categorising the banks in terms of market share which is the size, Table 11 shows that BOA, RBL, SG-GH, UBA, UMB, and GTB, which were in the category of small banks were among the first ten banks in terms of ranking using CRSTE. The average mean under CRSTE was Large Banks 0.806, Medium Banks 0.718 and Small Banks 0.861. In terms of VRSTE, Large Banks are 0.890, Medium Banks are 0.796 and Small Banks are

0.900. Under scale efficiency, Large Banks' average mean is 0.903, Medium Banks 0.911 and Small Banks 0.954.

Table 11: Results of Market share categorization of banks into large, medium and small

		CRSTE	VRSTE	SCALE
LARGE BANKS	EBL	0.762	1.000	0.762
	GCB	0.833	0.865	0.951
	ABSA	0.928	**0.993**	0.934
	SBG	0.744	0.773	0.956
	FBL	0.764	0.817	0.914
	MEAN	**0.806**	**0.890**	**0.903**
MEDIUM BANKS	SCB	0.865	0.922	0.939
	ZBL	0.531	0.673	0.843
	CAL	0.790	**0.942**	0.833
	ADB	0.838	0.862	0.974
	ABG	0.564	0.582	0.965
	MEAN	**0.718**	**0.796**	**0.911**
SMALL BANKS	UBA	0.922	0.936	0.984
	SG-GH	0.902	0.944	0.955
	UMB	0.922	0.925	0.996
	RBL	0.967	0.989	0.977
	GTB	0.877	0.979	0.892
	PBL	0.846	0.882	0.961
	BOA	0.925	**0.965**	0.953
	FBN	0.676	0.714	0.933
	FNB	0.715	0.767	0.935
	MEAN	**0.861**	**0.900**	**0.954**

3.6.3 To Gauge and Assess the Banks' Productivity Growth From 2015 Through 2023

For productivity analysis, the Malmquist DEA with input orientation and cost reduction was applied. An efficiency indicator that shows changes in efficiency from period t to period t+1 is the DEA Malmquist index. A Malmquist index greater (lesser) than 1 denotes either an increase (decrease) in productivity or a reversal in the rate of technological development. Increases in the relevant performance are indicated when the Malmquist index value or any of its components is greater than 1, whereas values less than 1 signify regression or performance deterioration. For the relevant time period and relevant performance metric, the average rise or drop each year is calculated by deducting 1 from the value shown in the table below. Also, keep in mind that these metrics reflect performance about either the sample's best practice or the relevant performance's best practice.

Efficiency and technological advancements provide total factor productivity (TFP). Pure technological efficiency advancements and scale efficiency advancements both contribute to the efficiency shift. The DEA Malmquist productivity changes were calculated using DEAP 2.1 statistical software. The summary of firms means Malmquist indices in Table 12 shows that Eco-Bank Ghana Limited (EBG) is the bank with the highest TFPCH with a growth of 19.5 percent. This comes from 3.4 percent efficiency increase and 15.5 percent of technological progress over the nine-year period (2015-2023). On the other hand, BOA had the lowest TFPCH, it regressed by 40.5 percent. Over the period BOA efficiency decreased by 7.4 percent and its technological innovation regressed by 35.8 percent.

Table 12: Results of Malmquist Index Summary of Firms Means for years 2015-2023

	BANK	Effch	techch	pech	Sech	Tfpch
1	Absa	1.054	0.904	1.073	0.982	0.953
2	ABG	0.950	0.931	0.950	1.000	0.885
3	ADB	0.943	0.953	0.913	1.033	0.899
4	BOA	0.926	0.642	0.954	0.971	0.595
5	CAL	1.005	0.941	1.081	0.930	0.946
6	EBG	1.034	1.155	1.000	1.034	1.195
7	FBN	0.935	0.933	0.955	0.979	0.873
8	FNB	0.951	0.931	0.960	0.990	0.885
9	FBL	1.012	0.841	1.027	0.985	0.851
10	GCB	1.001	0.907	1.022	0.980	0.908
11	GTB	0.963	0.761	0.984	0.979	0.733

12	PBL	1.007	0.911	1.010	0.998	0.918
13	RBL	1.068	0.860	1.022	1.045	0.918
14	SG-GH	0.962	0.936	0.964	0.998	0.900
15	SBG	0.897	0.824	0.904	0.992	0.739
16	SCB	0.942	0.906	0.994	0.948	0.853
17	UBA	1.000	0.962	1.000	1.000	0.962
18	UMB	1.000	0.842	1.000	1.000	0.842
19	ZBL	0.900	0.988	1.000	0.900	0.889
	MEAN	0.975	0.896	0.989	0.986	0.874

Analyzing the overall technical efficiency scores of the banks for the year 2015 to 2023 (Appendix 1) shows that most of the banks initially had a lower efficiency score and these banks have managed to catch up over the nine-year period (2015-2023). For instance, GTB, PBL, and UMB did show a lower technical efficiency score in the year 2015 but managed to catch up with the increase in efficiency score over the study period, there has been improvement in the catch-up process.

The other banks' catch-up seems to be consistent but to a small degree. In terms of technical change, all the banks regressed with the highest regression of 35.8 percent experienced in the Bank BOA. Although there were some improvements in some banks it was minimal and these affected strongly the TFPCH. For the nine-year period, the overall mean TFPCH regression is 12.6 percent. The main contribution to this regression is a technical change of 10.4 percent which is a lack of technological innovation and an efficiency decrease of 2.5 percent which is related to managerial, human resources and process inefficiencies. The efficiency change decrease was made up of a technical efficiency change decrease of 1.1 percent and a scale efficiency change decrease of 1.4 percent, these shows there were remarkable improvements in both pure technical and scale efficiencies, such development could be attributed to the recent comprehensive reforms to clean up the banking industry and strengthen the regulatory and supervisory framework which includes sound corporate governance structure as displayed in Table 13.

Table 13: Results of Malmquist Index Summary Means of Various Years (2015-2023)

YEAR	effch	techch	pech	Sech	tfpch
2015-2016	1.052	0.666	1.092	0.964	0.701
2016-2017	0.928	0.993	0.946	0.981	0.921
2017-2018	0.911	1.070	0.914	0.997	0.975
2018-2019	0.971	0.888	1.044	0.931	0.862
2019-2020	1.014	0.867	0.998	1.017	0.879
2020-2021	1.020	0.860	0.970	1.052	0.877
2021-2022	1.151	0.886	1.077	1.068	1.019
2022-2023	0.795	1.000	0.892	0.892	0.795
MEAN	0.975	0.896	0.989	0.986	0.874

Note: effch = efficiency change; techch = technical change; pech = pure technical change; Sech = scale efficiency change; tfpch = total factor productivity change

In terms of various years under study and their related productivity change, Table 13 depicts the Malmquist index summary of annual means for various years. The year 2015/2016 was the greatest regression in terms of technical change, 33.4 percent contributing to the greatest regress for TFPCH of 29.9 percent but there was efficiency growth of 5.2 percent the second greatest growth rate for efficiency change. In 2016/17 even though there was a slight improvement in terms of technical change, technical change regressed by 0.7 percent.

The year 2017/18 was the greatest growth for technical change of 7 percent. Efficiency change regressed by 8.9 percent and that contributed to the regression of TFPCH of 2.5 percent. In 2018/19 technical change started to regress from growth in 2017/18 year, these continued to the year 2019/20 and year 2020/21, the percent regressed for these years respectively are 11.2 percent, 13.3 percent and 14 percent. Efficiency change improved gradually in the year 2018/19 even though they regressed by 2.9 percent but saw changes in the year 2019/20 and 2020/21, 1.4 percent and 2.0 percent respectively. Even though there was an increase of

2.0 percent for efficiency change for the year 2020/21 the regression in technical change, was 14 percent in the same year which made the TFPCH regress by 12.3 percent.

In the year 2021/22, TFPCH progressed by 19 percent which was mainly contributed by efficiency change, progressing by 15.1 percent with pure technical change and scale change progressing by 7.7 percent and 6.8 percent. The major problem was technological change which regressed by 11.4 percent. TFPCH in the year 2022/23 regressed by 20.5 percent being the second highest regression for the period under study. The regression was mainly due to efficiency change regression, regressed by 20.5 percent. The analysis shows that technical efficiency is the major contributing factor to the regress in productivity.

Only four of the nineteen (19) banks showed advancement in their total productivity index (tfpch>1) in 2016, according to Appendix 11's Malmquist index, while fifteen banks showed a decline. The sources of tfpch are changes in efficiency (effch) and technology (techch), and their corresponding yearly means were 1.052 and 0.666, respectively. These show that technological change as well as efficiency change progression or regression are the sources of the productivity index's growth or reduction. In terms of technical change two (2) banks progressed (tech >1), seventeen (17) banks regressed (tech<1) and none neither progressed nor regressed (tech=1). GCB (1.479), UBA (1.315) and RBL (1.138) are ranked first, second and third respectively in terms of the tfpch index. The three (3) least tfpch are BOA (0.069), ADB (0.573) and ZBL (0.549).

BOA and ADB regressions were caused by significant technical change regression, with their annual technical changes as 0.069 and 0.735 which is 93.1 percent and 26.5 percent regress respectively. ZBL regression is caused by efficiency change regression of 60.2 percent. Efficiency changes results from both scale efficiency change and pure technological efficiency change. In ZBL, the corresponding regression shift was solely due to a scale change of 60.2 percent, not because of ineffective management.

By appendix 12, the Malmquist index for the year 2017 reveals that six (6) of the nineteen (19) banks had a rise in their total productivity index (tfpch>1), while thirteen (13) banks saw a decline (tfpch1). Since efficiency change (effch) and technical change (techch) are the components of tfpch, their respective yearly means were 0.928 and 0.989, respectively. These indicate that the source of the increase or decrease in productivity index is technical change as well as efficiency change progression or regression. In terms of technical change four (4) banks progressed (tech >1), fifteen (15) banks regressed (tech<1) and none neither progressed nor regressed (tech=1). EBG (2.338), UMB (1.369) and BOA (1.326) are ranked first, second and third respectively in terms of the tfpch index.

The three (3) least tfpch are ABL (0.521), SBG (0.597) and FNB (0.617). ABL, SBG and FNB regressions were caused by technical change regression, with their annual technical changes as 6.3 percent, 7.3 percent and 10.27 percent respectively. It was also caused by ABL and SBG efficiency change decrease of 44.4 percent and 35.6 percent respectively. Appendix 13 shows that in the year 2018, the Malmquist index shows that out of the nineteen (19) banks. Eight banks had an improvement in their total productivity index (tfpch>1), while eleven banks saw a decline (tfpch1). Ten (10) banks have a mean that is less than 1 and below the yearly mean of 0.975. The yearly means of efficiency change and technical change, which make up tfpch, were 0.911 and 1.070, respectively. This suggests that technological and efficiency advancement or regression is the cause of the productivity index's growth or decline. In terms of efficiency change, four (4) banks progressed (tech >1), ten (10) banks regressed (tech<1) and five (5) Banks neither regress nor progress. RBL (2.189), EBG (1.483) and ADB (1.227) are ranked first, second and third respectively in terms of the tfpch index. The three (3) least tfpch are GCB (0.523), BOA (0.685) and GTB (0.740). GCB regression was caused by an efficiency change decline, with an annual efficiency change decline of 51.3 percent. BOA and GTB regressions were caused by technical efficiency change regression of 31.5 percent and 44.2 percent respectively. Efficiency is a product of pure technical efficiency change and scale efficiency change. In GCB, the respective regression change was 1.9 percent for scale efficiency and 50.4 percent for pure technical change and that shows that the inappropriate scale inefficiency was moderate but the challenges were mostly from managerial inefficiencies.

According to Appendix 14, out of the nineteen (19) banks in the year 2019, ten (10) had an increase and nine (9) witnessed a decrease in their productivity index (tfpch1) and their overall productivity index (tfpch>1). Three (3) banks have means that are less than 1 and less than the 0.862 yearly mean. Because efficiency change and technological change are components of tfpch, their respective yearly means were 0.971 and 0.888, respectively. These suggest that technological and efficiency advancement or regression is the cause of the productivity index's growth or decline. In terms of technical change eleven (11) banks progressed (tech >1), and eight (8) banks regressed (tech<1). ADB (1.477), ABG (1.189) and CAL (1.068) are ranked first, second and third respectively in terms of the tfpch index. The three (3) least tfpch are RBL (0.343), BOA (0.395) and FBL (0.635).

According to Appendix 15, out of the 19 banks, five (5) saw a rise in their total productivity index (tfpch>1) in 2020, whereas fourteen (14) saw a decline (tfpch1), according to the Malmquist index. Twelve (12) banks have a mean that is less than one (1) and below the yearly mean of 0.879. The yearly means of efficiency change and technical change, which make up tfpch, were 1.014 and 0.867, respectively. These indicate that the source of the increase or decrease in productivity index is technical efficiency and efficiency change progression or regression. In terms of efficiency change six (6) banks increased (effch >1), ten (10) banks declined (tech<1) with three (3) neither declined nor increased (tech=1). GCB (1.420), BOA (1.256) and FNB (1.096) are ranked first, second and third respectively in terms of the tfpch index. The three (3) least tfpch are GTB (0.653), UMB (0.669) and SG-GH (0.718). UMB regression is caused by technical change with an annual regress of 33.10 percent. GTB tfpch regression is caused by an efficiency decline of 16.6 percent and a 21.7 percent regression of technical changes.

In 2021, according to Appendix 16's Malmquist index, six (6) out of nineteen (19) banks had a rise in their productivity index change (tfpch>1) and thirteen (13) saw a decline (tfpch1). Seven banks have a mean below 1 and also below the annual mean of 0.877. As tfpch is a product of efficiency and technical change their respective annual mean was 1.020 and 0.860 respectively. In terms of technical change eleven (11) banks regressed (tech<1), and eight (8) progressed. In efficiency change nine (9) increased (effch >1), seven (7) declined (effch<1) and three (3) banks neither increased nor declined. FNB (1.306), SBG (1.257) and PBL (1.037) are ranked first, second and third respectively in terms of the tfpch index. The three (3) least tfpch are UMB (0.464), SG-GH (0.654) and GCB (0.654). UMB regression is caused by a technical change of 53.6 percent, SG-GH is caused by an efficiency decline of 34.8 percent and GCB regression is caused by both an efficiency declines of 33.10 percent and a technical regress of 2.20 percent.

By appendix 17 of Malmquist index for the year 2022, ten (10) banks progressed in productivity factor change (tfpch>1), eight (8) banks regressed in productivity factor change (tfpch<1) and one (1) bank nether progressed or regressed. Ten (10) banks have a mean below the annual mean of 1.019. The mean for efficiency and technical change was 1.151 and 0.886 respectively. In terms of technical change thirteen (13) banks have their efficiency change more than one (1) (effch>1). One (1) bank regressed (effch<1) and five (5) banks neither regressed or progressed.

In terms of technical change only one(1) bank progressed (1>tech) with eighteen banks (18) regressing. Only one (1) bank neither regressed or progressed. The first three banks with highest tfpch are SG-GH (1.5), PBL (1.448), ZBL (1.466) and the banks with the least tfpch are RBL (0.78), SBG (0.624) and UMB (0.870).
According to appendix 18 for the year 2023, out of nineteen (19) banks six (6) banks progressed (tfpch> 1), whereas thirteen banks regressed (tfpch<1). Eight (8) banks had their means below the mean average of 0.795. The yearly means of effch and techch which makes up the tfpch are 0.795 and 1.00 respectively. In terms of efficiency change fourteen (14) banks had their mean less than 1 (14<effch), one (1) bank have efficiency change progressed with four (4) banks neither regressed or progressed..

Table 14: Results of Malmquist Productivity Index grouped into Banks Size (2015-2023)

	BANK	EFFCH	TECH	PECH	SECH	TFPCH
LARGE BANKS						
Ecobank	GBG	1.034	1.155	1.000	1.034	1.195
Ghana Commercial Bank	GCB	1.001	0.907	1.022	0.980	0.908
Absa Bank Ghana Limited	ABSA	1.054	0.904	1.073	0.982	0.953
Stanbic Bank Ghana Limited	SBG	0.897	0.824	0.904	0.992	0.739
Fidelity Bank Ghana Limited	FBL	1.012	0.841	1.027	0.985	0.851
	MEAN	**1.000**	**0.926**	**1.005**	**0.995**	**0.929**
MEDIUM BANKS						
Standard Chartered Bank Ghana Limited	SCB	0.942	0.906	0.994	0.948	0.853
Zenith Bank Ghana Limited	ZBL	0.900	0.988	1.000	0.900	0.889
CALBank Limited	CAL	1.005	0.941	1.081	0.930	0.946
ADB Bank Limited	ADB	0.943	0.953	0.913	1.033	0.899
Access Bank (Ghana) Plc	ABG	0.950	0.931	0.950	1.000	0.885
	MEAN	**0.948**	**0.944**	**0.988**	**0.962**	**0.894**
SMALL BANKS						
United Bank for Africa (Ghana)	UBA	1.000	0.962	1.000	1.000	0.962

	BANK	EFFCH	TECH	PECH	SECH	TFPCH
Limited						
Societe Generale Ghana Limited	SG-GH	0.962	0.936	0.964	0.998	0.900
Universal Merchant Bank Ghana Limited	UMB	1.000	0.842	1.000	1.000	0.842
Republic Bank Ghana Limited	RBL	1.068	0.860	1.022	1.045	0.918
Guranty TRUST Bank (Ghana) Limited	GTB	0.963	0.761	0.984	0.979	0.733
Prudential Bank Limited	PBL	1.007	0.911	1.010	0.998	0.918
Bank of Africa Ghana Limited	BOA	0.926	0.642	0.954	0.971	0.595
FBN Bank Ghana Limited	FBN	0.935	0.933	0.955	0.979	0.873
First National Bank Ghana Limited	FNB	0.951	0.931	0.960	0.990	0.885
	MEAN	**0.979**	**0.864**	**0.983**	**0.996**	**0.847**

Table 14 shows the categorization of the productivity index into Bank sizes. The average mean of TFPCH for the big banks was 0.929, the medium banks were 0.894 and 0.847 for the small banks. For the big banks' average efficiency change (EFFCH) was the highest driving force, while technical change regressed by 7.4 percent. For the medium-size banks, the TFPCH was 0.894, a regression of 10.6 percent which was mainly contributed by an efficiency change decline of 5.1 percent and a technical change regression of 5.5 percent.

The small banks also had TFPCH of 0.847 a regression of 15.3 percent mainly contributed by a 13.6 percent regression of technical change and a 2.1 percent decline of efficiency change. EBG one of the large banks had a progression in TFPCH of 19.5 percent and it is attributed to 3.4 percent progress in efficiency change and 15.5 percent technical change. From Table 14, the large banks were the least regress total factor productivity change (tfpch) mean regress of 7.1 percent for the period under review, followed by medium banks with a 10.6 percent regress and 15.3 percent regress for small banks. The analysis shows that the large banks neither improved or regressed on their efficiency change and these can be attributed to corporate governance improvements, manpower developments and improvement in work processes. On technical change, the medium banks show a regression of 5.6 percent followed by large banks at 7.40 percent then 13.60 percent for small banks.

Table 15: Results of Categorization of Banks Malmquist Index into Local and Foreign Banks (2015-2023)

	BANK CODE	EFFCH	TECHCH	PECH	SECH	TFPCH
Local Bank						
Ghana Commercial Bank	GCB	1.001	0.907	1.022	0.980	0.908
Fidelity Bank Ghana Limited	FBL	1.012	0.841	1.027	0.985	0.851
CALBank Limited	CAL	1.005	0.941	1.081	0.930	0.946
ADB Bank Limited	ADB	0.943	0.953	0.913	1.033	0.899
Universal Merchant Bank Ghana Limited	UMB	1.000	0.842	1.000	1.000	0.842
Prudential Bank Limited	PBL	1.007	0.911	1.010	0.998	0.918
	MEAN	**0.995**	**0.899**	**1.009**	**0.988**	**0.894**
Foreign Bank						
Ecobank	GBG	1.034	1.155	1.000	1.034	1.195
Absa Bank Ghana Limited	ABSA	1.054	0.904	1.073	0.982	0.953
Stanbic Bank Ghana Limited	SBG	0.897	0.824	0.904	0.992	0.739
Standard Chartered Bank Ghana Limited	SCB	0.942	0.906	0.994	0.948	0.853
Zenith Bank Ghana Limited	ZBL	0.900	0.988	1.000	0.900	0.889
Access Bank (Ghana) Plc	ABG	0.950	0.931	0.950	1.000	0.885
United Bank for Africa (Ghana) Limited	UBA	1.000	0.962	1.000	1.000	0.962

	BANK CODE	EFFCH	TECHCH	PECH	SECH	TFPCH
Societe Generale Ghana Limited	SG-GH	0.962	0.936	0.964	0.998	0.900
Republic Bank Ghana Limited	RBL	1.068	0.860	1.022	1.045	0.918
Guranty TRUST Bank (Ghana) Limited	GTB	0.963	0.761	0.984	0.979	0.733
Bank of Africa Ghana Limited	BOA	0.926	0.642	0.954	0.971	0.595
FBN Bank Ghana Limited	FBN	0.935	0.933	0.955	0.979	0.873
First National Bank Ghana Limited	FNB	0.951	0.931	0.960	0.990	0.885
	MEAN	**0.968**	**0.903**	**0.982**	**0.986**	**0.875**

Table 15 shows the categorization of productivity index into Local and Foreign Banks. The average mean of TFPCH for the local banks was 0.894, and that of the foreign banks was 0.875. For the local banks' average efficiency change (EFFCH) declined by 0.05, whiles technical change regressed by 10.10 percent. For the foreign banks, the TFPCH was 0.875, a regression of 12.5 percent which was mainly contributed by an efficiency change decline of 3.2 percent and a technical change regression of 9.7 percent. Comparing the two groups the Local bank TFPCH 0.894, was a little improvement than foreign banks at 0.875.

3.4 Discussion of Findings

3.4.1 The Ghanaian Universal Banks' Relative Technical Efficiency

Table 5 displays the technical efficiency analysis of Ghanaian banks' overall performance. Between 2015 and 2023, the technical efficiency ranged from 61.5 to 88.5 percent on average. This means that the banks may have decreased output levels from 11.5 percent to 38.5 percent throughout the five-year research period while using the same quantity of inputs. According to the findings, 19 banks showed a mean overall efficiency score of 80.3 percent in 2015, 85.5 percent in 2016, and 88.5 percent in 2017, before dipping gradually to 87.9 percent in 2018, 84.5 percent in 2019, 82.9 percent in 2020, 81.9 percent in 2021, 75.1 percent and 61.5 percent.in 2022 and 2023 respectively The period's total average mean was 80.9 percent (0.809).

The result shows that Ghana's average pure technical efficiency, scale efficiency and overall technical efficiency are lower than the best practice efficiency level of '1'.

3.4.2 To Examine Technical Efficiency in The Context of Frontier Operational Efficiency

The findings may substantiate the argument that being a small niche bank allows those banks to cater to a niche market of customers and may be the reason why it is consistently efficient. Except for UBA and PBL, all the small banks in terms of asset size were referenced by inefficient banks.

FBL, ABSA, and GCB being large banks were also referenced twenty-one, nineteen and sixteen respectively by inefficient banks. FBL and GCB are the only two local banks which are regarded as large banks out of five large banks which were referenced by inefficient banks in the sample for the study period. Because of their scale and efficiency, these banks may have been able to leverage their position in the market and have access to enormous client bases, which may have helped them stand out as efficient references. It can be in line with the market power theory and the efficiency structure hypothesis. According to the efficiency structure hypothesis, businesses that have advanced management and production technology become more effective and, as a result, generate more profits or have lower production costs. According to the market power hypothesis, only businesses with sizable market shares and distinctive goods may use market power. According to Avkiran (1999), the branch or bank that emerges as a peer in the peer counts the most frequently serves as the worldwide leader. In this instance, RBL was cited as a peer the most frequently during the course of the seven-year research period. So RBL will be a useful bank that other banks may study to raise their performance and operational efficiency.

Ownership identification impact on efficiency

According to Table 10's ownership identification of influence on efficiency, local banks have a slightly higher average mean score (0.832) than foreign banks (0.798). The home field theory claims that while foreign banks perform worse than domestic ones in wealthy countries, they do better in developing nations. This runs counter to Berger et al.'s global advantage hypothesis idea, which was published in 2000. Although the difference in the average efficiency score during the study period is not particularly substantial, Ghanaian or local banks are more efficient than international banks in the research under consideration.

Market share categorization of banks

The smaller banks performed well in terms of overall efficiency but much needed to improve in terms of VRSTE. When compared to larger banks, banks have a substantially greater average scale efficiency. However, the most efficient are the mid-size banks. The small banks UBA, SG-GH, UMB, RBL, PBL, and BOA, were relatively more scale efficient compared to larger banks except for GTB, FBN and FNB. Larger or big banks were consistently found to be experiencing lower scale efficiency which will point to the fact that a larger size results in the bank being harder to manage and having many branches and excess capacity which are not fully utilized.

3.4.3 To Guage and Assess the Banks' Productivity Growth From 2015 Through 2021

The findings show that the productivity of banks in Ghana has slightly increased over the years 2015 to 2023 but was not above "1" which indicates progression. The average mean for tfpch was 0.701 in 2016 increased to 0.921 in 2017 then moved further to 0.975 in 2018 after which it decreased to 0.862 in 2019 improved slightly to 0.879 in 2020 then decreased to 0.877 in 2021, progressed to 1.019 in year 2022 and decreased to 0.795 in 2023 The breakdown of the Malmquist productivity index into its constituent parts reveals that efficiency change (0.975) has a greater positive impact on productivity values than technical change (0.896). This indicates that some of the sample's banks moved toward the best frontier and caught up.

The results demonstrated that productivity gain was caused by the catch-up impacts of efficiency increases. The positive impacts of scale efficiency change (0.986) and pure technical change (0.989) have propelled this efficiency change. In terms of grouping banks based on total assets. Despite being below "1", productivity growth was on average stronger for large banks (0.929) than for medium banks (0.894) and small banks (0.847). Once more, when the banks were divided into local and international banks, the local banks saw a regression under the total factor productivity change (TFPCH) of 10.6 percent, which is somewhat less than the foreign banks' regression of 12.5 percent.

The biggest cause of productivity reduction, is technology change, as measured by the Malmquist total factor productivity index.

IV. Conclusions

In conclusion, the CCR and BCC model for efficiency and the Malmquist productivity index for productivity change scores were utilised in the DEA model to assess the efficiency score and productivity score for the period of 2015 to 2023 for 19 banks. All of the models employed the input-oriented technique.

4.1 Measure and Assess the Ghanaian Universal Banks' Relative Technical Efficiency

The results of the efficiency scores show that the problem is a mix of management and scale inefficiencies. The scores on average shows that banks' scores under the variable return to scale (VRSTE) using the BCC model were higher than those under the constant return to scale (CRSTE) using the CCR model. When the average mean 0.870 for the time period from 2015 to 2023 was compared to the best practice efficiency level of "1" it was significantly low percentage but it shows impressive improvements.

Further analysis of breaking down Overall Technical Efficiency (OTE) into Pure Technical Efficiency (PTE) and Scale Efficiency (SE), the average Pure Technical Efficiency (PTE) for the entire period is 92.9 percent.

4.2 To Examine Technical Efficiency in The Context of Frontier Operational Efficiency

Analyzing the Benchmarking of peers shows that small banks were referenced the most with Republic Bank Limited (RBL) being referenced the highest. According to Avkiran (1999), this bank can be classified as the global leader with banks in Ghana which will be useful for other banks to study their model of operations to improve their various operations. The findings will substantiate the argument that being a small niche bank allows those banks to cater for a niche market of customers to improve efficiency. Additionally, the data shows that local banks are somewhat more efficient than overseas banks. Foreign banks' average efficiency is 87.5 percent, whereas domestic banks' average efficiency is 89.2 percent. The research findings of Saka et al. (2012) are in line with this. The global advantage argument, put out by Berger et al. (2000), claims, in contrast, that international banks perform better than local ones in Ghana and other developing nations.

4.3 To Guage and Assess the Banks' Productivity Growth From 2015 Through 2023

To assess productivity improvements from the study, the DEA Malmquist Index was utilised to compute them. Tables 4.11 and 4.10 present, respectively, the Malmquist index of yearly means of businesses and the Malmquist index of summary of firms means, which demonstrate that technological development or regression is the primary cause of variations in the total factor productivity index (tfpch). The only bank with a

TFPCH score greater than one (tfpch>1), Eco-Bank Ghana Limited, demonstrated an improvement in bank productivity.

However, TFPCH scores for eighteen (18) banks fell below "1" (tfpch1), which is a sign of declining performance. Eco-Bank Ghana Limited (EBG), which has a TFPCH score of 1.195, is the bank with the greatest level of productivity, while Universal Bank of Africa Ghana Limited (BOA), which has a TFPCH score of 0.595, is the bank with the lowest level of productivity. Except for Eco-Bank Ghana Limited, nearly all of the banks exhibited declining performance (i.e., Tfpch<1) and a technical change score of less than "1" (techch<1). This suggests that practically all banks did not successfully remodel by integrating new technology to maximise their management efficacy. The finding is in accordance with Beatson et al. (2019), who claim that technological advancement is to blame for the general drop in productivity in African banks. From the study most of the improvements in TFPCH even though less than "1" was a result of an efficiency change increase that is shifting towards the best frontier (catching-up effect).

In conclusion, Ghanaian banks are to improve on their technical or technological innovation to change positively their productivity as well as efficiency. Also, policymakers and stakeholders should look into the gaps in efficiencies in the industry, to make the banks resilient to compete among the best in the industry.

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