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Efficiency Assessment of Mozambican Banks: A Slacks-Based Measure of Efficiency Approach

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Abstract: This study aims at assessing the efficiency of the banking sector in Mozambique. Data Envelopment Analysis (DEA) models were applied for that purpose. Concretely, the non-radial output-oriented Slacks-Based Measure (SBM-O) model under the assumption of variable returns to scale was applied to assess the technical efficiency of banks. This study can be considered one of the first to apply the SBM model to assess the efficiency of banks in Mozambique. Data for the fiscal year 2020 of 16 commercial banks operating in Mozambique were collected. Three input variables were considered: total assets, operating costs, and deposits; and two outputs: net interest income and loans. According to the results, the average efficiency of the Mozambican banking sector was 72.4%, which reveals a low performance of the sector. The SBM-O model found eight efficient banks, which was considered as a reference set for inefficient banks. The results gained can help bank managers in decision-making, especially for those banks classified as inefficient.

Keywords: Banks, Efficiency, DEA, SBM model.

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1. Introduction

The existence of an efficient financial system is a fundamental condition for Mozambique's sustainable economic and social development. A financial sector that allocates resources efficiently is the engine that drives economic growth in any country (Kamau, 2011). On the other hand, a strong financial system encourages investment through financing productive businesses, mobilizing savings, and facilitating commercial activities, and the financial sector as a whole plays a key role in the allocation of financial resources in the economy (Kizito, 2012). Evaluating the performance of banks is important because if financial institutions work more efficiently, they will have more profit and increase the liquidity of the economy. Without efficient financial institutions, it is very difficult to sustain the country's economic growth (Nguyen, 2007).

The strength of a banking sector is directly affected by various variables (internal and external) with an impact on economic growth and the welfare of a stable and efficient banking system, especially for emerging economies (Güneş and Yıldırım, 2016; Fernandes, Stasinakis, and Bardarova, 2018). Therefore, banks try to maintain their asset's quality, efficiency, and profitability, vital requirements for survival and development (Zimková, 2014). Also, efficient use of labour, better use of time, cheaper costs, and economies of scale, among others, can contribute to achieving these goals.

An efficient banking system plays a major role in the progressive economic growth of any country (Kumar and Singh, 2014). The efficiency of the banking sector on a country basis is an important issue as the success of the entire monetary system in the financial system and the stability of the banking sector are affected by this activity. Although assessment of bank efficiency is common in the United States (US), Europe, and Asia, few studies are available in the African banking sector (Wanke, Maredza, and Gupta, 2017) and the same is true for Mozambique, indicating a gap in the literature.

Many studies have been developed in different areas using different techniques to evaluate the efficiency or performance of companies, as a way of responding to the financial limitations of the organizations, demonstrating that it is possible to improve prices, the offer of services, increase transparency, and accountability of governments and improving the information used to support the strategic decisions (Worthington and Dollery, 2000).

For this purpose, new methodologies have been proposed to measure the efficiency of the most diverse entities. Among these methodologies is the Data Envelopment Analysis (DEA), a non-parametric method based on mathematical programming (linear programming), which allows the evaluation of the efficiency of a set of independent and homogeneous entities usually called Decision Making Units (DMUs) that use multiple inputs to produce multiple outputs.

Within DEA, the models proposed by Charnes, Cooper, and Rhodes in 1978 (CCR) and Banker, Charnes, and Cooper (BCC) in 1984 are the main models widely applied to measure efficiency. These two models are radial, that is, models in which the inputs are reduced in the same proportion while the outputs remain constant, in the case of input-oriented models, or in which the outputs are increased in the same proportion while the inputs remain constant, in the case of output-oriented models. Such models ignore the existence of an excess of inputs or a shortfall of outputs, normally called slack.

One of the problems associated to the efficiency value obtained through the CCR and BCC models is exactly that of not accounting for inefficiencies due to slack in inputs and/or outputs, which can lead to the DMU being classified as efficient, when really it is not. Several measures and models have been proposed in the literature to circumvent this problem, such as the SBM of Tone (2001).

The article is organized into six chapters. Following the introductory chapter, there is the second chapter, the literature review, which deals essentially with efficiency analysis studies carried out in the banking sector using DEA. The third chapter presents the Data Envelopment Analysis (DEA) and describes the Slacks-Based measure (SBM) in DEA. The fourth chapter presentsthe data and variables selected for the study. The fifth chapter is dedicated to the results and their respective discussion. The sixth chapter presents a summary of the main conclusions and some recommendations for future studies.

2. Literature Review

Data Envelopment Analysis (DEA) is seen as the most widely used non-parametric technique for efficiency measurement, especially in banking (Berger and Humphrey, 1997; Ali and Seiford, 1993). A bank's efficiency means that the bank can deliver its service with the minimum possible resources or produce the maximum possible products and services using a limited amount of input. The efficiency of the banking system is the most important issue in the financial market, as it affects the stability of the banking sector and then the efficiency of the country's monetary policy. There are many studies evaluating the efficiency of commercial banks using the DEA method; Reviews of these various studies are presented as follows:

In the international literature, the work of Sherman and Gold (1985) is considered by many authors to be a pioneer in the application of DEA methodology to analyze efficiency at the banking sector (Daraio and Simar, 2007; Liu et al., 2013; Forsund and Sarafoglou, 2002; 2005). In this pioneering study, the authors explored the use of DEA as a novel approach that can help to improve bank branch efficiency by providing efficiency information that goes beyond what accounting data provides. In other words, the study of Sherman and Gold (1985) provided the basis and inspiration for other studies applying the DEA methodology to be developed in the banking sector.

A range of studies evaluates efficiency in the financial sector using DEA, especially radial and non-radial models. It can be highlighted, for example, some studies involving radial models such as those made by Ataullah et al., (2004), Casu and Molyneux (2003), Favero and Papi (1995), and McAllister and McManus (1993). Radial models represented by CCR and BCC models are those in which the inputs are reduced in the same proportion while maintaining the outputs (input-oriented), or the outputs are increased in the same proportion keeping the level of inputs (output-oriented). Conversely, non-radial models, represented by the Additive and SBM models, do not assume the same proportionality relationship. This implies that an increase or decrease in the input does not necessarily imply a proportional change in output.

Pastor, Perez, and Quesada (1997) compared the efficiency, productivity, and differences in technologies of different European and US banks in 1992. In their study, 168 banks in the USA, 67 in France, 59 in Spain, 44 in Austria, 31 in Italy, 22 in Germany, 18 in the UK, and 17 in Belgium were selected and they used the DEA approach to investigate the efficiency levels of banks. They chose two inputs non-interest expenses and personal expenses, and three outputs loans, other productive assets, and deposits. According to his findings on cross-country efficiency scores, banks in Spain, Denmark, and Portugal were the most technically efficient banks. Banks from France and Italy were found to be less efficient. They also found that banks in the USA, Austria, and Germany were scale-inefficient.

The study conducted by Baidya and Mitra (2012) aimed at measuring and evaluating the technical efficiency of 26 Indian public sector banks for the 2009–2010 fiscal year. CCR and Andersen and Petersen's super efficiency model were used as DEA models. The results reveal that the average technical efficiency of the entire sample was 86.5% and only seven banks (23%) were fully efficient. Thus, 19 public sector banks in India have an efficiency improvement scope. The study found that banks that use more workforce to deliver their services are relatively inefficient.

Yıldırım (1999) conducted research on the efficiency of the Turkish banking sector by using the DEA method between 1988-1996. Guney and Tektas (2006) analyzed the efficiency of the Turkish banking sector during the crisis period using DEA, between 1990-2001. Şakar (2006) applied DEA Malmquist Index to study the efficiency and productivity of banks in Turkey between 2002 and 2005. Budak (2011) applied DEA to evaluate the efficiency of banks in Turkey in 2008, 2009, and 2010. In this study, the basic DEA models (CCR and BCC) were applied.

Raphael (2012) investigated the efficiency of commercial banks in Tanzania using a DEA from 2008 to 2011. The study used three input variables (deposit, interest, and operating expenses) and four output variables (credit, investment, interest income, and non-interest income). The analysis showed that most of the commercial banks in Tanzania are technically inefficient. Large banks outperformed smaller banks in terms of size. According to the study, commercial banks should minimize the use of input resources while maintaining the same level of output to increase technical efficiency. Gizaw (2019) in his study used DEA, to assess the technical and scale efficiency of private commercial banks in Ethiopia.

One of the first studies that used the SBM model, proposed by Tone (2001), was the application carried out in 24 commercial banks in Taiwan to evaluate and predict the performance of these banks (Liu, 2009).

In another study, Avkiran (2011) evaluated the efficiency of Chinese banks after economic liberation, marked by China's entry into the World Trade Organization in 2001, and presents the usefulness of DEA as a reference standard for investors, regulators, and society in general. The study was carried out with the financial information of 21 Chinese commercial banks to evaluate the profitability approach, using financial and non-financial expenses and income variables. In this case, the SBM model was appointed as the appropriate technique to assess efficiency. The author also states that financial indicators, normally used by the market, are not capable of discriminating against the efficiency of banks

(Avkiran, 2011). In this study, the author compared the results obtained by nine DEA models and the research concluded the SBM model is the most adequate, even when compared to the CCR and BCC models, stating that the SBM model is capable of presenting more discrimination between the DMUs (Avkiran, 2011).

The SBM model was applied to evaluate the efficiency of 130 banks in Indonesia between 2003 and 2007 (Hadad et al., 2012). One can also refer to a study carried out in Canada that used the SBM model to evaluate the efficiency of 1000 bank branches in that country. The study showed that even though belonging to the same bank, each branch carries out its stats and demands different management capabilities (Paradi, Zhu, and Edelstein, 2012).

Zinková (2014) analyzed the technical efficiency and super efficiency of a representative sample of commercial banking institutions in Slovakia. In this study, the CCR model, the SBM model by Tone (2001), and the super-efficient model by Tone (2002) were applied. According to the results, Komerční bank, a foreign bank branch, was found to be a super-efficient banking institution operating under variable returns to scale in 2012 in the Slovak Republic.

Chiu and Chen (2009) suggest that the SBM model provides a good representation of banking operations in real situations since banks are given a certain degree of control on both the input and output sides.

Kasim et al., (2019) applied the super-efficiency model based on SBM (SuperSBM) to assess the efficiency of nine commercial banks in Malaysia between 2004 and 2013. In this study, the selected banks were able to be ranked according to their efficiency scores.

Shah et al.(2022) analyzed the impact of non-performing loans on the operational efficiency of commercial banks in Pakistan. In this study, Super-SBM model with the undesirable output for the efficiency evaluation of commercial banks was used.

Nabilah and Al Arif (2022) applied DEA to analyze the efficiency of Islamic banks. In this study, in addition to determining the level of efficiency of the banks, the authors sought, through a regression model, difference-in-difference (DID), to understand the impact of the spin-off policy and other factors that affect the level of efficiency of the banks.

Boubaker et al. (2022) applied inverse DEA to evaluate the performance and efficiency of 49 Islamic banks in 10 countries during the period of the COVID-19 pandemic (2019-2020), to assess how these banks can preserve their performance and remain resilient after the pandemic.

Ben Lahouel et al., (2022) applied the combination of the CAMELS rating system and DEA to calculate the financial stability of European banks after the global financial crisis and during the implementation of Basel III liquidity rules.

Amirteimoori et al., (2023) applied DEA to measure scale elasticity in a set of 71 Indian banks over a period of eight years (1998-2005).

Wu et al., (2023), applied DEA and Tobit Regression to analyze the impact of interest rate liberalization on the efficiency of 27 commercial banks in China between 2006 and 2020.

Marlina et al. (2023) applied DEA Window Analysis to measure the level of efficiency of Islamic banks in Indonesia between 2011-2016.

In the case of Mozambique, two studies are highlighted that applied some DEA models to assess the efficiency of banks in that country (Wanke, Barros, and Emrouznejad, 2016; Lemequezane, 2020). Wanke, Barros, and Emrouznejad (2016) applied Fuzzy-DEA and bootstrapping to assess the productive efficiency of banks. In turn, Lemequezane (2020) applied DEA Malmquist Index to assess the productivity of banks. Aside from these studies, none was found that portrays the SBM model to assess the efficiency of the Mozambican banking sector. Thus, the authors see the present study as one of the first to apply the DEA-SBM model in the Mozambican banking sector.

3. Data Envelopment Analysis

Data Envelopment Analysis (DEA) was developed by Charnes, Cooper, and Rhodes (CCR) (Charnes et al., 1978) under the assumption of constant return to scale (CRS) and later modified by Banker, Charnes and Cooper (BCC) under the assumption of variable returns to scale (VRS) in 1984 (Banker et al., 1984). The basic ideas of DEA were developed based on the pioneering work of Farrell (1957). DEA is a non-parametric technique that uses mathematical programming (linear programming) to measure the relative efficiency of homogeneous units that consume multiple inputs to produce multiple outputs. These units, in the DEA literature, are called Decision Making Units (DMUs), in our case banks.

The inputs correspond to the resources used, and the outputs are goods or services obtained as a result of the production process. CCR or CRS model occurs when any variation in the inputs produces an equal proportional variation in the outputs. On the other hand, BCC or VRS model replaces the axiom of proportionality with the axiom of convexity, which means that a variation in the inputs produces a greater or lesser variation than the proportional one in the outputs, allowing DMUs with low values of inputs have increased returns to scale and DMUs with high input values have decreased returns to scale.

Normally, the efficiency value is obtained from two perspectives, input-oriented and output-oriented. There are also non-oriented models. In the input-oriented model, efficiency is achieved by minimizing inputs while maintaining at least the quantity of outputs. In turn, in the output-oriented model, efficiency is achieved by maximizing outputs while maintaining the level of inputs. The choice of orientation for the models varies according to the company's objectives, the control they have over inputs and outputs, and the socio-economic context.

In this study, output-oriented models under the assumption of variable returns to scale (VRS) were chosen. The envelope model used to calculate the efficiency of DMUs under the assumption of variable returns to scale (BCC model or VRS) is represented as follows (Cooper, Seiford, and Zhu, 2004):

$$\phi^* = \max \phi + \varepsilon \left(\sum_{i=1}^{m} S_i^- + \sum_{r=1}^{s} S_r^+ \right) \tag{1}$$

Subject to:

$$\sum_{j=1}^{n} x_{ij} \lambda_j + S_i^- = x_{io} \quad i = 1,2,\ldots,m \tag{2}$$

$$\sum_{j=1}^{n} y_{ij} \lambda_j - S_i^+ = \phi y_{ro} \quad r = 1,2,\ldots,s \tag{3}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{4}$$

$$\lambda_j \geq 0 \quad j = 1,2,\ldots,n \tag{5}$$

Where: $\phi^*$is the optimal value; s_i^- represents input excesses; s_i^+ represents output shortfalls, in the literature, they are called slacks; λ_j are the values that allow determining the reference set for the inefficient DMUs; $\varepsilon > 0$ is a very small positive value than any real number (non-Archimedean), generally considered $\varepsilon=10^{-6}$ (Cooper, Seiford and Tone, 2000). For output-oriented CCR and BCC models $\phi^* \geq 1$. A DMUo is said to be efficient if and only if $\phi^* = 1$ and all slacks are zero ($S_i^{-*} = S_r^{+*} = 0$).

3.1. Slacks-based Measure of Efficiency

This study employs the non-parametric SBM in Data Envelopment Analysis under the assumption of VRS to assess the efficiency of commercial banks in Mozambique. The SBM model was proposed by Tone (2001) and deals directly with input and output slack to generate an efficiency index that is invariant to the measurement units for both input and output variables. More generally, this measure is the same when, x_{io} and x_{ij}, are replaced by $k_i x_{io} = \hat{x}_{io}$, $k_i x_{ij} = \hat{x}_{ij}$, respectively, and are replaced by $c_r y_{ro} = \hat{y}_{ro}$, $c_r y_{rj} = \hat{y}_{rj}$, where k_i and c_r $(i = 1,2,\ldots,m;\ j = 1,2,\ldots,s)$ are arbitrary positive constants. This measure has the following important properties:

1. (P1) The measure is invariant withering the measurement of each input and output item. (Units invariant).

2. (P2) The measure is monotone decreasing in each input and output slack. (Monotone).

The production possibility set P of SBM model can be defined as follows

$$P = \left\{ (x, y) \mid x \geq \sum_j x_j \lambda_j, y \leq \sum_j y_j \lambda_j, \lambda_j \geq 0 \right\} \tag{6}$$

To estimate the efficiency of a DMU (x_o, y_o) is formulated the index ρ represented through the following fractional program in λ, s^- and s^+:

$$\text{[SBM]} \qquad \min \ \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{io}}{1 + \frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{ro}} \tag{7}$$

Subject to:

$$x_0 = X\lambda + s^- \tag{8}$$

$$y_0 = Y\lambda - s^+ \tag{9}$$

$$\lambda \geq 0, s^-, s^+ \geq 0 \tag{10}$$

This model assumes that $X \geq 0$. If $x_{io} = 0$, then the term s_i^- / x_{io} in the objective function is eliminated. If $y_{io} \leq 0$, then it is replaced by a very small positive number, so that the term s_r^+ / y_{ro} plays a penalty role. It is easy to verify that the value of the objective function, ρ, satisfies property 1 (P1) since the numerator and denominator are measured in the same units for each item in the objective of (1). It is also easy to verify that an increase in any of the slacks (s_i^-, s_r^+), all else remaining constant, will decrease the value of this target, and indeed in a strictly monotonic manner.

This index takes values between 0 and 1, that is,

$$0 \le \rho \le 1 \tag{11}$$

To see that this relationship holds, let us observe that $s_i^- \le x_{io}$ for each i such as $0 \le s_i^-/x_{io} \le 1 (i = 1,2, \ldots, m)$ with $s_i^-/x_{io} = 1$ only if the evidence shows that a zero amount of this input was required. It follows that

$$0 \le \frac{\sum_{i=1}^{m} s_i^- / x_{io}}{m} \le 1 \tag{12}$$

This same relation does not hold for outputs because an outputs shortfall represented by non-zero slacks can exceed the corresponding quantity of outputs produced. At any case, there is

$$0 \le \frac{\sum_{r=1}^{s} s_i^+ / y_{ro}}{s} \tag{13}$$

In this way, this represents average ratios of the mixing inefficiencies in inputs and outputs with the upper bound, ρ=1, obtained only in the case where the excesses in all inputs and the shortfalls in all outputs are zero.

The index presented in model (7) can be transformed into the following product

$$\rho = \left(\frac{1}{m} \sum_{i=1}^{m} \frac{x_{io} - s_i^-}{x_{io}} \right) \left(\frac{1}{s} \sum_{r=1}^{s} \frac{y_{ro} + s_r^+}{y_{ro}} \right)^{-1} \tag{14}$$

The ratio $\frac{x_{io}-s_i^-}{x_{io}}$ evaluates the relative reduction rate of input i, and, therefore, the first term corresponds to the mean proportional reduction rate of inputs or input mix inefficiencies. Likewise, in the second term, the ratio $\frac{y_{ro}+s_r^-}{y_{ro}}$ evaluates the relative proportional expansion rate of output r and $(1/s) \sum \left(\frac{y_{ro}+s_r^-}{y_{ro}} \right) / y_{ro}$ is the mean proportional rate of output expansion. Its inverse, the second term, measures *output mix inefficiency.* Consequently, SBM ρ can be interpreted as the ratio of mean input and output mix inefficiencies. Furthermore, If DMUA dominates DMU B so that $x_A \le x_B$ and $y_A \ge y_B$, then $\rho_A^* \ge \rho_B^*$.

Let an optimal solution for [SBM] be (ρ^*, λ^*, s^{-*}, s^{+*}). Based on this optimal the solution, DMU can be defined as being SBM – efficient as follows (Tone, 2001):

Definition 1 (SBM-efficient). A DMU (x_o, y_o) is SBM-efficient if ρ^*=1. This condition is equivalent to s^{-*}=0 and s^{+*}=0, that is, no input excesses
and no output shortfalls in any optimal solution.

For a DMU (x_o, y_o) SBM inefficient, we have the following expressions:

$$x_o = X\lambda^* + s^- \tag{15}$$

$$y_o = Y\lambda^* - s^+ \tag{16}$$

DMU (x_o, y_o) can be improved and become efficient by eliminating the excess inputs and increasing the output shortfalls. This is achieved with the following formulas, called SBM Projection on the efficient frontier:

$$\hat{x}_o \Leftarrow x_o - s^{-*} \tag{17}$$

$$\hat{y}_o \Leftarrow y_o + s^{+*} \tag{18}$$

The SBM projections on the efficient frontier can also be obtained by using the set of indexes ices corresponding to the positive λ^*, the so-called reference set for (x_o, y_o). The reference set is represented by

$$R_o = \{j| \ \lambda_j^* > 0\} \ (j \in \{1, \dots, n\}) \tag{19}$$

Then using R_o we can also express $(\hat{x}_o, \hat{y}_o)$ by

$$\hat{x}_o = \sum_{j \in R_o} x_j \lambda_j \tag{20}$$

$$\hat{y}_o = \sum_{j \in R_o} y_j \lambda_j \tag{21}$$

This means that $(\hat{x}_o, \hat{y}_o)$, a point on the efficient frontier, is expressed as a positive combination of the members of the reference set, R_o, which are also efficient.

The relationship between the CCR efficiency and the SBM efficiency is given by the following theorem: A DMU (x_o, y_o) is CCR-efficient if and only if it is SBM-efficient.

The model discussed above (7) is a non-oriented model. Input-oriented or output-oriented SBM models can be obtained from model (7) by re-evaluating the numerator and denominator of that index. An input-oriented SBM model is obtained by making the denominator equal to 1. In turn, the output-oriented SBM model is obtained by making the numerator equal to 1. This study aims at maximizing the outputs while keeping the level of inputs, the output-oriented SBM model was chosen, whose expression is given by (Tone, 2001; Cooper, Seiford, and Zhu, 2004):

$$\text{[SBM-O]} \qquad \min \rho_O^* = \frac{1}{1 + \frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{ro}} \tag{22}$$

Subject to:

$$x_0 \geq X\lambda \tag{23}$$

$$y_0 = Y\lambda - s^+ \tag{24}$$

$$\lambda \geq 0, s^+ \geq 0 \tag{25}$$

The optimal values of ρ for the oriented models are always greater than or equal to the value ρ for the non-oriented model, that is, $\rho_I^* \geq \rho^*$and $\rho_O^* \geq \rho^*$.

4. Data and variables

The population of this study consists of 20 commercial banks operating in Mozambique. Due to the lack of information for some banks, the final sample corresponds to a total of 16 commercial banks. Data were obtained through the financial reports of the banks for the year 2020 and cross-referenced with information from the reports of the Mozambican Banking Association (https://www.amb.co.mz/). Table 1 presents the list of 16 commercial banks selected for this study.

Table 1. List of 16 selected Mozambican commercial banks

No	Banks	Started year	Abbreviation
1	BIM - Banco Internacional de Moçambique, SA	1995	BIM
2	Banco Comercial e de Investimentos, SA	1996	BCI
3	Standard Bank, SA	1967	SB
4	Absa Bank Moçambique, SA	1977	ABSA
5	Banco Nacional de Investimento, SA	2011	BNI
6	FNB Moçambique, SA	2007	FNB
7	First Capital Bank, SA	2013	FCB
8	Moza Banco, SA	2008	MOZA
9	Banco Único, SA	2011	UNICO
10	Banco Mais	2016	MAIS
11	African Banking Corporation(Moçambique),SA	1999	BancABC
12	Banco Letshego, SA	2011	LETSHEGO
13	Ecobank Moçambique, SA	2000	ECOBANK
14	United Bank for Africa Moçambique, SA	2010	UBA
15	Société Générale Moçambique, SA	1999	SGM
16	Socremo Banco de Microfinanças, SA	1998	SOCREMO

Three main approaches are widely used in the literature for measuring efficiency in the banking sector, namely, production, financial intermediation, and value-added approach (Sufian and Kamarudin, 2014; Sealey and Lindley, 1977). The present study opted for the financial intermediation approach, which states that financial institutions normally employ labour, physical capital, and deposits as their inputs to produce earning assets (net interest income and loans). The financial intermediation approach is the most preferred approach among researchers investigating the efficiency of banking sectors in developing countries (Sufian and Kamarudin, 2014; Bader *et al.*,2008).

To fulfil the objectives of this study, three input variables were considered: total assets (TA), operating costs (OC), and deposits (D); and two outputs: net interest income (NII) and loans (L). The variables were chosen to take into account the various studies consulted on the analysis of efficiency in the banking sector (Zinková, 2014; Sufian and Kamarudin, 2014; Arrif and Can, 2008, among others).

Table 2 presents the descriptive statistics of the selected variables, in Metical amounts (MT or MZN), which is the currency unit of the Republic of Mozambique.

Table 2. Descriptive Statistics of the Input and Output Variables (in MZN'000)

Statistics	Total Assets	Deposits	Operating Costs	Net Interest Income	Loans
N	16	16	16	16	16
Mean	45,871.19	35,183.66	2,278.42	2,822.25	15,240.33
Std. Dev.	64,645.37	51,361.67	2,631.84	3,969.11	20,104.86
Min.	1,881.44	995,27	214,96	193,36	298,94
Max.	191,436.46	151,857.03	7,856.04	11,815.26	68,102.65

In applying DEA to measure efficiency, it is necessary to consider several principles, in addition to positive values of input and output variables. First, the "golden rule", is to achieve a reasonable level of discrimination between DMUs, the number n of DMUs must be at least three times the sum of inputs and outputs variables, that is, if m is the number of inputs and s the number of outputs, then $n \geq \max\{ms; 3(m+s)\}$ (Cooper, Seiford and Tone, 2000).

In the case of this study, this relationship holds. Second, the input variables must be independent from each other, just like the output variables. Third, there must be a positive correlation between input and output variables (Table 3).

Table 3. Correlation between input and output variables

Variables	Total Assets	Deposits	Operating Costs	Net Interest Income	Loans
Total Assets	1.000				
Deposits	0.999**	1.000			
Operating Costs	0.975**	0.974**	1.000		
Net Interest Income	0.992**	0.989**	0.968**	1.000	
Loans	0.969**	0.966**	0.965**	0,954**	1.000

**Correlation is significant at the 0.01 level (2-tailed).

5. Results and Discussion

This chapter presents the main empirical results of our study. Data were processed using the R Studio software and the results are shown in Table 4, which presents information about the CCR-O(θ_0^*), BCC-O (ϕ_O^*), SBM (ρ^*), and SBM-O(ρ_O^*) technical efficiency values. Also, there are illustrated the reference set, the respective weights (λ^*), and the slack values.

Table 4. The results of the SBM model

		CCR	BCC	SBM			Slacks in MZN'000				
No.	**Banks**	θ_O^*	ϕ_O^*	ρ^*	ρ_O^*	**Reference set and weights(λ^*)**	s_1^{-*}**[TA]**	s_2^{-*}**[D]**	s_3^{-*}**[OC]**	s_1^{+*}**[NII]**	s_2^{+*}**[L]**
1	BIM	1.5473	1.000	1.000	1.000		0	0	0	0	0
2	BCI	1.4995	1.000	1.000	1.000		0	0	0	0	0
3	SB	1.9733	1.072	0.851	0.888	BIM(0.30), BCI(0.45), LETSHEGO(0.25)	235	0	831	0	9525
4	ABSA	1.7684	1.000	1.000	1.000		0	0	0	0	0
5	BNI	1.000	1.000	1.000	1.000		0	0	0	0	0
6	FNB	3.2663	2.167	0.137	0.292	ABSA(0.27), LETSHEGO(0.73)	10284	15276	1113	1136	9992
7	FCB	2.2732	1.948	0.297	0.398	MAIS(0.58), LETSHEGO(0.42)	1343	3382	0	647	2202
8	MOZA	1.5014	1.000	1.000	1.000		0	0	0	0	0
9	UNICO	2.0574	1.568	0.381	0.613	BCI(0.11), ABSA(0.07), LETSHEGO(0.82)	5212	19688	777	1221	5364
10	MAIS	1.5834	1.000	1.000	1.000		0	0	0	0	0
11	BancABC	2.4138	2.007	0.235	0.440	ABSA(0.14), LETSHEGO(0.86)	5212	10236	643	1236	5252
12	LETSHEGO	1.0000	1.000	1.000	1.000		0	0	0	0	0
13	ECOBANK	2.6586	2.294	0.343	0.376	MAIS(0.38), LETSHEGO (0.17), SOCREMO (0.45)	0	642	0	337	1665
14	UBA	3.7122	2.729	0.189	0.190	MAIS(0.87), LETSHEGO(0.12), SOCREMO(0.01)	0	34	0	335	2039
15	SGM	1.8680	1.806	0.241	0.379	BIM(0.01), LETSHEGO(0.99)	4572	9732	67	1353	4013
16	SOCREMO	1.0000	1.000	1.000	1.000		0	0	0	0	0
	Mean		1.474	0.667	0.724						

From the results obtained, as shown in Table 4, the average efficiency of the Mozambican banking sector, according to the SBM model, is 72.4%. On the other hand, analysing the data, it can be said that the financial intermediation process was successfully achieved by eight commercial banks: BIM, BCI, ABSA, BNI, MOZA, MAIS, LETSHEGO, and SOCREMO. For the fiscal year 2020, these banks are classified as technically efficient, since $\rho_O^* = 1.000$. The remaining eight other banks are classified as inefficient: SB, FNB, FCB, UNICO, BancABC, ECOBANK, UBA, and SGM. From the SBM-O model, inefficient banks obtained efficiency values ranging from 19% (UBA) to 88.8% (SB). For example, UNICO bank obtained an efficiency value equal to 0.613 (61.3%). Because DEA is a benchmarking method, inefficient banks can reach the efficiency frontier if they mirror efficient banks. The eight efficient banks mentioned above constitute the reference cluster for the set of other eight inefficient banks. Therefore, the exercise here is to project inefficient banks, through good practices, to the efficiency frontier. In the table, for each inefficient bank, the reference group and the respective weights (λ^*) are presented, which must be considered, for the projection of target values, so that they can reach the efficiency frontier. For example, it can be seen that the SB bank has the BIM, BCI, and LETSHEGO banks as a reference, with weights of 0.30, 0.45, and 0.25, respectively. These weights are used to determine target values. But on the other hand, we determined the slacks that indicate how inefficient banks must increase their output (output-oriented) to reach efficiency. Thus, for the SB bank, the value s_2^{+*}[L]=9,525,000.00 means that, the achievement of efficiency would require augmenting the loans from their observed value by MZN 9,525,000.00.To achieve efficiency, FNB bank must increase net interest income and loans by MZN 1,136,000.00 and MZN 9,992,000.00, respectively. Another verified aspect, a greater number of foreign banks, namely, SB, FNB, FCB, BancABC, ECOBANK, UBA, and SGM were classified as inefficient, which means that the financial intermediation process for those banks was not achieved in a satisfactory way. This aspect gives evidence to state that these banks should review their operating profile. One of the ways is to follow good practices, through the reference set for each of the banks. George Assaf, Barros, and Matousek (2011) carried out a study of the efficiency of nine Saudi Arabian banks in 2004. The study used the output-oriented DEA-BCC model as a basis for financial intermediation, resulting from the volume of credit granted and insurance as well as interbank deposits. The finding was that foreign banks would be inefficient technically. According to Cooper, Seiford, and Zhu (2004), the results obtained via the SBM measure reflect not only the weak efficiency values in CCR or BCC, but also the other (slack) inefficiencies as well. Therefore, the results of the SBM model can bring better discrimination between the banks compared to the radial models (CCR and BCC). In general, and taking into account the average efficiency of the sector, banks should outline management policies to increase their efficiency and productivity, especially for banks that were classified as inefficient.

6. Conclusion

The efficiency assessment of banks is of great importance because banks that can achieve efficiency and can serve as a benchmark for competing banks. In this study, the efficiency of 16 commercial banks operating in Mozambique in 2020 is assessed by using Data Envelopment Analysis (DEA) models. Concretely, the non-radial output-oriented SBM model under the assumption of variable returns to scale was applied to assess the technical efficiency of banks. On average, the efficiency of the Mozambican banking sector is 72.4%, which translates to low performance of the sector during the analysed period. Despite the low performance, half of the banks were classified as efficient and can be considered as a reference set for the other eight inefficient banks. Inefficient banks should, through good practices, that is, looking at the reference set, improve their performance to improve the efficiency and productivity of the sector. On the other hand, the results obtained in this study can help bank managers in decision-making. The efficiency analysis through DEA is affected by the number of DMUs and variables, so making comparisons, further studies are needed in the same line, using other variables. Finally, an efficiency assessment of the Mozambican banking sector considering Window Analysis, Additive, and Super-efficiency DEA models can be suggested for future research.

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