Measuring Technical Efficiency and Productivity Change in the Nigerian Banking Sector: A comparison of Non-parametric and Parametric Techniques

Eze Simpson Osuagwu*^[1], Wakeel Isola[2], Isaac Chii Nwaogwugwu[2]

*Corresponding Author
^International Institute for Development Studies, Wilmington DE 19802, United States.
[1] Department of Economics and Development Studies, Covenant University, Ota Nigeria
Email: eze.osuagwu@covenantuniversity.edu.ng Phone: +2348033214346

[2]Department of Economics, University of Lagos, Nigeria. wisola@unilag.edu.ng (WI)
inwaogwugwu@unilag.edu.ng (ICN)

Abstract

This study estimates technical efficiency and total factor productivity change in the Nigerian banking sector for the period 2005 – 2014, which encapsulates the post consolidation era and subsequent regime of banking reforms aimed at stabilizing the sector from the effects of financial crisis. The study applies both non-parametric Data Envelopment Analysis (DEA) and parametric Stochastic Frontier Approach (SFA), using Malmquist Productivity Index, and error component production function respectively, to ascertain if any significant variation in efficiency exists on a sample of twelve banks covering over 80% of total bank assets in Nigeria. The theoretical intermediation approach is applied for selection of input and output variables. The input variables considered are total deposits, total equity and operating expenses including staff costs, and output variables are loans and operating income, which accounts for off-balance-sheet items such as non-interest or fee-based income. Findings reveal that the mean technical efficiency under SFA and total factor productivity change in DEA decreases as bank output move towards non-interest or fee-based income. Although the magnitude differs, both SFA and DEA follow similar direction for technical efficiency and total factor productivity change. Study implications suggest that policy makers should be concerned about arbitrariness in bank's ability to earn fee-based income, which portends high cost of banking services in the long-run.

Keywords: Bank Efficiency; Data Envelopment Analysis (DEA); Malmquist Productivity Index; Stochastic Frontier Approach (SFA);

JEL Classification Code: D21, D53, G21

1.0 Introduction

In the wake of bank consolidation exercise in Nigeria, the banking sector witnessed a wave of mergers and acquisitions, which brought together many strange bed fellows in the industry. While some scholars argue that the productive efficiency of banks in Nigeria has improved following the consolidation exercise (Assaf, Barros & Ibiwoye, 2012), others contend that consolidation has no significant effect on the efficiency of banks (Amel, Barnes, Panetta & Salleo, 2004). However, inefficiency in the allocation of resources in a liberalized environment could result in financial crisis, as a result bank's total factor productivity will be hampered (Tana, Luo and De Vita 2017).[1] To this end, monetary authorities are always concerned about the effect of a policy change on the efficiency and productivity of banks (Anginer & Demirguc-Kunt, 2014).[2] Because of output loss suffered through banking crises, and the sector-specific inefficiencies that unfolds, a negative productivity change has been observed both in the short and long-term (Oulton & Sebastia-Barriel, 2013). Nevertheless, Mester (2005) posits that consolidation is a positive for the banking industry in the sense that it eliminates inefficient firms and promotes a healthier banking system by diversifying risk and reducing cost of production since scale and scope is enlarged.

There is a lack of consensus among researchers regarding the preferred choice of frontier model for the estimation of banking sector efficiency. The non-parametric method imposes less restrictions and does not allow for the analysis of random errors that may arise from data, model misspecification, measurement error and environmental factors prevailing against or in favor of the banking system. The presence of random errors which obviously are unobservable to the researcher poses a significant threat to the conclusions reached if not captured adequately. In this case the parametric method seems plausible in order to capture unobservable heterogeneity in decision making with respect to use of funds and other resources, but the nonparametric method seem to absorb the homogenous nuances that are inherently bank specific such as identifying slacks in inputs and outputs. Berger and Humphrey (1997) posit that the difference between the nonparametric and parametric approaches is important because the two types of methods tend to have different degrees of dispersion and rank the same financial institutions somewhat differently. This study attempts to estimate technical efficiency and total factor productivity change for the banking sector in Nigeria using both non-parametric Data Envelopment Analysis (DEA) and parametric Stochastic Frontier Approach (SFA) on post consolidation data, to ascertain if any significant variation in the efficiency exists due to methodological differences that may affect policy decisions.[3] The motivation for this study stems from empirical evidence,

---

[1]Laeven and Valencia (2013) observed that a typical feature of financial crisis is that they are preceded with credit boom and greater financial integration, as was the case in Nigeria in 2009, following bank consolidation exercise of 2005, which seemed like a credit boom to the banking industry because it opened up banks for investment through the capital market.

[2] Gulamhussen, Pinheiro, and Pozzolo, (2014), and Fielding and Rewilak (2015) have documented greater bank risk taking and diversification in a liberalized banking system resulting in a negative effect on bank productivity growth.

[3]Technical efficiency is the ability of banks to maximize output from a given set of inputs, and technological change is the adoption of new methods of productivity. Total factor productivity change is captured by DEA using Malmquist productivity index, while technical efficiency is measured on both DEA and SFA.

which posits that the parametric and non-parametric approaches for measuring technical efficiency change and total factor productivity change may not always produce the same result and have obvious implications for policy formulation.[4]

This paper improves on previous bank efficiency studies by including operating income, which accounts for non-interest or fee-based income as an output variable in order to ascertain the degree of technical efficiency or productivity change for interest (loan) revenue and non-interest or fee-based income.[5] Results show that the degree of technical efficiency and total factor productivity change diminishes as bank revenue portfolio moves toward non-interest or fee based. Policy implications are further identified in order to limit the arbitrariness of banks in their increasing desire for fee-based income. This study is presented in six sections, the next section is a brief review of the structure of Nigerian banking system, the third section is a review of related literature and the underlining theories on bank intermediation, the fourth section is a presentation of data and methods of analyzing efficiency and productivity change, the fifth section presents a discussion of the results, while the sixth section concludes the study.

2.0 Banking Structure in Nigeria

The Nigerian banking system has over the years evolved through the process of restructuring since the Structural Adjustment Program (SAP) of 1986, which introduced a regime of deregulation. The number of banks increased from 29 in 1986 to 89 in 2004, down to 25 after consolidation in December 2005. Following a restructuring of the imbalances arising from consolidation exercise and global financial crisis the total number of banks in Nigeria settled at 20 as at 2014.[6] Within this period the banking system went through turbulence, albeit structural changes occasioned by internal managerial inefficiencies, industry wide factors and macroeconomic circumstances affecting the overall performance.

In view of the significant structural changes in the Nigerian banking system in 2007, the performance indicators were at the lowest level in 2009 with average return on assets for the four major banks dropping to 0.94% and average net profit and return on capital to an all-time low (7.60% and 5.28%) since the deregulation of the banking sector in 1986.[7] In any case, the response of monetary authorities to cushion the effect of banking crisis on the macro-economy was the establishment of the Asset Management Company of Nigeria (AMCON) for the

---

[4]Berger and Humphrey (1997) observed that the central tendency of efficiency estimates from non-parametric DEA and parametric SFA may be similar, but the degree of dispersion differs irrespective of the similarity in the structure of decision-making units.

[5] Osuagwu and Nwokoma (2017) finds that banks in Nigeria become less competitive for non-interest revenue or fee-based income. However, it is not known whether low competitiveness for fee-based income is driven by increased demand for banking services, which in turn requires managerial effectiveness and technological improvements.

[6]The bank consolidation exercise and recapitalization policy were part of a home-grown economic recovery and poverty reduction strategy tagged Nigerian Economic Empowerment and Development Strategy (NEEDS) introduced in 2003.

[7]The drastic fall in bank performance ratios might have been an aftermath of the global financial crisis coupled with the recklessness of bank management in the process of seeking funds for recapitalization.

management of bank toxic assets. According to Owolabi and Ogunlalu (2013), the performance ratios do not show any improvements despite the huge cost of consolidation; about fourteen banks failed during the process, because of inability to meet the capital requirements.

3.0 Literature Review and Theoretical Framework

3.1 Literature Review

The most widely studied area in bank efficiency literature is that of allocative and technical efficiencies using parametric and non-parametric frontier methods.[8] Kourouche (2008) reports that many studies tend to estimate technical efficiency rather than allocative efficiency because the later requires input prices, which is difficult to obtain, and the presence of technical inefficiencies is more prevalent amongst banks. Broadly speaking, productivity change is decomposed into technological change (TC) and technical efficiency (TE), while TE is a measure of managerial ability in the use of technology, TC captures the adoption of new methods of productivity. To say the least, improvements in TE emanate from the application of knowledge from experience and training, whereas TC improvements are products of investments in research and technology. However, technical efficiency arises from bank's investment in human capital, and technological change arises from improvements in physical capital such as acquiring state-of-the-art equipment like Automated Teller Machines (ATM) in banks. In the literature of banking sector performance, it is clearly evident that bank efficiency is strongly related to profitability (Osuagwu, 2013), and the level of competition in the industry (Mlambo and Ncube, 2011). There is also empirical evidence that bank profitability is largely determined by a bank's internal organization and managerial ability as opposed to external influences, which implies that efficient banks are inclined to improvements in technical efficiency and technological change (Osuagwu, 2014). Nonetheless, Mwenga (2011) observed that banking sector competition increasingly affects the level of efficiency and concentration in the Kenyan banking sector, which supports the finding in Poshakwale and Qian (2011) on short run significant relationship between banking sector productive efficiency and economic growth in Egypt.

Grigorian and Manole (2006) shows that in estimating technical efficiency using DEA, output variables could significantly differ the results in models of similar input variables. Using a sample of 17 transition economies for the period 1995 – 1998 on two distinct models 'A' and 'B'; specifying inputs of labor, fixed assets and interest expense and outputs of revenues, net loans and liquid assets for Model A, and in Model B using same inputs as model A, but with outputs of total deposits, net loans and liquid assets, results show that the technical efficiency scores for Model A ranged between 23.7% (Belarus) and 79.9% (Czech Republic) and for Model B technical efficiency scores ranged between 15.5% (Belarus) and 84.3% (Slovenia). The change in efficiency scores for both models could be attributed to the difference in output variables. For the manufacturing sector Cheruiyot (2017) argued that the location of a firm affects its technical efficiency, using a two-stage nonparametric DEA approach, the findings of the study indicate that firms located closer to the supply of resources tend to be more efficient.

---

[8]Kourouche (2008), Chen (2002), Lee, Worthington and Leong (2010) and Berger and Humphrey (1997) among others provide details of country specific bank efficiency studies.

In another two-model analysis, Attaullah, Hijazi and Javed (2004) in examining the technical efficiency of banks in India and Pakistan for the period 1988 – 1998, using DEA and two input variables (interest expense and operating expense) for both Model 'A' and 'B' and different output variables for Model 'A' (total loans and investment) and Model 'B' (interest and non-interest income) findings show that the mean technical efficiency of banks in India was 72.8% and 63.0% for models A and B respectively, and for Pakistan the mean technical efficiency score was 42.4% for Model A and 54.1% for Model B. These findings in Grigorian and Manole (2006) and Attaullah et al. (2004) demonstrate how the choice of inputs and outputs could determine the magnitude of efficiency.

Jreisat, Hassan and Shankar (2017) using the non-parametric input-oriented Malmquist index to study productivity change for a sample of 14 banks in Egypt from 1997 to 2013, finds a 0.9% decrease in productivity due to technological change. The study further reveals that banks with higher loans to deposit ratio and higher returns to equity have higher productivity growth, which may be due to improved managerial skills and the adoption of state-of-the-art equipment for banking services. However, studies that center on profit efficiency are also able to show improvements.[9] The existing literature on bank efficiency in sub-Saharan Africa show mixed results depending on whether profit or cost efficiency is estimated, and the analytical technique applied. Mwega (2011) investigates the competitiveness and efficiency of the financial services sector in Kenya using DEA and SFA, findings show that the average efficiency score in the banking sector was 0.58 (DEA constant returns to scale), 0.65 (DEA variable returns to scale) and 0.84(SFA). The evidence from this study suggests that the banking sector in Kenya experienced reduced concentration and became more competitive between 1998 and 2007.

Assaf et al. (2012), assessing the performance of Nigerian banks using post consolidation data for 2005 - 2007 show that the efficiency of Nigerian banks has increased post consolidation to reach a highest average of 91.2% in 2007 based on the Bayesian stochastic frontier model applied. Given the earlier observation by Berger and Humphrey (1997) that parametric and non-parametric methods yield significantly different results and corroborated by Chen (2002) where there are significant differences in efficiency scores between the chance-constrained DEA and stochastic frontier approach estimated for the Taiwanese banking sector. The motivation for this study is rife from literature because none of the studies reviewed has incorporated non-interest or fee-based income to determine the technical efficiency and total factor productivity change for the Nigerian banking sector in a post consolidation era and comparing the parametric and the non-parametric efficiency levels. The empirical evidence in Assaf et al. (2012) that Nigerian banks have become cost efficient following consolidation is contestable because of the short data period. This study therefore extends the data and innovates by considering non-interest or fee-based revenue as bank output in the analysis of non-parametric DEA and parametric SFA models.

3.2 Theoretical Framework

[9]Akhavein, Swamy and Taubman (1997) show that the profit efficiency improvements are mainly due to the ability of banks to shift their outputs from securities to higher yielding loans.

There are two major underlining theories to support bank productivity and performance based on the choice of input and output variables; the intermediation approach and the production approach. The Intermediation approach made popular by Sealey and Lindley (1977) considers financial institutions as intermediary between savers and investors, the input of funds and their interest cost is considered, and funds are considered the major instrument of the intermediation process. Berger and Humphrey (1997) does not consider any of these two approaches to be perfect, however, recommends different circumstances for the application of either of the theories based on the choice of input and output in the analysis. They posit that production approach may be suitable for the estimation of efficiencies of branches of financial institutions, because branches process customer documents and managers at the branch level make little or no investment decisions. However, Berger and Humphrey (1997) also suggests that the intermediation approach is most appropriate for evaluating the entire financial institutions because it considers interest expenses, which incorporates costs, and since minimization of total costs and not production costs is considered in profit maximization, it becomes relevant in the estimation of frontier efficiency of profitability.

Sealey and Lindley (1977) had earlier criticized the production approach stating that it failed to account for technical and economic aspects of production of financial services, hence they proposed a theory where a bank function as the intermediary between depositors and investors, and various types of earning assets such as loans are treated as outputs and deposits along with capital and labor as inputs. The input and output variables to be considered in this study are drawn from the intermediation role of banks. The advantage of the intermediation approach is that it allows for the inclusion of off-balance sheet (OBS) instruments like non-interest income and expenses in the analysis of bank productive efficiency. OBS activities, which includes trading financial instruments and generating income from fees and loan sales are increasingly seen as potential dependable income source for banks.

4.0 Methodology

4.1 Data

The data employed for this study is drawn from the annual reports (2005 to 2014) of selected banks, which constitute over 80% of the total market size. The banks not included in the sample are new banks formed out of the restructuring exercise of 2010. The financial year of all banks in the sample is assumed to begin in January and end in December. The banks in the sample are – Access Bank, Diamond Bank, Eco-Bank, Fidelity Bank, First Bank, Guaranty Trust Bank (GTB), Skye Bank, Sterling Bank, United Bank for Africa (UBA), Union Bank of Nigeria, Wema Bank and Zenith Bank.

4.2 **Model Specification:**

There are two basic models employed in this analysis, based on the dependent variables. In the first model, the dependent variable is total loans, which represents the output of banking firms and the explanatory variables are inputs – total deposit, staff cost and equity capital. In the second model, the dependent variable or output function is operating income, which incorporates non-interest or fee-based income, and the input variables or explanatory variables are total deposit, staff cost, total equity and operating expense. Both DEA and SFA are analyzed using the same output and input variables. The study assumes constant returns to scale and input orientation in DEA. When constant returns to scale exists, the input and output-oriented estimates of technical efficiency provide the same result, otherwise they will be unequal if increasing or decreasing returns is assumed.[10] The input-oriented functions estimate the minimum proportion of an input that could be used to generate a set of output, whereas the output orientation measures the maximal proportional expansion of outputs, given a set of inputs. Since banks do have a better control of their inputs over their outputs we adopt an input-oriented approach to compute total factor productivity.[11]

Data Envelopment Analysis - Malmquist Productivity Index

The non-parametric Malmquist Total Factor Productivity (TFP) model of DEA is employed to measure total factor productivity change in panel data and to decompose this change into technical efficiency and technological change. According to Fare, Grosskopf, Norris and Zhang (1994), a Malmquist TFP index greater than 1 indicates a positive growth from period t to period t+1, and on the other hand, being less than 1 indicates a decline. In other words, technical efficiency index being more than 1 implies that the organization has been able to fill its production units, and technological change index being more than 1 implies a positive leverage of its efficiency levels. A negative change in technological index means a reduction in output amount produced by a similar amount of input. Fare *et al* (1994), indicates the Malmquist TFP index between the base period s and the next period t, given a change in technology as follows;

$$\mathrm{TFPC}^{s,t}(Xs, Xt, Ys, Yt) = \frac{d_0^t(Xt,\ Yt)}{d_0^s\ (Xs,\ Ys)}\left[\frac{d_0^s(Xt,\ Yt)}{d_0^t(Xt,\ Yt)} \mathrm{x} \frac{d_0^s(Xs,\ Ys)}{d_0^t(Xs,\ Ys)}\right]^{0.5} \qquad [1]$$

$$\text{Technical Efficiency Change} = \frac{d_0^t(Xt,\ Yt)}{d_0^s\ (Xs,\ Ys)} \qquad [2]$$

$$\text{Technological Change} = \left[\frac{d_0^s(Xt,\ Yt)}{d_0^t(Xt,\ Yt)} \mathrm{x} \frac{d_0^s(Xs,\ Ys)}{d_0^t(Xs,\ Ys)}\right]^{0.5} \qquad [3]$$

where TFPC is the Malmquist Total Factor Productivity Change index, X is the input variable and Y is the output variable, s and t stand for two different periods as stated earlier. The Malmquist total factor productivity index is calculated assuming a constant return to scale model. The first component of equation 1, measures technical efficiency change from period s to the next period t, while the second part measures the technological change that has taken place in the bank between the period s and the next period t. The Malmquist index has two distinct features; there is no behavioral assumption and prices of resources and services provided are not required.

Stochastic Frontier Approach – Error Component model

The stochastic frontier model assumes a given functional form relationship between

[10]This means the orientation in DEA is examining how much the input levels are reduced, while maintaining the output levels of each bank (see Kourouche, 2008).
[11]See Jreisat et al. (2017) on the application of DEA in determining productivity change for the banking sector in Egypt.

inputs and outputs. Stochastic frontier models introduced by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), made popular by Kumbhakar and Lovell (2000), fits both production and cost frontier models with distinct specifications of the inefficiency term. The random error term, ν_i, is assumed to be two-sided (usually normally distributed), and the inefficiency term, μ_i, is assumed to be one-sided (usually half-normally distributed). The parameters of the two distributions are estimated and can be used to obtain estimates of firm-specific inefficiency.

A stochastic frontier model follows a production function $f(z_{it}, \beta)$. Assuming there is no disturbance term, error or inefficiency in time t, the ith firm would produce

$$q_{it} = f\,(z_{it}, \beta) \qquad [4]$$

Secondly, assuming that each firm in the industry operates at less than optimum; that is producing less, given available resources. In this case

$$q_{it} = f\,(z_{it}, \beta)\xi_{it} \qquad [5]$$

Where ξ_{it} is the efficiency level for firm i at time t; ξ_i lies in the interval (0, 1]. If $\xi_{it} = 1$, the firm is producing optimal output, when $\xi_{it} < 1$, the firm is not making the most of its inputs z_{it} given the level of technology in the production function $f\,(z_{it}, \beta)$.

Because output is assumed to be positive $q_{it} > 0$, the degree of technical inefficiency is also assumed to be strictly positive, $\xi_{it} > 0$

Since output is assumed to be subjected to random shocks, the production becomes,

$$q_{it} = f\,(z_{it}, \beta)\xi_{it} \exp\,(\nu_{it}) \qquad [6]$$

Taking the natural log of both sides yields

$$\ln(q_{it}) = \ln\{f\,(z_{it}, \beta)\} + \ln(\xi_{it}) + \nu_{it} \qquad [7]$$

If the production function is linear in logs and assuming there are k inputs,

then $\mu_{it} = -\ln(\xi_{it})$, which yields

$$\ln(q_{it}) = \beta_0 + \sum_{j=1}^{k} \beta_j \ln(z_{jit}) + v_{it} - u_{it} \qquad [8]$$

Subtract μ_{it} from $\ln(q_{it})$, and restricting $\mu_{it} \geq 0$, implies that $0 < \xi_{it} \leq 1$ as stated earlier.

The Stochastic Frontier Analysis applied in this study is based on Battese and Coelli (1992) error component specification for a production function:

$$\ln(y_{it}) = f(x_{it}, t, \beta) + v_{it} - u_{it} \qquad [9]$$

$$\ln(y_{it}) = \beta_0 + \sum_n \beta_n \ln X_{it} + v_{it} - u_{it} \qquad [10]$$

where y_{it} is the output (total loans, operating income) of the i-th (i = 1, 2, …, 12) bank firm in the t–th (t = 1, 2, …, 10) year; x_{it} denotes a vector of inputs (total deposit, staff cost, total equity and operating expense); $f(\cdot)$ is the functional form; t is a time trend for technological change; β is a vector of parameters to be estimated; v_{it} are random errors, assumed to be *identically independently distributed (*iid) and follows N(0, δ_v^2) distribution, independent of u_{it}; and u_{it} are non-negative random variables, which accounts for technical efficiency effects in production, as truncations at zero of N(0, δ_u^2) distribution.

An error component production function indicates sigma-squared

$(\delta^2) = \delta_v^2 + \delta_u^2$, gamma $(\gamma) = \frac{\delta_u^2}{\delta_v^2 + \delta_u^2}$, $0 \leq \gamma \leq 1$.

A fundamental difference between DEA and SFA is that the former generates a deterministic frontier as an outcome of the observed data, which implies that some efficient firms or decision-making units are on the frontier and other inefficient firms are inside, while the latter is based on maximum likelihood estimates or classical or Bayesian parametric techniques. DEA efficiency score of 1 indicate full efficiency within a technology set, and this may occur for one or more decision making units in the sample, but for SFA, an efficiency score of 1 does not occur except when $\mu = 0$, and the distribution is continuous indicating a probability of 0.

Below is a presentation of the input and output variables.

Variable Identification

	Model A	Model B
Output (Dependent variables)	Total Loans	Operating Income
Input (Explanatory variables)	Total Deposit, Staff Cost and Total Equity.	Total Deposit, Staff Cost and Total Equity, Operating Expense

5.0 Discussion of Empirical Results

This study employs a panel data of 12 banks from 2005 – 2014, in 120 observations as shown in Table 1, summary statistics for bank level data. The non-parametric Malmquist Productivity index is estimated using the software DEAP version 2.1 developed by Coelli (1996). From Table 2 column (A), we observe that Nigerian banks were more productive during the period 2006-07 and 2013-14 with Total Factor Productivity Change (TFPC) of 34.1% and 70.5% respectively. This reflects the years immediately after recapitalization and when banks seem to be recovering from the effect of financial crisis following the establishment of Asset Management Corporation of Nigeria (AMCON) for management of toxic assets in the banking system. The increase in productivity change is accounted for by technological change, which is a result of banks acquiring new products or applying new techniques for the efficient allocation of resources in line with the findings in Lee *et al*. (2010) on the improvements in total factor productivity due to technological efficiency following bank deregulation in Singapore. On the other hand, the worst performance in terms of productivity of loan assets was the period between 2010 and 2012, when the banking industry witnessed the most difficult years after the consolidation exercise and average TFPC dropped from 26% to 7% in 2010-11 and 2011-12 respectively supporting the argument in Laeven and Valencia (2013), which predicts a decline in productivity following a credit boom during a consolidation exercise.[12] It is important to state that technological change accounts for changes in total factor productivity for the period in question.

Table1: Summary statistics of bank level data

Variable	Obs	Mean	Std. Dev.	Min	Max
TL	120	465206.3	437267.9	1723	2178980
OPINC	120	86152.08	76973.84	2596	360065
SC	120	22282.61	20106.53	1139	102542
OE	120	55210.97	44119.78	5008	234087
TE	120	156031.1	127897.7	1278	522890
TD	120	766584.2	668022	12380	3050853

Data Source: Bank Annual reports 2005 – 2014. Authors' computation using Stata 14. Note: TL – total loans, OPINC – operating income, SC – staff cost, OE – other operating expense, TE – total equity (shareholders' capital), TD – total deposits.

In Table 3 column (A), we observe that the bank with the highest improvements in TFPC is UBA with an average of 51.1% and the least performing was Wema Bank with a drop of .02% below the frontier. The improvements in the productivity of loanable funds at UBA is attributable to changes in technology, while the poor performance of Wema Bank is attributed to a decline in technical efficiency.

Considering operating income as output variable the results are presented in Tables 2 and 3 column (B), we find that in Table 2 column (B) the most productive period was 2013 – 14, when TFPC improved by 41.6% above the frontier of optimum performance, and the worst period was 2010 – 11 with a decline of 16.6% below the production frontier, which follows the results in DEA estimation for total loans as output variable in column (A) of Tables 2 and 3. We have earlier stated that a bank does not only produce loans but also generate income from interest and non-interest services which is ploughed back into its operations. UBA was the most productive for the period with an average TFPC increase of 32.1%, and the least performing

[12]In the same vein, Gulamhussen et al., (2014), and Fielding and Rewilak (2015) have observed a negative effect on bank productivity due to greater risk and diversification in periods of liberalization and restructuring, which is evident during the recapitalization process and subsequent consolidation of banks in Nigeria.

bank is Skye bank, with an average decline in TFPC of 0.034%. The improvements in TFPC for the period is a result of technological change, this finding supports Jreisat et al. (2017) for productivity change in the Egyptian banking sector. Empirical evidence from this study also indicate that overall mean total factor productivity change decreases from 13.7% in (A) to 8.9% in (B) as bank's productivity or output tend towards the inclusion of non-interest or fee-based income (see Tables 2 and 3). This supports the finding in Grigorian and Manole (2006), on the technical efficiency of banks in India and Pakistan for the period 1988 - 1998, with mean technical efficiency for Model A at 72.8% and 63.0% for Model B, which includes non-interest revenue accounts. The implication is that as banks move from the traditional intermediation services of collecting deposit and issuing loans to fee based non-interest income accounts, the productive efficiency declines.[13]

Table 2: DEA Malmquist Index Summary of Annual Means – Models A and B

Year	TE (A)	TE(B)	TC (A)	TC (B)	TFPC (A)	TFPC (B)
2005-06	1.036	0.959	1.153	1.270	1.194	1.217
2006-07	0.941	1.022	1.426	1.134	1.341	1.159
2007-08	0.977	0.887	1.051	0.984	1.026	0.873
2008-09	0.992	0.962	1.182	1.075	1.173	1.034
2009-10	1.022	1.034	1.168	1.220	1.193	1.262
2010-11	0.991	0.981	0.743	0.850	0.736	0.834
2011-12	1.072	1.054	0.869	1.004	0.931	1.058
2012-13	1.043	1.057	1.129	1.014	1.177	1.072
2013-14	1.071	1.026	1.593	1.380	1.705	1.416
Mean	1.015	0.997	1.120	1.093	1.137	1.089

Data Source: Bank Annual Reports 2005 – 2014. Author's computation with DEAP 2.1. Note: TE refers to Technical Efficiency Change, TC is Technological Change and TFPC is Total factor Productivity Change.

Table 3: Malmquist Index Summary of Firm Means – Models A and B

[13]This assertion corresponds with the findings in Osuagwu and Nwokoma (2017) regarding competitiveness of banks in Nigeria for interest and non-interest or fee-based revenue accounts. As banks revenue portfolio tends toward non-interest income, the competitiveness among banks decrease. The empirical evidence in this study equally suggests that mean technical efficiency declines as banks seek fee-based income.

Firms	TE (A)	TE (B)	TC (A)	TC (B)	TFPC (A)	TFPC (B)
Zenith Bank	0.985	0.988	1.093	1.097	1.077	1.084
GTB	1.009	1.000	1.089	1.026	1.099	1.026
Access Bank	1.000	0.992	1.053	1.052	1.053	1.044
Skye Bank	1.039	0.963	1.075	1.014	1.117	0.976
Diamond Bank	0.960	0.973	1.063	1.042	1.020	1.014
Fidelity Bank	1.001	0.967	1.035	1.020	1.036	0.986
Sterling Bank	1.164	1.016	1.087	1.009	1.266	1.025
EcoBank	0.998	1.000	1.223	1.180	1.220	1.180
First Bank	1.036	1.000	1.323	1.273	1.371	1.273
UBA	1.078	1.014	1.402	1.303	1.511	1.321
Union Bank	0.968	1.009	1.042	1.102	1.008	1.112
Wema Bank	0.961	1.039	1.019	1.042	0.980	1.083
mean	1.015	0.997	1.120	1.093	1.137	1.089

Data Source: Bank Annual Reports 2005 – 2014. Author's computation with DEAP 2.1 Note: TE refers to Technical Efficiency Change, TC is Technological Change and TFPC is Total factor Productivity Change.

The results presented in Tables 4 and 5 are the Stochastic Frontier Analysis of Models A and B, generated from the FRONTIER version 4.1 developed by Coelli (1996). For Table 4 column A, we observe that Mu which is a measure of inefficiency in the error component model, shows that the degree of inefficiency in the sampled banks decrease by 32% in their use of inputs to generate output (loans) within the period. All the input variables in model A are insignificant for the determination of output, however this insignificance stems from the inefficiency factor in the use of input resources in the model, holding other conditions constant. The results in Table 5 Model A for the SFA show that UBA was the least technically efficient bank for the period under study, given that the bank only utilized an average of 76.9 percent of the input resources (total deposit, staff cost, and total equity) to generate output (total loans). On the other hand, Ecobank was the most technically efficient because it used 98.2 percent of input resources to generate output (total loans).

In the case of Model B, sampled banks inefficiency factor increased by 13.8 percent (see Table 4), but not significant. However, staff cost, operating expenses and total equity are significant in explaining changes in the output variable (operating income). This implies that a degree of inefficiency in the use of these input variables unintentionally generate operating income, which includes non-interest and fee-based revenue. The least technically efficient bank in the use of inputs (total deposit, staff cost, operating expense and total equity) to generate output (operating income) was Wema Bank with an average technical efficiency score of 72.8 percent, and the most technically efficient bank was GTB with a mean technical efficiency score of 96.7 percent for the period under study (see Table 5). The implication of this finding is that mean technical efficiency scores vary with respect to the input and output variables under consideration. However, evidence from this analysis indicate that in the SFA model, the mean technical efficiency of banks decreases from 0.922 (92.2%) in Model A to 0.862 (86.2%) in Model B, which implies that as output changes from interest (loan) income to (operating) non-interest or fee-based income, the mean technical efficiency score decreases, the value of the log likelihood function decreases from 0.9189 in Model A to 0.7894 in Model B, also the magnitude of inefficiency increases from (negative) -31.8% in Model A to (positive) 13.8% in Model B, which corroborates the finding in the DEA model for a decline in mean total productivity change as bank output tend towards operating income, which is largely non-interest or fee based.

Table 4: Error Component Production Function Frontier OLS – Models A and B

Explanatory Variables	Output: Total Loans (Model A) Coefficients	Output: Operating Income (Model B) Coefficients
Constant	-0.4406 (0.2191)	-0.634 (0.3200)
Total Deposit	0.1172 (0.6207)	0.6504 (0.8708)
Staff Cost	-0.1338 (0.6121)	0.2864** (0.1311)
Operating Expenses		0.8139** (0.1505)
Total Equity	-0.2998 (0.1961)	0.4950** (0.2334)
sigma-squared	0.3593 (0.5838)	0.2071 (0.6646)
Gamma	0.7045 (0.5027)	0.3618 (0.2005)
Mu	-0.3182 (0.9684)	0.1379 (0.1646)
Eta	0.7524** (0.3552)	0.4814 (0.3857)
Log Likelihood function	0.9189	0.7894

Standard errors in parenthesis, ** significant @ 5%

Table 5: Technical Efficiency Estimates of Error Component Production Frontier OLS – Models A and B

Firm	Mean technical efficiency scores for Model A	Mean technical efficiency scores for Model B
Zenith Bank	0.878	0.862
GT Bank	0.968	0.967
Access Bank	0.979	0.932
Skye Bank	0.968	0.882
Diamond Bank	0.969	0.904
Fidelity Bank	0.961	0.834
Sterling Bank	0.848	0.852
EcoBank	0.982	0.874
First Bank	0.950	0.895
UBA	0.769	0.810
Union Bank	0.880	0.805
Wema Bank	0.906	0.728
Mean	0.922	0.862

Data Source: Bank Annual Reports 2005 – 2014. Authors' computation with FRONTIER 4.1

Overall, for the entire period of the study, the mean total factor productivity change decreases from 13.7% in model A (total loans – interest income model) to 8.9% in model B (operating income – includes non-interest and fee-based income) under the DEA estimation, also the mean technical efficiency score decreased from 92.2% in model A, to 86.2% in model B, under the SFA estimation technique. From all indications, this empirical evidence supports what Aghion, Angeletos, Banerjee and Manova (2005) referred to as incomplete financial markets, where bank firms face tight credit constraints and are likely to reduce long-term investments because of its relatively less pro-cyclical return and a higher liquidity risk.

6.0 Conclusion

This study has applied Malmquist Productivity Index and error component production function in the estimation of total factor productivity change and technical efficiency in Data Envelopment Analysis (DEA) and Stochastic Frontier Approach (SFA) respectively, for a sample of twelve banks in Nigeria, to ascertain if any significant variation exists in the choice of input and output variables, that may affect policy decisions. From the empirical results, we find that technological change is a major determinant of changes in total factor productivity in the

Nigerian banking sector for the period under study. Technological change may be interpreted as employing new methods of banking services such as automated teller machines and improved skilled manpower that is ready to adapt to the application of new technologies for the improvement of banking services. It is also observed that bank's total factor productivity improved under DEA immediately after the consolidation exercise; which to a large extent is a boom period for the banking sector in Nigeria emerging from recapitalization.

In the determination of technical efficiency and total factor productivity change for the Nigerian banking sector with respect to output variables; interest (loan) and non-interest revenue (operating income), this study reveals that mean total factor productivity change in DEA decreases for non-interest accounts. In the same vein, the mean technical efficiency of banks under SFA estimation also decreases as bank revenue tends toward non-interest or fee-based. In comparison, both DEA and SFA yield similar results in the determination of technical efficiency and total factor productivity change for bank's output portfolio. Inefficiency term in the error component model of SFA decreases for interest (loan) output and increases in the case of non-interest or fee-based income. In other words, banks become laxer or inefficient when they earn non-interest income, because fee-based charges are already fixed or determined.

These findings corroborate recent studies that banks' revenue portfolio in Nigeria is increasingly becoming more of non-interest income or fee-based accounts, because it is less competitive to earn. This study shows that banks become less efficient when they seek non-interest income. Nonetheless, since non-interest or fee-based transactions are gradually becoming a cheap or easy source of revenue, policy makers need to monitor the arbitrariness that is exhibited by bank management in the application of these service charges. Because arbitrariness may increase the cost of services in the banking sector in the long-run and reduce the potency of the intermediation role of banks in the economy. Although, the magnitude of total factor productivity change and technical efficiency scores for DEA and SFA respectively, differ, the direction of productive efficiency for both the non-parametric and parametric estimation are similar for our choice of input and output variables. The direction for future research is to determine the profit and cost efficiency profile of Nigerian banks in a bid to generate non-interest and fee-based income. This will provide the framework for understanding whether bank's desire to increase their revenue through off balance sheet instruments or fee-based services would be sustainable.

References

Aghion, P., Angeletos, G. M., Banerjee, A. and Manova, K. (2005). Volatility and Growth: Credit Constraints and Productivity-Enhancing Investment, Working Paper no. 11349, *National Bureau of Economic Research*, Cambridge, MA

Aigner, D. J., Lovell C. K. A. and Schmidt P. (1977). Formulation and estimation of stochastic frontier production function models, *Journal of Econometrics* 6: 21–37.

Akhavein, J. D., Swamy, P. A. V. B. and Taubman, S. (1997). A General Method of Deriving the Efficiencies of Banks from a Profit Function, *Journal of Productivity Analysis*, 8

Allen, L., and Rai, A. (1996). Operational Efficiency in Banking an International Comparison, *Journal of Banking and Finance*, 20, 655–72.

Amel, D., Barnes, C., Panetta, F. and Salleo, C. (2004). Consolidation and efficiency in the financial sector: A review of the international evidence. *Journal of Banking and Finance*, 28, 2493–2515.

Anginer, D., and Demirgüc-Kunt, A. (2014). Has the global banking system become more fragile over time? *Journal of Financial. Stability*. 13, 202–213.

Assaf, G. A., Barros, C. and Ibiwoye, A. (2012). Performance assessment of Nigerian banks pre and post consolidation: evidence from a Bayesian approach. *The Service Industry Journal*, 32 (2). February 215 – 229.

Attaullah, S., Hijazi, T. and Javed, A. Y. (2004). The determinants of capital structure of stock exchange-listed non-financial firms in Pakistan (with comments), *The Pakistan Development Review* Vol. 43, No. 4, Papers and Proceedings PART II Twentieth Annual General Meeting and Conference of the Pakistan Society of Development Economists Islamabad, January 10-12, 2005 (Winter 2004), pp. 605-618

Battese, G. E. and Coelli, T. J. (1992). Frontier production functions, technical efficiency and panel data: with application to Paddy farmers in India. *Journal of Productivity Analysis*, 3, 153-169.

Berger, A. N., and Humphrey, D. B. (1997). Efficiency of financial institutions: International survey and directions for future research. *European Journal of Operational Research*, 98, 175–212.

Chen, T. (2002). A comparison of chance-constrained DEA and Stochastic Frontier Analysis: bank Efficiency in Taiwan. *The Journal of the Operational Research Society,* 53(5), 492-500.

Cheruiyot, K.J., (2017). Determinants of technical efficiency in Kenyan manufacturing sector. *African Development Review* 29(1), 44-55

Coelli, T. (1996). *A Guide to DEAP Version 2.1: A Data Envelopment Analysis* (Computer Program). Centre for Efficiency and Productivity Analysis, Working Paper 96/08.

Fare, R., Grosskopf, S., Norris, M., and Zhang, Z. (1994). Productivity growth, technical progress and efficiency change in industrialized countries. *The American Economic Review*, 84(1), 66-83.

Farrell, M. (1957). The measurement of productive efficiency. *Journal of Royal Statistical Society A*, 120, 253-281.

Fielding, D. and Rewilak, J. (2015). Credit booms, financial fragility and banking crises. *Econ. Lett.* 136, 233–236.

Grigorian, D. A., and Manole, V. (2006). Determinants of commercial bank performance in transition: An application of Data Envelopment Analysis. *Comparative Economic Studies*, 48(3), 497-522.

Gulamhussen, M.A., Pinheiro, C. and Pozzolo, A. F. (2014). International diversification and risk of multinational banks: evidence from the pre-crisis period. *Journal of Financial Stability* 13, 30–43.

Isik, I., and Uysal, D. (2006). The Sources of Productivity Growth in Turkish Banks by Ownership: The Initial Responses of Public, Private, and Foreign Banks to Liberalization. *Journal of Turkish Studies*, 7(3). 365 – 403.

Jreisat, A., Hassan, H. and Shankar, S. (2017). Determinants of the productivity change for the banking sector in Egypt. *Global Business Review*, 19(2), 280 – 296.

Kourouche, K. (2008). *Measuring efficiency and productivity in the Australian banking sector*. Unpublished Doctoral Thesis, School of Economics and Finance, University of Western Sydney, Australia.

Kumbhakar, S. C., and Lovell, C. A. K. (2000). *Stochastic frontier analysis*. New York: Cambridge University Press.

Laeven, L., and Valencia, F. (2013). Systemic banking crises database. *IMF Econ. Rev*. 61, 225–270.

Lee B. L., Worthington, A. C. and Leong, W. H. (2010). Malmquist indices pre – and post-deregulation productivity, efficiency and technological change in the Singaporean banking sector. *The Singapore Economic Review,* 55(4), 599 - 618

Meeusen, W., and Broeck, J. V.D. (1977). Efficiency estimation from Cobb–Douglas production functions with composed error. *International Economic Review* 18: 435–444.

Mester, L. J. (2005). Optimal industrial structure in banking. Working Paper No. 08-2, Federal Reserve Bank of Philadelphia. July

Mlambo, K., and Ncube, M. (2011). Competition and efficiency in the banking sector in South Africa. *African Development Review* 23(1), 4-15.

Mwega, F. (2011). The competitiveness and efficiency of the financial sector in Africa: A case study of Kenya. *African Development Review,* 23(1), 44-59.

Osuagwu, E. S., (2013). *Banking sector reforms and bank performance in Nigeria*. Unpublished Doctoral Thesis, Department of Economics, University of Lagos, Nigeria.

Osuagwu, E. S., (2014). Determinants of bank profitability in Nigeria. *International Journal of Economics and Finance,* 6(12) 46-63.

Osuagwu, E. S. and Nwokoma, N. (2017). Empirical assessment of the competitive conduct of Nigerian banks in a post-consolidation era, *Research in International Business and Finance,* 41 (2017) 412 – 422.

Oulton, N., and Sebastiá-Barriel, M. (2013). Long and short-term effects of the financial crisis on labor productivity, capital and output. In: *Bank of England Working Paper* No. 470.

Owolabi, S. A., and Ogunlalu, A. E. (2013). Banking industry consolidation and financial performance of selected quoted banks in Nigeria. *Journal of Applied Finance & Banking*, 3(3), 219-238.

Poshakwale, S. S., and Qian, B. (2011). Competitiveness and efficiency of the banking sector and economic growth in Egypt. *African Development Review* 23(1), 99-120.

Sealey, C.W. Jr., and Lindley, J. T. (1977). Inputs, outputs, and a theory of production and cost at depository financial institutions. *Journal of Finance*, 32(4), 1251–1266.

Tanna S., Luo, Y. and De Vita, G. (2017). What is the net effect of financial liberalization on bank productivity? A decomposition analysis of bank total factor productivity growth. *Journal of Financial Stability* 30, 67 – 78.