RESEARCH ARTICLE

An Empirical Analysis of Bank Efficiency in Gambia

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Abstract

This study evaluates the Technical Efficiency [TE], Pure Technical Efficiency [PTE] and Scale Efficiency [SE] of commercial banks in the Gambian banking sector. In the first stage, a non-parametric approach [DEA] is used to evaluate the relative efficiency of 12 banks from 2009 to 2017 based on "the production approach" of modeling bank efficiency. In the second stage the relationship between certain bank-specific and environmental variables and efficiency scores are examined by employing the Tobit regression model. The empirical analyses from the first stage reveals that about 42% of commercial banks were CRS technically efficient and 83% of them were VRS technically efficient in 2017. Only 42% of the banks were at the optimal size for their particular input-output mix, the remaining eight banks were scale inefficient. The level of overall technical efficiency of commercial banks in the Gambia accounted 86.5% in terms of TE, 93.1% in terms of PTE and 92.5% in terms of SE. The second stage analyses reveal that banks with the ability to charge lower interest on deposits and maintain higher interest rates on loans attain higher efficiency scores. Further, banks with large market share and market power in pricing their products can improve their efficiency levels. Lower liquidity risk is associated with higher efficiency scores. There is a weak evidence of negative association with bank size and efficiency, suggesting that smaller banks may obtain operational advantages that bring about higher efficiencies.

Key Words: *Technical efficiency; Data envelopment analysis; Tobit regression; The gambian banking*

JEL *Classification:* G2; G21; C67

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1. Introduction

The financial sector in the Gambia has undergone major policy changes in the last two decades following the implementation of structural reform program. The country's banking system has been the focus of regulatory interventions with the introduction of a new banking act in 2005. The financial sector reform was introduced to promote financial liberalization, institutional development and enhancing the stability of the financial sector. The liberalization program relaxed or abolished regulations to increase competition and the efficiency of the financial system. Following this program change, new banks were allowed to enter the industry, leading to a real growth in banking.

One of the main challenges in the Gambian financial sector is low level of financial intermediation due to commercial banks' appetite in holding government securities. Gambian banks usually invest most of their financial assets in low-risk, high-yielding government securities, mainly treasury bills and sukuk al-salam. The high opportunity cost of not investing in government securities is the main reason for the slowdown in extending credit to consumers and businesses. The growth in private sector credit was near zero in real terms over the past decade. Banks to some extend focused on three principal activities: aside from investing in government paper they offer short-term trade financing and involve in the foreign exchange market to create fee and commission revenue IMF Country Report, [1].

The Gambia is a small country with a population of 2.1 million. There are 12 banks operating in the Gambia since 2013, 11 of which are conventional commercial banks and one Islamic bank. Some observers argue that the country is over-banked though no empirical support was provided to support this argument. The banking sector plays crucial function in channeling funds between savers and investors, engaging in financing private sector trade and investment. Since it does not have well-established capital markets, it is predictable that the entry of new banks would enhance financial inclusion. The banks feel the pressure to operate efficiently to play their intermediary role effectively and to stay competitive. The upsurge in competition, however, can negatively impact the commercial banks in the Gambia. Indeed, weaker banks might experience drop in their profitability level and naturally exit the industry while the strongest will benefit from improved scale and scope efficiency. Therefore, measuring the efficiency of commercial banks in the Gambia is timely and relevant. In order to address this need, this study aims to estimate the overall technical efficiency of commercial banks in the Gambia from 2009 to 2017. Also, the study further examines the likely determinants of efficiency such as banks' specific characteristics and macroeconomic factors [*i.e.*, profitability and market power, bank size, liquidity, capital adequacy, earnings, GDP, and inflation].

The study is expected to provide useful insights for bank managers, governmental supervisory authorities, bank customers and investors, as well as academics. For bank managers, this study will allow them to evaluate the efficiency level of their bank compared to best practicing peers. The evidence on the determinants of efficiency can provide hints on maintaining banking performance at the optimal level. It will also help the customers and investors in their decision-making process. For the supervisory authorities, the empirical findings can provide insights in establishing a strong and resilient banking system for sustainable economic growth. For academics, this work will certainly contribute to the relatively scant literature on the Gambian banking.

The current study is organized into five sections. Section 2 reviews the empirical literature. Section 3 presents the methodology, the data and selection of variables. Section 4 presents the empirical results and Section 5 concludes.

2. Literature Review

Measuring the performance of financial institutions has long attracted the interest of practitioners, bank managers, regulators, as well as academicians. As a result, the literature offers great number of works that evaluate the efficiency of banks and determinants of the efficiency levels. Numerous studies have been conducted to estimate efficiency levels of banks by utilizing the parametric or non-parametric techniques. Some of these studies concentrated on technical efficiency while others focused on allocative efficiency. As a non-parametric method, the Data Envelopment Analysis [DEA] was first applied in the banking sector by [2] to measure the efficiency of bank branches. Later, the application of the DEA in banking research become common in the efficiency literature. Most of the earlier research on the topic focused on the banking markets of developed countries. [3] provide a comprehensive summary on 130 studies on efficiency of financial institutions covering 21 countries, between diverse periods and using different techniques. [4] lists over 400 papers in inclusive bibliography and [5] also provide over 2000 DEA references.

The application of the DEA model to the less developed banking markets of African countries is relatively scant. For example, [6] provide a comparative analysis of the performance of 17 Libyan banks over the period 2004 to 2010. Their analyses reveal that specialized banks have higher technical efficiency than commercial and private banks. They find a positive relationship between bank efficiency and ROA, the size of operation, capital adequacy, and government-linked banks. [7] examine and compare the efficiency of 63 Islamic banks in the Middle East and North Africa [MENA] and Asia, using DEA. Over the period 2006-2009. They find the major source of technical inefficiency for Islamic banks is the scale of their operations. They also report that country-specific factors, the country's economic situation measured by GDP per capita, have a significant positive impact on overall technical efficiency [OTE].

[8] find that under the assumptions of CRS and VRS, the average technical efficiency scores for the commercial banking sector in Zimbabwe are 70.95% and 81.5%. The average scale efficiency for commercial banks operating in Zimbabwe is 73.7%. [9] establish that most community banks in Tanzania are inefficient. [10] reveal that Ivorian banks do not operate efficiently in terms of loan allocation. Said, [11] argues that, on average, Islamic banks in other MENA countries and North Africa are relatively technically inefficient. [12] evaluates the relative technical efficiency and productivity changes of a panel of 10 Ethiopian commercial banks over the years 2007 to 2011. The results show that on average, the Ethiopian commercial banks are technically inefficient. Inadequate scale contributes significantly to their inefficiency levels. [13] estimated the technical efficiency [TE] of 21 commercial banks in Ghana between 2009 and 2013. The results show that the average TE differs directly from the size of the bank in the upper two quartiles, but big banks do not benefit from the economies of scale compared to small banks. Finally, gross domestic product [GDP] per capita, inflation, credit risk, size, and operating costs have a negative impact on efficiency while market share positively affects efficiency. In the Gambian context [14] measure the overall technical efficiency of the commercial banks in the Gambia from 2005 to 2009. Their results show that most of the banks are fully efficient under the assumption of a variable return to scale [VRS] but inefficient under the assumption of constant return to scale and scale efficiency Overall, these findings imply that banking system in Africa is still underdeveloped thus, there is a need for improvement.

3. Methodology

3.1. Sample Selection and Database

Following the implementation of the structural adjustment program in 2005, the Gambian sector has experienced significant growth over the past two decades. Deregulation and liberalization in the financial system eliminated the barriers in the banking sector and promoted the entry of new banks, both domestic and foreign. Our sample includes the banks operated in Gambia over the period 2009-2017 which coincides with the era following the financial crisis of 2008. The initial sample contained 14 commercial banks one of which is an Islamic bank. In order to be included in the analysis a bank must have complete data from 2009 to 2017. Two banks [Oceanic Bank Gambia Ltd. and Prime Bank Gambia Ltd.] with missing data over the sample period were dropped from the sample, because they withdrew from banking industry after failing to meet the capital requirement in 2011 and 2013 respectively. Our final sample of 11 commercial banks and one Islamic bank covers the whole banking universe in Gambia. The sample contains 108 observation. The data is extracted from the banks' annual report [individual banks' income statements and balance sheets] reported in the CBG and individual banks' websites. The data related to macroeconomics variables were obtained from World Bank database. [Table 1] exhibits the commercial banks included in this study.

Table 1: *Gambian Commercial Banks Included in the Study.*

No.	Bank name	Established	Abbreviation used
1	Standard Chartered Bank (Gambia) Ltd	1894	SCB
2	Arab Gambia Islamic Bank	1997	AGIB
3	Trust Bank Ltd	1997	TBL
4	First International Bank	1999	FIB
5	Guaranty Trust Bank (Gambia) Ltd	2002	GTB
6	International Commercial Bank (Gambia) Ltd	2005	ICB
7	Platinum Habib Bank (IBC before, MBL now)	1997/2008/2015	PHB/MBL
8	Access Bank (Gambia) Ltd	2007	ABL
9	Ecobank (Gambia) Ltd	2007	EBL
10	Banque Sahelo-Saherienne Pour L'investissement Et Commerce (BSIC)	2008	BSIC
11	Skye Bank (Gambia) Ltd	2008	SKBL
12	Zenith Bank	2008	ZBL

3.2. Efficiency Estimation Method

This study follows a two-stage analysis. The first stage estimates the overall technical efficiency [TE] of commercial banks in the Gambia from 2009 to 2017 by using data envelopment analysis method. TE is further decomposed to "pure technical efficiency [PTE]" and "scale efficiency [SE]".

As DEA lacks statistical inference, the study further utilizes the "Tobit regression model" in the second stage to examine the factors that determine the efficiency of banks.

The DEA methodology is a "linear programming technique" to develop efficient frontiers, which are then used to generate relative efficiency measurements. It is used for evaluating the relative performance of a set of firms or Decision-Making Units [DMUs] that uses a variety of inputs to produce a variety of outputs. The main objective of DEA is to examine how efficiently DMUs use the resources available to produce a set of outputs. DEA methodology was originally proposed by [15], in their seminal paper where the authors evaluated the efficiency of public sector non-profit organizations employing an input orientation and assumption of constant returns to scale [CRS], which is known as "CCR model". The CRS hypothesis only applies when all DMUs operate at an optimal scale. Subsequent studies have examined the assumptions of variable returns-to-scale [VRS]. The assumption of VRS was initially presented by Banker [16], which is known as "the BCC model". VRS includes "increasing and decreasing returns-to-scale". By incorporating increasing and decreasing returns-to-scale assumptions into the model, VRS makes it possible to break down "technical efficiency" into "pure technical efficiency [PTE]" and "scale efficiency [SE]". This paper uses CCR and BCC models.

Technical efficiency can be estimated based on an "input-oriented approach" or an "output-oriented approach". Input-oriented approach aims to minimize the amount of input as much as possible at a given level of output, while an "output-oriented approach" maximizes output levels at a given input level [17]. The DEA sets different weights for different companies' inputs and outputs or DMUs so that one company maximizes its efficiency compared to another. The efficiency score for all units range between zero and one, where the DMU achieves a score of one will be determined as the best practice unit.

The model employed assumes that there are n BANKs under investigation and each bank uses different quantities of j inputs to produce i different outputs, *i.e.* BANKr uses xjr quantities of input to produce y_{ir} quantities of output. It is expected that these inputs x_{jr} and outputs y_{ir} are assume non-negative values, and each BANK has one positive "input and output value" at minimum. The CCR model aims to maximize the ratio of weighted outputs to weighted inputs of the bank under examination. The efficiency score α_r for the r^{th} bank is maximized under the constraint that each other bank in the sample cannot go beyond unit efficiency by using the same weights.
The Mathematical programming equations can be defined as follows:

$$Max\, \alpha_r = \frac{\sum_{i=1}^{t} u_i y_{ir}}{\sum_{j=1}^{k} v_j x_{jr}} \quad [1]$$

Subject to the following condition:

$$\sum_{i=1}^{t} u_i y_{ir} / \sum_{j=1}^{k} v_i x_{jr} \leq 1, \quad [2]$$

$$uj, vi \geq 0 ; r = 1, \ldots, n \quad [3]$$

where: "j= j^{th}input, j=1, ..., k; i = i^{th} output, i=1, ..., t; r = r^{th} bank, r=1, ..., n; α_r= objective measure of efficiency for r^{th} bank; r=a particular bank to be estimated; y_{ir} = the amount of output $\boldsymbol{i}$ from bank

r; x_{jr} = the amount of input j to bank r; u_i = weight placed for output i; v_j= weight placed for input j; n =the number of banks; t=the number of outputs; k=the number of inputs". The fractional linear program of "Constant Return to Scale CRS" can be changed into an ordinary linear program as below

$$Max\,\alpha_r \sum_{i=1}^{t} u_i y_{ir} / \sum_{j=1}^{k} v_j x_{jr}$$

Subject to:

$$\sum_{j=1}^{k} v_j x_{jr} = 1 \qquad [4]$$

$$\sum_{i=1}^{t} u_i y_{ir} - \sum_{j=1}^{k} v_j x_{jr} \le O, r = 1,2 \ldots, n; \qquad [5]$$

$$uj, vi \ge 0, \qquad [6]$$

i = 1,2,……t, j = 1,2,….k and r =1,2,…..n.

The above solution for the linear programming provides technical efficiency score [α_r] for bank r, where $0 \le \alpha_r \le 1$.

3.3. Inputs and Outputs

This study selects bank inputs and outputs based on "the production approach" under which banks are considered as institutions that use labor and capital resources to offer financial products and services to their clients. The resources consumed, such as labor and operating costs, are treated as bank inputs, while products and services, such as loans and deposits were considered as bank outputs. According to [3], production approach assumes that financial institutions [banks] are considered as primarily producing services for account holders such as loan applications, credit reports, cheques or other payment instruments. In this approach, services and products are considered as outputs while the resources are considered as inputs. Since the aim of this approach is minimizing the cost, the input-oriented DEA model was adopted. The inputs used in this study are Interest Expenses [X1], Personnel Expenses [X2], and Noninterest Expenses [X3], while the outputs are Interest Income [Y1] and Noninterest Income [Y2]. [Table 2] presents the descriptive statistics on inputs and outputs used in this study.

Table 2: *Descriptive Statistics of Inputs and Outputs, 2009-2017 (in 000's GMDs).*

Variable Name	N	Minimum	Maximum	Mean	Std. Deviation
Inputs					
Interest Expense(X1)	108	180	292,614	58,269	56,012
Personnel Expenses(X2)	108	2,064	153,355	31,719	32,896

Non-interest Expenses(X3)	108	16,209	496,969	140,511	112,243
Outputs					
Interest Income(Y1)	108	6,359	565,186	170,913	158,937
Non-interest Income(Y2)	108	248	285,551	93,729	79,378

3.4. Regression Analysis

After estimating the efficiency scores in the first stage, the study then utilizes "the Tobit regression model" to determine the factors that influence the efficiency measures in the second stage. The model is proposed by [18] to describe the association between a censored dependent variable and independent variables. Adopting a simple OLS evaluation procedure on a dependent variable can result in biased estimates in the event of a significant observation position of 1. Tobit model is used due to the censored nature of the dependent variable [Technical efficiency are in the range of 0 to 1] and extreme values of the independent variables which deviate from a normal distribution and highly skewed in nature [19]. Tobit model used for ith bank can be estimated as follows:

$$\alpha_i = a + \beta 1\, BSit + \beta 2\, MPit + \beta 3\, Pit + \beta 4\, TL_{TAit} + \beta 5\, EQ_{TAit} + \beta 6\, II_{TAit} + \beta 7\, GDPit + \beta 8\, INFit + uit$$

$$\alpha_i = 0\, if\ \alpha_i \le 0\, ;\ \alpha_i = \alpha_i\, if\ 0 < \alpha_i \le 1\, ;\ \alpha_i = 1\, if < \alpha_i$$

As the dependent variable $\alpha_i$positioned for relative efficiency scores that lie between 0 and 1, it is filtered to the left as in the right. The α_i is a dormant variable and $\alpha_i$is the efficiency scores obtained for an ith bank from the DEA model. The regression variables in the model are listed in [Table 3].

Table 3: *Dependent and Independent Variables.*

Dependent Variables	Explanation of the Variables
TE	Technical efficiency (TE) of a bank under analysis would be given by the ratio PTE/SE, which takes a value between zero and one. A value of one implies that the bank is fully technically efficient.
PTE	Pure technical efficiency (PTE) of a bank is the ratio of TE/SE, merely reflects the management performance to control the inputs during the production process.
SE	Scale efficiency, is the ratio of TE/PTE, and it indicates the ability of the management to decide the optimum size of the resources.

Independent Variables

Internal Factors	
Bank Size (BS)	Natural logarithm of total assets
Market Power(MP)	Bank deposits to total deposits in the state which the bank operates
Profitability (P)	Net operating income to total equity (ROE)
TL_TA	Total loan and advances to total assets
EQ_TA	Equity to total assets
II_TA	Interest income to total assets
GDP	Gross domestic product growth rate
INF	Inflation rate

To examine the determinants of efficiency, this study used overall technical efficiency scores from first stage DEA analyses as the dependent variable and several bank-specific and macroeconomic factors as independent variables. Based on earlier literature, the following independent variable are selected: Bank Size, measured as log of total assets, Profitability, measured as return on equity, Market Power, measured as bank's total deposit to total deposits of the banking industry, Total Loan over Total Assets as a proxy for Liquidity, Equity over Total Assets as a proxy for Capital Adequacy, Interest Income to Total Asset as a proxy for Interest earnings, Gross Domestic Product and Inflation. We don't have a priori expectations on any of the explanatory variables.
[Table 4] presents the descriptive statistics of the dependent and independent variables of the regression model employed.

Table 4: *Descriptive Statistics of Regression Variables*.

Variable	N	Minimum	Maximum	Mean	Std. Deviation
TE	108	.2190	1.0000	.864685	.1853322
PTE	108	.3010	1.0000	.931296	.1478349
SE	108	.4590	1.0000	.925148	.1182104
TL_TA	108	-.5417	1.2575	.133771	.2831225
ROE	108	.0010	.2810	.076980	.0732630
EQ_TA	108	209,943	6,908,404	1,963,691	1,746,365
II_TA	108	.0091	1.0257	.254558	.1754658
MP	108	.0307	.8206	.247458	.1885384
BS	108	.0154	.3709	.089800	.0506314
GDP	108	-4.2951	6.5263	3.580059	3.326649
INF	108	4.2545	6.8083	5.214418	.7840180

4. Empirical Results

4.1. The Efficiency Scores of Commercial Banks in the Gambia

[Table 5] exhibits the result of the overall technical efficiency of commercial banks in the Gambia, *i.e*. technical efficiency [CRS-BCC model], pure technical efficiency [VRS-BCC model], and scale efficiency under the "production approach". The results show that commercial banks in the Gambia on average scored 86.5% for technical efficiency, 93.1% for pure technical efficiency and 92.5% for scale efficiency respectively. These numbers indicate that Gambian banks are slightly better in pure technical efficiency compared to scale efficiency.

The mean of TE under the assumption of CRS ranged between 79.4% and 93.6% over the sample period. Considering the mean TE in 2017 as an example, the conclusion can be drawn that the banks on average could have produced the same level of output by basically using only 80.4% of the inputs mix. In other words, in 2017, on average the banks were about 20 percent technically inefficient. This suggests that by adopting best practice technology banks, on average, can reduce their inputs by at least 20%. Since the banks were operating under CRS, much of their technical inefficiency can be attributed to input wastage. However, under the assumption of VRS, the PTE ranged between 85.8% and 96.3%, between 2009 and 2017. Under VRS, the SE ranged from 85% and 97.3%. VRS ranking is obtained by controlling the scale size of the bank. This is the only difference in how the two measures of efficiency are obtained.

Panel A of [Table 5] illustrates the TE measures for individual banks across years under the assumption of CRS. In 2017 five [42%] banks were CRS efficient, and the remaining seven [58%] were relatively inefficient. Among the latter, 3 banks had a CRS technical efficiency score of 71-80%, 2 scored 61-70%, and 2 scored less than 61%. Across all the banks the mean CRS technical efficiency was 86.5%, with a standard deviation of 8.84%. This means on average all banks could simply produce the same level of output by employing 86.5% of their input mix. The average CRS technical efficiency score varied from a minimum of 68.9% at Ecobank Gambia Ltd [EBL] to a maximum of 99.1% at Standard Chartered Bank [Gambia] Ltd. [SCB]. As seen from the Table, Skye Bank [Gambia] Ltd. [SKBL] is constantly efficient throughout the selected period except 2016.

Table 5: *Technical Efficiency, Pure Technical Efficiency, and Scale Efficiency Scores.*

Panel A: *Technical efficiency (CRS*).

Bank	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
SCB	1.000	1.000	0.957	0.961	1.000	1.000	1.000	1.000	1.000	0.991
TBL	1.000	1.000	0.895	0.645	1.000	0.734	1.000	0.854	0.712	0.871
PHB	0.973	1.000	1.000	1.000	0.816	0.219	0.383	1.000	0.739	0.792
GTB	1.000	0.817	0.827	1.000	1.000	0.734	1.000	1.000	0.637	0.891
FIB	1.000	0.856	1.000	0.716	0.937	0.935	0.484	1.000	0.707	0.848
AGIB	0.988	0.375	1.000	0.378	0.991	0.834	0.784	1.000	0.527	0.764
ICB	0.894	0.620	0.621	0.710	1.000	1.000	0.712	1.000	1.000	0.840
ABL	0.686	1.000	0.875	1.000	1.000	0.632	1.000	1.000	1.000	0.910
EBL	0.489	0.838	0.748	0.964	0.690	0.519	0.380	1.000	0.571	0.689
BSIC	0.911	0.718	1.000	0.691	0.788	1.000	1.000	0.829	0.754	0.855
SKBL	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.842	1.000	0.982
ZBL	1.000	1.000	1.000	1.000	1.000	1.000	0.786	0.703	1.000	0.943

Mean	**0.912**	**0.852**	**0.910**	**0.839**	**0.935**	**0.801**	**0.794**	**0.936**	**0.804**	**0.865**

Panel B: *Pure Technical Efficiency (VRS).*

Bank	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
SCB	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
TBL	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.938	1.000	0.993
PHB	0.985	1.000	1.000	1.000	0.817	0.301	0.415	1.000	1.000	0.835
GTB	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
FIB	1.000	0.901	1.000	1.000	1.000	0.973	0.541	1.000	1.000	0.935
AGIB	1.000	0.615	1.000	0.824	1.000	0.905	1.000	1.000	0.649	0.888
ICB	0.936	0.778	0.641	0.720	1.000	1.000	0.938	1.000	1.000	0.890
ABL	0.825	1.000	1.000	1.000	1.000	0.648	1.000	1.000	1.000	0.941
EBL	0.492	1.000	0.750	0.965	0.723	1.000	0.406	1.000	0.680	0.780
BSIC	1.000	0.754	1.000	0.847	1.000	1.000	1.000	1.000	1.000	0.956
SKBL	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.895	1.000	0.988
ZBL	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.718	1.000	0.969
Mean	**0.937**	**0.921**	**0.949**	**0.946**	**0.962**	**0.902**	**0.858**	**0.963**	**0.944**	**0.931**

Panel C: *Scale Efficiency (SE).*

Bank	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
SCB	1.000	1.000	0.957	0.961	1.000	1.000	1.000	1.000	1.000	0.991
TBL	1.000	1.000	0.895	0.645	1.000	0.734	1.000	0.911	0.712	0.877
PHB	0.988	1.000	1.000	1.000	0.999	0.728	0.922	1.000	0.739	0.931
GTB	1.000	0.817	0.827	1.000	1.000	0.734	1.000	1.000	0.637	0.891
FIB	1.000	0.949	1.000	0.716	0.937	0.961	0.896	1.000	0.707	0.907
AGIB	0.988	0.610	1.000	0.459	0.991	0.921	0.784	1.000	0.813	0.841
ICB	0.955	0.796	0.968	0.986	1.000	1.000	0.759	1.000	1.000	0.940
ABL	0.831	1.000	0.875	1.000	1.000	0.976	1.000	1.000	1.000	0.965
EBL	0.993	0.838	0.997	0.999	0.955	0.519	0.936	1.000	0.840	0.897
BSIC	0.911	0.951	1.000	0.816	0.788	1.000	1.000	0.829	0.754	0.894
SKBL	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.941	1.000	0.993
ZBL	1.000	1.000	1.000	1.000	1.000	1.000	0.786	0.979	1.000	0.974
Mean	**0.972**	**0.913**	**0.960**	**0.882**	**0.973**	**0.881**	**0.924**	**0.972**	**0.850**	**0.925**

Pure technical efficiency reflects the way in which bank resources have been managed. Panel B shows the PTE scores of commercial banks under VRS for individual years. As shown in the table, the banks experienced the highest level of PTE in 2016 with an average of 96.3%, while the lowest level was observed in 2015 with an average of 85.8%. In 2017, 10 [83%] banks were VRS technically efficient, scoring 100%, and the remaining 2 [17%] banks were VRS technically inefficient. These two inefficient banks had VRS technical efficiency scores between 61 and 70%. The overall sample average VRS technical efficiency score was 93.1% [with a standard deviation of 7.3%], meaning that inefficient banks could, on average, produce 6.9% more financial service outputs using their current input endowment. SCB and GTB were constantly efficient throughout the nine-year period, as they scored an annual average of 1. The least efficient bank was EBL [78%] followed by PHB [83.5%] and AGIB [88.8%].

Scale efficiency refers to the extent to which a bank deviates from optimal scale. A scale efficiency score of 1 implies that the bank under examination is operating at the optimal size whereas a score less than 1 would imply the bank is either too small or too large relative to its optimal size. It can be observed from the Panel C of Table 5 that only five [42%] banks had a SE score of 100%, meaning they were at the optimal size for their particular input-output mix, the remaining eight banks were scale inefficient in 2017. Among the inefficient banks, 1 bank had a SE score of less than 70%; 4 banks had a SE score between 71-80%; and 2 banks had a SE of between 81-99%. The average scale efficiency score was 92.5% with a standard deviation of 4.85%, meaning that on average, the scale inefficient bank could reduce their size by 7.5% without affecting their current output levels. SKBL is constantly efficient in term of SE during the period except for 2016. when scored 94.1%. This shows that SKBL is the most efficient bank during the study period. The least efficient bank is AGIB with just an annual average level of 84.4%. The banks obtained an average SE level of 92.5% during the study period 2009-2017.

Overall, under the production approach, the efficiency scores imply that increasing the quantity of all inputs in Gambian banking sector by a given proportion will result in
- Constant returns to scale in the relationship between inputs and outputs in 5 [42%] banks, implying that their financial service outputs would increase in the same proportion. This means that SCB, ICB, ABL, SKBL, ZBL were operating at their most productive scale sizes in 2017.
-Decreasing returns to scale in 2 [17%] banks, implying that their financial service outputs would increase by a smaller proportion. Therefore, AGIB and EBL banks would have needed to reduce their size to achieve optimal scale.

4.2. Determinants of Efficiency

The second stage of this study examines the determinants of banking efficiency in the Gambia. The efficiency scores obtained [TE, PTE and SE] using the DEA in the first step, are regressed against a set of variables by employing Tobit regression. In the models, all three efficiency measures are employed as dependent variables while bank-specific characteristics, and macroeconomic factors are used as independent variables.

[Table 6] displays Tobit regression results on the relationship between independent variables and efficiency scores.

Table 6: *Determinants of bank efficiency.*

	Panel A: CRS (TE)		**Panel B: VRS (PTE)**		**Panel C: (SE)**	
	Coefficient	**Prob.**	**Coefficient**	**Prob.**	**Coefficient**	**Prob.**
Constant	1.8655	0.0030	1.8777	0.0001	1.6393	0.0015
ROE	-0.0147	0.8722	0.0436	0.5454	-0.0609	0.2381
MP	**0.8263**	**0.0687***	**0.7595**	**0.0372****	0.0179	0.5501
BS	-0.0831	**0.0596***	**-0.0643**	**0.0664***	-0.0357	0.2961

TL_TA	**-0.1891**	**0.0801***	-0.0914	0.2776	**-0.0411**	**0.0111****
EQ_TA	-0.0055	0.9701	0.0183	0.8762	-0.0383	0.6862
II_TA	**0.9250**	**0.0109****	**0.0643**	**0.0230****	**0.0792**	**0.0005*****
GDP	0.0078	0.1426	0.0016	0.6976	**0.0056**	**0.0928***
INF	0.0096	0.6841	0.0140	0.4592	-0.0046	0.7615
M.D.V	0.8646		0.9312		0.9251	
SD Dep. Var	0.1853		0.1442		0.1182	

*(***; **; *)= Significant at 0.01; 0.05 and 0.10 levels respectively*
ROE= Return on Equity, MP= Market Power, BS=Bank Size measured by log of total asset. TL_TA= Total loan to total asset, EQ_TA = Equity to Total asset, II_TA= Interest Income to Total asset. GDP= Gross Domestic Product. INF= Inflation. M.D.V = Mean of Dependent Variable, SD Dep.Var= Standard Deviation Dependent Variable.

Among the bank-specific variables, the coefficients on the profitability [ROE] and capital adequacy [EQ_TA] variables have a negative sign, but they are not statistically significant at any conventional level. The coefficient on the interest earnings ratio [II_TA] is positive and statistically significant under all three regression models, implying that the banks with higher interest income have higher technical efficiency scores. This ratio is an important proxy to measure bank's core income. The higher this ratio the better the bank earnings from total assets. The positive relationship between earnings ratio and bank efficiency indicates that banks with the ability to charge lower interest on deposits and maintain higher interest rates on loans attain higher efficiency scores. Other bank specific variables and macroeconomic variables do not yield significant effect on technical efficiency level [TE].

According to panel B, the market power coefficient [MP] measured by bank deposits to total deposits in the banking industry within which the bank operates is significant under PTE [at 5% level] regression. This positive relationship is consistent with the Theory of Relative Market Power [RMP] which posits that only firms with large market share and well product differentiation are able to exercise market power in pricing these products and earn supernormal profits [20]. Similar to panel A, bank size coefficient is negative but significant only at the 10 percent level. Size can improve bank efficiency if there are significant economies of scale. However, a quite number of studies find a significant negative relationship between size and banking efficiency and suggest that small banks may obtain operational advantages that bring about higher efficiencies [21-23].
Under SE regression in panel C, the coefficient on the asset structure variable [TL/TA] is negative and significant at the 5% level under. Total loan to total asset is a measure of bank's liquidity, and it can be interpreted as liquidity risk. The negative coefficient on this variable indicates that lower liquidity risk is associated with higher efficiency scores. Coefficients on other bank specific variables [ROE, EQ_TA] and the macroeconomic explanatory variables [GDP, INF] are not significantly correlated with efficiency levels.

5. Conclusion

Gambia has undergone a number of major policy changes in bank regulation over the last 20 years. Following the structural financial reform program in 2005, deregulation in the sector has eliminated the barriers to entry and led to significant growth in banking. These structural changes have greatly increased competitive pressures and forced banks to improve efficiency in ways they conduct their business.

This study examines the technical efficiency of 12 commercial banks operated in the Gambia between 2009 and 2017, using two-stage procedures. In the first stage relative efficiency scores for individual banks are calculated using the DEA method. Under the "production approach" of modeling banks' inputs and outputs, the study uses interest expenses, personnel expenses, and noninterest expenses as inputs, while interest income and noninterest income as outputs. In the second stage, the relation between certain bank-specific and environmental variables and bank efficiency scores are examined by employing Tobit regression model.

The empirical analyses from the first stage reveals that about 42% of commercial banks were CRS technically efficient and 83% of them were VRS technically efficient in 2017. Only 42% of the banks were at the optimal size for their particular input-output mix, the remaining eight banks were scale inefficient. Using the production approach to bank modeling, the level of overall technical efficiency of commercial banks in the Gambia accounted 86.5% in terms of TE, 93.1% in terms of PTE and 92.5% in terms of SE. Therefore, the magnitude of inefficiency accounted 13.5%, 6.9% and 7.5% respectively. This means on average all banking industry could simply produce the same level of financial services by employing 86.5% of their input mix under CRS. Results also confirm that inefficient banks could, on average, produce 6.9% more financial service outputs using their current input endowment under VRS. The average CRS technical efficiency score varied from a minimum of 68.9% at Ecobank Gambia Ltd [EBL] to a maximum of 99.1% at Standard Chartered Bank [Gambia] Ltd. [SCB]. Overall, SCB appears to be the most efficient bank within the Gambian banking sector, while EBL bank appeared to be least efficient bank over the period. Skye Bank [Gambia] Ltd [SKBL] was constantly efficient throughout the selected period except 2016. The overall sample average VRS technical efficiency score was 93.1%, meaning that inefficient banks could, on average, produce 6.9% more financial service outputs using their current input endowment. The average scale efficiency score was 92.5%, indicating that on average, the scale inefficient banks could reduce their size by 7.5% without affecting their current output levels.

Our second stage analyses reveal that the interest income ratio variable is significantly correlated with all three measures of efficiency levels. The positive relationship between interest income ratio and bank efficiency indicates that banks with the ability to charge lower interest on deposits and maintain higher interest rates on loans attain higher efficiency scores. Under PTE regression model, the market power coefficient [MP] measured by bank deposits to total deposits in the banking industry is found to be positively related with efficiency scores. This positive relationship is consistent with the view that firms with large market share and well product differentiation can exercise market power in pricing their products and earn supernormal profits. Under SE regression model, the asset structure variable [TL/TA] is found to be negative related with scale efficiency. Since total loan to total asset can be considered as a measure for liquidity risk, the negative relation indicates that lower liquidity risk is associated with higher efficiency scores. Two technical efficiency models [TE, PTE] detected a negative but weak [significant only at the 10% level] relationship between bank size and efficiency scores, suggesting that smaller banks may obtain operational advantages that bring about higher efficiencies. Other bank specific variables [ROE, EQ_TA] and the macroeconomic explanatory variables [GDP, INF] did not produce any significant relationship with efficiency levels.

Overall, under the production approach, the efficiency scores imply that for some of the Gambian banks there is room to improve their productive efficiency and attain their optimal scale size. Second stage analyses reveal that interest earnings and liquidity risk ratios are significantly correlated with efficiency levels. Increase in interest earnings causes an increase in efficiency of banks while increase in liquidity risk reduces the efficiency levels. While market power may lead to higher efficient levels.

The findings of this study are expected to help the bank executives to manage their bank resources more effectively. It may also provide insights to policymakers for improving and optimizing the usage of valuable resources in commercial banking. Further, it also contributes to the scant literature on the efficiency of the banking sector in the Gambia. Some caveats and limitations of the study should be noted. First, although the twelve banks investigated in this study represent the overwhelming majority of the Gambian banking industry, the sample size nevertheless is relatively small compared to other studies. Second, due to data limitation, our model employs three inputs and two outputs. It is known that efficiency measures from DEA are highly sensitive to the selection of inputs and outputs. Finally, data limitation also precludes using more sophisticated parametric efficiency estimation techniques such as stochastic frontier models.

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