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Banks Performance Evaluation in Tanzania: A Non-Parametric Approach

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Abstract
This paper endeavours to evaluate the extent of technical, pure technical and scale efficiencies of banking sector in Tanzania using the non-parametric technique of data envelopment analysis. The empirical results show that only 9 of the 25 banks operating in the period from 2011 to 2013 are found to be efficient and thus, define the efficient frontier of Tanzanian banking sector, the TE scores range from 76.4% to 100%, with an average of 94.9% thus, the magnitude of technical inefficiency is to the tune of 5.1%, i.e., inputs could be reduced by 5.1% without sacrificing output if all banks were efficient as 9 benchmark banks identified by DEA and the study notes that managerial inefficiency is the main source of overall technical inefficiency of banking sector in Tanzania. From the analysis of returns-to-scale, it has been noticed that 36% of banks in Tanzania operate in the zone of decreasing returns-to-scale.
Keywords: Technical efficiency: Pure technical efficiency; Scale efficiency; Data envelopment analysis; Super-efficiency; Returns-to-scale

1.0 Introduction

The importance of performance evaluation in the banking sector is related to the extremely extensive impact that an efficient banking system has on the microeconomic as well as macroeconomic level. Banking system deeply affects the allocation of financial resources, helping to find their best productive employment in the most effective way, reducing misallocation and unnecessary wastes. In order to properly allocate the financial resources, the banking system needs to be efficient. Efficiency in banking sector then supports the fruitfulness of implemented macroeconomic policies, generating durable development, economic growth and welfare. Society benefits when a country's banking system becomes more efficient, offering more services at a lower cost (Valverde *et al*., 2003). Therefore an understanding of banking system performance over the period of time is an important to regulators, analysts, banks managers and academicians. The information obtained from banking performance analyses can be used either: (i) to inform government policy by assessing the effects of deregulation, mergers, or market structure on efficiency; (ii) to address research issues by describing the efficiency of an industry, ranking its firms, or checking how measured efficiency may be related to the different efficiency techniques employed; or (iii) to improve managerial performance by identifying 'best practices' and 'worst practices' associated with high and low measured efficiency, respectively, and encouraging the former practices and while discouraging latter (Berger and Humphrey, 1997).

The banking industry has undergone significant transformation all over the world since the early 1980s under the impact of technological advances, deregulation, and globalization. The Tanzanian banking sector has not remained insulated from the global trends, and deregulated its banking sector in 1991 by introducing a series of banking reforms measures. Consequently, the operating environment for the banks has changed significantly, and they are faced with increased competitive pressures and changing customer demands. This has engendered the banks to bring changes in their business strategies, so as to keep their survival intact and maintain a sustainable level of growth. Further, these pressures forced the banks to reduce operating costs while maintaining or improving the quality of their services. As the marketplace continues to evolve at a rapid pace, it has become imperative for banks to remain efficient in production process so that they can withstand the forces of competition and thrive in a changing environment. Against this backdrop, we have carried out this study with the primary objective to measure the magnitude of performance in 25 banks operating in Tanzania in the period from 2011 to 2013. To sum up, the aim of this paper is three fold:

- To obtain a measure of overall technical, pure technical, and scale efficiencies for individual banks;
- To decomposes OTE into two mutually exclusive and non-additive components, namely, pure technical efficiency (PTE) and scale efficiency (SE)
- To provide a complete ranking to Tanzanian banks on the basis of super-efficiency scores.

To achieve the above objectives of the study, the study used the non-parametric frontier approach, data envelopment analysis (DEA), to measure the extent of OTE and its components (i.e. PTE and SE), and to determine the nature of RTS in individual banks and the Anderson and Peterson's super-efficiency model for ranking of efficient banks. The study used the average data for the year from 2011 to 2013 for recent cross-section sample of 25 banks in Tanzania.

The paper unfolds as follows. Section 2 provides a relevant literature review. Section 3 provides

Methodological framework which outlines CCR and BCC models for obtaining efficiency measures corresponding to constant returns-to-scale (CRS) and variable returns-to scale (VRS) assumptions, respectively and the Anderson and Peterson's super-efficiency model for ranking of banks. The description of the data and the specification of input and output variables are reported in the Section 4. Section 5 presents the empirical results and discussion. The relevant conclusions and directions for future research are provided in the Section 6.

2.0 Literature Review

The performance of the banking industry is one of the most important aspects for, regulators, analysts, shareholders, managers and customers worldwide. In supporting of this statement there are numerous studies which aim at evaluating the performance banks around the world. Although there are numerous approaches for measuring the performance of banks, however Data Envelopment Analysis is the most popular in literature. There is an extensive literature review on efficiency of financial institutions (more details see Berger et al., 1993; Berger and Humphrey, 1997). Besides using traditional financial statement analysis (financial ratios analysis), DEA approach has been emerged over the years as a most popular method for evaluating efficiency of banking sector around the world due to its intrinsic advantages over others. In more than 120 studies by Berger and Humphrey (1997), DEA approach has been used in 62 studies (more than 50%). This evidence shows DEA's significance, popularity and relevance in banking sector efficiency analyses. Numerous applications of DEA have appeared in the bank performance literature, for example, only for the United States there are over 40 such studies. The following is a brief review studies about using DEA in measuring banks' performance. Casu and Molyneux (2000) used the DEA approach to evaluate the performance of banking sector in Europe, the study attempted to examine whether the productive efficiency of European banking systems has improved and converged towards a common European frontier, following the process of EU legislative harmonization. Noulas (2001) studied the effect of banking deregulation on private and public-owned banks by employing DEA approach. The study found that the private banks were more efficient than the public-owned, although the gap between levels of efficiency is not relevant from a statistical viewpoint. Barr (2002) employing DEA approach evaluated the productive efficiency of U.S. commercial banks and results found a close interdependence between efficiency and independent measures of performance, including confidential ratings made by bank examiners. Wu (2005) employing DEA approach measured productivity and efficiency of Australian banks for the period of 18 years from 1983 to 2001 and the study found that, efficiency of banks in Australia increased in times of deregulation. Kirkpatrick et al (2008) in their study of Anglophone SSA countries found that, the degree of foreign bank penetration is inversely related to X-inefficiency, suggesting that foreign bank ownership in Africa has contributed to better management and performance of commercial banks. Cihak and Podpiera (2005) investigated banking sector reforms in East African countries, the study found that the banking systems in Kenya, Tanzania, and Uganda were inefficient and had only a limited intermediation role, despite recent reforms and even with international banks present.

Although an extensive and sprawling literature on the banking efficiency using DEA approach exits for developed economies, however, there have been few studies to evaluate banks performance in Tanzania using DEA approach. The contribution of this study to the existing literature on the banking sector performance in Tanzania stems from three areas in which very scant attention has been paid by the previous researchers. These areas are i) decomposition of overall technical efficiency (OTE) into its components, namely, pure technical efficiency (PTE) and scale efficiency (SE), ii) to provide a complete ranking to Tanzanian banks on the basis of super-efficiency scores and iii) targets setting for potential outputs' addition and inputs' saving in inefficient banks, this study aims to contribute the existing literature by focusing on all the aforementioned areas.

3.0 Methodological framework

3.1 Measurement of overall, technical, pure technical and scale efficiencies:

The methodology used in this study is an extension upon the Farrell's (1957) work by Charnes et al. (1978), which they coined it as DEA. DEA floats a piecewise linear surface to the rest on top of the observations (Seiford and Thrall, 1990). The DMUs that lie on the frontier are the best practice institutions and retain a value of one. Those DMUs enveloped by the external surface are scaled against a convex combination of the DMUs on the frontier facet closest to it and have values somewhere between 0 and 1. Several different mathematical programming DEA models have been proposed in the literature for more detailed information about theory of DEA models can be found in: (Cooper, Seiford, and Tone, 2007; and Zhu, 2003). In the present study, we have 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 DMUo, under the different scale assumptions are as follows:

Input oriented models

$$Min = \theta - \ell\left(\sum_{i=1}^{m} S_t^{-} + \sum_{k=1}^{r} S_k^{+}\right) \qquad 1$$

St. $$\sum_{j=1}^{n} \lambda_j x_{ij} + S_t^{-} = \theta x_{iq}{}' \qquad 2$$

$$\sum_{j=1}^{n} \lambda_j y_{kj} - s_k^{+} = y_{kq} \qquad 3$$

$$\lambda_i \geq 0, s_i^{+} \geq 0, s_i^{-} \geq 0 \qquad 4$$

CRS $$\sum_{j=1}^{n} \lambda_j - free \qquad 5$$

VRS $$\sum_{j=1}^{n} \lambda_j = 1 \qquad 6$$

where λj, j = 1,2,..., n are weights of all decision making units, s-i, i = 1,2,..., m are slack variables of particular inputs and s+k, k = 1,2,..., r are surplus variables of particular outputs. Index q represents the index of evaluated unit and θ *are* plain variables expressing the level of efficiency. The evaluated unit q is recognized as efficient in input oriented model if θ = 1 and all slack and surplus variables equal to zero. Except this standard formulation there were formulated many modifications but the mentioned ones are the most often used. The restriction limits the intensity variables to be non-negative. The model involving 1) – 5) is known as envelopment form of CCR model and provides Farrell's input-oriented TE measure under the assumption of constant returns-to-scale. The measure of efficiency provided by CCR model is known as overall technical efficiency (OTE) and denoted as CCR θ_o^{CCR} .The last restriction imposes variable returns-to-scale assumption on the reference technology. The model involving 1) – 5) and 6) is known as BCC model and provides Farrell's input-oriented measure under the assumption of variable returns- to-scale. The measure of efficiency provided by BCC model is known as pure technical efficiency (PTE) and denoted as θ_o^{BCC} . The ratio θ_o^{CCR} / θ_o^{BCC} provides a measure of scale efficiency (SE). Note that all aforementioned efficiency measures are bounded between one and zero. The measure of scale efficiency (SE) does not indicate whether the DMU in question is operating in the area of increasing or decreasing returns-to-scale. The nature of returns-to-scale can be determined from the magnitude of optimal $\sum_{j=1}^{n} \lambda^*$ In the CCR model (Banker, 1984). Seiford and Zhu (1999) listed following three cases

If $\sum_{j=1}^{n} \lambda^* = 1$ in any alternate optima, then CRS prevail on DMUo;

If $\sum_{j=1}^{n} \lambda^* < 1$ in any alternate optima, then IRS prevail on DMU o; and

If $\sum_{j=1}^{n} \lambda^* > 1$ in any alternate optima, then DRS prevail on DMU o.

3.2 Ranking of DMUs: Super - efficiency data envelopment analysis (SE - DEA)

It is significant to note that all efficient DMUs have the same efficiency scores equal to 1 in the CCR model. Therefore, it is impossible to rank or differentiate the efficient DMUs with the CCR model. However, the ability to rank or differentiate the efficient DMUs is of both theoretical and practical importance. Theoretically, the inability to differentiate the efficient DMUs creates a spiked distribution at efficiency scores of 1. This poses analytic difficulties to any post-DEA statistical inference analysis. In practice, further discrimination across the efficient DMUs is also desirable to identify ace performers. For getting strict a ranking among efficient DMUs, Andersen and Petersen (1993) proposed the super-efficiency DEA model. The core idea of super-efficiency DEA model is to exclude the DMU under evaluation from the reference set. This allows a DMU to be located on the efficient frontier, i.e. to be super-efficient. Therefore, the super-efficiency score for efficient DMU can, in principle, take any value greater than or equal to 1. This procedure makes the ranking of efficient DMUs possible (i.e. the higher the super-efficiency score implies higher rank). However, the inefficient units which are not on the efficient frontier, and with an initial DEA score of less than 1, would find their relative efficiency score unaffected by their exclusion from the reference set of DMUs. In the super-efficiency DEA model, when the linear programme (LP) is run for estimating the efficiency score of DMUo, the DMUo cannot form part of its reference frontier, and hence if it was a fully efficient unit in the original standard DEA model (like CCR model in the present study) it may now have efficiency score greater than 1. This LP is required to be run for each of the n DMUs in the sample, and in each of these LPs, the reference set involves n 2 1 DMUs. In particular, Andersen and Petersen's model for estimating super-efficiency score for DMUo (denoted by TE_o^{Super}) can be outlined as below:

$$MinTE_o^{Super} = \theta_o^{Super} - \ell\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

$$\theta_o^{Super} \lambda s_i^-, s_r^+$$

Subject

$$\sum_{j=1}^{n} \lambda_j \lambda_{rj} - s_r^+ = y_{rk} \qquad r = 1,2,\ldots s$$

$$j \neq 0$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} - s_i^- = \theta_k^{Super} x_{ik} \qquad i = 1,2\ldots m$$

$$j \neq 0$$

$$s_j^-, s_r^+ \geq 0$$

$$\lambda_j (j \neq 0) \geq 0 \qquad j = 1,2\ldots n$$

4. Data and specification of inputs and outputs

In the banking efficiency literature, there is a considerable disagreement among researchers about what constitute inputs and outputs of banking sector (Sathye, 2003). However, production approach' and 'intermediation approach are the most two common approaches appear in the literature regarding the measurement of inputs and outputs of a bank. The intermediation approach views the banks as using deposits together with purchased inputs to produce various categories of bank assets. Outputs are measured in monetary values and total costs include all operating and interest expenses (Sealey and Lindley, 1977). In contrast, the production approach view banks as using purchased inputs to produce deposits and various categories of bank assets. Both loans and deposits are, therefore, treated as outputs and measured in terms of the number of accounts. This approach considers only operating costs and excludes the interest expenses paid on deposits since deposits are viewed as outputs. Although the intermediation approach is most commonly used in the empirical studies, neither approach is completely satisfactory, largely because the deposits have both input and output characteristics which are not easily disaggregated empirically. Berger and Humphrey (1997) suggested that the intermediation approach is best suited for analyzing bank level efficiency, whereas the production approach is well suited for measuring branch level efficiency. This is because, at the bank level, management will aim to reduce total costs and not just 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. Also, in practice, the availability of flow data required by the production approach is usually exceptional rather than in common. Therefore, following Berger and Humphrey (1997), this study used a modified version of intermediation approach as opposed to the production approach for selecting input and output variables because this study focused on the analysis on the bank level. The study collected its bank-related data from published annual financial statements from Bank of Tanzania and various annual reports and publications from individual banks. The study is confined to 25 commercial banks operating in Tanzania in the period from 2011 to 2013. In this study, the inputs used for computing various efficiency scores are i) physical capital (measured as the value of non-current assets) ii) Deposits and iii) labour (measured by number of employees. The output vector contains two output variables: i) total loans, and ii) Earning assets.

Since DEA results are influenced by the sample size, the sample size utilized in this study is consistent with the various rules of thumb available in DEA literature. The study followed the DEA convention that the minimum number of DMUs are greater than three times the number of inputs plus output [(n > 3(m + s)], where n=number of DMUs, m=number of inputs and s=number of outputs(Cooper et al. 2007) . Given m=3 and s=2, the sample size (n=25) used in this study exceeds the desirable size as suggested by the abovementioned rules of thumb to obtain sufficient discriminatory power.

5.0 Results and discussion

This section provides the empirical results obtained from input-oriented CCR and BCC, return to scale and super-efficiency DEA models. It is significant to note that input-oriented efficiency measures give the extent of inputs which can be proportionately reduced by keeping output unchanged. Given efficiency scores, the amount of inefficiency can be obtained as: Inefficiency (%) = (1- efficiency score) x 100.

5.1 Results on Overall Technical, Pure Technical, and Scale Efficiencies

Table 1 in column 3 provides the results of OTE scores for 25 banks. The results show that, there exist wide variations in the level of OTE across banks, which varies between 76.4% and 100%. The average of OTE scores turned out to be 94.9% indicating that the magnitude of overall technical inefficiency (OTIE) is to the tune of 5.1% (see Table 3 for the descriptive statistics of various efficiency measures). This suggests that by adopting best practices, banks can, on an average, reduce their inputs by at least 5.1%, and still produce the same level of outputs. However, the potential reduction in inputs from adopting best-practice technology varies among different banks. Recall that bank with OTE score equal to 1 is deemed to be efficient and represent a point on the efficient frontier. Of the 25 banks, nine banks are found to be technically efficient since they have OTE score of 100%. These banks together define the best-practice or efficient frontier, and thus form the reference set for inefficient banks. The resource utilization process in these banks is functioning well. It means that the production process of these banks is not characterizing any waste of inputs. In DEA terminology, these banks are called peers and set an example of good operating practices for inefficient banks. The efficient banks are Akiba Bank, Azania, Banc ABC, Bank M, BOB, Citi Bank, I & M bank, NIC and Standard Chartered (Table 2 column 3). From the Table 2, we further note that the remaining 16 banks are relatively inefficient with OTE score less than 100%. The results indicate a presence of marked deviations of banks from the best-practice frontier. These inefficient banks can improve their efficiency by reducing inputs. OTE scores among the inefficient banks range from 76.4% for UBA to 99.5% for BOI. This finding implies that UBA and BOI can potentially reduced their inputs by 23.6% and 0.5%, respectively, while leaving their output levels unchanged. This interpretation of OTE score can be extended for other inefficient banks in the sample. On the whole, we observed that OTIE levels range from 0.5% to 23.6% among inefficient banks.

Table 2 in column 5 also provides the PTE scores for 25 banks. The results showed that there exist slightly variations in the level of PTE across banks, PTE scores range from the lowest figure of 88.2% to the highest of 100%. The average of PTE scores turned out to be 98.3% indicating that the magnitude of overall technical inefficiency (PTIE) is to the tune of 1.7% (see Table 3 for the descriptive statistics of various efficiency measures). This suggests that by adopting best practices, banks can, on an average, reduce their inputs by at least 1.7%, and still produce the same level of outputs. However, the potential reduction in inputs from adopting best-practice technology varies among different banks.. Of the 25 banks, 16 banks have been identified as relatively efficient under VRS assumption since they have attained PTE score equal to 100% and the remaining nine banks are relatively inefficient with PTE score less than 100%. However, the efficiency scores and overall average results 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).

5.2 Results on Decomposition of OTE: PTE and SE

In DEA literature overall technical efficiency (OTE) assist to measure combined inefficiency which results from both pure technical inefficiency (PTIE) and scale inefficiency (SIE) due to inappropriate DMU size. OTE measure is obtained from CCR model under CRS while pure technical efficiency (PTE) is obtained from BCC model under assumption of VRS. Hence, the PTE scores provide that all the inefficiencies directly result from managerial underperformance (i.e., managerial inefficiency) in organizing the bank's inputs. Thus the efficiency scores of the banks rise on allowing VRS because, BCC forms a convex hull of intersecting planes which envelops the data points more tightly than CRS conical hull and provides efficiency scores which are greater than or equal to those obtained using the CCR model. It is significant to note here that the efficiency scores of the banks rise on allowing VRS because BCC model (i.e., a DEA model under VRS assumption) forms a convex hull of intersecting planes which envelops the data points more tightly than CRS conical hull and provides efficiency scores which are greater than or equal to those obtained using the CCR model (i.e., a DEA model under CRS assumption). However, in contrast to OTE measure, the PTE measure derived from BCC model under assumption of VRS devoid the scale effects. Thus, the PTE scores provide that all the inefficiencies directly result from managerial underperformance (i.e., managerial inefficiency) in organizing the bank's inputs. It is significant to note here that the efficiency scores of the banks rise on allowing VRS because BCC model (i.e., a DEA model under VRS assumption) forms a convex hull of intersecting planes which envelops the data points more tightly than CRS conical hull and provides efficiency scores which are greater than or equal to those obtained using the CCR model (Banker et al, 1984). In DEA literature, the banks attaining OTE and PTE scores equal to 1 are known as globally efficient and locally efficient banks, respectively (Kumar and Gulati, 2008). In table 2 the results show that, 16 banks acquired the status of 'locally efficient' banks because they have the PTE score equal to 1. Further to those 9 banks that have acquired the status of 'globally efficient' banks and lie on efficient frontier under CRS assumption. In addition 7 banks which have the PTE score equal to 1 and lie on the efficient frontier under BCC model (i.e. VRS assumption). For these 7 banks that became efficient under VRS assumption however found to be inefficient under CRS assumption, then the OTIE in these banks is not caused by poor input utilization (i.e., managerial inefficiency) rather than by the operations of the banks with inappropriate scale size.

Table 1 in column 7 also shows the results of SE scores for individual banks. As mentioned earlier, SE score for each bank can be obtained by taking a ratio of OTE score to PTE score. The value of SE equal to 1 implies that the bank is operating at most productive scale size (MPSS) which corresponds to constant returns-to-scale. At MPSS, the bank operates at minimum point of its long-run average cost curve. Further, SE<1 indicates that the bank is experiencing OTIE because it is not operating at its optimal scale size. Further the results show that, only 11 banks attained SE score equal to 1 and are, thus, operating at most productive scale size (MPSS). The remaining 14 banks are operating with some degree of SIE and have either DRS or IRS. In addition, most of banks in Tanzania are operating with scale efficiency above 90%.

Table 1: Overall Technical Efficiency, Pure Technical Efficiency, and Scale Efficiency Scores for Banks in Tanzania

Code	Bank	OTE score	OTIE (%)	PTE Score	PTIE	SE score	SIE (%)	RTS
B1	Access Bank	0.875	12.5	1.000	0	0.875	12.5	IRS
B2	Akiba Bank	1.000	0	1.000	0	1.000	0	CRS
B3	Azania	1.000	0	1.000	0	1.000	0	CRS
B4	Banc ABC	1.000	0	1.000	0	1.000	0	CRS
B5	Bank M	1.000	0	1.000	0	1.000	0	CRS
B6	Barclays	0.917	8.3	0.942	5.8	0.974	2.6	DRS
B7	BOA	0.949	5.1	0.950	5	0.999	0.1	IRS
B8	BOB	1.000	0	1.000	0	1.000	0	CRS
B9	BOI	0.995	0.5	1.000	0	0.995	0.5	CRS
B10	CBA	0.980	2	0.990	1	0.989	1.1	DRS
B11	Citi Bank	1.000	0	1.000	0	1.000	0	CRS
B12	CRDB	0.925	7.5	1.000	0	0.925	7.5	DRS
B13	D. Trust Bank	0.990	1	1.000	0	0.990	1	DRS
B14	EXIM	0.968	3.2	1.000	0	0.968	3.2	IRS
B15	Habib bank	0.945	5.5	0.947	5.3	0.998	0.2	IRS
B16	I & M	1.000	0	1.000	0	1.000	0	CRS
B17	ICM	0.937	6.3	0.951	4.9	0.985	1.5	DRS
B18	KCB	0.902	9.8	0.980	2	0.920	8	CRS
B19	NBC	0.867	13.3	0.967	3.3	0.897	10.3	DRS
B20	NIC	1.000	0	1.000	0	1.000	0	CRS
B21	NMB	0.895	10.5	0.977	2.3	0.916	8.4	DRS
B22	PZB	0.872	12.8	0.882	12.8	0.988	1.2	DRS
B23	Stanbic	0.940	6	1.000	0	0.940	6	IRS
B24	Standard Chartered	1.000	0	1.000	0	1.000	0	CRS
B25	UBA	0.764	23.6	1.000	0	0.764	23.6	DRS

Source: Authors

Table 2 provides the descriptive statistics of OTE, PTE and SE scores. From the table, the results show that OTE scores range between 0.764 and 1, and their mean and standard deviation (SD) are 0.949 and 0.061, respectively. Thus, the average level of OTIE in Indian domestic banking industry is to the tune of about 5.1%. It can, therefore, be concluded that the same level of outputs the banking sector in Tanzania could be produced with 5.1% lesser inputs. Further, we note the presence of significant variations in OTIE at the level of individual banks. The highest and lowest levels of OTIE have been noted for UBA (23.6%) and BOI (0.5%), respectively (see Table 1 for OTE scores of these banks). The mean value of PTE scores has been observed to be 0.983 with standard deviation of 0.029, and PTE scores range from the lowest figure of 0.882 to the higher of 1. Thus, the extent of pure technical inefficiency (PTIE) of banking sector in Tanzania has been observed to be 1.7%. the results in table 3 reveals that, mean SE for banking sector in Tanzania as a whole is quite high being 0.965 with standard deviation of 0.056 and SE scores range from a minimum of 0.764 to maximum of 1. The connotation of this finding is that average level of SIE in the Tanzanian banking sector is to the tune of about 3.5%.

Table 2: Descriptive Statistics

Efficiency Scores	OTE	PTE	SE
Mean	0.949	0.983	0.965
Median	0.968	1.000	0.990
Std dev	0.061	0.029	0.056
Minimum	0.764	0.882	0.764
Maximum	1.000	1.000	1.000
Range	0.236	0.118	0.236

Source: Authors

5. 3 Results on Returns-to-Scale

In economics, the quantitative change in output of a firm or industry resulting from a proportionate increase in all inputs referred to Returns to scale. In the theory of the firms the basic objectives of the firms is to operate at MPSS, i.e. with CRS in order to minimize costs and maximize revenue. In the short run, firms may operate in the zone of IRS or DRS. However, in the long run, they will move towards CRS by becoming larger or smaller to survive in the competitive market. The process may involve the changes of a firms' operating strategy in terms of scaling up or scaling down of its size. If the quantity of output rises by a greater proportion than rises in inputs, then the production process of the firm is said to exhibit increasing returns to scale. Such economies of scale may occur because greater efficiency is obtained as the firm moves from small- to large-scale operations. Decreasing returns to scale occur if the production process of the firm becomes less efficient as production is expanded, as when a firm becomes too large to be managed effectively as a single unit. The process might involve changes of a firms' operating strategy in terms of scaling up or scaling down of size. The regulators may use this information to determine whether the size of representative firm in the particular industry is appropriate or not. Column nine in table 1 also provides the nature of returns-to-scale for individual banks in Tanzania. The results indicate that 11 efficient banks (44%) are operating at most productive scale size and experiencing CRS. Further 5 banks (20%) are operating below their optimal scale size and thus, experiencing IRS. The policy implication of this finding is that these banks can enhance OTE by increasing their size and other 9 banks (36%) have been observed to be operating in the zone of DRS and, thus, downsizing seems to be an appropriate strategic option for these banks in their pursuit to reduce unit costs.

5.4 Results on Discrimination of Efficient Banks: Super-Efficiency DEA model

The Anderson and Peterson's super-efficiency scores obtained for the efficient banks and their ranks are reported in Table 3. It has been noted that among nine efficient banks, Standard Chartered Bank scored the highest super-efficiency score equal to 1.981, and thus attained first rank at the top position among the 25 banks under consideration. Citi Bank ranked the second place with super-efficiency score equal to 1.764. The third and fourth ranks were attained by Banc ABC and NIC with super-efficiency scores of 1.548 and 1.465, respectively. With the super-efficiency scores of 1.421, 1.384 and 1.208 the Akiba Bank, I & M and Azania bank placed at fifth, sixth and seventh positions respectively. BOB and Bank M have occupied eighth and ninth place, respectively.

Table 3 Andersen and Petersen's super-efficiency scores and ranks of efficient banks

Code	Bank	Super-efficiency scores	Rank
B 24	Standard Chartered	1.981	1
B 11	Citi Bank	1.764	2
B 4	Banc ABC	1.548	3
B 20	NIC	1.465	4
B 2	Akiba Bank	1.421	5
B 16	I & M	1.384	6
B 3	Azania	1.208	7
B 8	BOB	1.081	8
B5	Bank M	1.045	9

Source: Authors

5.5 Results on Discrimination of Efficient Banks

DEA approach being a widely used tool for benchmarking enables identification of efficiency DMU for inefficiency ones. This group of efficient DMUs when used for defining the operating procedures and goals for the inefficient units, in literature this group is being referred as peer group or reference set for the inefficiency DMU. Hence, the DMU which appears frequently on the reference set is considered to be a good example of efficiency performer. 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). Table 4 shows the results of frequency counts in the reference sets and categorized the efficient banks into two broad categories: (i) Highly Robust Banks; (ii) Marginally Robust Banks on basis of frequency counts. Banc ABC (B4) and BOB (B8) are highly robust banks which appear in the reference sets of inefficient banks more frequently than other efficient banks; their frequency counts have been observed to be 8 and 7, respectively. On the basis of such a high frequency count, they have been appropriately considered as global leaders of banking sector in Tanzania. However, Azania (B3), I & M (B16) and Standard Chartered (B24) are categorized as marginally robust banks because; these banks have got low frequency counts of 4, 5 and 3 respectively. It is interesting to note that although Akiba Bank (B2), Bank M (B5) and NIC (B 20) are efficient banks but these banks do not exemplify any best practices to be followed by the inefficient banks in their pursuit to enhance their efficiency levels. These banks may be rightly regarded as'efficient by default

Table 4: Reference Sets for Inefficient Banks

Inefficient Bank	OTE Score	Reference Set								
		B2	**B3**	**B4**	**B5**	**B8**	**B11**	**B16**	**B20**	**B24**
B1	0.875	0	0	0.359	0	0	0	0	0	0
B6	0.917	0	0	0.897	0	0	0	0.037	0	0
B7	0.949	0	0.126	0.863	0	0	0	0	0	0
B9	0.995	0	0	0	0	0.925	0	0	0	0
B10	0.980	0	0	0	0	0.529	0	0	0	0
B12	0.925	0	0	0	0	0	0	0.551	0	0
B13	0.990	0	0.451	0	0	0	0	0	0	0
B14	0.968	0	0	0	0	0	0	0	0	0.306
B15	0.945	0	0	0.266	0	0.734	0	0	0	0
B17	0.937	0	0	0.567	0	0.687	0	0.675	0	0
B18	0.902	0	0	0.456	0	0.786	0	0.768	0	0
B19	0.867	0	0.563	0	0	0	0	0	0	0.786
B21	0.895	0	0	0	0	0	0	0	0	0.453
B22	0.872	0	0.235	0.876	0	0.668	0	0.567	0	0
B23	0.940	0	0	0.673	0	0	0	0	0	0
B25	0.764	0	0	0	0	0.786	0	0	0	0
Frequency Count		0	4	8	0	7	0	5	0	3

Source: Authors'

Calculation: Bold figures are λ_j *values* obtained from solution of CCR model for individual inefficient banks

6. Summary and Conclusions

This study endeavors to measure the performance of banking sector in Tanzania using the average cross-sectional data for 25 banks in the year 2011 to 2013. Besides this, an attempt has been made to decompose OTE into two mutually exclusive and non-additive components, namely, pure technical efficiency (PTE) and scale efficiency (SE) and further more to provide a complete ranking in banking sector in Tanzania on the basis of super-efficiency scores. To realize the research objectives the study used the non-parametric frontier approach, data envelopment analysis (DEA), to measure the extent of OTE and its components (i.e. PTE and SE), and to determine the nature of RTS in individual banks and the Anderson and Peterson's super-efficiency model for ranking of efficient banks. The study followed an intermediation approach to select input and output variables. The output vector contains two outputs: i) loans and ii) Earning assets, while input vector contains three inputs: i) physical capital (i.e. Non-Current assets ii) deposits and iii) labour.

The results indicate that the level of overall technical efficiency of banking sector in Tanzania is around 94.9%. Thus, the magnitude of technical inefficiency is to the tune of 5.1%. The 9 banks scored OTE score of unity and, thus, defined the efficient frontier. On the basis of frequency count in the reference set of inefficient banks, two banks, Banc ABC and BOB found to be the 'global leaders in Tanzanian banking sector and the worst performer banks in the sample have been noticed to be UBA followed by NBC , PZB and Access Bank. Turning to the sources of overall technical inefficiency, it has been noticed that the observed technical inefficiency of banking sector in Tanzania is due to both poor input utilization (managerial inefficiency) and failure to operate at most productive scale size (scale inefficiency). From the analysis of returns-to-scale, it has been noticed that 9 banks (36%) operate in the zone of decreasing returns-to-scale and, thus, need a downsizing in their operations to observe an efficiency gains.

In the present study, we also carried out the Anderson and Peterson's super-efficiency model for ranking of efficient banks in Tanzania, It has been noted that among nine efficient banks, Standard Chartered Bank attained first rank at the top position among the 25 banks under consideration, Citi Bank ranked the second. The third and fourth ranks were attained by Banc ABC and NIC respectively followed by Akiba Bank, I & M and Azania bank at fifth, sixth and seventh positions respectively, while BOB and Bank M have occupied eighth and ninth place, respectively. On the whole, the study suggests that there is an ample scope for improvement in the performance of inefficient banks by choosing a correct input-output mix and selecting appropriate scale size
The future work could extend our research in various directions not considered in this study. First, we could examine other inputs and outputs variables. Second, using other frontier techniques such Stochastic Frontier Analysis for comparative purpose

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