A Study of Bank Efficiencies in Ghana

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Abstract
An investigation of technical and scale efficiencies and returns to scale properties of 16 Ghanaian banks was conducted for insight into bank size and efficiency. A data enveloping analysis was performed on annual bank data from 2000 to 2006. Both intermediation and production approaches to bank behavior were modeled. Findings suggest higher average returns to scale for small banks than big banks with a p-value of 0.12. Also, there is indication that small banks as a group are operating closer to their lowest average cost than large banks. Based on these historical evidences, this study suggests that increased bank sizes may not translate to higher technical nor higher scale efficiencies in Ghana.
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Introduction

Financial sector reforms in Ghana have been on-going since 1988. In the view of the central bank, these reforms have achieved considerable success based on such indicators as the entry of more foreign banks into the system, substantial increase in bank-intermediated debt, a diversified range of financial services, and some integration of the Ghanaian financial system with the global economy. See for example, Bank of Ghana (2007).

However, early in 2008, the central bank declared that upon analysis, it had concluded that the industry was populated by a cluster of banks with relatively low capital base and depth. It added that, that situation was inadequate to support significant levels of lending, especially on the international scene. In addition, in its opinion, such small banks are easily vulnerable to swings in macroeconomic fundamentals. In particular, the central bank believes that the deposit money banks have not developed the capacity required for them to actively use the capital market as a vehicle for raising substantial equity and other forms of financing. In an effort to address this situation, the central bank issued the following directive (Bank of Ghana, 2008):

i. All domestic deposit money banks (majority owners are resident in Ghana) are to increase their minimum paid-up capital from approximately US$ 7million at the time of announcement to US$ 25 million by the end of 2010, then US$ 60 million by the end of 2012;
ii. All foreign owned deposit money banks (majority owners are non residents) are to increase their minimum paid-up capital from US$ 7 million to between US$ 50 and US$ 60 million by the end of 2009.

Given that the bank capital adequacy ratio in Ghana under the prevailing law, Banking Act, 2004 (Act 673), is 10% of total assets, it is natural to expect that the new requirement of the central bank will effectively result in banks getting bigger (since banks will optimize their risk-return trade-off through the equity multiplier). The questions we ponder in this paper are:

i. will the policy improve the efficiency of the banking system?
ii. have larger banks in Ghana been more efficient than smaller banks?

These questions are posed because of issues in the literature about the Ghanaian banking industry. For one thing, Buchs and Mathison (2005) have suggested that the Ghanaian banking environment is uncompetitive. For another, Aboagye et al. (2008) have found that the concentration of banks has significant positive impact on interest rate spreads in Ghana.

Wide interest rate spreads have dogged the Ghanaian economy for many years and remain a major issue of concern to policy makers and the general public. See for example, Gockel and Mensah (2006), Buchs and Mathison (2005), and Bawumia, Belnye and Ofori (2005) among others. Table 1 shows interest rate spreads in a sample of eight African countries for 2000 and 2004. Clearly, for each year, the spread in Ghana is highest.

Table 1: Interest Rate Spreads in Selected African Countries for 2000 and 2004

	Spread		
	2000	**2004**	**2008**
Gabon	17.0	13.0	
Ghana	30.2	21.3	22.1
Kenya	14.2	10.1	8.7
Mauritius	11.2	12.8	
Mozambique	9.3	9.3	
Uganda	13.1	12.9	9.8
Zambia	18.6	19.2	12.5

Source: Bamumia et al. (2005).

To answer the question whether the bigger the bank the higher the efficiency, we analyze the efficiency and returns to scale characteristics of banks in Ghana in order to draw lessons for future policy. If there is evidence that efficiencies are realized at higher scales of operation in the banking industry, then allowing large industry players to emerge is to be preferred, assuming that benefits that accrue are passed on to consumers. Specifically, this study investigated the technical efficiencies and scale efficiencies in the banking system and returns to scale characteristics of the industry.

The next section presents briefly an overview of the Ghanaian banking system, then discusses some of the issues that are pertinent to studies of firm efficiencies. We follow this with a discussion of the data enveloping analysis (DEA) approach, which was adopted in this study. We then presented the results of this study followed by discussions and conclusions.

The Financial Environment and Literature Overview

The Financial Environment

The banking system in Ghana today reflects the policy adopted in the late 1980s to liberalise the banking sector to enhance performance. The policy involved enhancing the soundness of the system through improved regulatory framework, strengthening of banking supervision, restructuring financially distressed banks, improving deposit mobilization, increasing efficiency in credit mobilization, and strengthening competition and efficiency within the banking sector.

A look at the structure of the banking industry gives us some idea about the impact of liberalising the industry. At the start of liberalisation the banking system consisted of seven banks. By the end of 2006, 23 banks (re-christened deposit money banks) were in operation. Table 2 shows how the number of banks has

Table 2: Total number of banks and branches and proportion of total industry assets and branches owned by six biggest banks in Ghana.

Year	Total number of banks	Proportion of industry assets owned by six biggest banks %	Total number of bank branches	Proportion of branches owned by six biggest banks %
1999	14	83	300	87
2000	16	85	304	86
2001	17	84	326	84
2002	17	82	322	83
2003	18	77	329	80
2004	18	73	384	73
2005	19	69	378	74
2006	23	65	350	76

Source: Authors' computations from central bank data.

changed in recent times. Table 2 also presents the proportion of total bank assets and branches that are owned by the six biggest banks annually, from 1999 to 2006. Clearly, the proportion of total industry assets and branches that belong to the six biggest banks has remained overwhelming in spite of increasing number of banks. One wonders whether this is in the interest of the consumer.

Efficiency in the Literature

In the literature, substantial evidence exists for and against bank size. They theoretical arguments for banks getting bigger include the fact that big banks have the potential to realize economies of scale. If banks get bigger through mergers and acquisitions, efficiency gains may arise from implementation of operational improvements, replacement of inefficient management, rationalization of existing branch networks, etc. The argument against bank consolidation is that costs associated with mergers and acquisitions along with downsizing disruptions, the difficulties in merging organizational cultures, and managerial turf battles lead to efficiency losses, which are invariably passed on to consumers.

Within the past two dozen years or so, researchers have spent substantial effort measuring or estimating the efficiency of financial institutions, particularly banks. Different researchers have come up with different results, stemming from either differences in the efficiency concept used, differences in measurement methods used or possibly exogenous factors. See for example, Berger and Humphrey (1997) and Berger and Mester (1997).

The concept of firm efficiency can be viewed from many perspectives. Here we focus on technical and scale efficiencies. Technical efficiency refers to the extent to which firms are able to attain maximum possible output with their input bundles at existing scale size and technology. Scale efficiency refers to the extent to which firms are producing as close to their most productive scale size as possible. If a firm does not generate output at a scale of operation which is closest to its most productive scale size, there exists scale inefficiency which tends to increase the average costs of production. That is to say that within an industry, firms of different sizes can exist because each firm operates at a different scale of output generation. Due to reasons relating to, say, the financial, marketing and risk-bearing capabilities of firms, there may be no one optimal size, dictated by technological considerations, nor a master production function for the industry as a whole. Each firm may have a most productive scale size for its given capability set and operating production function.

Estimating Efficiency

Estimating efficiency usually involves establishing an efficient frontier of operation for the best performing firms. The deviations of the points of operation of others from the efficient frontier are measures of their inefficiencies. Both parametric and non-parametric methods are used to establish the efficient frontier and deviations from it. Widely used functions for efficiency estimation are production, cost, profit and revenue functions. For example, the cost-frontier approach uses the cost frontier of best-practicing firm(s). When found, this may be used to assess the relative cost efficiencies of other firms. However, this function is really unknown and has to be estimated from sample data. Common parametric approaches include the stochastic frontier approach, the thick frontier approach and the distribution-free approach. They have the capacity to distinguish between (managerial) inefficiency and exogenous shocks.

Non-parametric approaches, such as the data enveloping analysis, have the advantage of making no assumption about the (unknown) functional form of the data. On the other hand, they attribute any deviation from best practice frontier to managerial inefficiency, even if they arise exogenously. They are thus sensitive to outliers. They also assume the data are free of measurement errors.

The modelling of a bank's approach to doing business poses another challenge as to what qualifies as input and output. Two approaches have emerged as the most widely used, namely, the production and intermediation approaches. The production approach models banks as using labour and physical capital as well as interest and non-interest expenses as inputs to produce output in the form of deposits, loans, investments (securities), deposits with other banks (other than the central bank) and non-interest income.

The intermediation approach, on the other hand, views banks as intermediating funds between savers and investors. Here, banks are often modeled as using borrowed funds and resources (inputs) such as deposits, other liabilities, shareholders' equity, labour, physical capital as well as non-interest expenses to generate output in the form of loans, investments (securities), deposits with other banks (including the central bank) and non-interest income.

Empirical Studies

Numerous studies of bank efficiencies have been conducted using United States bank data. Many of them have investigated operating efficiencies as a basis for proceeding with bank mergers. A number of these studies find that while some banks experience reductions in unit cost, others experience increases. For example, Berger (1998) finds that mergers improve profit efficiency and suggests that this may be linked to diversification that results. Rhoades (1993) compared pre- and post-merger costs of merging banks, and Berger and Humphrey (1992) assessed merger related changes in frontier cost efficiencies when mergers occur. Both find that that even when an acquiring firm is more efficient, this efficiency was not necessarily maintained after the merger.

A number of other studies have focused on developing economies. Isik and Hassan (2003) investigated bank performance in Turkey following liberalization of the industry. They found that all forms of Turkish banks, although in different magnitudes, have recorded significant productivity gains driven mostly by efficiency increases rather than technical progress. Efficiency increases realized were mostly due to improved resource management practices rather than improved scales of operation. Yu and Luu (2003) evaluated the competitive forces that impact the Taiwanese banking sector and concluded that Taiwanese banks could obtain the benefit of scale economies by merging with other banks rather than expanding by opening more branches.

Closer to Ghana, Hauner and Peiris (2005) analysed the impact of banking sector reforms undertaken in Uganda with a view to improving competition and efficiency. They found that on average, larger banks and foreign-owned banks have become more efficient, while smaller banks have become less efficient in the face of increased competitive pressures.

For Ghana, Buchs and Mathisen (2005) assessed the degree of bank competition and discussed efficiency with regard to banks' financial intermediation roles in Ghana. They found that size has strong influence on total and interest revenue. In the authors' view, this denotes strong economies of scale effect which indicates that the profitability structure of the banking sector in Ghana is skewed toward the larger banks and also implies that small banks have a definite disadvantage in the system. They argued that this could indicate scope for greater consolidation in the sector.

This Study

The above review suggests that the outcome of expansion and/or consolidation in the banking sector is a matter of empirical investigation. This study uses the data enveloping approach (DEA) to study the efficiencies of Ghanaian banks. DEA is a technique commonly used to evaluate the efficiency of a number of producers referred to as decision making units (DMUs) in the DEA literature. A fundamental assumption behind DEA is that if a given producer, A, is capable of producing *Y(A)* units of output with *X(A)* inputs, then other producers should also be able to do the same if they were to operate efficiently. Similarly, if producer B is capable of producing *Y(B)* units of output with *X(B)* inputs, then other producers should also be capable of the same production schedule. Producers A, B, and others can then be combined to form a composite producer with composite inputs and composite outputs. Since this composite producer does not necessarily exist, it is sometimes called a virtual producer. The heart of the analysis lies in finding the "best" virtual producer for each real producer. If the virtual producer is better than the original producer by either making more output with the same input (called output-oriented), or making the same output with less input (called input-oriented) then the original producer is *inefficient*. Thus DEA compares each producer with only the "best" producers, (DEA, 1996).

The procedure of finding the best virtual producer can be formulated as a linear programme. There are numerous DEA model variations. However, the underlying principles are similar and can be illustrated as follows:

Consider n DMUs, each of which produces k products by utilizing m input factors. The *input-oriented DEA* model can be expressed as follows (Banker, Charnes and Cooper, 1984).

(1) *Minimise* θ_i
Subject to
(2) $Y\pi_i - y_i \geq 0$
(3) $\theta_i x_i - X\pi_i \geq 0$
(4) $\pi_i \geq 0$ (DEA-CCR)
(5) $\Sigma\pi_i = 1$ (DEA-BCC)

where, X is the $m \times n$ input matrix and Y is the $k \times n$ output matrix represented by the vector x_i and y_i for the i^{th} firm respectively. π_i is an $n \times 1$ vector of constants, and θ_i is a scalar which stands for the efficiency of the i^{th} firm.

Solving this linear programme for each of the n firms, yields the efficiency score for each firm. We note the following:

a) The system of equations (1) through (4) is referred to as the DEA-CCR (Charnes, Cooper and Rhodes, 1978) model. This model assumes that the technology under which the DMUs operate exhibits constant returns to scale;
b) The system of equations (1) through (5) is referred to as the DEA-BCC model (Banker, Carnes and Cooper, 1984). This model assumes that the DMUs operate under a variable returns to scale technology. The vector, π, describes the percentages of other producers used to construct the virtual producer;
c) The first constraint forces the virtual DMU to produce at least as many outputs as the studied DMUs do;
d) The second constraint finds out how much less input the virtual DMU would need; and
e) The factor used to scale back the inputs is θ and this value is the efficiency of the DMU

Methodology

In this study, DEA is applied to both the production and intermediation models of banking in order to determine both the technical and scale efficiencies of banks in Ghana and to determine their returns to scale characteristics. As indicated earlier, use of such a non-parametric approach has the advantage of making no assumption about the functional form of the data.

The determination of which inputs and outputs to use in an efficiency study is particularly important as they define the basis on which the efficiency of the units are assessed. Only those inputs and outputs which are most relevant to the functioning of the units should therefore be included in the analysis. To this end, the analysis discussed here is conducted with respect to several models as indicated later.

DEA-CCR and DEA-BCC Models

Banker et al. (1984) analytically demonstrate that the *DEA-CCR* output are efficiency scores, (called *CCR*), that are the products of two terms, i) a pure technical efficiency component (*TE*), (as to whether firms are able to attain maximum possible output with their input bundles at existing scale size) and ii) a scale efficiency (*SE*) component, indicating whether firms are producing as close to their most productive scale size as possible. Thus, $CCR_i = (SE_i)\times(TE_i)$ for each DMU *i*.

On the other hand, *DEA-BCC* output are technical efficiency scores, (called *BCC*), which capture the pure resource-conversion efficiencies attained by firms, irrespective of whether these firms enjoy increasing, decreasing or constant returns to scale. Thus, $BCC_i = TE_i$.

Thus, from the two models (*DEA-CCR* and *DEA-BCC*) one can calculate scale efficiencies. For DMU *i*, scale efficiency, SE_i, is given by $SE_i = CCR_i / BCC_i$, (Färe, Grosskopf and Lovell, 1994).

Referring to the linear programme discussed above, increasing or decreasing returns to scale can be determined by inspecting the sum of weights, , under the specification of the *DEA-CCR* model (Banker, 1984, and Banker et al., 1994). If this sum is less than one, then increasing returns to scale prevail, whereas if this sum is greater than one then decreasing returns to scale prevail.

Windows Analysis

In its early years of application, DEA was used to analyze cross-sectional data. Currently however, the use of panel data is regarded as a preferred option since it not only allows a unit to be compared with other units at one time period but also allows an examination of changes in efficiency over time. This is achieved through a concept referred to as *Windows Analysis*. Such analysis gives a better indication of the efficiency of a DMU. In *Windows Analysis*, DEA is performed over time by using a moving average analogue, where a DMU in each different period is treated as if it were a different DMU. Each DMU is then compared with alternative subsets of panel data instead of with the whole dataset.

Data Issues

In this study, the data used were extracted from the annual profit and loss and end of year balance sheet statements of the banks obtained from the Banking Supervision Department of the central bank. Since a balanced panel is required for the analysis, and in order to achieve reasonable degrees of freedom, we decided on 2000 as the starting year, and annually until 2006 for 16 banks, giving a total of 112 observations. The following models were considered.

A. Intermediation Approach

Model 1

Inputs	*Outputs*
Deposits	Loans and Overdrafts
Other liabilities	Investments in securities
Shareholders' equity	Deposits with other
banks	
Staff costs	Non-interest income
Fixed assets	
Non-interest expense	

Model 2

Inputs	*Outputs*
Deposits	Loans
Other liabilities	Investments
Shareholders' equity	Deposits with banks
Non-interest expense	Non-interest income

Model 3

Inputs	*Output*
Interest expense	Interest income
Staff costs	Deposits with other banks
Fixed assets	Non-interest income
Non-interest expense	

Model 4

Inputs	*Outputs*
Deposits	Interest income
Other liabilities	Deposits with other banks
Shareholders' equity	Non-interest income
Fixed assets	
Staff costs	
Non-interest expense	

B. Production Approach

Model 5

Inputs	*Outputs*
Staff costs	Deposits
Fixed assets	Loans
Interest expense	Investments
Non-interest expense	Deposits with other banks
	Non-interest income

Results

The software *Efficiency Measurement System, version 1.3* was used for these analyses. Results for the DEA windows analysis for the **intermediation** approach in which *deposits*, *other liabilities*, *shareholders' equity*, *staff costs* (proxy for labour input), *fixed assets* (proxy for capital input) and *non-interest expense* are used as inputs, while *interest income*, *deposits with other banks* and *non-interest income* represent output are reported. This model is referred to as *Model 4*. The model takes a pragmatic view of a shareholder of a bank that what is important is income generated by engaging in banking activities.

DEA-CCR and DEA-BCC Intermediation Model (4)

A window width of four is used for the analysis. No theory really underpins the definition of window size. Table 3 illustrates the results for the *DEA-CCR* model for seven banks.[1]

In the table, the four separate

[1] Because of space considerations, results for seven banks which fit on one page are used for illustrative purposes.

Table 3: Illustrative table of DEACCR composite efficiencies (product of technical and scale efficiencies). 4-Year Windows Analysis for *Intermediation Model 4.*

Bank		BANK EFFICIENCY %									
		2000	2001	2002	2003	2004	2005	2006	*Window mean*	*s.d*	*Overall mean*
1	W1	85.7	100.0	79.2	100.0				91.2	0.1	
	W2		100.0	96.4	100.0	100.0			99.1	0.1	
	W3			100.0	100.0	100.0	81.2		95.3	0.1	
	W4				100.0	100.0	81.2	80.8	90.4	0.1	94.0
2	W1	75.6	79.4	100.0	100.0				88.8	0.11	
	W2		83.6	100.0	100.0	100.0			95.9	0.08	
	W3			100.0	100.0	100.0	91.3		97.8	0.04	
	W4				100.0	100.0	91.9	100.0	98.0	0.04	95.1
3	W1	100.0	100.0	100.0	98.5				99.6	0.10	
	W2		100.0	100.0	100.0	100.0			100.0	0.00	
	W3			100.0	100.0	100.0	100.0		100.0	0.00	
	W4				100.0	100.0	100.0	100.0	100.0	0.00	99.9
4	W1	100.0	100.0	96.6	87.2	86.7			96.44	0.06	
	W2		100.0	100.0	94.1	87.8			95.20	0.06	
	W3			100.0	97.3	93.3	100.0		96.3	0.06	
	W4				100.0		100.0	94.0	96.8	0.04	96.2
5	W1	100.0	93.7	89.8	82.2				91.4	0.07	
	W2		97.6	100.0	100.0	88.6			96.6	0.05	
	W3			100.0	100.0	96.0	97.5		98.4	0.02	
	W4				100.0	97.8	100.0	93.6	97.7	0.03	96.1
6	W1	100.0	100.0	100.0	100.0				100.0	0.00	
	W2		100.0	100.0	100.0	70.6			92.7	0.15	
	W3			100.0	100.0	73.1	79.6		88.2	0.14	
	W4				100.0	73.7	81.4	81.0	84.0	0.11	91.2
7	W1	100.0	100.0	73.4	81.4				88.7	0.09	
	W2		100.0	83.9	86.9	95.9			91.7	0.08	
	W3			100.0	100.0	93.8	100.0		98.5	0.03	
	W4				100.0	94.6	100.0	94.5	97.3	0.03	94.0

windows are represented as separate rows called W1, W2, W3, and W4. Taking *Bank 2* as an example in Table 3, its CCR efficiencies ($CCR_i = SE_i \times TE_i$ as discussed earlier) in the first window, W1, are 75.6%, 79.4%, 100%, and 100%. These figures correspond to the estimated relative efficiency of *Bank 2* in 2000, 2001, 2002, and 2003. In the second window, W2, the relative efficiency estimates of *Bank 2* are 83.6%, 100%, 100%, and 100% for the years 2001, 2002, 2003, and 2004. The same interpretative process applies throughout the table. The average of the efficiency estimates for each window and associated standard deviations are presented in the columns denoted "*Window Mean*" and "*s. d.*" respectively. The last column titled '*Overall Mean*' represents the mean for each bank for the seven-year period, which is the mean of the window means.

The arrangement of the results of the windows analysis as given in Table 3, facilitates the identification of trends in performance, and the examination of the 'stability' of efficiency across, as well as within windows by the adoption of 'row views' and 'column views' respectively. The table reveals a mixed picture of changes in the efficiency of the banks over time. Still taking *Bank 2* as an example, its efficiency varies from 75.6% in 2000 to 100% in 2003. In the first two years (2000 and 2001) its relative efficiency in the first window remained fairly stable in the 70% range but jumped to 100% in 2002 (adopting a 'row view'). On the other hand, if we adopt a 'column view', we see, for example, that in the years 2002 and 2003 its efficiency was stable at 100% within the windows.

These results illustrate the performance of *Bank 2* over time ('row view') as well as its performance in comparison with other banks in the sample ('column view'), for any year.
Some banks experienced stable performance both across time and within windows. For example *Bank 3* had a 100% relative efficiency throughout the period except in 2003 in the first window. *Bank 6* on the other hand, had consistently 100% efficiency from 2000 to 2003 but this fell to consistently low values in 2004, 2005 to 2006. The *overall mean* efficiency scores (last column of the table) indicate that the mean efficiency of the sample of seven banks varies from 91.2% for *Bank 6* to 99.9% for *Bank 3*.

Table 4 summarizes the results in Table 3 for all 16 banks. Only window means, W1, W2, W3, and W4 and overall means are reported for each bank. *Bank 14* has the lowest overall mean, followed by *Bank 13*. On the other hand, *Bank 3* has the highest overall mean, followed by *Bank 9*. It is clear from the table that bank efficiencies vary. Scores as high as 99.9%, 99.3% and 98.*% are impressive.

Table 5 presents a summary similar to Table 4, but this time the figures are output of the DEA-BCC analysis, which are technical efficiencies. An inspection (eyeball) of the table suggests that variations in window means and overall means are lower than for the average efficiencies reported given in Table 4. That is, on the whole, it would appear that banks are either operating at or closer to levels that are technically feasible than the composite DEA-CCR efficiencies given in Table 4.

Table 4: 4-Year moving averages and overall DEACCR composite efficiencies - product of technical and scale efficiencies for *Intermediation Model 4*

Bank	W1 %	W2 %	W3 %	W4 %	Overall %
1	91.2	99.1	95.3	90.4	94.0
2	88.8	95.9	97.8	98.0	95.1
3	99.6	100.0	100.0	100.0	99.9
4	96.4	95.2	96.3	96.8	96.2
5	91.4	96.6	98.4	97.7	96.1
6	100.0	92.7	88.2	84.0	91.2
7	88.7	91.7	98.5	97.3	94.0
8	99.1	100.0	100.0	96.3	98.8
9	100.0	99.9	99.0	98.2	99.3
10	100.0	97.3	94.1	90.6	95.5
11	100.0	100.0	90.3	83.5	93.5
12	99.3	98.6	96.9	96.9	97.9
13	87.3	85.3	86.2	85.9	86.2
14	89.5	87.2	85.4	79.7	85.4
15	99.3	100.0	94.6	87.8	95.4
16	94.8	96.6	99.6	94.8	96.4

Source: tabulated from DEA-CCR output file

W1 ≥ mean of 2000-2003; W2 ≥ mean of 2001-2004;
W3 ≥ mean of 2002-2005; W4 ≥ mean of 2003-2006;

Table 5: DEABCC technical efficiencies for 4-Year moving averages and overall for Intermediation Model (4)

Bank	W1 %	W2 %	W3 %	W4 %	Overall %
1	97.1	99.5	97.3	94.5	97.0
2	100.0	100.0	98.0	98.1	99.0
3	99.7	100.0	100.0	100.0	99.0
4	100.0	100.0	100.0	100.0	100.0
5	92.2	96.7	99.3	99.3	96.9
6	100.0	94.8	95.3	94.2	96.0
7	100.0	100.0	100.0	100.0	100.0
8	99.1	100.0	100.0	96.7	98.8
9	100.0	100.0	99.4	99.9	99.8
10	100.0	98.9	96.3	99.1	98.5
11	95.1	100.0	91.6	87.4	93.5
12	100.0	99.2	100.0	100.0	99.7
13	100.0	100.0	98.9	98.9	99.4
14	99.6	95.7	91.2	87.0	93.3
15	99.8	100.0	94.7	88.0	95.6
16	97.6	97.8	99.7	98.3	98.3

Model Comparisons

Table 6: Estimates of Overall CCR Efficiency Scores (product of technical efficiency and scale efficiency Percent) for models defined in sub-section 3.3

Bank	Model 1	Model 2	Model 3	Model 4	Model 5
Bank 1	93.5	89.6	89.6	94.02	99.2
Bank 2	98.1	95.6	95.6	95.1	100.0
Bank 3	88.2	85.3	85.3	99.9	86.4
Bank 4	85	84.9	84.9	96.2	76.1
Bank 5	97.2	93.1	93.1	96.1	92.8
Bank 6	90.6	88.6	88.6	91.2	89.7
Bank 7	92	92.5	92.5	94	94.7
Bank 8	94.4	98.9	98.9	98.8	87.6
Bank 9	95.2	94.8	94.8	99.3	81.1
Bank 10	91.8	90.4	90.4	95.5	98.9
Bank 11	96.7	97.4	97.4	93.5	93.5
Bank 12	91.4	93.08	93.08	97.9	69.6
Bank 13	94.3	87.4	87.4	86.2	81.2
Bank 14	97.1	96.7	96.7	85.4	94.0
Bank 15	97.3	94.6	94.6	95.4	82.8
Bank 16	91.9	96.4	96.4	96.4	88.4
Mean for Big Banks	**92.1**	**89.5**	**77.7**	**95.4**	**90.7**
Mean for Small Banks	**94.2**	**94.2**	**83.5**	**94.2**	**87.2**
Mean for All Banks	**93.4**	**92.5**	**91.3**	**94.7**	**88.5**

Source: Authors' computations.

In all, we estimated efficiencies for the four intermediation models - *Models (1), (2), (3)* and *(4)* and the production model (*Model 5*) indicated in sub-section 3.3. Table 6 presents the overall mean efficiencies under DEA-CCR for all five models. The efficiency scores range from 85.0% for *Bank 4* to 98.1% for *Bank 2* in *Model 1*, 84.9% for *Bank 4* to 98.9% for *Bank 8* in *Model 2*, 66.4% for Bank 12 to 93.29% for *Bank 15* in *Model 3* and, as previously stated, 85.4% for *Bank 14* to 99.9% for *Bank 3* in *Model 4*. For the production model - *Model (5)* - the overall mean ranges from 76.1% for *Bank 4* to 100% for *Bank 2*.

Models (1), (2) and *(4)* yield reasonably close mean efficiencies for all banks. A statistical test of difference in means suggests that indeed at the 5% significance level, the mean of the overall efficiencies under *Model (1), (2)* and *(4)* exceed the mean of the overall efficiency under *Model (3)*. There is no statistical difference between the pairs of the means of the overall means of *Model (1), (2)* and *(4)*. The interesting thing about *Model (3)* is that it has the same outputs as *Model (4)*. However, all inputs of *Model (3)* except one are expenses, unlike *Model (4)*. Could this be a suggestion that bank expenses are relatively high?

We also tested for differences in means between the big banks (Bank 1 to Bank 6) and small banks (all others) under each model. Recall that in section two we discussed how the big banks dominate the industry. The test results however suggest no statistical differences in means between the big and small banks for DEA-CCR efficiencies.

Technical and Scale Efficiencies

Here, we focus our discussion on *Model (4)*, which we have suggested would appeal to a shareholder. Table 7 summarizes the technical efficiency and scale efficiency of the 16 banks. The table reveals that the mean technical efficiency for the six big banks as a group was 97.7% and for the small banks as a group as 98.3%. Further, the mean scale efficiency for the six big banks as a group was 93.4%, and 98.7% for the smaller banks. These suggest that the technical efficiency of the two groups are close. However, it would appear that smaller banks are operating at higher scale efficiencies than the big banks on average. Indeed, the t-statistic for the test of equality of means yields a t-statistic that is not significant at any reasonable level for differences in technical efficiencies (t-value -0.205 for the difference between 97.7% and 98.3%), whereas the t-statistic for differences in scale efficiencies has a t-value of -1.514 for the difference between 93.4% and 98.7), p-value 0.12.

Table 7: Average Technical and Scale Efficiencies of Banks, 2000 - 2006 for Model (4)

Bank	Mean Technical Efficiency %	Mean Scale Efficiency %
1	100.0	94.0
2	100.0	96.2
3	99.5	86.6
4	93.4	91.5
5	97.1	96.9
6	96.0	95.0
7	99.0	96.1
8	99.9	100.0
9	99.9	99.1
10	98.9	99.9
11	99.8	99.4
12	98.6	96.9
13	93.5	99.9
14	99.8	98.1
15	95.6	99.8
16	98.3	98.1
Mean for Big Banks	**97.7**	**93.4**
Mean for Small Banks	**98.3**	**98.7**

Source: Computed from *DEA-CCR* and *DEA-BCC* results, Tables 2 and 3.

Returns to Scale

Table 8 shows a summary of the returns to scale properties of the banks for each window and over the period of the study. The returns to scale characteristics are derived from the *DEA-CCR Model (4)* using the sum of weights of the efficient banks that serve as benchmarks for a particular inefficient bank. An analysis of these results suggests that for the industry as a whole, 58.2% of the banks were operating at constant returns to scale, while 32.4% and 9.4% were operating at decreasing returns to scale and increasing returns to scale respectively.[2] For the six big banks, 43.8% of them were operating at constant returns to scale, while 56.3% were operating at decreasing returns to scale. There was no case of increasing returns to scale for the six big banks. The corresponding figures for the small banks were 66.9% for constant returns, 18.1% for decreasing returns and 15% for increasing returns.

Table 8: Summary of results of returns to scale computations Model (4)

Return to scale	All Banks	Big Banks	Small Banks
CRS	58.2%	43.8%	66.9%
DRS	32.4%	56.3%	18.1%
IRS	9.4%	0.0%	15.0%

Source: Summary of computations.

Legend:
CRS ≥ constant returns to scale; DRS ≥ decreasing returns to scale; IRS ≥ increasing returns to scale.

Discussion of Results

The results of the DEA analyses have important policy implication. For the version of the intermediation model reported, our results suggest that the difference between the mean technical efficiencies of the six big banks and the 10 small banks is not statistically significant, but the difference between the mean scale efficiencies of the six big banks and the 10 small banks gives food for thought since it has a p-value of 0.12. The suggestion is that, on the average at least, the big banks in Ghana are not closer to their point of lowest average costs than the small banks.

We also note that the analysis of the returns to scale properties of the banks reveals that on the whole, small banks are doing better than bigger banks. This observation, together with that made in the previous paragraph, suggests that the central bank should be careful about encouraging banks to get bigger with the objective of improving bank efficiency. The evidence on the ground does not suggest that bigger banks are more efficient.

These are really interesting results for the banking industry in a developing country like Ghana. An interesting question here is *do the results reflect more efficient and productive behaviour by small banks?* If so how do they achieve this? Alternatively, do they reflect less efficient behavior by big banks in the industry? What is causing this? These are matters for future investigation.

One more finding has important implications. That one intermediation model yields DEA-CCR estimates that are statistically different from other intermediation models investigated suggests that caution is warranted in modeling bank behaviour in Ghana.

[2] Additional computations were needed to determine increasing and/or decreasing returns to scale

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