# “Consistency conditions for bank efficiency analysis in Ghana: A comparison of parametric and non-parametric techniques”



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| **ARTICLE INFO** | John-Mark Akandekumtiim and Busani Moyo (2024). Consistency conditions for bank efficiency analysis in Ghana: A comparison of parametric and non-parametric techniques. *Banks and Bank Systems*, *19*(3), 187-199. doi:10.21511/bbs.19(3).2024.16 |
| **DOI** | http://dx.doi.org/10.21511/bbs.19(3).2024.16 |
| **RELEASED ON** | Monday, 23 September 2024 |
| **RECEIVED ON** | Friday, 05 April 2024 |
| **ACCEPTED ON** | Thursday, 12 September 2024 |




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|---|---|
| **JOURNAL** | "Banks and Bank Systems" |
| **ISSN PRINT** | 1816-7403 |
| **ISSN ONLINE** | 1991-7074 |
| **PUBLISHER** | LLC “Consulting Publishing Company “Business Perspectives” |
| **FOUNDER** | LLC “Consulting Publishing Company “Business Perspectives” |

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10,
Sumy, 40022, Ukraine
www.businessperspectives.org

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# CONSISTENCY CONDITIONS FOR BANK EFFICIENCY ANALYSIS IN GHANA: A COMPARISON OF PARAMETRIC AND NON-PARAMETRIC TECHNIQUES

**Abstract**

This paper extends the concept of methodological crosschecking by examining whether bank efficiencies computed by the two frontier techniques, stochastic frontier analysis (SFA) and data envelopment analysis (DEA), are consistent. The study used a panel of 220 unbalanced observations from 27 Ghanaian banks between 2007 and 2016 to estimate cost and technical efficiencies and check for consistency using five criteria: efficiency distribution, ranking, ability to identify best or worst banks, stability of efficiencies, and relationship with accounting ratios. The results suggest that there is no consistency in the way parametric and non-parametric techniques rank or identify the best or worst banks. Also, there exists a weak relationship between the efficiency scores generated by both SFA and DEA and the non-frontier accounting ratios of Ghanaian banks. This suggests that the latter may contain some exogenous variables that make them weak measures of efficiency and should be used with caution, especially for bank supervision. However, the SFA approach yielded efficiency scores that were comparatively more stable over time. Therefore, the study concludes that the SFA approach is more practical and thus more appealing for regulatory purposes in Ghana due to the relatively consistent efficiency scores under the SFA approach compared to those under the DEA.

**Keywords** SFA, DEA, banks, Ghana

**JEL Classification** G21, E58, C33

**Received on:** 5th of April, 2024
**Accepted on:** 12th of September, 2024
**Published on:** 23rd of September, 2024



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**Conflict of interest statement:**
Author(s) reported no conflict of interest

## INTRODUCTION

The Ghanaian banking industry, like that of many sub-Saharan African countries, has seen significant developments since the introduction of financial sector reforms in the late 1980s. The reforms were necessitated by the fact that the pre-reform policies such as government control of financial markets had severely damaged the financial systems, leading to financial repression characterized by both financial shallowing and bank distress (Brownbridge & Gockel, 1998). It is argued that "a well-functioning banking sector contributes to economic growth via more efficient allocation of resources and risk diversification" (Moyo, 2018). The efficiency of banks is therefore crucial for economic development since it facilitates efficient financial intermediation and hence encourages savings and investments (Moyo, 2018). Considering the vital role banks play in economic development in any country, it is imperative for all stakeholders (government, shareholders, and managers of banks) to be interested in the way banks efficiently utilize resources and offer services. Berger and Humphrey (1997) support the importance of assessing the efficiency of banks because it helps identify the best and the worst performers. It is argued that better bank efficiency can improve bank solvency, which is important for enhanced banking system stability (Schaeck & Cihak, 2014). At the macroeconomic level, bank efficiency is a socially desirable goal, since it lowers financial intermediation cost. Thus, central banks strive to create operating environments that ensure maximum productive efficiency of their banking systems (Resti, 1997).

In Ghana, accounting-based indicators of bank efficiency have historically been used by regulators and bank managers to make management decisions and develop policy. Much as these measures are easy to compute, they are limited in many ways. For instance, these measures are not only static but they also embody some exogenous factors that are outside the control of decision-making units (DMUs), and hence are poor proxies for measuring productive efficiency. On the other hand, frontier techniques estimate efficiency as a deviation of a DMU's performance from the ideal efficient frontier, while holding all external factors constant. Hence, frontier techniques are said to be superior to accounting ratios. Different frontier methodologies may, however, generate different efficiency conclusions when applied to the same dataset and, as a result, may have distinct policy implications. Therefore, comparing the consistency of frontier techniques speaks to the robustness of the efficiency analysis of results. Efficiency results obtained should be used with caution because they depend on the technique employed. Taking a cue from Bauer et al. (1998) that there is considerable variation of efficiency scores across different studies, the need to provide robust estimates of bank efficiency measures using alternative frontier techniques cannot be overemphasized. This is important particularly when making policy recommendations. There is a significant body of empirical literature on bank efficiency studies across the world and yet "only a few apply two or more techniques to identical dataset" (Fiorentino et al., 2006), and most of these (Resti, 1997; Bauer et al., 1998; Weill, 2004; Fiorentino et al., 2006; Beccalli et al., 2006; Sakouvogui, 2020) have focused their research on developed countries.

## 1. LITERATURE REVIEW

The measurement of productive efficiency dates back to the 1950s with the works of Koopmans (1951), Debreu (1951), Shephard (1953) and Farrell (1957). According to Koopmans, "a producer is technically efficient if, and only if, it is impossible to produce more of any output without producing less of some other output or using more inputs" (Kumbhakar & Lovell, 2000). Building on the foundation of the prior works of Koopmans (1951), Debreu (1951), and Farrell (1957) demonstrated that total efficiency can be broken down into technical and allocative components. "Technical efficiency reflects the ability of a firm to obtain maximal output from a given set of inputs while allocative efficiency reflects the ability of a firm to use the inputs in optimal proportions, given their respective prices and productive technology" (Coelli et al., 2005, p. 51). Overall or economic efficiency, which has to do with either cost minimization or profit maximization is, therefore, a combination of technical and allocative efficiencies (Coelli et al., 2005).

It is argued that while there is no need for a generally accepted frontier technique for the evaluation of bank performance, the application of two or more frontier approaches to the same dataset enables one to be aware of the potential conflicting information that may arise from the different techniques (Bauer et al., 1998; Fiorentino et al., 2006). However, few empirical studies have concentrated on using two or more analytical methodologies to similar banking datasets, especially in the setting of Africa, notwithstanding the enormous body of literature on bank efficiency. Earlier studies in this field began in the United States (US) with the seminal work by Ferrier and Lovell (1990). The paper applies DEA and SFA to a 1984 sample of 575 US banks and finds a higher average overall efficiency score for DEA (80%) compared with SFA (74%). However, the study finds a weak relationship between DEA and SFA efficiency scores, which indicates that other factors not controlled for may have accounted for the insignificant correlation of efficiency scores between the two methods (Fiorentino et al., 2006). Resti (1997) applies DEA and SFA techniques on a common panel of 270 observations of Italian banks over the period 1988 to 1992 and concludes that there are no significant differences between the efficiency scores from the two frontier techniques. In his view, in the event of any differences at all, it can be resorted to the unique features of the models for expla-


http://dx.doi.org/10.21511/bbs.19(3).2024.16

nation. Nevertheless, Resti (1997) reported higher efficiency scores for SFA (81%-92%) compared with DEA (60%-78%), unlike the results of Ferrier and Lovell (1990).

Perhaps a study by Bauer et al. (1998) is the most significant among studies comparing bank efficiency measures using different techniques. This study not only applies four different techniques (DEA, SFA, Thick Frontier Analysis (TFA), and Distribution Free Analysis (DFA)) but also tests the consistency of efficiency measures across six consistency criteria. Consistent with the results of Resti (1997), the study indicates that the efficiency scores for the parametric techniques (SFA, TFA, and DFA) averaged 83%, whereas the non-parametric technique (DEA) had an average of 30%. The study also finds that all three parametric methods produced efficiency scores consistent with one another, but efficiency scores from the non-parametric approach were inconsistent with the parametric methods. The study concludes that an efficient frontier can be specified in various forms and hence at the theoretical level, there is no preferred technique. Therefore, applying different methods can help policymakers be well-informed about the possible conflicting conclusions that may arise via diverse approaches. Other banking efficiency studies comparing parametric and non-parametric frontier techniques using European data include Casu and Girardone (2002), Weill (2004), and Fiorentino et al. (2006). Weill (2004) investigates the consistency of efficiency frontier techniques on a sample of 688 banks from five European countries using DEA, SFA, and DFA. The study compares efficiency scores and correlation coefficients across the three approaches and with standard measures of performance and finds that even though there are similarities between parametric techniques, there is a lack of consistency between approaches. However, the study finds a correlation between all three frontier techniques with accounting-based measures. Fiorentino et al. (2006) apply DEA and SFA approaches on 34,192 observations for German universal banks for 1993-2004 to test the consistency of cost efficiency scores using five of Bauer et al. (1998) consistency criteria. As expected, their findings indicate that the DEA approach is susceptible to measurement errors and outliers. The study also finds that accounting for different sub-groups among banks is vital to prevent a misunderstanding of the efficiency results of the entire industry.

The most recent bank efficiency studies comparing parametric and non-parametric techniques include Tabak et al. (2014) and Sakouvogui (2020). Tabak et al. (2014) apply both DEA and SFA to a sample of Chinese local banks for the period 2001–2012 to investigate the extent to which each frontier technique is reliable. Their findings show that although the two approaches produced efficiency scores that have a consistent trend over the study period, individual performance diverge between the techniques. Sakouvogui (2020) also applied DEA and SFA to a sample of 650 US commercial and domestic banks to examine the consistency of cost efficiency estimates of the two approaches according to four consistency criteria namely efficiency levels, ranking of efficiencies, consistency over time, and consistency between clustering groups. The study concludes that the clustering approach is very vital for the efficiency rankings of US banks, with homogeneous banks recording higher average cost efficiencies compared with their heterogeneous counterparts across both DEA and SFA techniques.

The literature reviewed makes it abundantly evident that studies on banking efficiency that combine a variety of frontier techniques have primarily been conducted in Europe and the United States. Considering the fact that Africa is unique in terms of economic and political structure, banking culture, as well as the lack of consensus in the empirical literature on the consistency of parametric and non-parametric techniques, a study of this nature using an African example can be very vital for policymakers. The purpose of this study therefore, is to extend the concept of methodological crosschecking by examining whether both cost and technical efficiency scores derived from the two most popular frontier techniques, SFA and DEA yield consistent results using an African sample of Ghanaian banks. By analyzing both concepts using identical datasets from Ghana, the study is expected to provide a broader understanding of the levels and evolution of efficiency of Ghanaian banks, which can be useful to bank regulators and other decision-makers in the banking industry.

The hypotheses to be tested in this study include the following:

*H1:* *Efficiency distributions do not vary significantly between SFA and DEA.*

*H2: DEA and SFA are consistent in ranking the efficiency scores of banks.*

*H3: DEA and SFA can identify best-practice and worst-practice banks consistently.*

*H4: Efficiency scores generated by DEA and SFA are consistently stable over time.*

*H5: Frontier efficiency measures are consistent with accounting ratios.*

## 2. METHODS

Banks are complex business entities as they use a variety of inputs to produce multiple outputs. In accordance with similar other studies (Fiorentino et al., 2006; Tabak et al., 2014; and Sakouvogui, 2020), this study postulates that to produce output $y_q$, Ghanaian banks require input quantities $X_j$ at given prices of $W_j$ to minimize total operating cost, $C$ or maximizes total output, $Y$. To measure the efficiency of a productive unit, one needs to compare the actual performance of that productive unit with optimal performance located on the true production frontier. However, since the relevant true frontier is not known, there is a need to estimate such a frontier. The two most commonly used techniques to estimate a frontier and hence measure efficiency are the SFA approach and the DEA approach.

The SFA approach was proposed concurrently but independently in 1977 by Aigner et al. (1977), and Meeusen and van den Broeck (1977), Coelli et al. (2005). This model is stochastic because, in addition to the inefficiency term incorporated in the deterministic model, it also includes a random error term that captures effects such as measurement and specification errors, which are out of the control of the decision-making unit (DMU). This formulation, which has now become the platform for stochastic frontier analysis, is motivated by the fact that deviation of production outcomes from the ideal should not entirely be attributable to inefficiency on the part of decision-making units because not all factors are under the control of such DMUs. In this study, cost efficiency is measured using a stochastic cost frontier while technical efficiency is measured using a stochastic output distance function.

The stochastic cost frontier may be specified in the general log form as follows:

$$\ln C_{it} = f[(\ln w_{jit}, \ln y_{qit}, T), \beta] + \varepsilon_{it}, \quad \text{with} \quad \varepsilon_{it} = v_{it} + u_{it}, \tag{1}$$

where $C_{it}$ is total operating cost for the $i$-th bank at time $t$, $y_{qit}$ measures the $q$-th output of bank $i$ at time $t$, $W_{jit}$ is the price of the $j$-th input of bank $i$ at time $t$, $X_{jit}$ measures $j$-th input of bank $i$ at time $t$, $T$ denotes time trend common to all banks and intended to measure technical progress over time and $\beta$ is an unknown parameter to be estimated. The error term $\varepsilon_{it}$ is composed of two components ($v_{it}$ and $u_{it}$). The symmetrical random error term $v_{it}$.is assumed to be i.i.d., with $N(0, \sigma_v^2)$, while the distribution of the one-sided inefficiency term $u_{it}$ is assumed to be truncated at zero, with $N(u_{it}, \sigma_u^2)$, and independent of the error term $v_{it}$. The cost efficiency (CE) of bank $i$ for any period is given by

$$CE = \frac{C(y_{it}, w_{it})e^{v}e^{u}}{C(y_{it}, w_{it})e^{v}} = e^{u} = \exp(u), \tag{2}$$

where the numerator represents the cost frontier defined in equation (1) while the denominator represents the observed cost of production. All variables are as defined under equation (1). A bank is fully cost-efficient when equation (2) is equal to 1 and less cost-efficient otherwise.

To estimate cost efficiency, the study specifies a multi-product translog cost frontier with three outputs, three input prices, and non-neutral technology as follows:

$$\begin{aligned}
\ln C_{it} &= \beta_0 + \sum_{q=1}^{3} \beta_q \ln y_{qit} + \sum_{j=1}^{3} \beta_j \ln w_{jit} \\
&+ \frac{1}{2}\sum_{q=1}^{3}\sum_{k=1}^{3} \beta_{qk} \ln y_{qit} \ln y_{kit} \\
&+ \frac{1}{2}\sum_{j=1}^{3}\sum_{c=1}^{3} \beta_{jc} \ln w_{jit} \ln w_{cit} \\
&+ \sum_{q=1}^{3}\sum_{j=1}^{3} \beta_{qj} \ln y_{qit} \ln w_{jit} + \sum_{q=1}^{3} \beta_{qj} T \ln y_{qit} \\
&+ \sum_{j=1}^{3} \beta_{tj} T \ln w_{jit} + \beta_t T + \frac{1}{2}\beta_{it} T^2 + v_{it} + u_{it},
\end{aligned} \tag{3}$$

where all variables are as defined under equation (1). The use of duality implies that the cost frontier must be monotonically increasing in outputs and input prices, and concave in input prices, hence symmetry and linear homogeneity in input prices have been imposed, resulting in the following restrictions in line with Fiorentino et al. (2006):

$$\beta_{jk} = \beta_{kj}, \text{for all } j, k;$$
$$\beta_{jc} = \beta_{cj}, \text{for all } j, c; \tag{4}$$
$$\sum_{q=1}^{3} \beta_q = 1; \quad \sum_{c=1}^{3} \beta_{jc} = 0; \quad \text{and} \quad \sum_{j=1}^{3} \beta_j = 0.$$

Also, in accordance with Fiorentino et al. (2006) and Pasiouras et al. (2009), total cost and input prices are normalized with the price of labor as the numeraire input. The (in)efficiency scores of the individual bank are estimated as $CE_{kt} = \exp(u_i)$ while the index of cost efficiency is estimated as $CEF_{kt} = 1/CE_{kt}$, with an efficiency that ranges between 0 and 1 (Coelli et al., 2005).

Technical efficiency (TE) on the other hand may be estimated using a stochastic multi-output distance function. The study follows Beattie and Taylor (1985) and Fare and Primont (1995) and specifies the general stochastic multiple outputs and inputs distance function in the general log form as follows:

$$-\ln y_{Qit} = f[(\ln x_{jit}, \ln y^*_{qit}, T), \beta] + \varepsilon_{it}, \tag{5}$$

where $y_{Qit}$ is one of the outputs, selected at random to ensure linear homogeneity of degree 1 in outputs such that $y_{qi}{}^* = (y_{1it}/y_{Qit}, y_{2it}/y_{Qit}, , y_{q-1it}/y_{Qit})$; $x_{jit}$ measures $j$-th input of bank $i$ at time $t$, $\varepsilon_{it} = v_{it-} u_{it}$, $T$, $\beta$, $v_i$, and $u_i$ are as defined under (1). This means that all summations in the empirical model in (6) involving ($y_{qi}{}^*s$) are now over $q$–1 and not $q$. The technical efficiency (TE) of bank $i$ in any period is given by

$$TE = \frac{f(x_{jit}, y^*_{qit}) e^{v_i} e^{-u_i}}{f(x_{jit}, y^*_{qit}) e^{v_i}} = e^{-u_i} = \exp(-u_i), \tag{6}$$

where the numerator represents the output distance function defined in equation (5) while the denominator represents the observed output distance function. All variables are as defined under equation (5). A bank is fully technically efficient when equation (6) is equal to 1 and less technically efficient otherwise.

To estimate technical efficiency, a translog output distance function with three inputs, three outputs, and non-neutral technology is specified as follows:

$$\begin{aligned}
-\ln y_{Qit} &= \beta_0 + \sum_{j=1}^{3} \beta_j \ln x_{jit} + \sum_{q=1}^{2} \beta_q \ln y^*_{qit} \\
&+ \frac{1}{2} \sum_{j=1}^{3} \sum_{k=1}^{3} \beta_{jk} \ln x_{jit} \ln x_{kit} \\
&+ \frac{1}{2} \sum_{q=1}^{2} \sum_{l=1}^{2} \beta_{ql} \ln y^*_{qit} \ln y^*_{lit} \\
&\frac{1}{2} \sum_{j=1}^{3} \sum_{q=1}^{2} \beta_{jq} \ln x_{jit} \ln y^*_{qit} + \sum_{j=1}^{3} \beta_{tj} T \ln x_{jit} \\
&+ \sum_{q=1}^{2} \beta_{tq} T \ln y^*_{qit} + \beta_t T + \frac{1}{2} \beta_{tt} T^2 + v_{it} - u_{it},
\end{aligned} \tag{7}$$

where all variables are as defined under equation (5). Equations (3) and (7) will be estimated using the Battese and Coelli (1992) time-varying model in frontier 4.1 (Coelli & Henningsen, 2013).

The second approach employed in the study is the DEA technique. "DEA involves the use of linear programming methods to construct a non-parametric piece-wise surface (or frontier) over the data" (Coelli et al., 2005). Charnes et al. (1978) who first coined the term DEA proposed an input-oriented model, with the assumption of constant returns to scale (CRS). It is, however, argued that the CRS model is inappropriate for an imperfect competitive environment like the banking system (Hackethal, 2004; Fiorentino et al., 2006; Alexander et al., 2016). Therefore, this study employs the model that assumes variable returns to scale (VRS) proposed by Fare et al. (1983) and Banker et al. (1984) since Ghanaian banks are assumed to operate in an imperfect competitive environment. To estimate cost efficiency under DEA, the study assumes that banks in Ghana minimize cost and consider an input-oriented cost-minimizing DEA formulation, similar to that in Fiorentino et al. (2006) as follows:

$$\min \sum_{j=1}^{m} w_{jo} x_{jo},$$
$$x_{jo} \geq \sum_{i=1}^{m} x_{ji}\lambda_j, (j = 1, 2, ..., m),$$
$$y_{qo} \leq \sum_{i=1}^{n} y_{qi}\lambda_j, (q = 1, 2, ..., p), \tag{8}$$
$$\sum_{i=1}^{n} \lambda_i = 1, \lambda_i \geq 0,$$

where $i = 1, \ldots, n$ are the number of banks, $x_{ji}$ (j = 1, …, $m$) is the $j$-th input employed by the $i$-th bank, $y_{qi}$ ($q = 1, \ldots, p$) is the $q$-$th$ output produced by bank $i$, and $W_{jo}$ is the benchmark unit cost of input $j$ of the benchmark bank or decision making unit ($DMU_O$). Since the study adopts the VRS specification, the restriction $\Sigma_{i=1}^{n}(\lambda_i) = 1$ is imposed. Given an optimal solution ($x^*$, $\lambda^*$) to the linear programming problem above, the total cost efficiency ($CE_O$) of $DMU_O$ for $o$-th bank is the minimum cost divided by the observed cost.

The linear programming problem for estimating technical efficiency with $n$ banks, $m$ inputs, and $p$ outputs can be formulated as follows:

$$\max(\theta i) = \sum_{q=1}^{p} u_q y_{qi},$$
$$\sum_{q=1}^{p} u_q y_{qi} - \sum_{i=1}^{m} v_j x_{ji} \leq 0; \quad i = 1, 2..., n, \tag{9}$$
$$\sum_{j=1}^{m} v_j x_{ji} = 1, \quad u_q \geq 0, \quad q = 1, 2, ..., p,$$
$$v_j \geq 0, \quad j = 1, 2, ..., m,$$

where $y_{qi}$ = the amount of output $q$ produced by bank $i$; $x_{ji}$ = the amount of input $j$ utilized by bank $i$; $u_q$ = weight given to output $q$; and $v_j$ = weight given to input $j$. This implies that the technical efficiency score of the $i$-$th$ bank defined by the objective function $\theta_i$ is maximized subject to the constraint that the efficiency score of no other bank can exceed 1.

The R Software procedure (Coelli & Henningsen, 2013) is then employed to estimate the cost and technical efficiencies in equations (8) and (9), respectively.

The study employed 220 unbalanced annual panel data observations extracted from the annual financial statements of 27 banks operating in Ghana over the period 2007 to 2016. The data was sourced largely from the Bank of Ghana as well as publicly available audited annual reports of the banks, mainly from the websites or by directly contacting the various banks. The study adopts the widely used intermediation approach, and hence, treats bank deposits as inputs since bank deposits are regarded as raw material used to create bank loans and investments. The study employs three inputs ($x_1$, $x_2$, $x_3$), which are physical capital, labor, and financial capital respectively. The physical capital is represented by the net total value of plant, machinery, equipment, fixtures and fittings as stated on the annual balance sheets of the banks. The labor input is represented by the average number of permanent employees on payroll for the year. All customer deposits including demand deposits, savings and time deposits, fixed deposits, as well as other borrowed funds represent the finance input. Several other studies (Fiorentino et al., 2006; Simpasa, 2010; Barth et al., 2013; Alhassan & Ohene-Asare, 2016; Moyo, 2018) also employed similar inputs. The study also employs three outputs namely interbank loans ($y_1$), customer loans ($y_2$), and investments in securities ($y_3$). Interbank loans refer to all placements and fixtures with other banks. Customer loans are made up of outstanding term loans and overdraft facilities granted to businesses and individuals less provision for bad or doubtful debts or impairment losses. Investments in securities include short-term investments such as government treasury bills, medium-term investments such as treasury notes, and long-term investments like treasury and other bonds and equities. Studies such as Fiorentino et al. (2006) and Barth et al. (2013) have employed similar outputs; while studies such as Simpasa (2010) and Moyo (2018) combined all three outputs above into a single output in their estimations.

The price of physical input ($w_1$) is represented by the ratio of depreciation expenses to the net value of fixed assets defined above, while the price of the finance input ($w_3$) is represented by all interest expenses divided by customer deposits as well as other borrowings. The price of labor ($w_2$) is represented by staff or personnel expenses including


http://dx.doi.org/10.21511/bbs.19(3).2024.16

**Table 1.** Descriptive statistics of the banking data

| Variable | No. of obs. | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| Total Cost (TC or C) (in GHS) | 220 | 154,000,000 | 164,000,000 | 2,123,595 | 1,290,000,000 |
| Total Revenue (TR) (in GHS) | 220 | 167,000,000 | 199,000,000 | 1,331,111 | 1,200,000,000 |
| Total Assets (TA) (in GHS) | 220 | 1,360,000,000 | 1,400,000,000 | 14,000,000 | 8,030,000,000 |
| Total Equity (E) (in GHS) | 220 | 187,000,000 | 191,000,000 | 3,512,724 | 1,020,000,000 |
| Profit After Tax (PAT) (in GHS) | 220 | 41,000,000 | 69,600,000 | (79,000,000) | 328,000,000 |
| Profit After Tax (PBT) (in GHS) | 220 | 57,700,000 | 97,100,000 | (106,000,00) | 461,000,000 |
| TC/TR | 220 | 1.4120 | 2.5804 | 0.1969 | 29.0597 |
| TC/TA | 220 | 0.1202 | 0.0449 | 0.0223 | 0.2900 |
| ROE | 220 | 0.1510 | 0.2039 | -1.2287 | 0.5126 |
| ROA | 220 | 0.0222 | 0.0285 | -0.1710 | 0.0856 |
| **Inputs** | | | | | |
| Physical capital (*x*1) (in GHS) | 220 | 37,100,000 | 45,500,000 | 59,111 | 317,000,000 |
| Labor (*x*2) | 220 | 670 | 512 | 19 | 2,314 |
| Financial capital (*x*3) (in GHS) | 220 | 1,100,000,000 | 1,130,000,000 | 5,061,311 | 6,180,000,000 |
| **Outputs** | | | | | |
| Interbank Loans (*y*1) (in GHS) | 220 | 179,000,000 | 258,000,000 | 1,559,616 | 2,270,000,000 |
| Customer Loans (*y*2) (in GHS) | 220 | 567,000,000 | 594,000,000 | 2,247,845 | 3,480,000,000 |
| Investments in securities (*y*3) (inGHS) | 220 | 342,000,000 | 434,000,000 | 51,000 | 2,630,000,000 |
| **Input prices** | | | | | |
| Price of physical capital (*w*1) | 220 | 0.2016 | 0.1260 | 0.0215 | 0.9626 |
| Price of labor (*w*2) (in GHS) | 220 | 57,115.80 | 37,150.36 | 7,268.65 | 209,910.40 |
| Price of financial capital (*w*3) | 220 | 0.0649 | 0.0404 | 0.0133 | 0.2531 |

*Note:* Obs = number of observations; Min = minimum; Max = maximum; Std.dev. = standard deviation; GHS = Ghana cedis.

wages and salaries, social security and provident fund contributions, training, and other staff costs all divided by the number of employees during the year. The definitions of input prices above are standard in the empirical literature. However, especially in the absence of information on the number of employees, some studies such as Ohene-Asare (2011), Barth et al. (2013) and Adjei-Frimpong et al. (2014) among others have defined the price of labor as the ratio of personnel expenses to total assets. The total cost (*C*) is made up of all interest and non-interest expenses derived from the banks' annual consolidated income statements. This definition of total cost is standard in the empirical literature. The descriptive statistics of the variables employed are presented in Table 1.

# 3. RESULTS AND DISCUSSION

The presentation and discussion of the results have been carried out in accordance with the stated hypotheses. The first criterion to consider is whether efficiency scores estimated by the two methods are consistent in terms of their distribution. Table 2 provides some characteristics of the estimated efficiencies. The mean efficiencies per the SFA approach for technical efficiency (TE) and cost efficiency (CE) are 97% and 80%, respectively. In contrast, that of the DEA models was 83% and 65% for TE and CE, respectively. This means that on average, the parametric approach yielded efficiency scores that are 15 percentage points higher than that of the non-parametric method. The average standard deviation of the two concepts based on DEA efficiency scores is about 46% above that of SFA. The higher mean efficiency scores recorded under SFA compared with DEA as well as, the lower standard deviations of SFA efficiency scores compared with that of DEA are consistent with other studies such as Bauer et al. (1998), Weill (2004) and Fiorentino et al. (2006). As indicated in earlier studies such as Fiorentino et al. (2006), the significant differences between DEA mean efficiencies and standard deviations and that of SFA could be due to the sensitivity of the former to outliers as it neglects a random error. Hence, the DEA tends to overestimate inefficiencies since it treats all deviations, including the random error, as part of inefficiency.

It can also be observed from Table 2 that, for each approach, mean technical efficiency scores are higher than cost efficiency. The lower mean cost ef-

**Table 2.** Descriptive statistics of efficiency scores by concept and technique

| Efficiency | Obs. | Min | Quart-1 | Median | Quart-3 | Max | Mean | Std. dev. |
|---|---|---|---|---|---|---|---|---|
| SFA-TE | 220 | 0.4961 | 0.9765 | 0.9975 | 0.9998 | 1.0000 | 0.9705 | 0.0654 |
| SFA-CE | 220 | 0.4603 | 0.7146 | 0.8253 | 0.8877 | 0.9839 | 0.7960 | 0.1207 |
| DEA-TE | 220 | 0.3878 | 0.7372 | 0.8476 | 0.9624 | 1.0000 | 0.8298 | 0.1483 |
| DEA-CE | 220 | 0.2816 | 0.5172 | 0.6394 | 0.7715 | 1.0000 | 0.6538 | 0.1949 |

*Note:* Obs = number of observations; Min = Minimum, Quart-1 = 1$^{st}$ quartile; Quart-3 = 3$^{rd}$ quartile; Max = Maximum; Std. dev = standard deviation; TE = Technical Efficiency; CE = Cost Efficiency.

ficiency scores compared with technical efficiency scores recorded under DEA in the present study are consistent with other previous studies on bank efficiency in Ghana, such as Alhassan and Ohene-Asare (2016) who applied the DEA approach to 26 Ghanaian banks over the period from 2004 to 2011 finding mean efficiency estimates of 95%, and 46% for TE and CE, respectively. The higher mean technical efficiency scores compared with that of cost efficiency scores is expected. This is because, cost efficiency is an aspect of economic efficiency and as noted by Bauer et al. (1998), "Technological efficiency scores will tend to be higher than economic efficiency scores on average, all else equal, because economic efficiency sets a higher standard that includes allocative efficiency".

The second hypothesis has to do with whether efficiency scores estimated by the two frontier techniques are consistent in ranking banks. In Table 3, the Spearman rank-order correlation coefficients are presented to show how close or otherwise the ranking of banks by each of the two methods across the two concepts of efficiency is. As expected, there is a weak correlation between the methods, and in some instances, the two methods produce the opposite ranking of banks. The failure of the two methods to consistently rank banks similarly may be attributable to the inability of the non-parametric methods to delineate inefficiency from random error and therefore interpret differences among banks purely as inefficiency (Fiorentino et al., 2006). Therefore, as noted in Bauer et al. (1998), parametric and non-parametric methods cannot be relied upon to consistently rank banks in similar order and hence may give conflicting results, which is also the case in the present study. The results are also similar to Berger and Humphrey (1997) who reported differences in the ranking of firms by parametric and non-parametric techniques. It is therefore important for caution when drawing conclusions from a single approach.

**Table 3.** Spearman rank-order correlations of efficiency scores

| Efficiency | SFA-TE | SFA-CE | DEA-TE | DEA-CE |
|---|---|---|---|---|
| SFA-TE | 1.0000 | – | – | – |
| SFA-CE | 0.2690 | 1.0000 | – | – |
| DEA-TE | –0.3667 | –0.1932 | 1.0000 | – |
| DEA-CE | –0.4676 | 0.1077 | 0.6959 | 1.0000 |

The next hypothesis to consider is whether the two frontier methods are consistent in identifying extreme performance. Table 4 presents the level of correspondence between SFA and DEA in identifying the best-practice or the worst-practice banks across the two concepts of efficiency. The upper right triangle in Table 4 presents the percentage of banks identified by SFA as the most efficient 25% of banks that the DEA also identifies as part of the most efficient 25%. Conversely, the lower left triangle provides the percentage of banks identified by SFA as part of the bottom 25%, which the DEA also identified as part of the bottom 25%. For example, only 43% of the banks recognized by SFA-CE as being among the top 25% most efficient banks were also identified by DEA-CE as being among the top 25% most efficient banks. Additionally, of the banks identified as the bottom 25% least efficient banks by SFA-TE, only 14% of these banks were identified by DEA-TE as among the bottom 25% least efficient banks. Fiorentino et al. (2006) indicated that "random chance alone would yield an expected value of 25% correspondence, while perfect correspondence gives a 100% level". Hence, the value of 14% correspondence between SFA and DEA in identifying the bottom 25% least efficient banks is not significantly different from the random chance figure of 25%. Overall, the SFA and DEA average correspondence in identifying the best and worst efficient banks is 40% and 30%, respectively, which are both less than 50%. This implies that parametric and non-parametric techniques do not generally identify extreme performance consistently. This finding is consistent


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with earlier research from studies like Bauer et al. (1998) and Fiorentino et al. (2006), which means that policies aimed at either inefficient or efficient Ghanaian banks may produce different outcomes depending on which technique informs the policy formulation process. Therefore, one must be careful when using only one of these approaches in policy formulation.

**Table 4.** Identification of extreme banks by technique and concept

| Efficiency | SFA-TE | SFA-CE | DEA-TE | DEA-CE |
|---|---|---|---|---|
| SFA-TE | – | 0.2857 | 0.5714 | 0.2857 |
| SFA-CE | 0.2857 | – | 0.2857 | 0.4286 |
| DEA-TE | 0.1429 | 0.0000 | – | 0.5714 |
| DEA-CE | 0.4286 | 0.5714 | 0.4286 | – |

*Note:* Each number in the upper triangle is the proportion of banks that are identified by one technique and concept as having efficiency scores in the most efficient 25% of banks that are also identified by other techniques and concepts. Each number in the lower triangle is the proportion of banks that are identified by one technique and concept as having efficiency scores in the least efficient 25% of banks that are also identified by other techniques and concepts.

Table 5 shows the Spearman rank-order correlations of efficiency scores generated for the two efficiency concepts by method across the period from 2007 to 2016 to evaluate the consistency of efficiency scores from year to year over time. For example, each figure in the first column of Table 5 shows for each efficiency measure the average correlations of efficiencies over the years; 2007 with 2008, 2008 with 2009, …, 2015 with 2016. Over the study period of 10 years, the t-year apart figures, as depicted in Table 5, are the means of (10 – t) correspondences of efficiencies that are t years apart.

It can be observed in Table 5 that the year-apart average correlation coefficients under SFA are relatively high compared with those under DEA. Overall, the SFA approach recorded averages of 99.9% and 99.7% for TE and CE, respectively, while the DEA approach recorded averages of 23.7% and 40.7% for TE and CE, respectively, over the sample period. These results are inconsistent with other studies such as Bauer et al. (1998) and Fiorentino et al. (2006), who reported higher year-apart correlations among DEA approaches than SFA approaches. It can also be observed from Table 5 that the year-apart correlations for the two approaches across the two efficiency concepts have declined consistently over the period with average evolutions of –0.19% and –0.66% for TE and CE, respectively, under SFA compared with –83.4% and –94.7% for TE and CE, respectively, under DEA. This suggests that efficiency scores of later years under SFA are more highly correlated with initial years compared with those under DEA, making the SFA approach more stable than the DEA approach. The relative stability of efficiency scores as suggested by the SFA approach implies that worst-practice banks tend to remain inefficient, while best-practice banks remain relatively efficient during the period under review. The downward trend in the year-apart correlations over time also suggest a stronger relationship among efficiency scores in the short run compared with the long run. This trend has also been observed in earlier studies such as Bauer et al. (1998) and Fiorentino et al. (2006). In summary, the analysis suggests that the SFA approach produced efficiency estimates that were more stable over time than that of the DEA approach.

Finally, the study tests the hypothesis that frontier efficiencies are consistent with accounting measures. In this regard, the Spearman rank-order correlation coefficients for SFA and DEA generated efficiency scores, and four non-frontier accounting ratios are presented in Table 6. Generally, efficiency scores generated by frontier

**Table 5.** Stability of measured efficiencies over time

| Efficiency | One Year Apart | Two Years Apart | Three Years Apart | Four Years Apart | Five Years Apart | Six Years Apart | Seven Years Apart | Eight Years Apart | Nine Years Apart |
|---|---|---|---|---|---|---|---|---|---|
| SFA-TE | 1.0000 | 0.9999 | 0.9998 | 0.9996 | 0.9994 | 0.9993 | 0.9989 | 0.9986 | 0.9981 |
| SFA-CE | 0.9999 | 0.9997 | 0.9992 | 0.9987 | 0.9979 | 0.9971 | 0.9960 | 0.9948 | 0.9933 |
| DEA-TE | 0.4946 | 0.3177 | 0.2601 | 0.2718 | 0.2235 | 0.1572 | 0.1886 | 0.1358 | 0.0821 |
| DEA-CE | 0.6783 | 0.5841 | 0.5635 | 0.4868 | 0.4115 | 0.2570 | 0.3343 | 0.3080 | 0.0357 |

*Note:* Efficiency scores of only the 13 banks that have operated consistently over the period 2007 to 2016 have been used in the analysis of stability of efficiency scores.

techniques are not expected to be perfect or even highly correlated with non-frontier accounting-based performance measures since the computation of the latter are not underpinned by microeconomic theory and may not account for additional information about performance required for robust efficiency estimation (Fiorentino et al., 2006). Nevertheless, if efficiency scores generated by frontier techniques are at least reasonably correlated with accounting ratios, it would mean that frontier techniques are not just artificial products of microeconomic theory based on the underlying assumptions made regarding the chosen optimization concept but that they can be realistic and hence credible (Bauer et al., 1998).

**Table 6.** Spearman rank-order correlations between efficiencies and accounting ratios

| Accounting ratio | SFA | | DEA | |
|---|---|---|---|---|
| | TE | CE | TE | CE |
| ROE | 0.0510 | 0.0452 | 0.2889 | 0.1269 |
| ROA | –0.0378 | 0.0635 | 0.3998 | 0.1697 |
| TC/TR | 0.0319 | 0.0044 | –0.3650 | –0.0164 |
| TC/TA | –0.0546 | –0.1678 | –0.1793 | –0.0058 |

*Note:* ROE = Return on Equity, ROA = Return on Assets, TC = Total Cost, TR = Total Revenue, TA = Total Assets.

The non-frontier accounting-based measures as indicated in Tables 6 and 7 include the ratio of profit to total assets (ROA), the ratio of profit to equity (ROE), the ratio of total cost to total revenue (TC/TR), and the ratio of total cost to total assets (TC/TA). As shown in Table 6, the results demonstrate a weak correlation between the traditional bank performance measures and efficiencies computed by frontier techniques. The weak relationship between frontier efficiency measures and traditional measures reported in the present study confirms that accounting-based measures may not fully account for bank performance information, making these traditional methods weak measures of efficiency and should be used with caution, especially for bank supervision. These results are consistent with earlier studies such as Bauer et al. (1998) and Fiorentino et al. (2006).

Just as in the case of the consistency of the two frontier techniques in identifying least efficient and most efficient banks, it will be interesting to also investigate the consistency of frontier techniques and accounting measures in identifying extreme performing banks. Table 7 shows how accounting ratio, on the one hand, and efficiency scores, on the other hand, are consistent in identifying extreme performing banks in Ghana. From the table, the average correspondence between the SFA measures and the accounting-based measures in identifying the top and bottom 25% of banks is 25%, while that of the DEA measures and the accounting ratios is 30%. As indicated earlier, with random chance alone, a 25% predicted correspondence value is expected between accounting ratios and frontier techniques. Hence, the average correspondence of 25% for the SFA approach and 30% for the DEA approach and accounting measures are not statistically different from the random chance value of 25%. This suggests that frontier techniques and accounting measures of bank performance do not identify best-practice banks and worst-practice banks consistently.

As noted in Bauer et al. (1998), the first three criteria – efficiency distributions, ranking of efficiencies, and identifying extreme performing banks – allow us to assess the degree of consistency between the efficiency scores produced by the two frontier techniques. On the other hand, the final two consistency criteria – consistency with non-frontier standard accounting measures and stability of efficiencies over time – allow us to assess how efficiencies produced by the two frontier techniques are con-

**Table 7.** Identification of extreme banks by efficiencies and accounting ratios

| Efficiency | Bottom 25% of banks | | | | Top 25% of banks | | | |
|---|---|---|---|---|---|---|---|---|
| | ROE | ROA | TC/TR | TC/TA | ROE | ROA | TC/TR | TC/TA |
| SFA-TE | 0.7143 | 0.5714 | 0.0000 | 0.1429 | 0.2857 | 0.4286 | 0.1429 | 0.1429 |
| SFA-CE | 0.1429 | 0.0000 | 0.2857 | 0.1429 | 0.2857 | 0.2857 | 0.2857 | 0.1429 |
| DEA-TE | 0.4286 | 0.5714 | 0.0000 | 0.0000 | 0.4286 | 0.4286 | 0.2857 | 0.4286 |
| DEA-CE | 0.4286 | 0.2857 | 0.2857 | 0.1429 | 0.2857 | 0.1429 | 0.2857 | 0.4286 |

*Note:* Each number in the left-hand side of the table is the proportion of banks that are identified by each accounting ratio as having efficiency scores in the least efficient 25% of banks that are also identified by each efficiency. Each number on the right-hand side of the table is the proportion of banks that are identified by each accounting ratio as having efficiency scores in the most efficient 25% of banks that are also identified by each efficiency.


http://dx.doi.org/10.21511/bbs.19(3).2024.16

sistent with reality and, hence credible. It is argued that "measured efficiency by acceptable approaches should yield efficiencies which are fairly stable over time, and regulatory policies targeted specifically at either very efficient or very inefficient firms should still hit their marks after normal policy implementation lags" (Bauer et al., 1998). Although the changing business operating environment, including changes in the macroeconomics, market competition, and technology, among others may result in changes in the operational efficiencies of banks, a bank that is extremely efficient in year one is not likely to suddenly become extremely inefficient in year two. Therefore, the possible enabler, which may help choose between parametric and non-parametric techniques for regulatory policy purposes is whether efficiency scores generated from either SFA or DEA are credible.

It was noted earlier that, the SFA's main benefit over the DEA is the explicit incorporation of a random error term in the former. Therefore, the low degree of consistency between the two frontier techniques may be due to among other factors, the neglect of random error by the DEA approach. The DEA's inability to isolate the random error from the inefficiency term makes it sensitive to measurement errors. In a developing country like Ghana where data quality is an issue, if one or two banks understate or overstate their outputs or inputs, such banks can become outliers that can affect the efficiencies of other banks and hence this may make the DEA efficiency estimates unstable compared with those of the SFA. This may explain why the SFA efficiency scores in the present study were comparably more stable over time.

## CONCLUSION

This paper aimed to extend the concept of methodological crosschecking using an African example of Ghanaian banks. Specifically, the study tested whether efficiency scores generated by SFA and DEA were consistent in terms of their distributions, rankings, identifying extreme performing banks, stability across time, and relationship with non-frontier accounting-based measures. The study concludes that parametric and non-parametric techniques neither rank nor identify the best and worst practicing banks consistently. This suggests that depending on which technique is used to guide a policy-making process, interventions directed at either inefficient or efficient Ghanaian banks may generate various results. Hence, the choice of frontier technique is important in policy formulation since regulatory policy conclusions may differ depending on which frontier technique is used. The study also found a weak correlation between traditional measures of bank performance and frontier efficiency scores. This shows that accounting ratios are inadequate indicators of efficiency since they take into consideration not only efficiencies but also other exogenous factors that bank managers have little control over. This is concerning because the accounting-based measures are the ones mostly used by regulatory authorities in Ghana when doing bank supervision. Also, these results suggest that the SFA approach produced efficiency estimates that were more stable over time compared with those of the DEA approach. The fairly stable efficiency scores under the SFA approach compared with those of the DEA approach in this study make the SFA approach more credible and hence, more useful for regulatory purposes in Ghana. Taking a cue from past, comparable studies, this study concludes that it is not essential for an agreement on the optimal frontier technique for examining bank efficiency. Rather, what is important is to employ alternative methods to identical datasets to provide methodological crosschecking to arrive at the method that will yield results that are more consistent with reality on the ground and hence are more believable by bank managers and policymakers. Hence, the choice of the most suitable method in a particular study ultimately should be an empirical question.

## AUTHOR CONTRIBUTIONS

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Formal analysis: John-Mark Akandekumtiim.

Funding acquisition: John-Mark Akandekumtiim.
Investigation: John-Mark Akandekumtiim.
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