Technical and Scale Efficiency of Saving and Credit Cooperatives: Evidence from Tanzania

By

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Abstract: This paper used the audited financial statements data from 103 Tanzanian Saving and Credit Cooperative to measure their performance in terms of efficiency. Non-parametric data envelopment analysis framework was employed in estimating technical, pure technical and scale efficiency scores. The results show that average efficiency scores are 42%, 52% and 76% for technical efficiency, pure technical efficiency and scale efficiency respectively. In terms of firm size, too small firms and very large firms were relatively less efficient compared to medium and large firms. About 77% of the firms were operating in an increasing return to scale while 15% and 8% of the firms were operating at constant and decreasing returns to scale respectively. Since most of the inefficiencies are either technical or scale in nature, the study recommends increasing the operating scale for firms operating below optimal scale. Also the managers from technically inefficient firms should reduce the waste of the productive resources by efficiently utilizing their inputs. About 16 firms which are operating beyond the optimal scale may need to downsize.

Key Words: *Efficiency, Saving and Credit Cooperatives, Data Envelopment Analysis, Tanzania*

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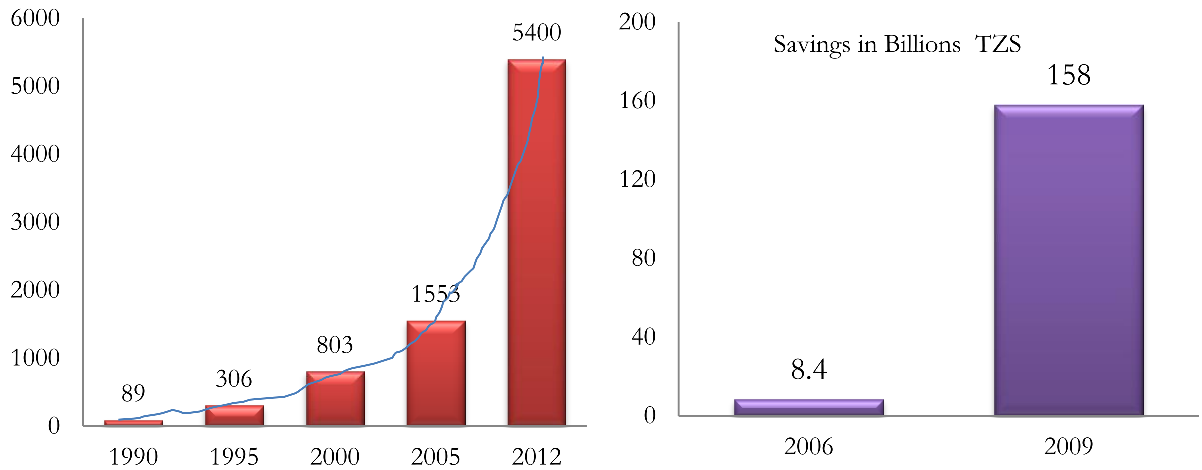
1. Introduction

The financial sector in Tanzania is highly underdeveloped, with a private sector credit to GDP ratio of 20%, and about 90% of the population is excluded from the main stream financial sector (WB, 2013; Finscope, 2009). As a result of such market failures, saving and credit cooperatives (SACCOs) and other microfinance institutions have emerged as an alternative solution. Saving and Credit Cooperatives particularly have experienced strong growth as an alternate financial service provider for the poor. According to the Ministry of Agriculture, Food Security and Cooperatives (2012) and Bank of Tanzania (2009), the number of SACCOs has increased from 803 in 2000 to 5,344 in 2009. Such an increase is about 565% over nine years. The number of members and direct beneficiaries has increased from 133,134 to 911,873 in the same period, which is about a sevenfold growth rate within 9 years. Members' savings have increased from 8.4 billion to 158 billion Tanzanian shillings (TSHS), equivalent to about a 19-fold growth in the same period as demonstrated by Figure 1 below.

Figure 1: SACCOs' Growth in numbers (left hand panel) and Savings (right hand panel)



While the recorded growth rate is impressive, the speed at which SACCOs are growing warrants a systematic investigation to discern their performance based on sound and rigorous economic methodology. Such investigation is further justified by the unique nature of the industry due to their size and operating environment. Most of these institutions operate in a relatively small scale and high risk environment with low potential for cost and loan recovery (at least in theory). Hence, the observed growth record despite the odds makes the systematic investigation of their performance a timely undertaking. Against this backdrop, this study investigates the technical and scale efficiency of SACCOs in Tanzania. Such analysis could foster a better understanding of the performance of the SACCOs and provide evidence-based inputs for informed policy dialogue and decision making in the microfinance sectors. The findings of such a study could also provide insights needed to formulate long-term policy and development management strategy for SACCOs in the country.

2. Literature Review and Theoretical Framework

This section first presents the key distinguishing features of typical financial cooperatives. In the second sub-section it presents the theoretical and empirical literature on efficiency modelling in the banking and microfinance sector with a focus on sub-Saharan Africa and Tanzania in particular.

3.1 Distinguishing Features of Financial Cooperatives

Cooperative organizations are a special type of economic entities whose objective is to maximize the members' welfare/benefits. In a typically cooperative organization, members are also users of the service(s). For example in a credit cooperative, the services may be exclusively for members, who have a common bond through an associational, occupational or residential relationship. Prospective clients need to be a qualified member first before they can take advantage of saving or borrowing services from the cooperative (Fried, Lovell and Eeckaut, 1993). The implication of this unique and voluntary model is that the objective of a typical cooperative may not necessarily reflect the standard neoclassical assumption of profit maximization in the theory of a firm. Instead, the objective of the cooperative is to pursue both economic and social objectives.

In its simplest form, a financial cooperative is both a producer cooperative and a consumer cooperative. It is a producer cooperative when accepting savings from the members, and a consumer cooperative when it is providing loans to the members. This suggests that profit maximization may not be an appropriate objective function since there are no non-members to exploit (Fried *et al.*, 1993). As such, SACCOs are treated as if they are seeking to maximize benefits to the members, where the maximum benefit is defined as service provision (loans and deposits mobilization) subject to resources available and given operating environments.

SACCOs are responsible to provide savings services to the depositors and loans services to the borrowers. In providing these services, SACCOs incur costs in hiring and retaining human resources, office space and other operating expenses. On the other hand, because of the social objective orientation of the SACCOs, they occasionally receive voluntary services in terms of free labour and sponsorship or donations from the government, community and other philanthropical organizations. While the first set of inputs may be relatively easier to quantify, voluntary services and subsidies are tricky to capture and are not reflected in the audited financial statements of SACCOs. We acknowledge that the prevalence and depth of the voluntary services and subsidies if they are not included in modelling process may lead to upward bias of the empirical estimate of the performance. However, for this study it was not possible to capture the value of voluntary labour and subsidies, which may or may not affect our estimates depending on their actual prevalence.

2.2 Theoretical and Empirical Literature on Efficiency Modelling in the Financial Sector

2.2.1 Theoretical Literature on Efficiency Estimation

Both theoretical and empirical literature evaluating organizational performance is dominated by the use of frontier models. There are diverse frontier models, including parametric and non-parametric models. Despite their diversity, they share common characteristics in modelling relative efficiency as a quantitative measure of performance. In its simplest version, the efficiency of the decision-making unit (DMU) is defined as its ability to produce maximum possible output(s) with minimum possible inputs relative to its peers, subject to resource constraints and operating environments (Sufian, 2011; Coelli *et al.*, 1996; Banker *et al.*, 1984). When evaluating the relative efficiency of different firms, the best practice frontier function is estimated using the most productive units which share a common technology.

The dominant model under the parametric approach is the Stochastic Frontier Approach (SFA). In the non-parametric approach, Data Envelopment Analysis (DEA) is widely used in both theoretical and empirical literature. The SFA approach assumes the specific production function which maps the relationship between the inputs and outputs to estimate economic efficiency which is further decomposed into pure technical efficiency and allocative efficiency (Fried *et al.,* 1993). The advantage of this approach is its ability to control for the stochastic error component in its econometric estimation, but it suffers from being data intensive. Apart from the inputs and outputs data, it also requires the price information for the inputs (Drake, 2003). Such price information may not be readily available, since it is not commonly captured in basic financial statements. Another downside of this approach is the possibility of mis-specifying the production function and the unresolved issues of the actual probability distribution of the random component which may lead to biased results (Drake, 2001).

Alternatively, the Data Envelopment Analysis (DEA) method developed by Charnes, Cooper and Rhodes (1978) has become an increasingly popular approach for efficiency estimation in banking literature. The method uses a piecewise linear programming procedure in identifying the empirical production functions based on the actual data. DEA compares all the similar units in a given population by taking several dimensions of the output and inputs into account simultaneously. Every unit is considered as a DMU which transforms inputs into outputs.

Among the different versions of DEA models, we used two models which are most frequently used in empirical studies: the model developed by Charnes, Cooper and Rhodes, also known as the CCR-model (Charnes *et al.*, 1978) and the model developed by Banker, Charnes and Cooper also known as the BCC-model (Banker *et al.,* 1984). The main difference between these two models is the way they treat the return to scale: while the latter takes into account variable returns to scale, the former supposes that every DMU operates with constant returns to scale. Because of the inadequate relevant data on price of inputs, this study will use the DEA as the main analytical framework.

2.2.2 Empirical Literature on Efficiency Estimation

DEA have been extensively used in modelling efficiency in diverse fields including: banking sector, microfinance, health sectors, and agriculture, just to mention a few. According to Lee (2013) there are over 446 empirical works which have used the DEA approach, mainly published in operation research, management science, production analysis, applied economics etc. Of interest to this paper is the empirical work on efficiency estimation in the banking and microfinance literature. There is extensive empirical research on the efficiency of financial institutions, however most of the literature is clustered around the banking sector with limited work on microfinance. When assessing the geographical distribution of the existing literature, most of the work is skewed towards North America and Europe with some notable work in Asia and Latin America but little in the African region. Among others, the existing empirical literature on banking performance in North America, Asia and Latin America can be accessed in Fukuyama (1993), Berger (1993), Berger and Humphrey (1997), Berger and Mester (1997), Drake and Hall (2003), Berger (2007), Tahir *et al.* (2009), Saez-Fernandez and Picazo-Tadeo (2011), Sufian (2011) and Charles *et al.* (2011).

In sub-Saharan Africa the empirical work on banking performance focuses on Kenya, Tanzania, Botswana, Uganda, and South Africa and some traces in other countries. The most comprehensive study which provides a comparative analysis of sub-Saharan African commercial banks is the study by Kiyota (2011). However this study focused more on profit and cost efficiency using the stochastic frontier approach. Kamau (2011), Aikaeli (2008), Oberholzer and Westhuizen (2009) and Moffat (2008) investigated the efficiency of commercial banks in Kenya, Botswana, Tanzania and South Africa respectively. Due to the fragmented nature in terms of methodological approach and frequency of data used by these studies, the comparative analysis of these studies is limited. For example, while most studies used annual data in their analyses, Oberholzer and Westhuizen (2009) used monthly data in their analysis.

Most of the empirical literature on Microfinance performance modelling is based on Asia and Latin America with some focus on credit unions from North America and UK (Jayamaha and Mula, 2011; Haq *et al.*, 2009; Qayyam and Ahmad, 2006; Gregoriou and Sedzro, 2005; Nghiem ,2004; Fried *et al.*, 1993). The mix market[3] has been a dominant data source for most of the recent empirical work on microfinance performance. Unfortunately the mix market data does not include most small microfinance institutions such as saving and credit cooperatives (Louis and Baesens, 2013; Arrasen and Avouyi-dovi 2013: Haq *et al.*, 2009: Bassem, 2008). This has led to structural omission of such a segment of microfinance in empirical research due to data problems. The current study tries to explore this frontier and make the first attempt in exploring the data challenges and solving the existing knowledge gap on the performance of these institutions.

The overall finding from the empirical literature is that the average relative technical efficiency of the banking sector ranged between 70%-94% for OECDs (Favero and Papi, 1995). For the sub-Saharan African banking sector, the average efficiency ranges from 60%-90% (Kamau, 2011; Moffat, 2008; Aikaeli, 2008; Oberholzer and Westhuizen, 2009). In the domain of microfinance the technical average efficiency estimates range between 8.7% and 94.0% (Kipesha, 2013; Jayamaha and Mula, 2011 Kipesha, 2012; Haq *et al.,* 2009). The observed inter and intra region heterogeneity of efficiency scores is expected due to the differences in firms' specific factors and operating environments. Apart from the contextual factors, the choice of variables included as inputs and outputs have been documented to influence the empirical results on efficiency. More discussions on the different approaches which have been used by the previous studies and the justification of the selection of the variable in banking literature are presented in the next section.

2.3 Specification of Inputs and Outputs

According to Nghiem (2004), Moffat (2008) and Qayyum and Ahmad (2006), there are three widely used basic approaches of specifying inputs and outputs for any decision making unit. These approaches include: (i) the production approach, (ii) the intermediation approach, and (iii) the assets approach. Under the production approach the financial institutions are considered as

[3] Mix Market (Microfinance Information Exchange) is an online data base portal for microfinance around the world. It is important to note that most of the small microfinance organizations, such as saving and credit cooperatives from poor countries, are not included in the data base. The data set can be accessed at http://www.mixmarket.org/

the producers of deposits and loans. The number of employees and capital expenditures are important inputs in this approach. The second approach considers financial institutions as intermediaries, and as such they have the responsibility of transferring financial assets from the savers (surplus unit) to the investors (deficit unit). In this case the inputs can be defined as labour, capital cost and interest payable on deposits, while the loans and financial investments are considered as outputs in this approach. Finally under the assets approach it is assumed that the basic function of any financial institution is the creation of credit (loans), whereas the value of assets of financial institutions acts as output in this approach.

Depending on the approach adopted, the choice of the inputs and outputs may be different (Moffat, 2008; Drake, 2003), and the empirical results may be sensitive to the choice of inputs and outputs. Favero and Papi (1995) posit that there is no simple solution for the problem of input and output specification since reasonable arguments can be made in all the approaches. Hence the nature of the study and data availability plays a significant role in the final choice of the input and output variables. Since the intermediation approach closely matches the main objective of SACCOs, i.e. mobilizing the savings and offering loans, this study adopts the intermediation approach in selecting the inputs and outputs. The choice of the intermediation approach for this study is also partly influenced by the data issues. In the intermediation approach the SACCOs are treated as financial intermediaries between the savers and borrowers. They seek to maximize the outputs (total loans and other incomes) given the input levels: deposit, labour and capital (Sufian, 2011).

Another challenge on the efficiency estimation is the choice of the orientation, that is, input or output orientation. Input orientation has been recommended for cost minimization focused policies, while output orientation has been recommended for impact maximization policies (Cooper *et al.*, 2011). On the other hand it is argued that the orientation choice must be chosen according to the quantities of inputs and outputs that the managers are able to control (Coelli *et al.,* 2005). In our case, managers are more able to control the inputs (personnel, total assets and total costs) than the outputs (demand for loans, and returns on assets) which are subject to external market forces. Therefore, in this paper we adopted the input orientation and intermediation approach.

3. Methodology

3.1 Estimation Technique

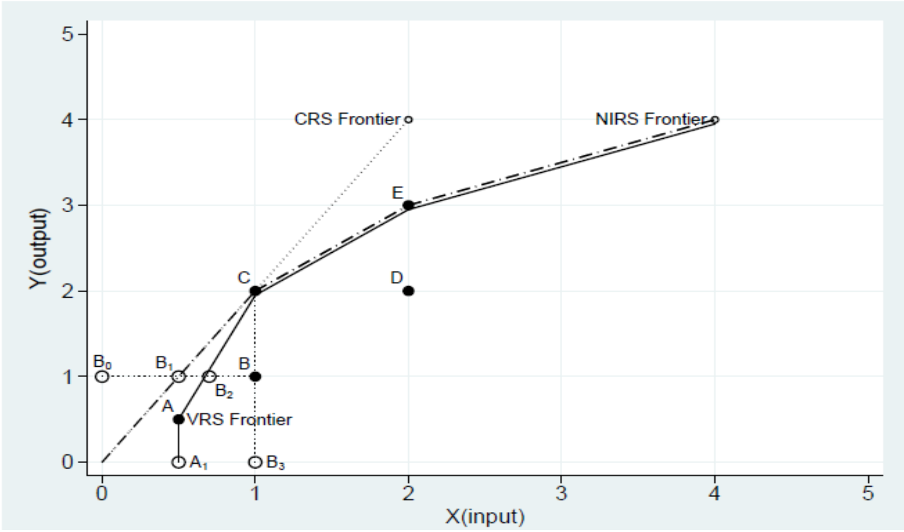
Data Envelopment Analysis is used for estimation under constant returns to scale and variable returns to scale assumption. To put things into perspective, Figure 2 demonstrates the estimation procedures for technical and scale efficiency within the framework of DEA using one input and one output with five firms (A, B, C, D and E). Basically DEA derives the data envelopment surface by joining those points in the input–output space such that it is no longer possible to produce more output with the same input or the same output with less input. In case of constant returns to scale the frontier will be linear, and for variables returns to scale the frontier will be convex hull (Favero and Papi, 1995). Once the data envelopment surface is established it is then used as a benchmark to measure the relative efficiency or inefficiency of all other firms outside the envelopment surface. For example, in this case only firm C is efficient and will be assigned score 1 in the case of constant returns to scale. Under variable returns to scale, firms A, C and E are efficient and each of them will be assigned the score of 1. The remaining firms will be benchmarked to locus ACE to measure their inefficiency scores. The efficient frontier is classified under constant returns to scale (CRS), increasing return to scale (VRS) and non-increasing returns to scale (NIRS).

According to Yue (1992) a firm is said to be in a decreasing return to scale space if a proportionate decrease in both inputs and outputs will place the firm inside the production frontier, whereas if a proportionate increase or decrease will move the firm either along or above the production frontier the firm is said to be in constant returns scale space. In the case of decreasing returns to scale, a proportionate decrease in a firm's output and inputs will place it inside the frontier and a proportionate increase is not possible because it moves the firm outside the frontier. Therefore depending on the actual behaviour experienced by the firm it is categorized in any of the three scale categories: increasing returns to scale, decreasing returns to scale, or constant returns to scale.)

Technical efficiency is estimated by measuring the ratio of the distance between reference points distance to constant returns to scale frontier and inefficient firm's distance from the same frontier. The distance measured can be either in the input space or output space depending on input orientation. It is possible to decompose technical efficiency into scale efficiency and "pure" technical efficiency (Lee and Ji, 2013). Pure technical efficiency (PTE) is measured as the ratio of the distance between inefficient points to VRS efficient frontier. For example in Figure 2, ray $\overline{B_2B}$ contributes to technical efficiency of point B regarding VRS model and ray $\overline{B_1B}$ contributes to technical efficiency of point B regarding CRS mode, whereas $\overline{B_1B_2}$ contributes to scale efficiency. More compactly, based on the graph below and using firm B for demonstration purposes:

Technical Efficiency (TE) is estimated as $\frac{B_oB_1}{B_oB}$, Pure Technical Efficiency (PTE) is estimated as $\frac{B_oB_2}{B_oB}$, and Scale Efficiency (SE) is estimated as TE/PTE $= \frac{B_oB_1}{B_oB} / \frac{B_oB_2}{B_oB}$.

Figure 2: Technical and Scale Efficiency Estimation Concepts



Source: Lee, 2013

In a multiple outputs and inputs settings with large number of firms, DEA can be formulated either as constrained maximization or minimization objective function under the general framework of linear programming. The optimal solution is iteratively solved using a simplex algorithm. Hence for every DMU k, the "ratio" of the DEA consists of maximizing (in case of output maximization) the efficiency score h_k in the presence of r outputs and i inputs as follows:

$$Max\left[h_k = \frac{\sum_{r=1}^{s} u_r Y_{rk}}{\sum_{i=1}^{m} v_i X_{ik}}\right] \quad \text{Subject to} \quad \frac{\sum_{r=1}^{s} u_r Y_{rk}}{\sum_{i=1}^{m} v_i X_{ik}} \leq 1 \quad \text{for:} \quad j = 1,\ldots\ldots,\ and\ u_r\ \&\, v_i \geq 0$$

……..………………………………………………………………………………………………(1)

Where k is the k[th] DMU; h_k is the ratio of the technical efficiency score for the firm k; Y*rk* is the quantity of output r for the DMU*k*; u_r is the coefficient of weighting of the output *r*; X_{ik} is the quantity of input i for the DMU k; V_i is the coefficient of weighting of the input *i;* and *j* is the DMU. One particular problem of the ratio formulation above is that it has infinite number of solutions (Coelli *et al.*, 2005). To avoid this, one can impose the constraint $\sum_{i=1}^{m} v_i X_{ik} = 1$ which provides the following alternative formulation:

$$Max\left[h_k^{'} = \sum_{r=1}^{s} u_r Y_{rk}\right] \quad \text{Subject to:} \quad \begin{cases} \sum_{i=1}^{m} v_i X_{ik} = 1 \\ \sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \le 0 \\ u, v \ge 0 \end{cases}$$

…………………………………(3)

Where *u* is the weighting coefficient for each of r output. The dual form of the maximization problem can be presented as a minimization problem as follows.

$$Min_{(\theta,\lambda)}\theta \quad subject \quad to \quad \begin{cases} -Y_o + \sum_j \lambda_i Y_i \ge 0 \\ \theta X_o - \sum_j \lambda_j X_i \ge 0 \\ \lambda \ge 0 \\ \sum_j \lambda = 1 \end{cases}$$ ……………………………………………………………

(4)

Where θ is technical efficiency score; Y_θ is the observed output for the firm whose efficiency is being measured ; X_θ is the observed input for the firm whose efficiency is being measured, Y_j is quantity of output for firm j ; X_j is the quantity of inputs for firm j and λ_θ is a weighting coefficient.

Since the dual formulation is mathematically easier to estimate and less restrictive in terms of constraints, it will be used in the empirical estimation process. To estimate variable returns to scale the BCC model was used. This model is an extension of CCR model which includes piecewise linear envelopment surface with assumption of variable returns to scale in contrast to CCR model (Banker *et al.*, 1984). The BBC model corresponds to the CCR Model but with the addition of the constraint of convexity i.e. $\sum_j \lambda = 1$.

3.2 Further Analysis

After estimating efficiency scores, one sample t test is used to test if average technical efficiency, scale efficiency and pure technical efficiency scores were statistically significantly different from one. Since the efficiency scores may be exhibiting positive skewness (technical efficiency) and negative skewness (scale efficiency and pure technical efficiency), the Wilcoxon rank sum test (a non-parametric alternative of the one sample t test) is used to check the robustness of the results. The estimation process was implemented in STATA version 11. For efficiency scores we used a DEA user written command developed by Lee[4] and Ji (2013).

The data sets were further decomposed into four quartiles based on the loan size to probe the variation of efficiency scores across different firm sizes. Technical Efficiency, Pure Technical Efficiency and Scale Efficiency scores were evaluated in each quartile. The median spline plot was used to plot the median scores of technical efficiency over different loan sizes. The box plot was used to study the distribution of different efficiency scores in each quartile.

3.3 The Data Set

The study used secondary data from annual audited financial statements for 2011. The auditing was done by the Cooperative Auditing and Supervisory Corporation (a third party), an agency appointed by the government to conduct SACCOs' auditing country wide. The SACCOs included in the study were from four regions: Dar Es Salaam, Mwanza, Kilimanjaro and Arusha. The complete list of available audited SACCOs during 2011 were compiled and made accessible. The main documents which were collected are audited financial statements which include both income statements and balance sheets for each individual SACCO. In total the information from 139 SACCOs were collected but only 103 had complete information and were used in the analysis. The key variables extracted from financial statements are: Total Cost in TZS, Total Fixed Asset in TZS (a proxy for capital), Total Deposit in TZS, and Total Loan Portfolio in TZS. The first three were used as inputs and the last two variables were used as outputs in the analysis. Table 1 provides a detailed breakdown per region.

According to Charnes and Coopers (1990) the rule of thumb suggests that the minimum sample size required for data envelopment analysis is three times the sum of total number of inputs (X) and total number of outputs (Y), that is, N = (Y+X) *3. Further empirical studies using simulation data demonstrated that as sample size increases, the DEA frontier converges to a true relative efficient frontier for a specific industry under study. The improvement follows a negative exponential trend with the optimal sample size between 50-160 observations (Zhang and Bartels, 1998). Based on this literature our sample size is considered reasonable for data envelopment modelling.

4. Empirical Results and Discussion

Descriptive statistics (mean, minimum, maximum, standard deviation) are presented in Table 1 for total loans, total expenditure, total deposit, total revenue and total assets. In addition the

[4] The technical support in terms of DEA estimation within STATA from Prof Lee is highly appreciated. Professor Lee shared his user-written commands and has been very helpful in guiding the authors step by step on how to implement the DEA framework in STATA.

average regional contribution to average loan portfolio is included. In the lower part of the table the ratio of average total deposit, average total revenue and average total expenditure to average total loans is presented in the last column. Such a proportion is useful for checking the percentage of external funding and the percentage of total cost to loan portfolio. Based on the summary statistics, the average total loan portfolio outstanding during 2011 was TZS 869 million. The average total deposit and total expenditure are 555 million and 61.2 million respectively. The percentage of the average deposit to average loans is 64%, implying that on average about 36% of the total outstanding loans is being financed by the external funding sources. It is also important to note that on average SACCOs spent around 7% of their loan portfolio as a total expenditure.

Table 1: Averages loans per region (upper sub-table) for all 138 SACCOs and summary statistics (lower sub-table) for 103 completes cases

Region	Audited SACCOs	Complete Cases	Mean (000000)	Std. Dev. (000000)	Min (00000)	Max (000000)	Average regional
Arusha	25	22	518	729	3.5	2540	0.15
Dar Es Salaam	85	57	1120	1430	0.94	7460	0.32
Kilimanajaro	11	10	491	567	11.7	1700	0.14
Mwanza	17	14	656	779	18.8	2010	0.19
Total	138	103	869	1190	0.94	7460	1.00
Variable			Mean (000000)	Std. Dev. (000000)	Min (000000)	Max (0000000)	Ratio to average total
Total Loans			869	1190	0.94	7460	1.00
Others Assets			126	243	1.5	1590	0.14
Total Deposit			555	1020	2.05	7160	0.64
Total Revenue			116	154	0.26	813	0.13
Total Expenditure			61.2	94.9	0.46	586	0.07

Source: Computed by authors

Table 2 presents the individuals firms' efficiency scores. The key results are technical efficiency, pure technical efficiency, scale efficiency and returns to scale classifications for each firm. The ideal situation is to have all three efficiency scores as close as possible to one. In the case of returns to scale the desirable situation is to have as many firms as possible under constant returns to scale space.

A firm is said to be technically efficient if it produces maximum outputs at the minimum possible inputs compared to its peers. The technical efficiency (TE) scores are further decomposed into pure technical efficiency (PTE) and scale efficiency (SE). The decomposition provides more insights into the sources of inefficiencies. Pure technical efficiency measures how a SACCO utilizes the resources to produce output under exogenous environments. Scale efficiency measures if the SACCOS are operating at their optimal scale. The returns to scale helps determine whether the SACCOs have been operating at the most productive scale size (constant returns to scale), increasing returns to scale (IRS) or decreasing returns to scale (DRS). The performance ranking is reported based on the composite efficiency score (Technical efficiency).

Table 2: Estimates for Technical Efficiency (TE), Pure Technical Efficiency (PTE), Scale Efficiency and Returns to Scale

ID	Region	TE	PTE	SCALE	RTS	Rank	ID	Region	TE	PTE	SCALE	RTS	Rank
33	DSM	1	1	1	crs	1	20	DSM	0.3	0.34	0.87	irs	53
13	DSM	1	1	1	crs	2	121	MWZ	0.3	0.86	0.34	drs	54
46	DSM	1	1	1	crs	3	50	DSM	0.29	0.69	0.42	drs	55
98	AR	1	1	1	crs	3	120	MWZ	0.29	0.51	0.57	drs	56
48	DSM	1	1	1	crs	5	77	KLM	0.28	1	0.28	irs	57
110	MWZ	1	1	1	crs	5	43	DSM	0.28	0.4	0.69	irs	58
108	MWZ	1	1	1	irs	7	64	DSM	0.28	0.29	0.97	drs	59
56	DSM	1	1	1	crs	8	72	KLM	0.27	0.34	0.81	irs	60
41	DSM	1	1	1	crs	9	52	DSM	0.27	0.34	0.79	irs	61
116	MWZ	0.97	1	0.97	irs	10	102	AR	0.26	0.34	0.77	drs	62
82	AR	0.91	1	0.91	drs	11	19	DSM	0.26	0.49	0.54	irs	63
10	DSM	0.89	0.97	0.93	drs	12	79	AR	0.26	0.94	0.28	irs	64
34	DSM	0.86	1	0.86	irs	13	117	MWZ	0.26	0.52	0.49	irs	65
53	DSM	0.83	0.83	1	irs	14	69	KLM	0.25	0.31	0.82	drs	66
42	DSM	0.82	1	0.82	irs	15	93	AR	0.24	0.26	0.93	irs	67
119	MWZ	0.81	1	0.81	irs	16	17	DSM	0.24	0.24	1	irs	68
95	AR	0.79	0.83	0.95	irs	17	26	DSM	0.24	0.26	0.94	irs	69
84	AR	0.77	0.77	0.99	irs	18	21	DSM	0.23	0.29	0.8	irs	70
101	AR	0.76	1	0.76	irs	19	14	DSM	0.23	0.25	0.93	irs	71
22	DSM	0.76	0.8	0.94	irs	20	76	KLM	0.22	0.33	0.67	irs	72
94	AR	0.69	0.99	0.69	irs	21	11	DSM	0.22	0.22	0.98	irs	73
44	DSM	0.65	1	0.65	drs	22	49	DSM	0.22	0.24	0.9	drs	74
63	DSM	0.65	0.7	0.92	irs	23	58	DSM	0.22	1	0.22	irs	75
51	DSM	0.63	1	0.63	irs	24	70	KLM	0.22	0.3	0.72	irs	76
39	DSM	0.62	0.63	0.99	irs	25	73	KLM	0.21	0.23	0.94	irs	77
96	AR	0.59	0.81	0.74	irs	26	68	KLM	0.21	0.22	0.98	irs	78
65	DSM	0.59	1	0.59	drs	27	103	AR	0.21	0.28	0.76	irs	79
27	DSM	0.58	0.65	0.89	drs	28	32	DSM	0.2	0.21	0.95	irs	80
90	AR	0.54	0.57	0.94	irs	29	38	DSM	0.2	0.31	0.66	irs	81
47	DSM	0.53	0.53	0.98	drs	30	35	DSM	0.2	0.61	0.32	irs	82
60	DSM	0.51	0.51	1	drs	31	113	MWZ	0.19	0.31	0.62	irs	83
37	DSM	0.49	0.97	0.51	irs	32	3	DSM	0.19	0.21	0.89	irs	84
83	AR	0.49	0.53	0.91	irs	33	71	KLM	0.18	0.18	1	irs	85
59	DSM	0.47	0.48	0.99	irs	34	36	DSM	0.17	0.2	0.85	irs	86
9	DSM	0.43	1	0.43	irs	35	106	MWZ	0.17	0.39	0.45	irs	87
112	MWZ	0.42	0.64	0.67	irs	36	25	DSM	0.17	0.17	1	irs	88
87	AR	0.42	0.48	0.87	irs	37	91	AR	0.17	0.96	0.18	irs	89
100	AR	0.41	0.45	0.91	irs	38	18	DSM	0.17	0.24	0.69	irs	90
15	DSM	0.4	0.4	0.99	irs	39	85	AR	0.16	0.7	0.23	irs	91
109	MWZ	0.4	0.41	0.98	irs	40	86	AR	0.16	0.18	0.9	irs	92
29	DSM	0.39	0.78	0.5	irs	41	61	DSM	0.16	0.16	0.98	irs	93
16	DSM	0.38	0.65	0.59	irs	42	118	MWZ	0.15	0.17	0.9	irs	94
105	MWZ	0.37	0.37	1	irs	43	5	DSM	0.15	0.2	0.77	irs	95
4	DSM	0.37	0.39	0.96	irs	44	99	AR	0.15	1	0.15	irs	96
2	DSM	0.37	0.38	0.98	irs	45	57	DSM	0.14	0.3	0.47	irs	97
111	MWZ	0.36	0.52	0.7	irs	46	74	KLM	0.13	1	0.13	irs	98
23	DSM	0.36	0.6	0.6	drs	47	75	KLM	0.12	0.12	0.99	drs	99
81	AR	0.35	0.35	0.99	irs	48	62	DSM	0.11	0.5	0.21	irs	100
45	DSM	0.33	0.41	0.81	irs	49	7	DSM	0.1	1	0.1	irs	101
88	AR	0.32	0.47	0.69	irs	50	55	DSM	0.09	0.13	0.67	irs	102
80	AR	0.31	0.32	0.96	irs	51	12	DSM	0	0.06	0.06	irs	103
31	DSM	0.31	0.31	0.97	irs	52							

Note: The first column represents the SACCOS identifier, the second column represents the regions in which SACCO belong and third to seventh columns represent technical efficiency, pure technical efficiency, scale efficiency, returns to scale and ranking score.

To make sense of the individual scores from Table 3 the results were aggregated into overall average scores for technical, pure technical and scale efficiency as reported in Table 3. The results of efficiency estimates reveal that 9 firms were technically fully efficient (had a score of 100% under technical efficiency), 24 firms had a score of 100% under pure technical efficiency, and 9 firms had a score of 100% under scale efficiency. The average technical efficiency score is about 42%. This implies that on average the sample SACCOs only needed 42% of the inputs currently in use to produce the same amount of output. The estimated average efficiency score is relatively low compared to what is observed in the banking industry in Tanzania (about 80%) as reported in Aikaeli (2008). When compared to the results from Microfinance in the East Africa using a mix market data set, SACCOs still lag behind as compared to scores of 82%-89% reported by Kipesha (2012).

Table 3: Summary of Efficiency Estimate with total number of DMU per category in brackets

Item		Estimate	
Number of DMU		103	
Number of Efficiency DMU under	TE	9	
	PTE	24	
	Scale	9	
Average	TE	0.42	
	PTE	0.52	
	Scale	0.76	
Returns to Scale	CRS	7.8 %	(8)
	DRS	15.5 %	(16)
	IRS	76.7%	(79)

Note: The actual number of firms is shown in the brackets

The results are quite close to the findings from cooperative rural banks reported in the study of Jayamaha and Mula (2011) from Sri Lanka. In their study, Jayamaha and Mula found that the average technical efficiency scores dropped from 66% during 2003 to 53.2% in 2005. The decline was mainly attributed to decreasing pure technical efficiency because the scale efficiency recorded positive growth during the same period.

The efficiency scores were tested to see if they were significantly different from one and the test results are reported in Table 4. All the three efficiency measures were found to be significantly lower than one. This implies that on average the industry is operating below the desired efficiency level as demonstrated by negative and significant test statistics based on both one sample t test and one sample Wilcoxon signed rank test approach. In an effort to understand the sources of the inefficiency, technical efficiency scores were decomposed into pure technical efficiency and scale efficiency. On average the scale efficiency seems to be relatively good compared to pure technical efficiency. This implies that most of the inefficiency is contributed by inefficient allocation of the factors of production. However, there is still a room for improvement in terms of scale efficiency.

Table 4: Parameter Estimates for Testing Efficiency Scores are different from 1

	T test (one sample)		Wilcoxon Signed Rank Text	
Variable	Test Statistics	Pvalue	Test Statistics	Pvalue
TE	-21	< 0.0001	-8.740	< 0.0001
PTE	-13	< 0.0001	-8.373	< 0.0001
SCALE	-9	< 0.0001	-8.740	< 0.0001

Note: The left hand panel of the table represents one sample t test results for different efficiency scores and the right hand panel of table represents one sample Wilcoxon Signed Rank Test of efficiency scores

In fact about 79 firms out of 103 (76.7%) are operating in sub-optimal scale. Only eight firms were operating in the optimal scale while 16 firms were operating beyond the optimal scale. From a policy and managerial perspective this means that those firms operating below the optimal scale may need to scale up and those operating beyond their optimal scale may need to improve their performance by scaling down. Figure 3 illustrates the distribution of SACCOs across constant returns to scale (CRS-optimal scale), increasing return to scale (IRS-too small) and decreasing returns to scale (DRS-too large).

Figure 3: Distributions of SACCOs across different categories of returns to scale

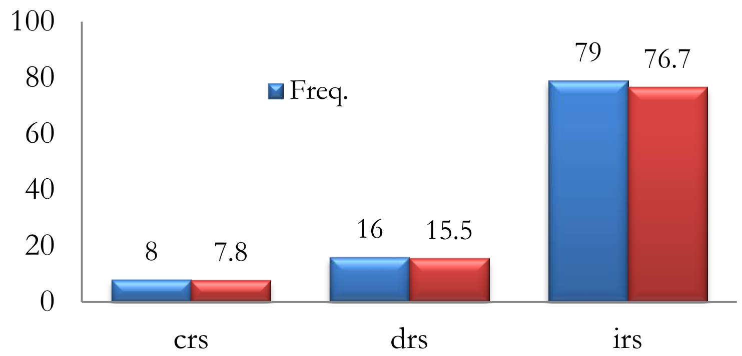
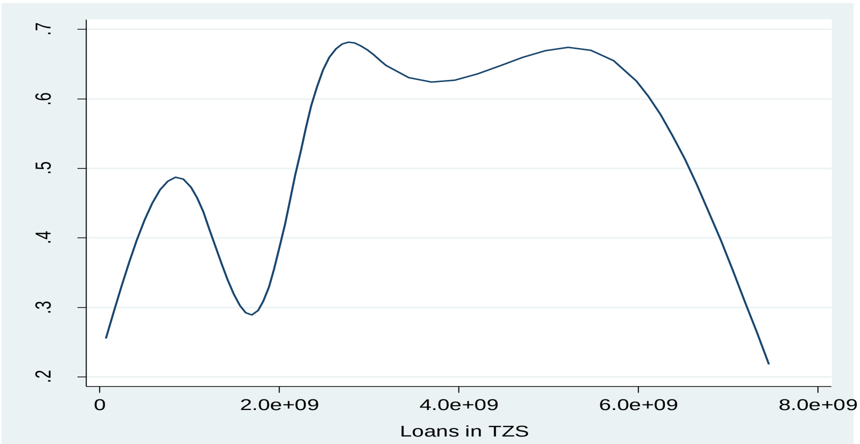


Figure 4 demonstrates the behaviour of technical efficiency across firm size using loan size as a measure of DMUs. The results show that technical efficiency follows an inverted U shape with a few irregularities for very small firms. The implication of these results is that on average medium-sized firms are more likely to be efficient than large firms. The smaller firms and very large firms are likely to be inefficient. The possible explanation of the observed inverted U shape is that the small firms may be incurring higher fixed costs in offering the services and may not be able to afford to attract the best talents in running their operations effectively. On the other hand relatively large firms are more likely to operate in diseconomies of scale. As pointed out by Coase (1937), large firms are more likely to suffer from resource misallocation, planning cost and cost of lack of motivation by the employee. Based on results reported in Figure 4, the optimal firm size seems to range between TZS 2.5 billion to TZS 6 billion. The range is wide which implies that, contrary to neoclassical economic theory, there is no single optimal point but there is a band of points which stretches between the ranges specified above.

Figure 4: Median Spline of Technical Efficiency Scores by Firm Size



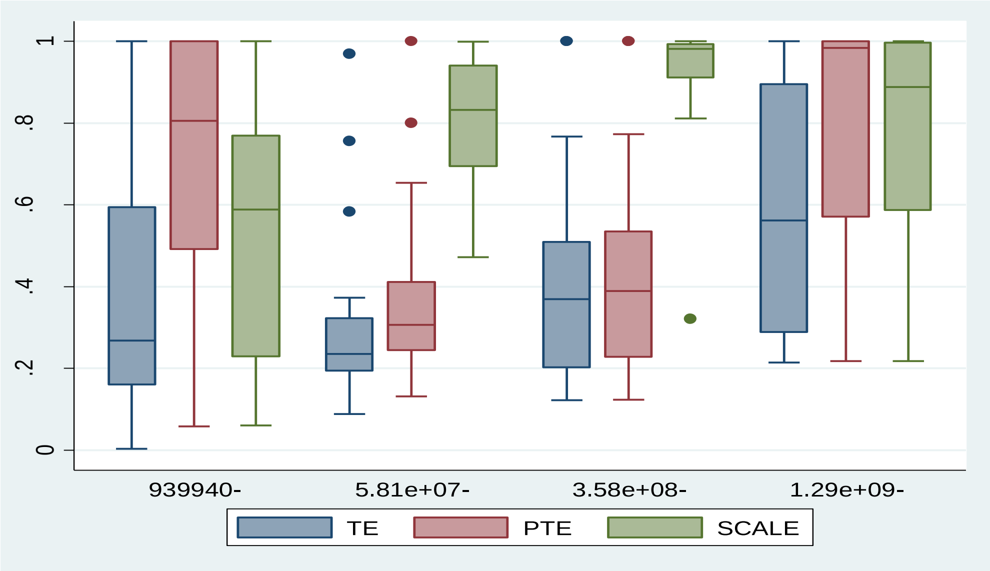
Our findings is in line with the McConnell and Stigler's illustration of the cost minimization curve of the firms in reality (Canback *et al.*, 2006). According to Canback *et al.* (2006), such a cost curve with a wide range of optimal output reconciles with several real world observations. The implication from such an inverted U efficiency curve with a stretched "saddle point" is the possibility of a wide range of output levels which can be produced within that range for which the unit cost per output is somewhat constant. This implies that small, medium and large SACCOs can co-exist at the same time without compromising efficiency and competitiveness. However, when the firm is too small or too large, it may become counterproductive. Such flexibility is particularly important in SACCOs because they can easily converge to their maximum growth capacity due to their upper ceiling.

When the technical efficiency score is decomposed into pure technical efficiency and scale efficiency it becomes apparent that the major source of inefficiency emanates from pure technical inefficiency as compared to scale efficiency. While there is room for improvement for scale efficiency, the need for improvement in pure technical efficiency is even more critical. To understand how the three efficiency scores are distributed across the firm size, the box plot approach was used for each quartile as demonstrated in Figure 5.

A closer look at Figure 5 reveals that the technical efficiencies score mimics a weak U shape. The U shape can be inferred by loosely connecting the median point of the corresponding box plot of the technical efficiency of each quartile. The observed U shape implies that the smaller firms and larger firms are relatively more efficient than the medium firms using loan quartiles as classification of firm size. The fourth quartile has the highest technical efficiency scores as demonstrated by the median scores in the box plot. The results for pure technical efficiency show the same pattern but with a more pronounced U shape with the fourth quartile almost fullly efficient. This demonstrates that smaller firms and large firms are leading by efficiently utilizing the inputs under their disposal to produce the same amount of outputs. In contrast, the scale efficiency shows an inverted U shape. This can be observed by loosely connecting the median point of each corresponding box plot. The third quartile has the highest scale efficiency score followed by the fourth quartile. Based on the observed behaviour for scale efficiency it appears that the optimal scale size for SACCOs in terms of scale efficiency is within the third quartile. Comparing the results from Figures 4 and 5, it appears that the inverted U shape results of the technical efficiency scores are mainly influenced by the scale efficiency.

The breakdown of firm size by quartile reveals a very interesting pattern which may have important managerial and public policy implication. The observation that pure technical efficient scores is higher in smaller firms (quarter 1) and larger firms (quarter 4) are critical. The implication from this observation is that as firms grow in size they start struggling with the internal managerial challenges and this makes them become inefficient in allocating their inputs to produce maximum possible outputs. In the context of SACCOs the results may support the practice whereby as the SACCOs grow bigger they tend to shift from using member-based managerial skills to hiring external managers. However, they can afford to hire the mangers of a certain skill and education level which can be outgrown by the managerial challenges of the organization as it grows further. The process remains iterative and depends on their financial muscle to compensate, attract and retain appropriate candidates for the position.

Figure 5: Box Plot for Technical Efficiency (TE), Pure Technical Efficiency (PTE) and Scale Efficiency (SCALE) Scores across different categories of loan size

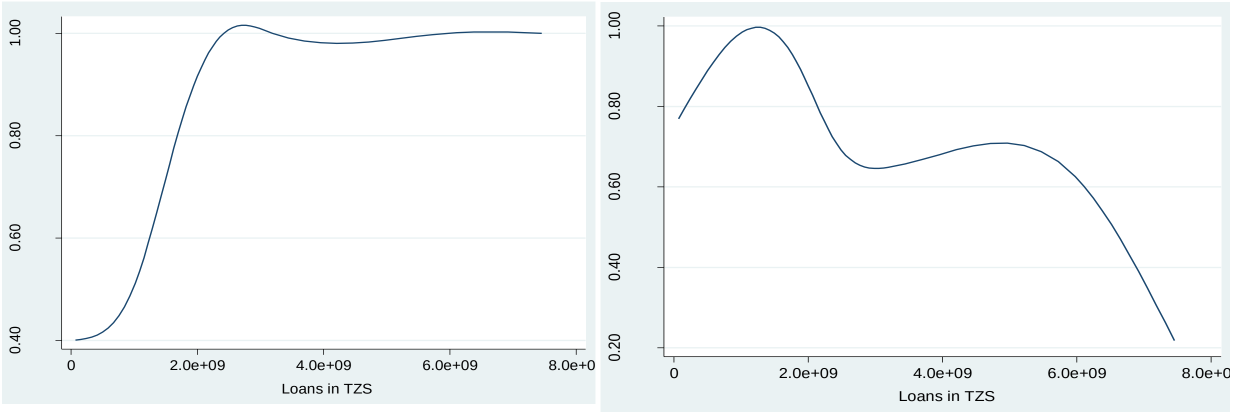


Note: *The isolated dots in figure 5 above represents outlying observations, the horizontal line indicates the median. If our efficiency scores were normal, the line (the median) would be in the middle of the box (the 25th and 75th percentiles, Q1 and Q3) and the ends of the whiskers (the upper and lower adjacent values, which are the most extreme values which within Q3+1.5(Q3-Q1) and Q1-1.5*(Q3-Q1) respectively) would be equidistant from the box. But boxplots for our efficiency scores shows positive skew (technical efficiency) and negative skew (scale and pure technical efficiency) i.e. the median is pulled to the low end and upper end of the box respectively.*

Furthermore, while people with low levels of education and financial literacy can manage to lead small size SACCOs well, a slight increase in size may outgrow their managerial competence. A corollary of the argument is that, as the firm grows beyond a certain threshold, in our case as they move from quartile 3 to quartile 4, their financial muscles increases, the size of their members increase and diversity increases. The interaction of these factors is likely to generate a new emergent complex pattern which may lead to a strong oversight, more willingness to hire external managers to manage the organization and an increased ability to afford such services. This may possibly explain the observed higher scores of pure technical efficiency in the fourth quartile. Also as firms grow bigger, they tend to improve their scale efficiency by cutting down per unit cost, as would be predicted by neoclassical economic theory. However, such scale advantage occurs only up to a point beyond which it starts to become self-destructive.

Based on our results, the optimal scale is reached in quarter three as demonstrated by Figure 5. Further analysis demonstrates that the optimal scale advantage can be reached as low as TZS 1.5 billion loan size and it starts decreasing the further the firm is from this point. On the other side, the optimal pure technical efficiency is achieved around TZS 2.3 billion and there is little gain beyond this point, as illustrated by Figure 6.

Figure 6: The median spline plot for PTE and Scale Efficiency score over the loan size



The observed declining efficiency in large SACCOs despite the highest scores of pure technical efficiency is rather surprising. The possible explanation may be that, as SACCOs grow larger, they are likely to become more specialized and start attracting the lower end of the middle income clients and micro, small and medium enterprises (MSMEs). By operating in such a space, they are exposed to stiff competitive environment with the sophisticated commercial banks. If this happens they are likely to lose through at least two channels. The first channel is that commercial banks are highly sophisticated and enjoy economies of scale which are relatively superior to those of large SACCOs. The second channel is that since the large SACCOS are attracting clients on the bottom of middle income clients and MSMEs, they are more likely to succumb to the riskier segment in this income category. If this happens, it means that large SACCOs are likely to increase their portfolio loans but with more risky clients.

5. Conclusion and Recommendation

The current study investigated the technical efficiency of 103 saving and credit cooperatives from Tanzania. The data used were collected from audited financial statements in 2011. The intermediation approach and input orientation was employed within a Data Envelopment Analysis Framework to estimate efficiency scores in terms of technical efficiency, scale efficiency and pure technical efficiency. The empirical findings show that the average technical efficiency is about 42%, and average pure technical efficiency was 52%, and scale efficiency was 76%. Most firms are struggling with how to efficiently utilize their resources to maximize the outputs. Smaller firms and larger firms seem to suffer from lack of economies of scale and diseconomies of scale respectively, while medium SACCOs experienced a significant increase in scale efficiency but a significant decrease in technical efficiency. Medium firms struggle with how to effectively manage and make effective decisions in resource allocation.

Large SACCOs experienced high levels of technical efficiency but seemed to struggle with the scale problem. Large SACCOs may be exposed to a more competitive market space where they are forced to compete with large commercial banks. Only 8% of the SACCOS were operating in the optimal scale and about 15% and 77% of the SACCOs were operating at decreasing and increasing return to scale respectively. This implies that about 18% of the SACCOs were too large to operate efficiently and about 77% of the SACCOs were too small to operate efficiently.

The policy implication from our finding is grouped into regulatory oriented and management oriented. The regulators (Bank of Tanzania, Ministry of Agriculture and Cooperatives, Cooperative Banks, Cooperatives Audit and Supervisory Corporation) need to work closely with SACCOs to create a supporting environment for small SACCOs to increase their size and managerial capacity. This may include the design for an in-services certificate course in SACCO management and accounting to improve managerial capacity and competence, constant monitoring and supervision, technical support and wholesale lending to increase their size of operation.

In terms of SACCO management, they need to be more and careful in the way they manage their inputs in producing the outputs. With a better usage of available resources there is room to improve technical efficiency by 55%. The 79 small SACCOs operating in the increasing return to scale space may wish to merge with other smaller ones or with larger and efficient ones. With the introduction of mobile banking such as M-Mpesa it should be easy to operate satellite offices virtually. Large SACCOs may need to spin out (demerger) since they have grown too big for efficient operation. Another option is to merge with a commercial bank and operate as a microfinance satellite branch of the commercial bank.

Future studies may wish to upscale the study to widen both the geographical coverage and non-audited SACCOs. This will help to validate the study by using more data. Also if data allows it may be important to analyze the performance over time to understand the dynamics within the industry.

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