IOSR Journal of Business and Management (IOSR-JBM)
e-ISSN: 2278-487X, p-ISSN: 2319-7668. Volume 16, Issue 7. Ver. IV (July. 2014), PP 50-64
www.iosrjournals.org

"Evaluating Efficiency of Commercial Banks in Tanzania and identifying efficiency drivers"

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Abstract: *Using data envelopment analysis (DEA), the purpose of this paper is to evaluate the efficiency of commercial banks operating in Tanzania in the year 2006 to 2013. The empirical findings reveal that, banks operate at 95.9% level of efficiency i.e. inputs could be reduced by 4.1% without sacrificing output if all banks were efficient as benchmark banks identified by DEA. The observed inefficiency of banks is due to poor input utilization i.e., managerial inefficiency. Large banks found to be the most efficient banks. The multivariate regression analysis using Tobit analysis highlights that; asset quality, management efficiency and liquidity are the most significant determinants of banks efficiency.*
Keywords: *Bank efficiency, Data envelopment analysis (DEA), Bank specific factors, Tobit analysis*

I. Introduction

The stability and development of an economy is dependent upon the performance of financial sector. Banking sector is the vital part of country's financial system, and thus for sound economical development, banks efficiency is crucial (Sathye, 2001: Gishkori and Ullah, 2013). Measuring the efficiencies of banks can give a resourceful insight into banking system and potential of economic development of a country. In analysisng banking system efficiency, the most important question which should stick in mind of researchers that, why regulators, shareholders, managers and customers bother about banks' performance? The answers of this question would be different depending upon the perspectives of interested parties. From the regulators' perspective, inefficiency banks are riskier and have a higher likelihood of failure. Further, efficiency banking system is directly accelerating the productivity of the economy. Without a sound and efficiently functioning banking system, the economy cannot function smoothly and efficiently (Kumar and Gulati, 2008). From the view of shareholders need to be ensured that, bank value is maximized and rewarded reasonable returns, is that only efficient banks ensure reasonable returns. From the standing point of customers, only efficient banks can offer better quality services at reasonable costs. The standing point of bank management is that in a dynamic and competitive market environment, only efficient banks will survive and maintain their market share, and products positioning, and inefficient ones will eventually not compete and survive in the market. The efficient banks are able to compete because of their lower operational costs and can steal business away from less efficient banks. Thus to improve the banks performance, evaluating its efficiency and identifying the sources of inefficiency is always a matter of serious interest (Yang, 2011)

Tanzania has introduced regulatory reforms to its financial-services sector since 1991, the expected result of these changes in financial reforms were to increase competition in banking sector, which was also expected to lead to an improvement in efficiency of banking system and contribute the progress of economic development. Despite the literature on bank efficiency and benchmarking are widely used methods to identify the best practices, as a means to improve the performance and increase productivity (Barros, 2004) studies on efficiency of the Tanzanian banks is virtually non-existent. The main reason for this deficit is the lack of data on the Tanzanian banking system to carry out meaningful analysis, thus little is known about banks efficiency in Tanzania. Measuring Tanzanian banks efficiency is an important issue for regulators, shareholders and managers alike, in addition, efficiency bank is offered professional services at reasonable costs to customers (Anderson et al., 1998). DEA approach is widely used to evaluate bank efficiency in US and Europe (Rickards, 2003). However, DEA approach is less known within the banking sector in developing countries, and Tanzania is no exception. In this study, we fill this research gap in the literature by analysing the efficiency of commercial banks with respect to developing countries and transition economies using data of the Tanzanian banks where there has been virtually no previous research. In this paper, we analyse the efficiency of a representative sample of large, medium and small commercial banks in Tanzania with a two-stage procedure. In the first stage, the DEA model used to calculate efficiency scores. The DEA approach was used in this paper because, this technique has been used since "recent researches have suggested that the kind of mathematical programming procedure used by DEA for efficient frontier estimation is comparatively robust" (Seiford and Thrall, 1990). Since introduction of DEA by (Charnes et al. 1978), large number of researches have extended and used the

DEA methodology (Coelli, 1996). More importantly, Tobit regression model used in this paper to provide an in-depth analysis of the sources of banks efficiency by studying the factors that may influence banks efficiency.
The present research is an endeavour in this direction, and particularly aims to

- Assess the efficiency of the Tanzanian commercial banks using 2006 -2013 operating data; and set the targets for the inefficient banks so that they can become efficient by adjusting their inputs and outputs
- Decompose the measure of overall technical efficiency (OTE) into its components, namely PTE and SE; and
- Explain the significant factors affecting banks efficiency by using Tobit regression analysis.

The remainder of the paper structured as follows. Section, 2 reviews of relevant literature on banks efficiency, section 3 summarizes the methodology used to conduct the analysis; the subsequent section presents empirical results of the study and finally presenting the conclusions, managerial implications, limitations and Future research.

II. Litrature review

Data Envelopment Analysis (DEA) method has been used extensively to analyze banking institutions. Well established efficiency literature has been mainly carried out in developed nations like the US and Europe. Berger and Humphrey (1997) provide a valuable summary on 130 studies of financial sector efficiency in 21 countries during different times using different estimation techniques, in their studies, they find that results from various efficiency methods are inconsistent. Sathye (2001) employed DEA approach to investigate the technical and allocative efficiency of Australian banks, the Australian banks found to have low levels of overall efficiency compared with the banks in the European countries and in the US. Domestic banks found to be more efficient than foreign owned banks and the source of overall inefficiency contributed by technical inefficiency. Grabowski et al (1994) examined the US multi-bank holding companies and branching banks by using Data Envelopment Analysis (DEA) approach, the study found that, on average input inefficiency of the US multi-bank holding companies and branching banks was about 68%. Pastor et el (1997) employed non- parametric approach, DEA by using three outputs (loans, other productive assets, and deposits) and two inputs (non-interest expenses and personal expenses), comparing the productivity, efficiency, and differences in the technology of different in European and U.S. banking sector for the year 1992. The results of the study found that, there was a difference in the efficiency level of the banking systems among the countries. The most efficient banks were in France, Spain, and Belgium, while the less efficient banks were in the U.K. Austria, and Germany. Wu (2007) employing DEA approach and Malmquist productivity index examined the efficiency and productivity performance of Australian banking sector during the post-deregulation period of 1983 to 2001. The results of the study showed that, major banks and existing regional banks found to be the least and the second least efficient groups, respectively while foreign banks and newly licensed regional banks showed superior performance. Miller and Noulas (1996) analyzed the efficiency of large banks in US and found the overall technical efficiency of banks is around 97 percent. Seiford and Zhu (1999) evaluated the efficiency of the top 55 US banks using a two-stage DEA approach. They found that, large banks exhibit better performance on profitability, whereas smaller banks tend to perform better with respect to marketability. Berg et al. (1993) employed DEA expanded the Norwegian study to an international comparison by including Finish and Swedish banking industries, the results indicated that, Swedish banks were more efficient than other two countries. Ramanathan (2007) examined performances of 55 banks operating in countries of the Gulf Cooperation Council (GCC) employed DEA and Malmquist productivity index using two outputs and four inputs, the results show that only 15 of the 55 banks are rated as efficient under constant returns to scale (CRS) assumption, and all the GCC countries have at least one efficient bank. Latter Mostafa (2007) employing DEA approach to investigate the relative efficiency of the top 50 GCC banks, the results indicated that, the performance of several banks in the regional is sub-optimal and suggested the potential for significant improvements was by possible reductions in resources used. Bhattacharya et al. (1997) using a two-stage DEA method to evaluate the effect of liberalization on the efficiency of the banking sector in India found that, in India publicly owned banks are the most efficiency banks followed by foreign owned banks and then Indian privately owned banks. Sathye (2003) using DEA measured the productive efficiency of three groups of banks in India, the results found that, the mean efficiency score of Indian banks compared well with the world mean efficiency score and the efficiency of private owned Indian commercial banks as a group was lower than that of public sector banks and foreign banks.

From this brief review, the evidences have shown that, an extensive and sprawling literature on the banking efficiency using non-parametric frontier exists for developed economies. However, DEA approach is less known within the banking sector in developing countries, and Tanzania is no exception. In this study, we aim to fill this research gap by empirically evaluating banks' efficiency in Tanzania

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III. Methodology

The paper adopted two-stage procedures to benchmark the banks. In the first stage, DEA model used to evaluate relative efficiency scores and in the second Tobit regression employed to estimate the efficient drivers. In this paper, we used the input-oriented CCR model named after Charnes et al. (1978), to get a scalar measure of OTE. We also applied the input-oriented BCC model named after Banker et al. (1984), to obtain the PTE (also known as managerial efficiency). Formal notations of used input-oriented CCR and BCC DEA models for measuring efficiency scores for DMU o, under the different scale assumptions are as follows:

$$\max ho(u,v) = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{n} v_i x_{io}} \tag{1}$$

Subject to:

$$\frac{\sum_{i=1}^{n} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \qquad \text{j=1, 2… n} \tag{2}$$

$$u_r \geq 0 \qquad \text{r=1, 2…s} \tag{3}$$

$$v_i \geq 0 \qquad \text{i=1, 2…m.} \tag{4}$$

Where x_{ij} is the observed amount of input ith of the jth DMU ($x_{ij} > 0$, I = 1, 2 …n, i= 1, 2…n) and y_{ij} = observed amount of output of the rth type for the jth DMU ($y_{ij} > 0$, r = 1, 2…3, j = 1, 2…n)

The above ratio form yields an infinite number of solutions; if (u*, v*) is optimal, then (αu*, αv*) is also optimal for α > 0. However, the transformation developed by Charnes and Cooper (1962) for linear fractional programming selects a representative solution [i.e., the solution (u, v) for which = 1] and yields the equivalent linear programming problem in which the change of variables from (u, v) is a result of the Charnes-Cooper transformation one can select a representative solution (u, v) for which:

$$\sum_{i}^{m} v_i x_{io} = 1 \tag{5}$$

To obtain linear programming problem that is equivalent to linear fractional programme problem (equations 1- 4). Thus, denominator in the above efficiency measure h_o is set to equal to 1 and transformed linear problem for DMU_O can be written as:

$$\max z_o = \sum_{r=1}^{s} u_r y_{ro} \tag{6}$$

Subject to:

$$\sum_{r=i}^{s} u_r y_{rj} - \sum_{i=1}^{n} v_i x_{ij} \leq 0 \qquad \text{j= 1, 2…n} \tag{7}$$

$$\sum_{i=1}^{m} v_i x_{io} = 1 \tag{8}$$

$$u_r \geq 0, r = 1,2...s$$

$$v_i \geq 0, i = 1,2...m$$

For which the Linear Programming dual problem is

$$Min\ z_o = \theta$$

Subject to:

$$\sum_{j=1}^{n} \lambda_i y_{rj} \geq y_{ro} \qquad \text{r=1, 2,...s} \tag{9}$$

$$\theta_o x_{io} - \sum_{j=i}^{n} \lambda_i x_{ij} \geq 0 \qquad \text{j = 1, 2...n} \qquad (10)$$

Both the above linear problem yield the optimal solution θ which is the efficiency score (so-called technical efficiency) for the particular DMU_o and repeating them for each DMU_j, j= 1, 2…n, efficiency scores for of them are obtained. The above θ is always less than or equal to unity (since when tested, each particular DMU_o is constrained by its own virtual input-output combination too). DMU_s for which θ is less than unity are relatively inefficient and for which θ is equal to unity are relatively efficiency, having their virtual input-output combination points laying on the frontier. The frontier itself consists of linear facets spanned by efficient units of the data and the resulting frontier production function (obtained with the implicitly constant return to scale assumption) has unknown parameters.

The CRS assumption is only appropriate when all DMUs are operating at an optimal scale, meaning that, one corresponding to the flat of the long run average cost (LRAC). However, imperfect competitions, constraints on finance and other factors may result a DMU to be not operating at optimal scale. Banker, Charnes and Cooper (1984) suggest an extension of the CRS DEA model to account for Variable Return to Scale (VRS) situations. The use of the CRS specification when not all DMUs are operating at the optimal scale will result of TE, which confounded by scale efficiencies (SE). Hence, the use of the VRS specification will permit the calculation of TE devoid of these SE effects. The CRS linear programming problem easily modified to account for VRS by adding the convexity constraint

$\sum\lambda = 1$

Since there are no constraints for the weight λ_j, other than the positivity conditions in the problem (9 – 10), it implies constant return to scale, it is necessary to add the convexity condition for the weight λ_j i.e. to include in the model (9 – 10) the constraint.

$$\sum_{j=1}^{n} \lambda_i = 1 \qquad (11)$$

The resulting DEA model that exhibits the Variable Return to Scale (VRS) called BCC model (Banker, Charnes and Cooper 1984). The input-oriented BCC model for the DMU_o written formally as:

$$Min\ z_o = \theta$$

Subject to:

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro} \qquad \text{r = 1, 2…s} \qquad (12)$$

$$\theta_o x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0 \qquad \text{i = 1, 2…m} \qquad (13)$$

$$\sum_{j-1}^{n} \lambda_j = 1 \qquad (14)$$

$$\lambda_j \geq 0 \qquad \text{j = 1, 2…n} \qquad (15)$$

Running the above model for each DMU, the BCC efficiency scores obtained (with similar interpretations of its values as in CCR model). These scores are also called 'Pure technical efficiency scores' since they are obtained from model that allows variable returns to scale (VRC) and hence eliminate 'the scale part' of the efficiency from analysis. Generally, for each DMU the CCR-efficiency score will not exceed the BCC efficiency score, what is intrusively clear since in the BCC-model each DMU is analysed ' locally' i.e. compared to subset of DMUs, that operate in the same region of return to scale rather than globally.

3.1 Selection of inputs and outputs

Substantial studies conducted around the issues of banks efficiency. Besides, inputs and outputs used by these studies published in the literature vary widely. In evaluating banks efficiency, the most difficult task that researchers always face is to select the relevant inputs and outputs for modeling bank behaviour. It well known that, no general agreement exists about either the definition or the choice of relevant outputs and inputs in the banking industry (Casu and Girardone, 2002; Sathye, 2003: Ray and Mukherjee 1998). In Table I, we present a summary of inputs and outputs used in the various papers published on banks efficiency using DEA. In the literature, the inputs and outputs used in evaluating of banks efficiency can be defined by using different five approaches: intermediation approach, production approach, asset approach, user cost approach and value added approach. However, production approach and intermediation approach used more frequently for measuring of banks efficiency in banking industry. The production approach addresses physical inputs, such as capital and labour and treats a bank as firms producing different deposits and loan accounts. Banks deal with transactions and document for its customers who own these accounts. The number of accounts and transactions regarded as the best measures of the bank output; to some extent, this is not practical. In practice, the number of deposit and loan account usually used as the measure of bank output rather than the detailed in transaction and documents (Ferrier and Lovell, 1990). The intermediation approach (Sealey and Lindley, 1997), treats banks as financial intermediaries that channels funds between depositors and creditors in the bank production process, the value of bank loans and investment are thought as output, while labor, deposits, total expenses and capital are treated as inputs.

Neither of these two approaches is perfect for measuring of banks efficiency because they cannot fully capture the dual role of banks as providers of transactions/document processing services and being financial intermediaries. However, it suggested that the intermediation approach is best suited for analyzing bank level efficiency and the production approach well suited for measuring branch level efficiency. This is because, at the bank level, managers aim to reduce total costs and not only non-interest expenses, while at the branch level a large number of customer service processing take place and bank funding and investment decisions are mostly not under the control of branches. In practice, the availability of flow data required by the production approach is usually exceptional rather than in common. Thus, majority of the empirical literature adopted the intermediation approach as opposed to the production approach for selecting input and output variables for computing the various banks efficiency scores.

Table 1: A summary of inputs and outputs considered in selected DEA studies on bank efficiency analysis

Author(s)	Inputs	Outputs
Bhattacharyya et al. (1997)	Interest Expense	Advances
	Operating Expense	Deposits
Darrat et al. (2002)	Labour	Loans
	Capital	Investments
	Deposits	
Seelanatha (2012)	interest expenses,	loans and advances
	personnel costs	interest income
	establishment expenses	
Fukuyama and Weber (2002)	Labour	Loans
	Physical capital	Security investments
	Funds from customers	Other income bearing assets
Grifell-Tatje´ and Lovell (1999)	deposits and other liabilities	value of loans
	Employees	financial investments
	Average fixed assets	Deposits
Seiford and Zhu (1999)	Stage 1	Stage 1
	Employees	Revenue
	Assets	Profit
	Equity	Stage 2
	Stage 2	Market value
	Revenue	Total return to investors
	Profit	
Sathye (2003)	Model A	Model A
	Interest expenses	Net interest income
	Non-interest expenses	Non-interest income
	Model B	Model B
	Deposits	Net loans
	Staff numbers	Non-interest income

Source: literature review

Depending upon, the literature reviewed and the dominant role of intermediation function of banking system in Tanzania lead this study to adopt intermediation approach for the analysis which, was originally developed by Sealey and Lindley (1977). The selected variables for measuring banks efficiency scores shown in table 2, inputs variables are i) total deposits ii) number of employees iii) total expenses The outputs used for computing the efficiency scores are i) total loans ii) total interest income

Table 2: Data variables selected for DEA Models

Inputs	Authors
Total deposits (x_1)	Grifell-Tatje´ and Lovell (1999): Darrat et al. (2002): Fukuyama and Weber (2002: Seiford and Zhu (1999):
Number of employees (x_2)	Darrat et al. (2002)
Total expenses (x_3)	Bhattacharyya et al. (1997): Seelanatha (2012)
Outputs	
Total loans (y_1)	Sathye (2003): Seelanatha (2012)
Total interest income (y_2)	Seelanatha (2012): Sathye (2003)

Source: literature review

3.2 Determinants of Banks' Efficiency

Regulators and banks managers are normally interested to know about the factors attributing the efficiency differences among banks. In the present study, we have considered six important determinants, which may exert influence banks efficiency. Literatures identify the drivers that influence the efficiency of banks. Some studies examine only bank internal (specific) factors and others examine both bank internal and external determinants.

Based on previous studies this study examined only bank-specific variables. The reason behind this type of variables is controllable by the banks. Thus, the banks managers are able to alter the bank's efficiency level by controlling the variables that has significant relationship with the bank efficiency. We decided to use capital strength as a proxy of capitalization, loan quality as a proxy of asset quality, expenses as a proxy of management capability, profitability (ROA & NIM) as a proxy of earning robustness, and liquidity as a proxy of liquidity management to identify the determinants of bank efficiency and its relationship. Each of these independent variables discussed in turn.

Capital strength: Capital is the ratio of book value of equity to total assets (Equity/ TA). The past literatures have proven that bank efficiency is associated with equity-to-total asset ratio (Kaparakis et al., 1994; Esho, 2001).

Asset Quality: The quality of assets held by a bank depends on exposure to specific risks, trends in nonperforming loans, and the health and profitability of bank borrowers. Poor asset quality and low levels of liquidity are the two major causes of bank failures. Poor asset quality led to many bank failures (Olweny and Shipo, 2011). For the purpose of this study, non-performing loan to total loan ratio (NPL) used to measure asset quality.

Management quality: The ratio of non-interest expenses to average assets is the ratio that more frequently used on studies of bank efficiency in measuring the management quality (Kosmidou et al, 2006). The ratio measures the magnitude of administrative expenses; banks the higher the ratio, the higher the bank management risks, and the less efficient the bank be;

Profitability: Profits defined to be the ratio of total revenue to total assets. Referring to literature search, ROA commonly used on research of bank efficiency in measuring the profitability of banks compare ROE. In this study, we choose to use ROA in measuring the profitability of the banks. Net interest margin (NIM): This variable defined as the difference between interest income and interest expenses divided by total assets.

Liquidity: It is the ratio of loans to deposits. It assesses a bank's ability to transform deposits into loans. This variable expected to have a positive effect on efficiency. The higher this ratio, the more efficient the process of financial intermediation provided by the bank. Vu and Turnell (2011) found a positive and statistically significant relationship between liquidly ratio and efficiency, which indicates that the banks with a higher ability to transform deposits into loans would be more efficient. The data for independent variables selected for this study is shown in table 3

Table 3: Data variables selected for Tobit Model

Variables	Authors
Capital strength	Kaparakis et al., 1994): Esho, 2001: Chan and Liu, 2006)
Asset Quality	(Olweny and Shipo, 2011: Kumar and Gulati, 2008)
Management quality	(Kosmidou et al, 2006)
Liquidity:	Vu and Turnell (2011)
ROA	(Ahmad ,2011:Khizer at el 2011: Kumar and Gulati, 2008))
NIM	(Gwahula R, 2013):

Source: literature review

Table 4 provides a summary of the descriptions of the variables and their expected effect on banks efficiency. We hypothesize that capital strength; profitability and liquidity have positive effect on bank efficiency, while the poor asset quality (i.e., larger volume of non-performing in relation to total loans) and management quality have a negative effect on banks efficiency.

Table 4: Description and expected sign of the variables

Variables	Symbol	Descriptions	Expected Sign
Capital strength	EQTA	Equity/Total Assets	+
Asset Quality	NPL	NP/Total loans	-
Management quality	NIE	NIE/Average Assets	-
Liquidity	LD	Loans/ Deposits	+
Profitability	ROA	Net profit/Total Assets	+
Profitability	NIM	NI/Total Assets	+

Source: Authors

3.3 The Model

Based on the preceding theoretical explanation, this study specified the empirical model in equation (16) in order to study the impact of each determinant of efficiency it identified for banks in Tanzania and that factor's significance. The approach involves solving a DEA problem in a first stage analysis, involving only the traditional inputs and outputs; and then in the second stage, the efficiency scores from the first stage regressed upon bank specific variables. This method conducted by using the Tobit regression model because it can account for truncated data (Casu and Molyneux, 2003). The Tobit model is the most suitable when the dependent variable is limited or censored from below, above, or both. The use of OLS regression on such a censored distribution produces biased estimates and invalid inferences (Maddala, 1983; Greene, 1997). Instead, Tobit regression known to be more appropriate for censored dependent variables (Tobin, 1958; Wooldridge, 2006). The advantages of Tobit regression model are as follows: it adjusts the underestimation of coefficients; therefore, it can discover predictors that are more significant especially when the effect sizes are small; and it explains more variances in the dependent variable than OLS model does. DEA scores are limited to the interval [0; 1]. The two-limit Tobit model provides sensible estimates of the DEA scores. The original Tobit regression model, which referred to as censored regression model with reference to (Tobin 1958) who first proposed the model) specified generally in terms of the indexed function as

$$y_i^* = \beta_1 + \beta_2 X_{2i} + ...\beta_k X_{ki} + \mu_i \tag{16}$$

$$y_i = 0 \quad if \quad y_i^* \leq 0 \quad and$$

$$y_i = y_i^* \quad if \quad y_i^* \geq 0$$

Then, likelihood function maximized, to obtain the values for the coefficients and variance of the explanatory variables based on the observed values of the explanatory variables and the efficiency scores.

$$L = \prod_{y_o=0}(1 - P_o) \prod_{yo\succ 0} \frac{1}{(2\Pi\delta^2)^{0.5}} xe\left[\frac{1}{2\delta^2}\right](y_o - \beta_{xo})^2 \tag{17}$$

Where:

$$P_o = \int_{\infty}^{\beta x_o} \frac{1}{(2\Pi)^{0.5}} xe^{-t^2/2} dt$$

We can therefore extend the above equation, by including explanatory variables and efficiency estimates score as dependent variables as follows.

$$\Theta_{it} = \alpha_{it} + \beta_1 (EQTA_{it}) + \beta_2 (NPL_{it}) + \beta_3 (NIE_{it}) + \beta_4 (ROA_{it}) + \beta_5 (NIM_{it}) + \beta_5 (LD_{it}) + \mathcal{E}_{it}$$

Where, Θ_{it} indicates the efficiency scores, EQTAit indicates Capital strength; NPLit indicates Asset Quality; NIEit indicates Management quality; ROAit and NIMit; indicate Profitability LD_{it} indicates liquidity

3.4 Data and Sample

The number of banks operating in the country by the end of June 2013 is 51 and classified into three major peer groups, large, medium and small banks. The large banks dominate the market with the market share of 74%, medium banks 21%, small banks by 21%. The study analyzed the efficiency of Commercial Banks from 2006 to 2013 focusing on banks peer group as large banks, Medium banks and Small banks. With respect to sample size, the study employed 28 banks (8 large banks, 13 medium banks and 7 small banks) the selection of the sample size based on the availability of the data covered with the period of study. This study collected its bank-related data from published annual financial statements from the Central Bank of Tanzania and various annual reports and publications. Mester (1996) explained that DEA models need data that are free from measurement errors or noise to ensure accurate estimates. Since the data of this study used extracted directly from audited accounts and collected from audited financial statements, it is reasonable to assume that they are free of noise from data collection. To estimate the production frontier, we used panel data on three bank's peer group (large, medium and small) for the years 2006-2013 (8 years x 3 DMUs = 24 observations). We followed the DEA convention that the minimum number of DMUs are greater than three times the number of inputs plus output [(24 > 3(3 + 2)]. Frontier models require the identification of inputs (resources) and outputs (transformation of resources).

IV. Discussion of results

In this section, we discuss the results of the DEA and Tobit regression, and evaluate their managerial implications. In general, the analysis allows managers to identify which banks in the banking industry are relatively more efficient. In addition, as the present study investigates the drivers of efficiency; the results could be of particular importance in formulating efficiency improvement strategies. The general implication of the results is that there is room for improvement in the management of banking sector.

4.1 Results of Descriptive statistics

Before turning to empirical results on DEA and Tobit regression, we provide a summary of Descriptive statistics on the outputs and inputs for different of banks peer groups in Table 4. A few interesting points emerge from the table. First, the number of employees in large banks is almost three times the number in medium sized banks and fourteen times the number in small banks. In addition, the deposits in the large banks are almost five times of those held by medium banks, and sixty seven times of those of small banks. Second, the total loans extended to the customers by Tanzanian banks of all sizes are about 63.9% of those total deposits. In light of this, it inferred that Tanzanian banks are facing a risky business environment and so they may be reluctant to engage heavily in loan markets, as business credits are more costly to originate, maintain and monitor. Third, all inputs and outputs variables are more volatile for large banks compared to medium and small banks. As can be seen the standard deviations of all variables for the large banks are larger compared to the medium and small banks.

Table 4: Summary Statistics of inputs and output Variables

Variables	Units	Mean	Min	Max	SD
Large Banks					
Outputs					
Loans	TZS M	4311397.8	1867334	7879085	2039768.3
Interest Income	TZS M	505137.9	250222	850941	192279.7
Inputs					
Deposits	TZS M	7124374.1	3618124	11284324	2722675.3
Labour	labour	6938.1	4599	8414	1285.3
Total Expenses	TZS M	474840.9	186733	866699	224623.2
Medium banks					
Outputs					
Loans	TZS M	1311125	257224	3403746	1080053.0
Interest Income	TZS M	149419.5	28809	374412	117577.1
Inputs					
Deposits	TZS M	1706247	460234	3485356	1073163
Labour	labour	2372	904	4381	1199.993
Total Expenses	TZS M	169625.3	30867	442486	141265.4
Small Banks					
Outputs					
Loans	TZS M	85674.5	29814	169021	51394.85
Interest Income	TZS M	15782.38	4770	30424	9181.722
Inputs					
Deposits	TZS M	106474.9	40250	166896	54471.43
Labour	labour	471.75	110	1036	330.6037
Total Expenses	TZS M	16083.13	4174	33804	10916.87

Source: Authors

4.2 DEA Empirical Results

In this section, the input-oriented efficiency scores obtained from CCR and BCC models discussed. It is significant to note that, an input orientation provides information as how much proportional reduction of inputs is necessary while maintaining the current levels of outputs for an inefficient bank to become DEA-efficient (Mostafa, 2007). We applied CCR model for a comparative purpose, because the model is completely ignores the scale of operations and may results to unrealistic benchmarks.

Figure 5 shows the input-oriented efficiency scores obtained from CCR and BCC Models of small banking sector in Tanzania for period 2006 to 2013. The results indicate that the sector characterized with small asymmetry between banks as regards to their efficiency scores that ranges between 75.5% - 88.2% and 81.9% - 98.7% for CCR and BCC models respectively. The average efficiency scores turned out to be 0.821 and 0.904 for both models respectively. This suggests that average, small banks, if producing its outputs on the efficient frontier instead of its current (virtual) location, would need only 82.1% and 90.4% respectively of the inputs currently used. The connotation of this finding is that the magnitude of inefficiency scores in small banks in Tanzania is to the tune of 17.9% and 9.6% respectively. This suggests that, by adopting best practice technology the sector can, on an average, reduce their inputs of labour and operation expenses by at least 17.9% and 9.6%

respectively and still produce the same level of outputs. . In general, the results show that small banks are using more resources than what they are producing, in other words, small banks have wasted 17.9% and 9.6% respectively of resources in producing its levels of output. Still, Small banks found to be inefficient under whole period of study for both CCR and BCC models. However, the efficiency scores and overall average are higher in BCC model than in CCR model. The results obtained are not surprising because the scores generated through CRS are less than or equal to the corresponding VRS scores (Banker et al, 1984)

Table 5: Small banks Efficiency score results

Year	CCR	BCC	SE
2006	0.818	0.987	0.829
2007	0.757	0.927	0.817
2008	0.820	0.909	0.902
2009	0.803	0.899	0.893
2010	0.755	0.819	0.922
2011	0.853	0.885	0.964
2012	0.878	0.902	0.973
2013	0.882	0.904	0.976
Mean	0.821	0.904	0.908
Min	0.755	0.819	0.817
Max	0.882	0.987	0.976
SD	0.049	0.046	0.058
Range	0.127	0.168	0.159

Source: Authors

Table 6 shows the input-oriented efficiency scores obtained from the CCR and BCC Models for medium and small banks. `The results indicate that medium and small banks characterized with small asymmetry as regards to their efficiency scores that ranges between 98.2% to 100% and 91.7% and 100% respectively for BCC model. The average efficiency scores turned out to be 0.998 and 0.974 for BCC model respectively. This suggests that average bank, if producing its outputs on the efficient frontier instead of its current location, would need only 99.8% and 97.4% respectively of the inputs currently used. The connotation of this finding is that the magnitude of inefficiency scores in medium and small banks are to the tune of 0.2% and 2.6% respectively. Thus, by adopting best practice technology the banks can, on an average, reduce their inputs of labour and operation expenses by at least 0.2% and 2.6% respectively and still produce the same level of outputs. Recall that the bank with OTE score equal to 100% considered most efficient amongst the banks included in the analysis. The bank with OTE score less than 100% claimed to be relatively inefficient. Medium banks found to be efficient in two and five years for both CCR and BCC model, whereas small banks were efficient in three and four years for both models respectively, on average medium banks found to be most efficient banks.

Table 6: Efficiency Scores for Medium and Small Banks group

Banks	Medium Banks			Small Banks		
Years	CCR	BCC	SE	CCR	BCC	SE
2006	0.995	1.000	0.995	1.000	1.000	1.000
2007	1.000	1.000	1.000	1.000	1.000	1.000
2008	0.974	0.992	0.982	1.000	1.000	1.000
2009	0.990	1.000	0.990	0.911	0.929	0.981
2010	0.997	1.000	0.997	0.878	0.917	0.957
2011	0.982	0.993	0.989	0.870	0.975	0.892
2012	0.992	0.999	0.993	0.928	0.970	0.957
2013	1.000	1.000	1.000	1.000	1.000	1.000
Mean	0.991	0.998	0.993	0.948	0.974	0.973
Min	0.974	0.992	0.982	0.870	0.917	0.892
Max	1.000	1.000	1.000	1.000	1.000	1.000
SD	0.009	0.003	0.006	0.058	0.034	0.038
Range	0.026	0.008	0.018	0.130	0.083	0.108

Source: Authors

Table 7 shows the input-oriented efficiency scores obtained from the CCR and BCC Models of banks peer groups. For large banks, the results indicate that the sector characterized with small asymmetry between banks as regards to their efficiency scores that ranges between 95.6% and 97.4% and 100% for CCR and BCC models respectively. The mean efficiency scores turned out to be 0.988 and 0.994 for both models respectively. This suggests that average large banks, if producing its outputs on the efficient frontier instead of its current (virtual) location, would need only 98.8% and 99.4% respectively of the inputs currently being used. The connotation of this finding is that the magnitude of inefficiency scores in large banking sector in Tanzania is to the tune of 1.2% and 0.6% respectively. This suggests that, by adopting best practice technology the sector can, on an average, reduce their inputs of labour and operation expenses by at least 1.2% and 0.6% respectively and still produce the same level of outputs. For medium and small banks, the results indicate, the banks have means efficiency scores turned out to be 0.918 & 0.922 and 0.944 & 0.960 for CCR and BCC models respectively. This means that, the magnitude of inefficiency scores for medium and small banks in Tanzania are to the tune of 8.2% & 7.8% and 5.6% & 4.0% respectively. This suggests that, these banks on the average reduce their inputs by at least 8.2% & 7.8% and 5.6% & 4.0% respectively. Recall that the bank with OTE score equal to 100% considered most efficient amongst the banks included in the analysis. The bank with OTE score less than 100% claimed to be relatively inefficient. Large banks found to be fully efficient for CCR and BCC models in four years and five years respectively since they had efficiency scores of 100%. Small banks found to be efficient in three years in CCR model and four years in BCC model, whereas, medium banks found to be efficient in only one year of the study.

Table 7: Efficiency Scores for Banks group wise

Banks	Large			Medium			Small		
Years	CCR	BCC	SE	CCR	BCC	SE	CCR	BCC	SE
2006	1.000	1.000	1.000	0.890	0.910	0.978	0.988	1.000	0.988
2007	1.000	1.000	1.000	0.922	0.930	0.991	1.000	1.000	1.000
2008	1.000	1.000	1.000	0.900	0.902	0.998	1.000	1.000	1.000
2009	0.988	1.000	0.988	0.894	0.896	0.998	0.906	0.909	0.997
2010	0.956	0.974	0.982	0.870	0.871	0.999	0.858	0.873	0.983
2011	0.974	0.985	0.989	0.910	0.911	0.999	0.870	0.945	0.921
2012	0.988	0.993	0.995	0.958	0.958	1.000	0.928	0.952	0.975
2013	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Mean	0.988	0.994	0.994	0.918	0.922	0.995	0.944	0.960	0.983
Min	0.956	0.974	0.982	0.870	0.871	0.978	0.858	0.873	0.921
Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
SD	0.016	0.010	0.007	0.042	0.040	0.008	0.061	0.049	0.027
Range	0.044	0.026	0.018	0.130	0.129	0.022	0.142	0.127	0.079

Source: Authors

The above result implying that large banks could perform the role of financial intermediaries, using labors and total expenses to transfer deposits into loans and interest income, more efficiently than small and medium banks. This is not a surprising result, because revenues of commercial banks come from two major sources, which are interest incomes and non-interest incomes. However, large banks are normally superior to small and medium banks in several aspects such as amount of capital, number of labors and reputation, generating non-interest incomes from other sources such as investment banking services, money transfer services or foreign exchange services. Consequently, it is easier to obtain loans from large banks than small and medium banks. In addition, the liberalization has a significant impact on largest banks in Tanzania, which encourage them to starting to use high technology such as establishing ATM networks, associating to the SWIFT system, using on-line computer systems and mobile banking. Because these transfers are mostly to largest banks, they appear to have benefited more from this diffusion than smallest banks. That is why large banks are more efficient than small and medium banks. The results are consistent with the efficiency hypothesis suggests that technological development could increase scale economies over time and allow large banks to be managed more efficiently compared with small banks (Berger et al., 2007). For example, on the lending side of the bank, because large banks have comparative advantage in using hard-information that is based on quantitative data, such as valuations of collateral, financial ratios and credit scores (Berger, 2010), they are better in micro-business lending, asset-based lending, and financial statement lending than small banks.

4.3 Identification of Reference set

DEA being a widely known tool for benchmarking enables identification of efficient DMU for the inefficient ones. This group of efficient DMUs when identified used for defining the operating procedures and goals for the inefficient DMUs. The frequency, which an efficient bank shows up in the reference sets of inefficient banks, represents the extent of robustness of that bank relative to other efficient banks. The higher the frequency, the more robust it is. In other words, a bank which appears frequently in the reference set of inefficient banks is likely to be a bank which is efficient with respect to a large number of factors, and is probably a good example of a 'well-rounded performer' or 'global leader' or 'bank with high robustness' (Kumar and Gulati, 2008). The banks with less number of frequency in the reference set are the 'marginally efficient banks' and would likely to drop from efficient frontier if there is even a small drop in the value of an output variable (or a small increase in the value of an input variable). When the efficient banks have zero frequency in the reference set, may also observed in the analysis. In DEA terminology, the bank with zero frequency count is termed as 'efficient by default' because it does not possess the characteristics, which must be followed by other inefficient banks.

Table 8 provides the reference sets for small banks along with the frequency (or peer count) of each efficient bank in that, reference sets. On the basis of frequency in the reference sets Mbinga Community Bank and Uchumi Commercial Bank have the highest peer counts of two each which, rank first, followed by Dar es Salaam Community Bank (DCB) and Mwanga Community Bank which have peer counts of one each which, rank second.

Table 8: Reference sets for inefficient Small Banks

Banks	OTE score	Reference set
Kagera	0.866	Mbinga(0.071); Mwanga(0.363); Uchumi(0.250)
Kilimanjaro	0.753	DCB(0.023); Mbinga(0.463); Uchumi(0.182)

Source: Authors: Note: reference set figures are λ values obtained from solution for individual inefficiency small banks

Table 9 provide the reference sets for medium banks along with the frequency (or peer count) of each efficient bank in that, reference sets. In the reference sets, African banking Corporation has the highest peer counts of eight which ranks first, followed by NIC Bank (T) Limited which has peer counts of four rank second, Akiba Commercial Bank Limited which ranks third with the peer counts of two, whereas, I&M Bank (T) limited rank fourth with one peer count.

Table 9: Reference Sets for Inefficient Medium Banks

Banks	OTE score	Reference set
BOA	0.673	African(0.678); Akiba(0.025); NIC(0.780)
BOB	0.982	African(0.161); I & M(0.216)
CBA	0.907	African(1.091)
Diamond	0.719	African(0.911); NIC(0.952)
Habib	0.504	African(0.330); NIC(0.082)
ICB	0.528	African(0.123); NIC(0.164)
KCB	0.826	African(0.420); Akiba(0.237); NIC(0.697)
PBZ	0.466	African(0.393); NIC(0.165)

Source: Authors: Note: reference set figures are λ values obtained from solution for individual medium banks

Table10 provide the reference sets large banks with the frequency (or peer count) of each efficient bank in that, reference sets. Based on frequency in the reference sets, Standard Chartered Bank (T) Limited has the highest peer counts of two, which rank first, followed by Citibank Banks (T) limited, CRDB Bank PLC and EXIM Bank (T) Limited, which rank second with the peer counts of one for each bank.

Table 10: Reference Sets for Inefficient Large Banks

Bank	OTE score	Reference set
NBC	0.973	CRDB(0.020); EXIM(2.307); Standard(0.014)
NMB	1.000	NMB(1.000)
Stanbic	0.988	Citibank(0.095); Standard(0.462)

Source: Authors: Note: reference set figures are λ values for individual inefficient large banks

It should be noted that, the above-mentioned banks are benchmarked by other peers. These banks are the most efficient, which serve as the benchmark peers for inefficient banks in the sample. Thus, inefficient banks could improve their efficiency level by benchmarking efficient banks. It is interesting to note that although Mufindi Community Bank from small banks, Azania Bank Limited from medium banks and Barclays Bank (T) Limited from large banks are efficient banks yet they do not exemplify any best practices (as indicated by zero frequency count) to be followed by the inefficient banks in their pursuit to enhance their efficiency levels. In fact, these banks may be rightly designated as efficient by default

4.4. Areas for Efficiency Improvement: Slacks and Targets Setting Analysis

The optimum solution of linear programming provides non-zero input and output slacks corresponding to input and output constraints. Thus, slacks exist only for those DMUs that identified as inefficient in a particular DEA run. These slacks provide the vital information pertaining to the areas that an inefficient bank needs to improve upon in its drive towards attaining the status of efficient one.

Tables 11(a, b & c) provides the summary of input and output slacks derived from DEA model for inefficient large, medium and small banks for the year 2006 to 2013. For interpreting the contents of the table, consider the case of each group in a single year of 2010. The OTE score of large, medium and small banks are 0.974, 0.871 and 0.873 respectively, , implying that the banks in that year could become technically efficient (under the Farrell's definition) provided if all of its inputs are proportionally reduced by 2.6%, 12.9% and 12.7% respectively (i.e., (1-OTE score). However, even with this required proportional reduction in all inputs, these banks in that year would not be Pareto-efficient, as it would be operating on the vertical section of the efficient frontier. In order to project these banks to a Pareto-efficient point, some further slack adjustments are necessary because non-zero input and output slacks appear for these banks in that year. Thus, the adjustments are required in order to operate at the efficient frontier. It has to reduce all inputs by 2.6%, 12.9% and 12.7% respectively.

Table 11a: Slacks and targets for inefficient large banks

		Slacks			Targets					Inputs Reductions (%)		
Year	score	x_1	x_2	x_3	x_1	x_2	x_3	y_1	y_2	x_1	x_2	x_3
2010	0.974	961091	1278	11670	6493484	6030	441768	4122160	475534	2.6	2.6	2.6
2011	0.985	779724	967	8557	7771383	6666	555113	5124275	575669	1.4	1.4	1.4
2012	0.993	491783	589	4737	9339661	7446	694214	6354101	698558	0.7	0.7	0.7

Source: Authors: Notes: x_1=Total deposits. x_2=Number of employees, x_3 total expenses, y_1=Total loans, y_2=Total interest income

Table 11b: Slacks and targets for inefficient Medium banks

		Slacks			Targets					Inputs Reductions (%)		
Year	Score	x_1	x_2	x_3	x_1	x_2	x_3	y_1	y_2	x_1	x_2	x_3
2006	0.91	41497	330	2783	418737	492	28084	257224	31926	9	9	9
2007	0.93	43161	548	3157	569277	613	41640	375305	44797	7	7	7
2008	0.902	93777	393	8032	867713	1086	74316	633449	76647	9.8	9.8	9.8
2009	0.896	138752	284	11659	1191387	1469	100113	859788	104034	10.4	10.4	10.4
2010	0.871	229702	196	17917	1551705	1804	121035	1068864	129333	12.9	12.9	12.9
2011	0.911	198897	510	18259	2031731	2130	186510	1575152	177992	8.9	8.9	8.9
2012	0.958	117695	384	12706	2670590	3113	288305	2315475	259332	4.2	4.2	4.2

Source: Authors: Notes: x_1=Total deposits. x_2=Number of employees, x_3 total expenses, y_1=Total loans, y_2=Total interest income

Table 11c: Slacks and targets for inefficient Small banks

		Slacks			Targets					Inputs Reductions (%)		
Year	Score	x_1	x_2	x_3	x_1	x_2	x_3	y_1	y_2	x_1	x_2	x_3
2009	0.909	7847	60	877.54	78212	231	8746	60155	10166	9.1	9.1	9.1
2010	0.873	18423	40.	2016.1	126539	322	13848	93319	15958	12.7	12.7	12.7
2011	0.945	8391	0	1258.9	142989	564	21453	121009	21689	5.5	5.5	5.5
2012	0.952	7703	36.	1342.7	151247	777	26365	138542	25214	4.8	4.8	4.8

Source: Authors: Notes: x_1=Total deposits. x_2=Number of employees, x_3 total expenses, y_1=Total loans, y_2=Total interest income

Tables above also present the target values of inputs and outputs for inefficient for each group of banks in years of study along with potential reduction in inputs. The potential improvement shows those areas of improvement in input-output activity needed to put an inefficient bank onto the efficient frontier. For getting what these figures of potential input reduction show, consider the year 2010 for each banks groups. To move onto the efficient frontier, banks need to reduce their deposits, number of employees and total expenses: large banks need to reduce by 12.6%, 17.04% and 25.7% respectively, for medium banks need to reduce by 12.9%, 8.5% and 12.9% respectively and small banks by 12.7%, 9.6% and 12.7% respectively. We can also draw the similar conclusions for other inefficient years for each group of banks.

4.5 Results of Tobit regression

The second stage of our analysis we run a Tobit Regression with bootstrap to obtain the main determinants of bank efficiency. The results of explanatory factors, namely, capital strength, asset quality, management quality; Profitability, net interest margin and liquidity are given in Table 12. A positive coefficient implies an efficiency increase whereas a negative coefficient means an association with an efficiency decline. The results of the regression are significant at 95% level of significance. The Chi-Square test is 17.8 with five degree of freedom associated with P-value (0.000) obtained efficiency scores shows that the model is a good fit for the data

Table 12: Tobit regression results for non-discretionary VRS input-oriented models

Variables	Estimate	Std. Error	Z. Value	P Value
(Intercept):1	0.689	0.056	12.266	
(Intercept):2	-3.788	0.160	-23.726	
Capital Strength	0.078	0.346	0.226	0.411
Assets Quality	-0.505	0.164	-3.085	0.001
Management Efficiency	-1.701	0.706	-2.410	0.008
ROA	2.673	1.107	2.415	0.007

NIM	0.716	0.382	1.872	0.031
Liquidity	0.466	0.108	4.302	0.000

Source: Authors, (Significant at the 0.05 level)

The equation derived from the above result shown below

Θ_i = 12.2661 + 0.2261*EQTA - 3.0847*NPL -2.4101*NIE + 2.4149*ROA + 1.8720*NIM + 4.3022*LD

The regressions show evidence that, no statistically significant relationship is present between capital strength and bank efficiency. However, we find a statistically significant and negative relationship between asset quality and management efficiency with bank efficiency. The results fall within our expectation usually management is responsible in controlling noninterest expenses, an increase of non-interest expenses reduce profitability of banks, thus affect efficiency levels. Likewise, increase in nonperforming loans ((NPL) affect negatively the performance of banks, as pointed out by Millers and Noulas (1996) that when a given financial institution is accumulated with poor performing loans, reduces its profitability. On the other hand, the study used the net interest margin (NIM) and profitability (ROA) to proxy the banks' earning potential and both found statistically significant positive relationships with bank efficiency which indicates that banks with higher NIM and ROA tend to have more efficiency than other banks. This indicates that banks that are more profitable are also more efficient. It is common that banks having higher profitability are usually preferred by clients. Therefore, they attract the largest share of deposits and the best potential creditworthy borrowers as well. This creates favorable conditions for the profitable banks to be more efficient. Efficient banks may therefore be able to invest their funds in assets that offer relatively higher returns than less efficient banks (Casu.and Molynuex 2003: Mester 1996; Maudos et al 2002). We find also a significant and positive relationship between liquidity management, which is the ratio of loans to deposits, and bank efficiency. This indicates that the banks with a higher ability to transform deposits into loans would be more efficient, Vu and Turnell (2011) found a positive and statistically significant relationship between liquidly ratio and bank efficiency

V. Conclusions, managerial implications, limitations and Future research

This paper endeavors to evaluate the efficiency of banks in Tanzania using panel data for large, medium and small banks in the year 2006 to 2013. Besides this, an attempt has been made to explain the impact of specific factors (like capital strength, asset quality, management efficiency, profitability and liquidity) on efficiency of banks. To realize the research objectives a two-stage. DEA framework has been applied in which the estimates of technical, pure technical and scale efficiencies for individual group banks have been obtained by CCR and BCC models in the first stage; and Tobit regression analysis has been used to work out the relationship between banks efficiency and specific factors in the second stage. The present study followed an intermediation approach to select input and output variables. The output vector contains two outputs: i) total loans, and ii) total interest income, while input vector contains three inputs: i) total deposits ii) labour (number of employees and iii) total expenses. Several interesting and useful managerial insights and implications arising from the study are discussed

The remarkable comment from the findings of this paper is that efficiency status of commercial banks in Tanzania is not disappointing to financial sector reforms because the scores turned out to be high. The results indicate that the level of overall technical efficiency in Tanzanian banking sector is around 95.9%. Thus, the magnitude of inefficiency is to the tune of 4.1%. We can see from the results that, large banks are, on average, more efficient than the small and medium banks whereas small banks are on average more efficient than medium banks.

Turning to the sources of inefficiency it has been noticed that, the observed technical inefficiency in the Tanzanian banking sector is due to poor input utilization, (i.e., managerial inefficiency). However, the level of inefficiency is small when compared with what we can see in the other sectors. A reason for this result may be found in the increased level of competition in the banking industry resulting from financial sector reforms since 1991. These reforms have enhancing the productivity and efficiency of banking sector by creating a competitive environment hence, an improvement in performance is the expected result.

DEA does not identify the factors that cause inefficiency and only directs our attention towards those units in which there is inefficiency. However, the results lead us to state that the primary causes of inefficiency is poor utilization of resources, in some banks human resources are not proportional to the range of activities they have to do. Either more people than required are employed or the employees do not work, as they should do. A Tobit regression allows us to identify other efficiency drivers beyond poor utilization of resources. Thus, the findings proved that, asset quality, management efficiency, net interest margin (NIM), return on assets (ROA) and liquidity are significant driver of banks' efficiency, whereas capital strength is not. In view of the results, the managerial implications of this paper are as follows: firstly, in some banks human resources are not proportional to the range of activities they have to do. Either more people than required are employed or the employees do not work, as they should do. Such banks should accordingly implement policies aiming at enhancing efficiency and reactivation of the work morale. Banks should harness their underutilized resources, which can be used in the production of new variety of products. Secondly, banks management should consider these benchmark exercises, since they compare different units in the same market, allowing the less efficient banks to overcome their relative inefficiencies. Thirdly, banks' management should pay more attention on those banks' efficiency drivers for the improvement of performance of their banks, because the identification of the efficiency drivers makes it possible to define policies that focus in the right direction.

This paper has two limitations. The first limitation is in relation to the data set, and the second in relation to the DEA method. With reference to the data set, the homogeneity of the banks used in the analysis is questionable, since we compare banks of different sizes, different services offered, different capital requirements and locations, which might not be considered directly comparable. The DEA does not impose any functional form on the data, nor does it make any distributional assumptions for the inefficiency term, nor does it even establish a prior distinction between the relative importance of any combination of inputs and outputs. These limitations are simultaneously the most distinctive and attractive characteristics of DEA. This efficiency measurement assumes that the production function of the fully efficient outlet is known. In practice, this is not the case and the efficient isoquant must be estimated from the sample data.

A future research can be undertaken to apply different analytical models, such as parametric, Stochastic Frontier Approach (SFA), by using the different models, researchers can justify whether the efficiency scores generated by different frontier models are consistent with the DEA that is used or not. Besides, future researchers may choose more banks' inputs and outputs. This could help minimize sampling error by increasing possible input and output variables and be able to generate different results. On the other hand, future researchers may select other variables that differ from this study. In this study, the researchers used bank specific variables as independent variable to determine the determinant of bank efficiency. Future researcher may use macro environment variables such as regulatory, bank type, geographical region and ownership.

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