



EFFICIENCY OF MONEY DEPOSIT BANKS IN SELECTED SUB-SAHARAN AFRICAN COUNTRIES: A DATA ENVELOPMENT ANALYSIS APPROACH

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Abstract

The importance of performance efficiency in the financial sector is extremely vital because it has an extensive impact on the micro and macro levels of the economy. The study seeks to empirically establish whether listed banks in selected Sub-Saharan African countries are operating on production possibility frontier, that is, if they are technically and scale efficient. In pursuance of this, the study employed the Non-parametric Data Envelopment Analysis (DEA) with input variables as interest expenses, operating expenses, customer deposit and total asset while the output variables are interest income, profit after tax and loans and advances to customers. The study period was 2014/2015 fiscal year. The STATA DEA software was used to calculate the efficiency score. A bank with a score of one (1) is efficient, while a score below one (1) means the bank is inefficient. The finding of the study reveals that 11 banks out of the 20 in our sample within the period under study were efficient based on constant return to scale (CRS), while 13 are variable return to scale (VRS) efficient whereas, 11 banks were scale efficient. This means that majority of the banks in the banking industry in the selected Sub-Saharan African countries are being successful in converting their inputs to outputs. The study therefore recommends that the regulatory and supervisory authorities in the selected Sub-Saharan African countries should formulate and implement monetary policies that are effective in helping the banks to improve their operations, thereby leading to efficiency in resource allocation and utilization. Also, some of the banks, like First Bank Holdings Plc, Zenith Bank Plc, United Bank for Africa Plc, GTB Plc, Diamond Bank Plc, MCB Bank Plc and Kenya Commercial Bank Plc should realigned their operations so that they can be efficient, as they are not currently efficient in either on CRS, VRS and SE. The operation of efficient banks can be studied

Keywords: Data Envelopment Analysis, Technical Efficiency, Scale Efficiency, Banking Industry, Sub Saharan African Countries

JEL Classification: E50, G21

Introduction

The importance of performance efficiency in the financial sector is extremely vital because it has an extensive impact on the micro and macro levels of the economy. Due to the significance of the banking sector in the stability and welfare of any economy; it is imperative to constantly monitor and evaluate its performance. In order to properly allocate economic resources and carry out their intermediation function, the financial system; banks inclusive, needs to be efficient. Efficiency in banking then supports the fruitfulness of implemented macroeconomic policies generating durable development, economic growth and welfare (Alkhatlan & Malik, 2010). It is usual to measure the performance and efficiency of banks using financial ratios. According to Yeh (1996), the major demerit of this approach is its reliance on benchmark ratios. These benchmarks could be arbitrary and misleading. Further, Sherman and Gold (1985) noted that financial ratios do not capture the long –

term performance, and aggregate many aspects of performance such as operations, marketing and financing, thereby concealing so many characteristics and uniqueness that need to be manifest.

In recent years, there is a trend towards measuring bank efficiency using one of the frontier analysis methods. In frontier analysis, the institutions that perform better relative to a particular standard are separated from those that perform poorly. Such separation is done either by applying a non-parametric or parametric frontier analysis to firms within the financial services industry. The parametric approach includes Stochastic Analysis, Tick Frontier and the Distribution Free Approach (DFA), while the non-parametric approach is the Data Envelopment Analysis (DEA) and the Free Disposal Hull, (Molyneux, Althunbas & Gardener, 1996). Both of these sophisticated techniques attempt to benchmark the relative performance of production units, but the techniques differ from each other mainly due to their underlying assumptions. Unlike the parametric approach, the non-parametric approach puts relatively little structure on the specification of the banking technology (frontier) and thus it is relatively immune from the specification errors. In addition the latter approach does not make any assumptions regarding the structures and distributions of inefficiency. Whereas the parametric approach assumes that part of the deviations is due to pure luck or data problems and part to managerial errors. The Non-parametric approach believes that all deviations are due to inefficiency. Furthermore, non-parametric frontiers are estimated using a mathematical linear programming model, thus they mark well with small samples. The parametric frontiers are estimated using econometric techniques, thus they require relatively larger sample size to estimate the unbiased coefficient of the model variables such as inputs, outputs or output prices, environmental factors, inefficiency and error term.

Efficiency assessment of banks and other business area is an important issue for managers and stakeholders since the inherent inefficiencies can be identified and eliminated. Measuring the banks' efficiency and performance has been widely based on a number of key efficiency and performance indicators (KPIs) like, liquidity, profitability, asset quality and capital adequacy. However, each of these indicators gives an incomplete picture of the banks' efficiency and performance. In order to have a meaningful overall measure of the bank's efficiency, a more *sophisticated* method than the traditional efficiency and performance measurement techniques is needed, hence in this study; the Data Envelopment Analysis (DEA) Approach is employed.

Data Envelopment Analysis (DEA) has been widely used as an effective tool for measuring the relative efficiency of similar units by considering various input/output parameters. The Data Envelopment analysis (DEA) is a non-parametric method that was first developed by Charnes, Cooper and Rhodes in 1978; based upon the pioneer work on efficiency measures by Farrell (1957). The DEA measures efficiency by estimating an empirical production function which represents the highest values of output benefits that could be generated by input resources as given by a range of observed output/input measures and the relative efficiency of a group of similar units and identifies the best practice frontier. It also indicates targets for inefficient units to improve. Vassiloglou and Giokas (1990) points out that DEA is quickly emerging as a leading method for efficiency evaluation in terms of both the number of research papers published and the number of applications to real-world problems. The technique was first applied to the banking industry by Sherman and Gold in 1985, who used it to explore some operating aspects of bank branches. By explicitly considering the mix of resources used and services provided by individual branches they succeeded not only in identifying inefficient branches but also in locating specific areas of inefficiency at each branch. Since that time there have been considerable researches to extend and apply the model in banking industry in different countries and regions.

For the Sub-Saharan Africa banks, their efficiency need to be measured given that Sub-Saharan Africa countries have the world least developed financial sectors. Institutions in coverage are limited and even banking sectors which dominates among financial institutions are small. Although regulation is generally with international norms and financial systems are sound, a history of forbearance has left a number of weak banks many of them state-owned. Also while banks are on average profitable, their assets are more concentrated and the return on asset is lower than elsewhere in the world (Regional economic outlook SSA, May 2006). Studying if this sector is outperforming its predicament is worth noting with the case of Sub-Saharan Africa. Thus, study is motivated by the need to expand the existing literature on banking efficiency assessment to Sub-Saharan Africa as championed by Berger (2007) since the majority of previous studies focused more on developed countries.

Banking systems and banks are expanding within the Sub-Saharan Africa region, they are becoming more competitive. The share of banking assets held by the three largest banks is about one-tenth higher in SSA than other low-income countries. The small market size is a major factor contributing to concentration, given the need for institutions to reach economies of scale (Bossone, Honohan, and Long, 2002). Some of these big banks are, FirstRand Bank of South Africa, Bank Windhoek of Namibia, Barclays Bank and ECOBANK which are represented in a majority of the SSA Countries. Banking sectors in low-income SSA are less efficient than global

competitors. For all banks including foreign-owned institutions, low efficiency leads to high overhead net interest margins that are higher in low-income SSA than in other low income countries. While banking sector operational efficiency recently declined further in low income SSA, the efficiency indicators are considerably better in SSA middle-income countries. Despite overhead costs, SSA banks are profitable. Their main income source is from interest-related items. Given non-competitive market structures, banks charge high interest margins and remained profitable, the difficult operating environment notwithstanding. In fact, the market power of banks is large enough to support higher profitability than in other low-income countries given the large gap between what banks can charge borrowers and what they pay savers. Loan loss provisioning levels are similar to those in other low-income countries (Regional economic outlook SSA, May 2006).

There has been a considerable cross country DEA studies investigating the efficiency of banks for the developed countries of the world especially in Europe: (Pastor, Perez and Quesada,1997; Pastor, 2002; Casu and Molyneux, 2003; Beccalli, Casu and Girardone, 2006). Lozano-Vivas Pastor and Hasan (2002) examine ten EU countries; Bergendahl (1998) focuses on Nordic countries, while Pasiouras (2008a) examines an international dataset. However, empirical literature show that limited cross country DEA studies evaluating efficiency of banks in Sub-Saharan African countries exist, this study attempt to fill this gap.

Against this backdrop, this study will measure the relative performance efficiency of listed banks in Sub-Saharan Africa countries using Data Envelopment Analysis (DEA) Approach. The study seeks to provide answers to the research questions below.

1. Are listed banks technically efficient in Sub-Saharan African?
2. Do listed banks in Sub-Saharan Africa countries have constant return to scale technical efficiency?
3. Is there variable return to scale technical efficiency among listed banks in Sub-Saharan Africa countries?

The main objective of this paper is to measure performance efficiency of listed banks in Sub-Saharan Africa countries using Data Envelopment Analysis (DEA) Approach. In specific terms, the researcher seeks to:

1. Determine whether listed banks are technically efficient in Sub-Saharan Africa countries;
2. Ascertain if listed banks in Sub-Saharan Africa countries have constant return to scale technical efficiency; and
3. Find out if there is variable return to scale technical efficiency among listed banks in Sub-Saharan Africa countries.

This study covers 20 listed banks in five Sub-Saharan Africa countries (South Africa, Nigeria, Kenya, Mauritius and Ghana). The period that was covered during the study was 2014/2015 fiscal year. The choice of this period is based on the fact that it reflects the post global financial crisis when most of the banks must have overcome the losses that they suffered during the financial crisis. The remainder of the paper is organized in the following manner. The review of literature is presented in the second section while the third Section presents the methodology, and the fourth section provides the analysis of results. Finally, Section five concludes the paper.

Literature Review

Concept of Efficiency

The efficiency concept is used to characterize the utilization of resources to produce outputs. According to Forsound and Hjalmarsson (1974), efficiency is a statement about the performance of processes transforming a set of inputs into a set of outputs. The authors pointed out that efficiency is a relative concept, where the performance of an economic unit must be compared with a standard unit. The identification of a standard should involve value judgment about the objective of the economic activities. Important as it is from both the academic and practical viewpoints, the concept of efficiency has remained loosely defined in the literature (Farrel 1957). The concept means different things to different people in different circumstances. As Lau and Yotopoulos (1971) put it economic efficiency is an elusive concept in which the policy maker, economist and the engineers all have great stakes. For example, the cost accountant uses the ratio of standard cost to actual cost percent to measure production efficiency (Horngren, 1972). While an engineer describes the efficiency of his machine by the relation of output to theoretical capacity or output/ theoretical capacity percent (Amey 1970). However the economist breakdown the economic efficiency of a firm or industry into two separate components: price efficiency and technical efficiency. The former measures a firm's success in choosing an optimal set of inputs, the latter its success in producing maximum output from a given set of input (Farrel, 1957). Furthermore, Farrell states that once the adjective economics is dropped efficiency becomes a rather nebulous concept meaning only success in achieving planned objectives whatever they maybe.

According to Kumar and Gulati (2008), technical efficiency (TE) decomposes into two mutually exclusive and

non-additive components: pure technical efficiency (PTE) and scale efficiency (SE). TE measures corresponding to CRS assumption represents overall technical efficiency (OTE) which measures inefficiencies due to the input/output configuration and as well as the size of operations. The efficiency measure corresponding to VRS assumption represents pure technical efficiency (PTE) which measures inefficiencies due to only managerial underperformance. The relationship $SE = OTE / PTE$ provides a measure of scale efficiency.

Efficiency Measurement According To Farrell

The efficiency measurement discussion began with Farrell (1957) who, based on the work of Debreu (1951) and Koopmans (1951), defined a simple measure of firm efficiency that could account for multiple inputs. Farrell (1957) proposed that the efficiency of a firm consists of two components namely, technical and price efficiency (or allocative efficiency). The first component reflects the ability of a firm to obtain maximal output from a given set of inputs while the second reflects the ability of a firm to use the input in optimal proportions, given their respective prices and production technology. The combination of these two measures provides a measure of total economic efficiency (or overall efficiency). The production of the technical and allocative efficiency measures provides the measure of the overall economic efficiency. However, factor prices are often difficult to find, and Farrell recommends the technical efficiency concept.

Technical Efficiency

Technical efficiency, the most common of the efficiency measure, reflects the ability of the firm to obtain maximum output from a set of inputs. That is, it refers to the use of productive resources in the most technologically efficient manner (Worthington, 2004). In the context of bank services production, technical efficiency will refer to the physical relationship between the resources employed, for example, Deposit, labour, fixed assets and capital and some outputs like total loans extended and Investments. In microeconomic terms, a technically efficient production process is one that lies along the production possibilities frontier or isoquant.

Technical and Allocative (Price) Efficiency

Farrell proposed that the efficiency of a firm is of two parts: technical efficiency and allocative efficiency. Technical efficiency refers to the ability of a firm to produce maximal output from a given set of inputs over a certain time period. While allocative efficiency reflect the ability of a firm to use inputs in optimal proportion given their respective prices. It refers to whether inputs, for a given level of output and a set of input prices are chosen to minimize the cost of production, assuming that the organization being examined is already fully technically efficient (Steering Committee for the Review of Commonwealth/State Services Provision, 1997). However, a technically efficient firm could be inefficient in allocative efficiency if inputs are not being employed in proportions that minimize its costs, given their relative input prices (Coelli, 1996).

The Return to Scale Concept

The return to scale concept reflects the degree to which a proportional increase in all inputs increases output, in the long- term. There are basically two types - constant return to scale (CRS) and variable return to scale (VRS). The constant return to scale occurs when a proportional increase in all inputs results in the same proportional increase in output. The variable return to scale can be an increasing return or decreasing return to scale. Increasing returns to scale occur when a proportional increase in all inputs results in more than a proportional increase in output, while decreasing returns to scale exists when a proportional increase in all inputs results in a less than proportional increase in output. Koulenti (2006) posit that there are many reasons why a particular firm may possess certain returns to scale properties. The most commonly used example relates to a small firm exhibiting increasing returns in particular tasks. One possible reason for decreasing returns to scale is the case where a firm has become so large that the management is not able to exercise close control over all the aspects of the production process.

Concept of Data Envelopment Analysis (DEA)

DEA estimates and compares the relative efficiency of homogenous Decision Making Units (DMUs) which use similar multidimensional inputs to produce multiple outputs. The DMUs can be banks, bank branches, schools, hospitals, airlines, bank branches, mutual funds, utility companies etc. The technique measures efficiency relative to an unobserved true frontier by identifying a subset of efficient 'best-practice' DMUs that are used to construct the frontier which envelopes all observed DMUs. Then, the relative efficiency of each DMU is measured by the distance with respect to the boundary of the PPS by either increasing the outputs or reducing the inputs or both. The output-oriented efficiency estimate equals one for efficient DMUs and greater than one for inefficient ones.

Reasons for Choosing DEA

There are a number of reasons for selecting this DEA frontier method above other approaches. First, unlike the SFA or other parametric approaches, DEA can capture the interaction among multiple inputs and multiple outputs simultaneously (Charnes et al., 1978). The banking industry employs several inputs such as employees, deposits, financial and physical capital, borrowings and interest expenses to produce several outputs including loans, investments, interest income, fees and commissions. For this reason, it may be difficult to use the parametric techniques as they only account for single-output technologies at a time.

Second, DEA can be used to easily decompose profit, cost, and revenue efficiencies into several components including overall technical, pure technical and scale efficiencies, in order to determine the specific sources of efficiencies in a particular industry, such as the banking industry.

Third, DEA avoids the need to specify a functional relationship between the input and output variables as reflected in the production function. It therefore considers the firm as a black box without the need to know the basics of the underlying technological process. In other words, DEA allows the 'data to speak for themselves'. DEA also circumvents the need to specify a distributional functional form for the inefficiency term. Such assumptions can create specification errors (Cummins et al., 2010) which make DEA very flexible as opposed to the parametric frontier models.

Drawbacks of DEA

The envelopment estimator is not without some limitations. DEA is "deterministic" in the sense that all the observations are considered as being feasible with probability one. In other words, DEA contains no statistical noise but assumes that all frontier deviations are due to inefficiency. The "deterministic" nature of DEA means that in the case of noisy data in the Data Generating Process (DGP), there is an identification problem (i.e. we are unable to identify the part of the production technology, which is due to random error, and the part, which is due to inefficiency). Still, developments are underway in terms of stochastic DEA (Simar, 2007; Kuosmanen and Kortelainen, 2010), asymptotic results (Kneip et al., 2008) or bootstrapping (Simar and Wilson, 1998, 2007).

Another drawback of DEA estimator is that it is sensitive to measurement error due to outliers or missing explanatory variables. This is because DEA, like FDH, envelopes all the data points. Even so, there are recent developments on partial frontiers such as the order- m estimator that provides a robust estimator of the efficiency scores, sharing the same asymptotic properties as the envelopment estimators but being less sensitive to outliers. There is also the order- α estimator. It is argued that with the partial frontiers, the curse of dimensionality for the envelopment estimator may be overcome as they have root- n speed of convergence where n is the number of firms being evaluated (Daraio & Simar, 2007). However, partial frontiers are conditional measures. That is, the efficiency score in an input (output) orientation depends on the output (input) levels of the DMU under evaluation. Also, the computation of partial frontier may be time-consuming particularly for large sample size. This is because finding a suitable value of m or α may require several tries.

Empirical Review

In the empirical review, we highlight the various studies that have used DEA to evaluate performance efficiency of Banks. For example, Favero and Papi (1995) used the non-parametric Data Envelopment Analysis on a cross section of 174 Italian banks in 1991 to measure the technical and the scale efficiencies of the Italian banking industry. In implementing both the intermediation and the asset approach the traditional specification of inputs was modified to allow for an explicit role of financial capital. In addition, regression analysis was used on a bank specific measure of inefficiency to investigate determinants of banks' efficiency. According to the empirical results, efficiency was best explained by productivity specialization by bank size and to a lesser extent by location (North-Italian banks were more efficient than South-Italian banks).

Altunbas and Molyneux (1996) examined the banking systems of France, Germany, Italy and Spain for economies of scale and scope. They found differences among four markets regarding economies of scale. However, the latter was significant only for the Italian banks, which gained as they succeeded in lowering costs. Allen and Rai (1996) estimated a global cost function using an international database of financial institutions for fifteen countries. Their sample was divided into two groups according to the country's regulatory environment. Universal banking countries (Australia, Austria, Canada, Switzerland, Germany, Denmark, Spain, Finland, France Italy, United Kingdom and Sweden) permitted the functional integration of commercial and investment banking, while separated banking countries (Belgium, Japan and USA) did not. Large banks in separated banking countries exhibited the largest measure of input inefficiency and had anti-economies of scale. All other banks had significantly lower inefficiency measure. Moreover, small banks in all countries showed significant levels of economies of scale. Italian banks, along with French, UK and USA ones were found less efficient from Japanese, Austrian, German, Danish, Swedish and Canadian ones.

Pastor, Perez and Quesada (1997) as cited by Angelidis and Lyroudi (2006) analyzed the productivity, efficiency and differences in technology in the banking systems of United States, Spain, Germany, Italy, Austria, United Kingdom, France and Belgium for the year 1992. Using the non-parametric approach DEA together with the Mamquist index, they compared the efficiency and differences in technology of several banking systems. Their study used the value added approach. Deposits, productivity assets and loans nominal values were select as measurements of banking output, under the assumption that these are proportional to the number of transactions and the flow of services to customers on both sides of the balance sheet. Similarly, personnel expenses, no-interest expenses, other than personnel expenses were employed as a measurement of banking input. According to the results France had the banking system with the highest efficiency level followed by Spain, while UK presented the lowest level of efficiency.

Ayadi, Adebayo and Omolehinwa (1998) in their attempt to determine the quality of bank management used Data Envelopment Analysis (DEA) and found that the banks in Nigeria that were relatively efficient are those that have been in existence for a long period of time.

Hasan, Lozano-Vivas and Pastor (2000) analyzed the banking industries of Belgium, Denmark, France, Germany, Italy, Luxemburg, Netherlands, Portugal, Spain and the United Kingdom. First the authors attempted to evaluate the efficiency scores of banking industries operating in their own respective countries. Later, they used a common frontier to control for the environment conditions of each country. The results based on cross country efficiency scores suggested that the banks in Denmark, Spain and Portugal were relatively the most technically efficient and successful. Especially when the banks of these countries tried to enter any other European countries of the sample were most efficient. On the other hand, the banks in France and Italy were found to be the least efficient institutions among the ones in the sample.

Bikker (2001) examined the banking productivity of a sample of European banks in various countries amongst which were Italy, Spain, France, Belgium Switzerland and Luxemburg for the period 1989-1997. His results indicated that the most inefficient banks were first the Spanish ones, followed by the French and Italian banks. The most productive banks were the ones in Luxemburg, Belgium and Switzerland.

Fernandez, Gascon and Gonzalez (2002) studied the economic efficiency of 142 financial intermediaries from eighteen countries over the period 1989-1998 and the relationship between efficiency, productivity change and shareholders wealth maximization. The authors applied DEA to estimate the relative efficiency of commercial banks of different geographical areas (North America, Japan and Europe). The European banks were from Austria, Belgium, Denmark, Finland, Germany, Ireland, Italy, Luxemburg, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom. The three preferred outputs were total investments, total loans, and non-interest income plus other operating income. In parallel, the four inputs values were property, salaries, other operating expenses and total deposits. All these values are expressed in billions of US dollars. Their results showed that the productivity of commercial banks across the world has grown significantly (19.6%) from 1989-1998. This effect has been principally due to relatively efficiency improvement, with technological progress having a varying moderate effect.

Maudos (2002) analyzed the cost and profit efficiency of European banks in ten countries including Italy, for the period of 1993-1996. They used multiple regression analysis along with DEA and they split their sample into large, medium and small banks. Their result indicated that only medium size banks were profit efficient. Lozano-Vivas, Pastor and Pastor (2002) examined banking efficiency in ten European countries among which were Italy, Netherlands and so on for 1993. The authors adopted the value added approach and analyzed the macroeconomic environment where the banks operated. Their result showed that banking efficiency was low in Europe during that time period. Furthermore, the banks in Italy and Netherlands were the only ones which were not able to operate in a unified European banking system compared to the most efficient banks of other sampled countries.

Casu and Molyneux (2003) employed DEA to investigate whether the productivity efficiency of European banking systems have improved, and converge towards a common European frontier between 1993 and 1997. The geographical coverage of the study were France, Germany, Italy, Spain and the United Kingdom. Their results indicated relatively low average level of efficiency. Nevertheless, it was possible to detect a slight improvement in the average efficiency score over the period of analysis for almost all banking system in the sample with the exemption of Italy.

Schure, Wagenvoort and O'Brien (2004) estimated the productivity of the European banking sector for the period of 1993-1997. They found that larger commercial banks were more productive on the average than

smaller banks. However the Italian and Spanish banks were found to be the least efficient. On the other hand, Casu, Girardone and Molyneux(2004) evaluate the efficiency of the European banking institutions for the period 1994-2000 and found that Italian banks had an 8.9% productivity increase; Spanish bank has 9.5% increase, while German, French and English banks had 1.8%, 0.6% and 0.1% productivity increase, respectively.

Mostafa (2008) evaluated the performance of top 100 Africa banks using DEA analysis to measure their relative efficiency. He used a cross-sectional data for the year 2005 and found that the performance of several banks is sub-optimal, suggesting the potential for significant improvements. Chuling (2009) evaluate the efficiency of banks in Sub Saharan African Middle-Income countries and provide possible explanations for the difference in the efficiency levels of banks. He found that banks could save 20 – 30% of their total cost if they were operating efficiently (operating on the frontier) and the foreign-owned banks are more efficient than the public banks and domestic private banks.

Also Fadiran, Ogwumike and Adenegan (2010) in evaluating the relative efficiency of insured banks in Nigeria observed fluctuations in the performance of the banks. The number of efficient banks increases and decreases over time. The number of banks performing below the mean also increased over time.

Mohammad, Aryanezhadb and Naser (2011) evaluate the relative performance of efficiency of the Iranian banking system for the fiscal year 2006 using the Non parametric Data Envelopment Analysis (DEA). Four inputs: incentive cost, cost to revenue, outstanding bad loans and electronics services as well as six outputs: Asset Growth rate, return on equity, profit margins, market share, online services and advanced services were employed in the study. The result indicates that there are three inefficient banks while the rest of them are located on efficient frontier which means they are efficient. The study also emphasizes that there is a strong relationship between some non-financial and financial items such as financial asset growth and electronic services.

Omoankhanlen (2013) investigates the Nigerian Banks' Efficiency Performance for the period 2005-2009 using the Non parametric Data Envelopment Analysis (DEA) under the assumptions of Constant return to scale (CRS), Variable Return to Scale (VRS) and Scale Efficiency (SE) to estimate the efficiency scores of the banks. A bank with a score of 1 is efficient, while a score below 1 means the bank is inefficient. The findings of the study revealed that GTB was the most efficient bank and it has the least reduction in inputs (4.93%) needed to produce the same amount of output. Moreover it remained efficient throughout the years 2006-2009. Overall, the worst performers are Unity bank, Afribank and UBA. Also the banks did not achieve full efficiency under the CRS, VRS and SE in any of the five years.

Eriki and Osifo (2014) evaluate the performance efficiency of nineteen selected commercial banks in Nigeria for the year 2009 using Data Envelopment Analysis (DEA). Two outputs: interest income and gross earnings as well as two input: Total assets and Equity were employed in the study. Three performance efficiency scores of constant returns to scale (CRS), variable returns to scale (VRS) and scale efficiency models were used, unlike. The result reveals that small and medium banks were more efficient than mega banks.

Depren and Depren (2016) evaluated the efficiency of twenty deposit banks in Turkey from March 2014 to March 2015 using DEA and MPI. The input and output variables were prepared using intermediation and production approach. The result of their research showed that there were 11 and 14 efficient banks in 2014 and 2015. In the intermediation approach, sectoral efficiency decreased from 1.026 in 2014 to 1.018 in 2015. Besides, there were 12 efficient banks in terms of the total productivity index of Malmquist. In the production approach, the efficiency score of the banking sector in Turkey increased from 0.916 in 2014 to 0.926 in 2015. However, the banking sector in Turkey was not efficient in terms of MPI.

Geetha, Kishore and Shivaprasad (2017) analysed the quarterly efficiencies of selected public sector and private sector banks in India for recent three-quarters of FY 2016-17 using the non-parametric performance evaluation technique of Data Envelopment Analysis. A total of 20 banks, 15 public sector, and 5 private sector banks, were selected as samples for the study. Out of sample units studied, some of the banks proved consistency in performance during the study period, and also most of the banks did not have consistency, mainly public sector banks.

Yonnedi and Panjaitan (2019) examine the efficiency and productivity change of 26 regional development banks (BPDs) in Indonesia in 2011-2016 using a non-parametric approach of data envelopment analysis (DEA). This research was started by determining input and output variables based on three approaches, i.e., intermediation, operation, and the asset approach. The Multi-stage DEA was adopted to generate the efficiency score, and the input-orientated variable return to scale (VRS) assumption is specified in data analysis. The

Malmquist Productivity Index (MPI) was used to measure the total factor productivity change indicating the improvement or deterioration of performance of BPDs over time. The multi-stage DEA result shows a significant difference in the number of efficient BPDs using the three approaches. MPI shows that the highest productivity increase was in the asset approach of 84.0%, supported by the increase in efficiency change and technological change. While in intermediation and operation approach, the increase was only 44.0% and 36.0%, depending on the increase in efficiency change and scale efficiency change.

From the review of past studies above, we can say that the use of DEA to measure the performance efficiency of banks in Sub-Saharan African countries has not been addressed intensively compare to European countries. Given the limited studies on Sub-Saharan African countries, there is need to carry out more study, the present study is therefore an attempt to seek new evidence concerning the evaluation of performance efficiency of listed banks in Sub-Saharan African countries using DEA.

Methodology

The population of the study comprises of all banks listed on the floor of Sub-Saharan Africa countries stock exchanges for the fiscal year 2014/2015. Bank level data was source from annual audited reports of the selected banks. Exchange rate for conversion was sourced from African Development Bank Statistical Bulletin. In determining the sample, the researcher set the database to select the top 20 listed banks in Sub-Saharan Africa countries. The rationale behind selecting only listed banks is that the financial data related to the publicly traded institutions are more accurate due to their adherence to more restricted rules in terms of capital, practice, governance and disclosure. The banks selected in our sample include the top ranked banks according to total assets and the bank that has a complete data set for the 2014/2015 fiscal year using purposive sampling technique. Refer to Appendix 1 to view the details of each bank's total asset and their names. The input variables of the banks are interest expenses, operating expenses, customer deposit and total asset while the output variables are interest income, profit after tax and loans and advances to customers.

Data Analysis Technique

Non parametric, non-stochastic approach developed by Charnes et al. (1978) Data Envelopment Analysis (DEA) was used to estimate the relative performance efficiency scores of the banks. For decades, Data Envelopment Analysis (DEA) has become a very popular linear programming technique used as an invaluable benchmarking tool in examining efficiency in banking industry. Leibenstein and Maital (1992) argue that DEA is the superior method for measuring overall technical inefficiency. Since the original study by Charnes et al. (1978) considerable amount of published research using DEA has been documented. The main advantage of DEA is that, unlike regression analysis, it does not require a priori assumption about the analytical form of the production function, instead it constructs the best production function solely based on the observed data, and hence statistical tests for significance of the parameters are not necessary.

Model Specification

The DEA model used is derived as follow:

$$\begin{aligned} & \sum_{r=1}^z v_r y_{r0} \\ & \max h_0(u, v) = \\ & \sum_{i=1}^m u_i x_{i0} \\ \text{Subject to} & \\ & \sum_{r=1}^z v_r y_{rj} \\ & \sum_{i=1}^m u_i x_{ij} \leq 1; j = 1, 2, \dots, n \\ & u_i \geq 0 : i = 1, 2, \dots, m \\ & v_i \leq 0 : r = 1, 2, \dots, s \end{aligned}$$

Where:

x_{ji} = the amount of input i utilized by the j th DMU

y_{rj} = the amount of output r produced by the j th DMU

u_i = weight given to input i

v_i = weight given to input r

Following the Charnes Cooper

transformation (1962), one can select a representative solution (u, v) for which

$$\sum_{i=1}^m u_i x_{i0} = 1$$

Hence, the denominator in the efficiency score h_0 shown above is set equal to one, the transformed linear programming model for DMU0 can be written as follow:

$$\max z_0 \sum_{r=1}^z v_r y_{r0}$$

Subject to

$$\begin{aligned} & \sum_{r=1}^z v_r y_{rj} - \sum_{i=1}^m u_i x_{ij} \leq 0; j = 1, 2, \dots, n \\ & \sum_{i=1}^m u_i x_{i0} = 1 \\ & u_i \geq 0 : i = 1, 2, \dots, m \\ & v_i \leq 0 : r = 1, 2, \dots, s \end{aligned}$$

The linear programming mode shown above will be run n times in identifying the relative efficiency scores of all the DMUs. Each DMU selects input and output weights that maximize its efficiency score. Generally, a DMU is considered efficient if it obtain a score of 1.00, implying 100% efficiency;

whereas a score of less than 1.00 implies that it is inefficient. Maximizing the fraction can be accomplished by minimizing the denominator of the fraction and normalizing the denominator to one (Lehman et al., 2004).

$$\text{Min } \sum_{r=1}^m u_r, x$$

Subject to:

$$\sum_{r=1}^s v_r y_r = 1$$

$$\sum_{r=1}^s v_r y_{rj} + \sum_{r=1}^m u_r x_{rj} \geq 0, \quad j = 1, 2 \dots n$$

$$v_r \geq 0 \quad r = 1, 2, \dots s$$

$$u_r \geq 0 \quad r = 1, 2, \dots s$$

The duality theory from linear programming suggests that there is a dual program for each original linear program and the solution are always equal (Gale et al., 1951).

Empirical Analysis

In this section, we examined and measured the relative performance efficiency in twenty (20) listed banks in selected Sub-Saharan African countries for the fiscal year 2015. In measuring the relative efficiency of banks listed in Sub-Saharan African countries, an efficiency score was computed using Data Envelopment Analysis

(DEA) and the STATA DEA software will be used to perform the calculation. Before conducting the DEA, we first carry out descriptive statistics and correlation matrix in order to explain the behaviour of the data set in their levels as well as identify the behavioural patterns of the individual time series data used in the study. In the DEA model, we utilized four inputs and three outputs in evaluating the relative performance efficiency of the selected listed banks in Sub-Saharan African countries. In this regard, the data set used for the input and output variables is presented in Table 1.

Table 1: Input and Output Variables used in the Analysis

INPUT	OUTPUT
Interest Expenses (INT) Operating Expenses(OPX) Customer Deposit Base(DEP) Total Asset(TAS)	Interest Income(REV) Profit After Tax(PAT) Loans and Advances to Customer(LOA)

Source: Author’s Computations (2017)

The input and output adopted in this study clearly shows that our focus is on the relative performance efficiency of selected sub-Sahara African banks in terms of how well the banks can convert interest expenses, operating expenses, customer deposit and total asset (input) into interest income, profit after tax and loans and advances to customers (output).

Descriptive Statistics

Table 2 provides the descriptive statistics(including mean, standard deviation, minimum and maximum) of the selected banks output and input variables and the descriptive statistics show the summary of data and other basic characteristics within the series.

Table 2: Descriptive Statistics for DEA Input and Output Variables

STATISTICS	INPUT				OUTPUT		
	INTEREST EXPENSES (INT)	OPERATING EXPENSES (OPX)	CUSTOMER DEPOSIT (DEP)	TOTAL ASSET (TAS)	INTEREST INCOME (REV)	PROFIT AFTER TAX (PAT)	LOANS AND ADV. CUSTOMER (GCP)
MEAN	599.39	924.00	14191.8	25958.07	1440.96	412.60	17350.58
MEDIAN	323.95	567.80	4846.98	10152.04	924.38	192.99	7415.52
MINIMUM	78.45	1.928	1893.44	4104.64	210.82	54.50	2999.50
MAXIMUM	2746.11	4314.44	75307.78	176546.9	4872.13	2054.90	87926.48
SAMPLE	20	20	20	20	20	20	20

Source: Author’s Computations from DEA STATA Output (2017)

The descriptive statistics in table 2, shows that the sampled mean of the 20 banks for the period of 2014/2015 fiscal year, on the input side, total asset was \$25,958.07 million, customer deposit was

\$14,191.8 million, operating expenses was \$924.00 million while the interest expenses was at \$599.39 million. From the total asset mean result, it shows that banks like STANDARD BANK GROUP(JSE)

had a total asset of \$176,547 million, FIRSTRAND (JSE) \$78,816 million, NEDBANK GROUP (JSE) \$74,936 million and FIRST BANK HOLDINGS (NGSE) \$26,287 million which were far above the sampled peer banks average of \$25958.07 million. This implies that the mega banks in the selected Sub-Saharan African countries in terms of asset base were STANDARD BANK GROUP(JSE), FIRSTRAND (JSE), NEDBANK GROUP (JSE) and FIRST BANK HOLDINGS (NGSE). It should be noted that among these big four in the selected sub-Saharan African countries, FIRST BANK HOLDINGS is the only Nigerian bank that has a Total asset above their peers in the region. The three other mega banks are in South Africa. Furthermore, the table shows the mean operating expenses to be \$924.00 million, while banks like Standard Bank Group, FirstRand, Nedbank and Eco bank Transnational Inc. within the selected sampled banks had operating expenses higher than the mean of all the sampled banks valued at \$4314 million, \$2760 million, \$2272 million and \$1491 million respectively. While the bank with the maximum interest expenses was Nedbank Group

valued at \$2746.11 million and the minimum interest expenses was for State Bank of Mauritius valued at S78.45.

On the output side, the average net interest income of the sampled 20 banks stood at \$1440.96 million while banks like Standard Bank Group (Jse), FirstRand (Jse), Nedbank Group (Jse), First Bank Holding (Ngse) Eco bank Transnational Inc. (Gse), Zenith Bank (Ngse) had interest income of \$4144 million, \$4144 million, \$4872 million, \$2195 million, \$1732 million, \$1897 million above the average respectively while the bank that recorded the lowest interest income was State Bank of Mauritius (Ssm) at \$211.00 million and Ned bank Group had maximum at a value of \$4872.13 million.

Correlation Matrix

In examining the relationship among the variables we employed the Pearson Correlation coefficients (correlation matrix) and the results are presented in table 3 below.

Table 3: Pearson Correlation Matrix for DEA Input and Output Variables

	INT	OPX	DEP	TAS	REV	PAT	LOA
INT	1.000000						
OPX	0.845280	1.000000					
DEP	0.925200	0.959931	1.000000				
TAS	0.799018	0.971144	0.949293	1.000000			
REV	0.976524	0.900399	0.943812	0.841871	1.000000		
PAT	0.801646	0.964591	0.939051	0.968721	0.872309	1.000000	
LOA	0.913832	0.974209	0.996526	0.963794	0.941858	0.953690	1.000000

Source: Author’s Computations from DEA STATA Output (2017)

The Pearson's correlation coefficient result in Table 3 above shows the magnitude and direction of the relationships; whether they are strong or weak and positive or negative. Another purpose of correlation is to test for the multicollinearity problem, in other words whether the variables are highly correlated with each other or not. Since most of the variables have a correlation of more than 0.7, then this signals a strong relationship between each inputs and outputs variable and hence indicates presence of significant correlation between all inputs and outputs variables. This is expected as more inputs drive outputs. The four inputs (interest expenses, operating expenses, customer deposit and total assets) shows high positive correlation with all outputs (interest income, profit after tax and loans and advances. The positive relationship between inputs and outputs is due to the fact that higher inputs generate higher outputs to the banks. As inputs rises the corresponding outputs would rise. The high correlation among the variables also implies multicollinearity among the variable. This multicollinearity among the variables would not

endanger our results in any way since they only measure association and not causality (impact).

In the light of our analysis so far, it would be difficult to ascertain the efficiency of these banks in terms of how well they have use their Asset, customer deposit, interest expenses and operating expenses (input) to generate their interest income, loan and advances to customer and profit after tax (output). This single problem necessitated the need for DEA analysis since descriptive statistics and correlation matrix cannot show their relative performance in context of weighted inputs and outputs.

DEA Analysis

The performance efficiency scores that were generated from the DEA methodology is based on the three efficiency measures; (1) **DEA Overall technical efficiency score (CRS)**: This is obtained when we assume a constant return to scale for all the sampled banks. This implies increase in bank input (total asset, customer deposit, interest

expenses and operating expense) by 1% would lead to a 1% increase in its output (interest income, loans and advances to customer and profit after tax). These neglect management skills in converting small inputs to large outputs. (2) **DEA Pure technical efficiency score (VRS)**: This is obtained when we assume a variable return to scale for all the sampled banks. This implies that increase in bank input (total asset, customer deposit, interest expenses and operating expense) by 1% would lead to more than 1% increase in its interest income, loan and advances to customer and profit after tax output. This focuses on measuring the extent to which management skills was relevant in converting small inputs to large outputs and (3) **Scale efficiency score (SCALE)**: This is the ratio

of constant return to scale to variable return to scale (CRSE/VRSE).

Constant Return to Scale (CRS) Technical Efficiency DEA Results

The DEA models involved in assessing the performance of the selected 20 banks were solved using STATA DEA software. The “overall” technical efficiency score (i.e. technical efficiency relative to the CRS DEA model) for each of the 20 banks is presented in table 4. Also presented in the table are the referenced efficient banks (peer) sets for inefficient banks as well as frequency with which a particular bank appears in the efficient sets of other banks. The CRS DEA model is based on the assumption of constant return to scale for all the sampled banks.

Table 4: Technical efficiency scores of the 20 sampled listed banks in selected Sub-Saharan African countries based on CRS DEA model

DMU NO	COMPANIES	TECRS	RANK
1	Standard Bank Group (Jse)	1	1
2	FirstRand (Jse)	1	11
3	Nedbank Group (Jse)	1	10
4	First Bank Holding (Ngse)	0.835	19
5	Eco bank Transnational Inc. (Gse)	1	9
6	Zenith Bank (Ngse)	0.856	18
7	United Bank for Africa (Ngse)	0.943	13
8	Guaranty Trust Bank (Ngse)	0.881	17
9	Access Bank (Ngse)	0.961	12
10	Diamond Bank (Ngse)	0.892	16
11	Skye Bank (Ngse)	1	1
12	Mcb Group (Ssm)	0.898	15
13	Fidelity Bank (Ngse)	1	6
14	First City Monumental Bank (Ngse)	1	7
15	Union Bank Of Nig. (Ngse)	1	3
16	Stanbic Ibtc Holding (Ngse)	1	5
17	Kenya Commercial Bank (Ngse)	0.914	14
18	Sterling Bank (Ngse)	1	4
19	Capitec Bank Holdings (Jse)	1	8
20	State Bank Of Mauritius (Ssm)	0.822	20

Source: Author's Computations from DEA STATA Output (2017)

In the table 4, we found that on the basis of CRS Technical efficiency scores (**TEcrs**), that 11 out of the 20 selected banks were efficient. This means that majority of the banks within the selected sub-Saharan countries are technically efficient. This implies that they were able to use their input (interest expenses, operating expenses, customer deposit and total asset) to generate better outputs (interest income, profit after tax and loans and advances). The results also indicate that First Bank Holding which is one of the mega banks from Nigeria was not efficient but all the three other mega banks from South Africa (Standard Bank

Group, FirstRand and Nedbank Group) were efficient.

Following the above analysis, we therefore suggest that hypotheses one (**H1; Banks within the selected sub-Saharan countries are technically inefficient under a constant return to scale assumption**) in this study should be rejected.

Variable Return to Scale (VRS) Technical Efficiency DEA Results

The “pure” technical efficiency score (i.e. technical efficiency relative to the VRS DEA model) for

each of the 20 banks is presented in Table 5. Also presented in the table are the referenced efficient banks (peer) sets for inefficient banks. The VRS DEA model is based on the assumption of variable return to scale for all the sampled banks. This implies increases in bank input by 1% can lead to a

more than 1% increases in its output. This implies that management skills in converting small inputs to large outputs are captured by the VRS DEA model. The VRS DEA results are presented in table 4 and discuss below;

Table 5: Technical efficiency scores of the 20 sampled banks listed in Sub-Saharan African Countries based on VRS DEA model

DMU NO	COMPANIES	TEvrs	RANK
1	Standard Bank Group (Jse)	1	1
2	FirstRand (Jse)	1	13
3	Nedbank Group (Jse)	1	12
4	First Bank Holding (Ngse)	0.928	18
5	Eco bank Transnational Inc. (Gse)	1	11
6	Zenith Bank (Ngse)	0.997	14
7	United Bank for Africa (Ngse)	0.967	16
8	Guaranty Trust Bank (Ngse)	0.888	20
9	Access Bank (Ngse)	1	10
10	Diamond Bank (Ngse)	0.894	19
11	Skye Bank (Ngse)	1	1
12	Mcb Group (Ssm)	0.991	15
13	Fidelity Bank (Ngse)	1	7
14	First City Monumental Bank (Ngse)	1	8
15	Union Bank Of Nig. (Ngse)	1	3
16	Stanbic Ibt Holding (Ngse)	1	5
17	Kenya Commercial Bank (Ngse)	0.932	17
18	Sterling Bank (Ngse)	1	4
19	Capitec Bank Holdings (Jse)	1	9
20	State Bank Of Mauritius (Ssm)	1	6

Source: Author's Computations from DEA STATA Output (2017)

In the Table 5 above, we found that on the basis of VRS Technical efficiency scores (TEvrs), that thirteen (13) banks out of the 20 sampled banks were efficient while 7 banks were found to be inefficient. The results also indicate that first bank which is one of the mega bank from Nigeria was not efficient but the three mega banks from south Africa were efficient. The thirteen (13) efficient banks that were able to use their Asset, customer deposit, interest expenses and operating expenses (input) to generate better output (interest income, loans and advances to customer and profit after tax) are State Bank of Mauritius (Ssm), Capitec Bank Holdings (Jse), Sterling Bank (Ngse), Stanbic Ibt Holding (Ngse), Union Bank Of Nig. (Ngse), First City Monumental Bank (Ngse), Fidelity Bank (Ngse), Skye Bank (Ngse), Access Bank (Ngse), Eco bank Transnational Inc. (Gse), Nedbank Group (Jse), FirstRand (Jse) and Standard Bank Group (Jse). This implies that these banks used fewer

inputs to produce relative better output compared to other sampled banks. This in other words, means that management of these banks was successful in using their relatively small input resources to generate better income. In the same results we also observed that other banks (Zenith Bank, United Bank for Africa, Guaranty Trust Bank, Diamond Bank, Mcb Group and Kenya commercial bank) in the sample on the VRS DEA model were inefficient in converting their input to better output as compared to some of their peers. Thereby creating slacks or under-utilization.

Following the above analysis, we therefore suggest that hypotheses two (**H2; Banks within the selected sub-Saharan countries are technically inefficient under a variable return to scale assumption**) in this study should be rejected since we found thirteen (13) banks among our sampled banks to be efficient.

Scale Efficiency DEA Results

Following the above, we learned that overall technical efficiency (CRS DEA model) is based on relative efficiency in terms of using the right scale of operation combined with managerial skill while also the pure technical efficiency (VRS DEA model) shows the success of bank management at input to output “conversion”. The scale efficiency which is the ratio of overall technical efficiency (TEcrs) to pure technical efficiency (TEvrs) measures how much a bank can improve its efficiency by being projected from VRS to CRS, that is the ability to further increase its outputs.

This reflects the efficiency of the bank irrespective of whether it operate the at the right returns to scale or not. For a bank to become scale efficient it should increase its output further to reach the most productive scale size. In table 5 below, we found out that on the basis of scale efficiency scores (TEcrs/TEvrs) that eleven (11) of the sampled banks were scale efficient. This means that a good number of the banks were able to use their input to generate better outputs under both VRS and CRS DEA assumptions. The results of the scale efficiency are presented in Table 6 below;

Table 6: Scale efficiency scores of the 20 sampled banks based on DEA model

DMU NO	COMPANIES	TEcrs	TEvrs	Scale
1	Standard Bank Group (Jse)	1	1	1
2	FirstRand (Jse)	1	1	1
3	Nedbank Group (Jse)	1	1	1
4	First Bank Holding (Ngse)	0.835	0.928	0.899
5	Eco bank Transnational Inc. (Gse)	1	1	1
6	Zenith Bank (Ngse)	0.856	0.997	0.857
7	United Bank for Africa (Ngse)	0.943	0.967	0.975
8	Guaranty Trust Bank (Ngse)	0.881	0.888	0.992
9	Access Bank (Ngse)	0.961	1	0.961
10	Diamond Bank (Ngse)	0.892	0.894	0.997
11	Skye Bank (Ngse)	1	1	1
12	Mcb Group (Ssm)	0.898	0.991	0.906
13	Fidelity Bank (Ngse)	1	1	1
14	First City Monumental Bank (Ngse)	1	1	1
15	Union Bank Of Nig. (Ngse)	1	1	1
16	Stanbic Ibt Holding (Ngse)	1	1	1
17	Kenya Commercial Bank (Ngse)	0.914	0.932	0.979
18	Sterling Bank (Ngse)	1	1	1
19	Capitec Bank Holdings (Jse)	1	1	1
20	State Bank Of Mauritius (Ssm)	0.822	1	0.822

Source: Author’s Computations from DEA STATA Output (2017)

Following the above analysis, we therefore suggest that hypotheses three (**H3; Banks within the sub-Saharan countries are scale inefficient**) in this study should be rejected since we found a good number of the banks among our sampled banks to be efficient under both constant and variable return to scale assumptions.

Conclusion and Recommendations

This study empirically examines the relative performance efficiency of selected listed banks in Sub-Saharan African countries for a period of one year (2014/2015 fiscal year). We used a sample of the 20 largest listed banks in selected Sub-Saharan African countries based on total asset as revealed by their audited annual financial report for the

period under study. The Non-parametric methodology known as Data Envelopment Analysis (DEA) was employed to evaluate the relative efficiency of these sampled banks under the assumptions of constant return to scale (CRS), variable return to scale (VRS) and scale efficiency (SE) score. A bank with a score of 1 is efficient, while a score below 1 means the bank is inefficient. Descriptive statistics and correlation analysis were also conducted. The findings of the study revealed that 11 banks out of the 20 in our sample within the period under study were efficient based on constant return to scale (CRS), while 13 are variable return to scale (VRS) efficient whereas, 11 banks were scale efficient. This means that majority of the banks in the banking industry in selected Sub-Saharan African countries are being successful in converting their inputs to outputs. However, some of the banks, like First Bank Holdings, Zenith Bank, United Bank for Africa, GTB, Diamond Bank, Mcb Bank and Kenya Commercial Bank were not efficient either on CRS, VRS and SE.

Based on our findings, the following recommendations are enunciated:

1. The government and relevant regulatory bodies should continue to provide the necessary operating environment that will enhance the operation of the banks.
2. Some of the banks, like First Bank Holdings, Zenith Bank, United Bank for Africa, GTB, Diamond Bank, Mcb Bank and Kenya Commercial Bank should realigned their operations so that they can be efficient, as they are not currently efficient in either on CRS, VRS and SE. The operation of efficient banks can be studied.
3. It is essential that the regulatory and supervisory authorities in the selected Sub-Saharan African countries to formulate and implement monetary policies that are effective in helping the banks to improve their operations, thereby leading to efficiency in resource allocation and utilization.
4. For the banks that are inefficient, the management need to reallocate their resource input.

References

- Allen, L. & Rai, A. (1996). Operational efficiency in banking: An international comparison. *Journal of Banking and Finance*, 20, 655-672
- Altunbas, Y. & Molyneux, P. (1996). Economics of scale and scope in European banking. *Applied Financial Economics*, 6, 367-375
- Angelidis, D. & Lyroudi, K. (2006). Efficiency in the Italian banking Industry: Data Envelopment Analysis and Neural Networks. *International Research Journal of Finance and Economics*. Issue 5
- Ayadi, O.F., Adebayo A.O. & Omolehinwa E. (1998). Bank performance measurement in a developing economy: An application of data envelopment analysis. *Managerial Finance*, 24(7).
- Bikker, J.(2001). Efficiency in the European banking industry: An exploratory analysis to bank countries. *Cahiers Economiques de Bruxelles*, 172, 3-28
- Casu, B. & Molyneux, P. (2003). A comparative study of efficiency in European banking. *Applied Economics*, 35, 65-76
- Casu, B., Girardone, C. & Molyneux, P. (2004). Productivity change in European banking: A comparison of parametric and non-parametric approaches. *Journal of Banking and Finance*, 28(10), 21-40
- Charnes, A. & Neralic, L. (1990). Sensitivity analysis of the additive model in data envelopment analysis. *European Journal of Operations Research*, 48, 332-341
- Charnes, A., Cooper, W., Lewin, A.Y., Morey, R.C. & Rousseau, J. (1985). Sensitivity and stability analysis in data envelopment analysis. *European Journal of Operation Research*, 2, 139-156.
- Charnes, A., Cooper, W.W. & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operation Research*, 2, 429-444
- Charnes, A., Cooper, W.W., Seiford, L. & Stutz, J. (1982). A multiplicative model for efficiency analysis. *Socio-Economic Planning Sciences*, 16(5), 223-228
- Coelli, T. (1996). A guide to DEAP version 2.1: A Data Envelopment Analysis (computer) program. *Australia CEPA Working Paper* 96/08
- Cummins, J. D., Weiss, M. A., Xie, X. & Zi, H. (2010). Economies of scope in financial services: A DEA efficiency analysis of the US insurance industry. *Journal of Banking & Finance*, 34(7), 1525-1539.
- Daraio, C. & Simar, L., (2007). *Advanced robust and nonparametric methods in efficiency analysis: methodology and applications*. New York: Springer.
- Depren, S. K., & Depren, O. (2016). Measuring efficiency and total factor productivity using data envelopment analysis: An empirical study from banks of Turkey. *International Journal of Economics and Financial Issues*, 6(2), 711-717.

- Fadiran, T.P., Ogwumike, F.O. & Adenegan, K.O. (2010). Evaluating relative efficiency of insured banks in Nigeria. *Journal of Banking*, 4(1), 77-93
- Farrel, M.J. (1957). The measurement of production efficiency. *Journal of the Royal Statistical Society*, Series A120: 253-281
- Favero, C. & Papi, L. (1995). Technical efficiency and scale efficiency in the Italian banking sector: A non – parametric approach. *Journal of Applied Economics*, 27, 385-95
- Fernandez, A.I., Gascon, F. & Gonzalez, E. (2002). Economic efficiency and value maximisation in banking firms, Working Paper March 2002.
- Geetha, E., Kishore, L., & Shivaprasad, S. P. (2017). Quarterly performance benchmarking of selected banks in India – A DEA approach. *International Journal of Pure and Applied Mathematics*, 117(20), 676 - 691.
- Hasan, T., Lozanne-Vivas, A. & Pastor, J. (2000). Cross border performance in European banking, Frankfurt, Germany: *Competition Among Banks: Good or Bad?* April
- Kneip, A., Simar, L. & Wilson, P. W. (2008). Asymptotics and consistent bootstraps for DEA estimators in non-parametric frontier models. *Econometric Theory*, 24(06), 1663-1697.
- Kourenti, M. (2006). How Efficient are the Nordic Banks ? A DEA Application for the years 2002-2003 An Unpublished Master's Thesis in Industrial and Financial Economics, School of Business, Economics and Law. Goteborg University.
- Kumar, S., & Gulati, R., (2008). An examination of technical, pure technical, and scale efficiencies in Indian public sector banks using data envelopment analysis. *Eurasian Journal of Business and Economics* 2008, 1 (2), 33-69.
- Kuosmanen, T. & Kortelainen, M. (2010). Stochastic non-smooth envelopment of data: Semi-parametric frontier estimation subject to shape constraints. *Journal of Productivity Analysis*, 1-18.
- Maudos, S.J. (2002). Cost and profit efficiency in European banks, *Journal of International Financial Markets. Institutions and Money*, 12(1), 33-58.
- Mohammad, F. M. B., Aryanezhadb, S. E. N. & Naser S., (2011). An empirical study on measuring the relative efficiency using DEA method: A case study of bank industry. *Management Science Letters*, 1, 49 – 56.
- Omankhanlen, A. E. (201). Nigerian bank efficiency performance: A post 2004 banking reforms, Unpublished PhD Thesis. Covenant University: Department of Banking and Finance.
- Schure P., Wagenvoort P. & O'Brien D. (2004). The efficiency and conduct of European banks: Development after 1992. *Review of Financial Economics*, 13(4), 371-96
- Simar, L. & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. *Management Science*, 44(1), 49-61.
- Charnes A. (1976) *Data Envelopment Analysis: Theory, Methodology and Applications*, Boston: Kluwer Academic Press
- Simar, L. (2007). How to improve the performances of DEA/FDH estimators in the presence of noise? *Journal of Productivity Analysis*, 28(3), 183-201.
- Yonnedi and Panjaitan (2019). Efficiency and productivity analysis of Indonesian regional development banks: Multi-stage dea approach and malmquist productivity index. *Jurnal Bisnis dan Manajemen*, 20(2), 145-174