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Cost Efficiency of the Banking Industry in Malawi

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Abstract: Sustainable economic growth requires efficiency in the banking sector because of the vital role financial markets play in allocating resources. This study seeks to contribute to the discourse on banks' cost-efficiency performance in the context of market upheavals, evolving customer preferences, and industry and institutional reforms. The study examines the Malawi banking sector's cost-efficiency based on firm-level data from 2010 to 2019. The period coincided with significant developments in the sector namely: 1) the massive local currency (Malawi Kwacha) devaluation which impacted exchange rates against major trading currencies; 2) the adoption of International Financial Reporting Standard (IFRS) 9 that impacted credit risk measurement; 3) the adoption of Basel 2 framework that impacted the calculation of capital adequacy and; 4) mergers and acquisitions of banking institutions. Using single-stage translog Stochastic Frontier Analysis (SFA) applied to a cost function involving nine banks, the study finds that Malawi banks are on average, 8.5% cost-inefficient. Over the sample period, the results further indicate an upward trajectory for the sector's mean cost efficiency levels. Across the banks, varied cost efficiency scores affirm the underpinnings of managerial and behavioural theories of the firm in supplementing the neoclassical microeconomic view of efficiency performance of the banking firm. Cost-efficiency scores have been positively influenced by the macroeconomic environment (inflation) and elements of bank heterogeneity (asset concentration and bank size). The contributions of other elements, namely, market concentration and funding risk (liquidity risk) have been negative, suggesting these as policy intervention areas for cost efficiency in the sector.

Keywords: Banking Sector, Cost Efficiency, Stochastic Frontier Analysis, Malawi

1. Introduction

Measuring the banking sector performance continues to have prominence in the economics and finance literature, primarily because of financial liberalisation and globalisation of financial markets. The 2007-08 global financial markets upheavals and recent technological advancements have called into question the adequacy of existing performance measures and accentuated the importance of attaining efficiency in banking operations. This is especially the case considering that banks operate in highly regulated environments, usually punctuated by incessant mergers and acquisitions.

Financial intermediaries ensure efficient allocation of resources to productive units by channelling funds from depositors to investors and providing access to the nation's payment system [43]. If problems in the financial sector spill over to the real economy, general economic welfare may be significantly impaired.

Cost efficiency is extensively covered in banking efficiency literature as a measurement of performance [9, 10, 24, 32, 34, 39, 54]. Studies on efficiency estimation were pioneered by Debreu [20], who established that firm efficiency could be empirically estimated by introducing a resource utilisation coefficient. Later, Farrell [22] proposed the method of estimating the efficiency frontier.

As pointed out by Idialu & Yomere [30], in competitive sectors such as financial services, efficiency must be precisely measured to ensure sustainable growth through continuous improvement and organisational learning. Greater efficiency in the banking sector promotes financial system stability and drive economic growth which calls for effective efficiency-oriented policies to spur bank management performance. Such policies need a context-oriented base that may not be similar even among economies at a similar level of development: a least developed economy such as Malawi will have idiosyncratic characteristics that sets it apart from those of its neighbours. This not-withstanding, there still does not appear to be many comprehensive econometric studies on the efficiency of the banking sector of developing countries such as Malawi which need financial sector efficiency most and have unique experiences and regulations. While industry analysts have typically used accounting ratios to explain bank performance, this study offers new insights into banking industry efficiency by taking into account the properties of the cost function and, bank and industry-specific characteristics.

2. Theoretical Background

2.1. The Malawi Banking System

The financial system in Malawi is bank dominated but with a variety of institutions and markets. The banking sector comprises nine banks and was recently reported as well capitalised, highly profitable and moderately concentrated but vulnerable to liquidity and credit risk shocks [49]. The previous ten years are notable for a number of key events including merger and acquisitions of three smaller banks, the huge reductions in interest rates, the Malawi Kwacha devaluation of 2012, the fairly recent (2014) adoption of Basel II (as elsewhere in the world banks were on Basel III), and, the implementation of the International Finance Reporting Standards 9 (IFRS 9).

The total deposits of the banking sector stood at MK1.176 trillion (MK795= US$1) as of December 2019, made up as follows: 39% demand deposits, 18% savings deposits, 23% term or institutional deposits and 19% foreign currency denominated accounts (FCDA's). As indicated in Table 1 below, the industry is dominated by National Bank of Malawi (NBM) with 25% of the total market share of the deposits followed by Standard Bank (STD) with 21% then FDH with 12%, FCB and Ecobank Malawi (ECO) with 11% each. Since 2015, demand and savings deposits have been making gains at the expense of FCDAs with shares in 2015 standing at 29%, 15% and 32% respectively.

***Table 1.** Malawi banking industry dynamics, deposit shares (%).*

Bank	2015	2019
CDH Investment Bank Ltd	4	3
Ecobank Malawi Ltd	7	11
FCB Plc	11	11
FDH Bank	13	12
MyBucks Banking Corporation	1	4
National Bank Plc	27	25
NBS Plc	9	10
Nedbank Malawi Ltd	3	2
Standard Bank Plc	25	21

The trends in Figure 1 indicate declines in concentration and non-performing loans (NPL) ratio. The former was due to the performance of smaller banks and despite the spate of mergers in 2015 involving NBM and IndeBank, FDH and Malawi Savings Bank and in 2018 MyBucks Banking Corporation and Nedbank. The decline in NPL was a result of a stiffer regulatory environment and the 2012 devaluation that eased banks liquidity crisis which had built up since 2011 due to currency overvaluation. Capital adequacy as represented by Tier 1 Capital had slipped during 2014-15 but firmed up thereafter as a result of stiffer regulation. Performance, as measured by return on earnings (ROE), had an upward trend except for 2014-15 and 2017.

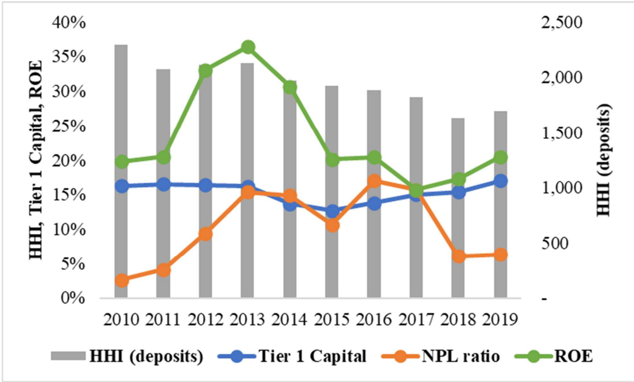

***Figure 1.** Malawi banking industry concentration, capital adequacy, credit risk and performance.*

2.2. Efficiency: Scope and Measurement

The notion of cost efficiency is grounded in the microeconomic theory of the firm and can be traced back to the pioneering studies of Debreu [20], Koopmans [36], Farrell [22] and Shephard [52] who developed a standard framework of productive efficiency based on the expectation that a more economically efficient firm possesses a competitive advantage over rival firms.

Berger and Humphrey [9] outlined two broad measurement categories of firm efficiency: parametric approaches and non-parametric approaches. Parametric approaches (PA) make assumptions about the parameters of the population distribution from which the sample is drawn and are therefore more restrictive. Three techniques are common in PA efficiency literature, namely, the Stochastic Frontier Analysis (SFA), Distribution Free Approach (DFA) and the Thick Frontier Approach (TFA). On the other hand, the non-parametric approaches to measuring firm efficiency are based on linear programming techniques and are generally light in terms of model specification assumptions. Non-parametric models assume that there is no random error such that the effects of these errors are accounted for as part of efficiency changes [9]. Common examples of these approaches include Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH).

This study adopts the parametric SFA to measure efficiency because of ease of application and the availability of relevant data. The SFA model imposes a functional form for the input-output relationship in the production or cost function and assumes a composite error term with two components: random error component that follows asymmetric standard normal distribution; and a technical inefficiency error term that follows an asymmetric half-normal distribution. Thus, the SFA model allows for efficiency to be measured even in the presence of statistical noise. Battese and Coelli [5] observed that SFA methods are generally resilient to data outliers and noise challenges associated with alternative methods. However, SFA approaches have attracted criticism because of their apriori model specification which may cause the efficiency estimates to be contaminated if the model is misspecified. To this end, several scholars have contributed to the various appropriate forms of the SFA [4, 5, 18, 25, 26, 37, 38, 50].

Berger and Mester [9] propose two approaches to measuring efficiency in financial institutions namely cost or profit efficiency. Although both concepts are grounded in economic optimisation and call for the same managerial attention, they are fundamentally different in scope. Cost efficiency deals with the bank's economic objective of cost minimisation, while profit efficiency deals with maximising profit, requiring a revenue perspective. In practice, the efficiency of a financial firm is commonly carried out through cost function estimation expressed as a translog or a Cobb Douglas function. The profit function approach is unpopular because it is plagued by data problems caused by the unavailability of output prices for most banks.

Second, the correlates of a firm's efficiency can be estimated in two ways. Aigner et al. [3], Meeusen and Van den Broeck [44], and Pitt and Lee [48] propose a standard two-step approach in which bank-level efficiency derived from a stochastic frontier function is regressed against firm-specific variables. This method accounts for the differences in efficiencies between individual banks [48]. Alternatively, Battese and Coelli [5] propose a single-stage approach using the maximum likelihood technique applied on a stochastic frontier cost model to derive technical efficiency effects. Exogenous factors are then included in the measurement of efficiency to account for heterogeneity in the distribution of the inefficiency term. The latter option is adopted in this study because of its ease of use.

2.3. Theories of a Firm

In determining firm efficiency, it is also critical to consider theories of the firm that may have a bearing on performance. According to Coarse [15], the motivation for developing theories of the firm is to respond to the following four questions relating to the nature of firms: Why do firms exist? Why are firms' boundaries as they are? What determines firms' structure? Why are firms heterogeneous?

The concept of banking efficiency is grounded in the neoclassical microeconomic theory based on Cournot's monopolists and duopolists framework developed in 1838. The neoclassical hypothesis models firms as 'black boxes' which transform information inputs into decision outputs. This transformation of resources into goods and services is defined by a production frontier. The neoclassical theory of the firm posits that firms operate in perfectly competitive markets where their main objective is profit maximisation. To accomplish this, firms must simultaneously maximise revenues and minimise costs. The result is that general competitive equilibrium is attained where all firms receive a reward equivalent to their marginal contribution to production [17]. Supernormal profits will attract new market entrants to compete with incumbents until the general equilibrium is restored. Firms whose earnings fall short of the normal profits because of inefficient operations, are either forced to wind up operations or are acquired by efficient firms.

However, empirical evidence has shown that not all firms operate on the efficient frontier. Firms survive in the market operating anywhere but along the efficient frontier. Demsetz [21] observed that neoclassical models are based on pricing fundamentals but disregard the internal factors and the decision-making process of the firm. As a result, other alternative models are available to supplement the neoclassical theory of the firm. First, managerial theories of the firm premised on separation of ownership from control postulate that organisational slack (inefficiency) is an outcome of conflicting interests between the owners and managers of the firm [11]. Three related notions are advanced in support of this paradigm: (1) that managers of the firm are largely concerned with maximising sales revenue, subject to satisfying a minimum profit constraint [6]; (2) that managers' primary objective is to maximise a firm's balanced growth rate focusing on growing products' demand and capital supply [42]; and (3) that managers advance policies that maximise their utility rather than the utility of owners [55]. Second, the behavioural theory of the firm by Cyert and March [19] defines the firm in terms of its organisational structure and decision-making processes and posits that firms are a coalition of different groups and individuals with varying degrees of influence or interests and objectives in the organisation's activities. No individual or group has complete information about every aspect of the firm's activities and operating environment. Instead, decision making takes place in an environment of uncertainty, or bounded rationality as opposed to global rationality championed by optimising behaviour [53]. As a result, firms tolerate production inefficiencies since there are no attempts to minimise costs.

2.4. Empirical Literature Review

Several methods have been used to estimate banking efficiency besides the SFA model. Berger and Humphrey [9] provide a comprehensive review of efficiency literature on financial institutions. A similar in-depth inventory is also provided by Bikker & Haaf [10] and Berger [8]. Although the results are varied, the use of non-parametric and parametric approaches is evenly split between the studies.

Recently, Khalil et al. [33] used a translog cost frontier function to estimate the cost efficiency of the Pakistan banking sector between 2005-2013. The findings suggest that Pakistani banks could improve cost efficiency by adopting either stringent cost-containment measures or diversifying operations i.e. input restructuring or expanding the product space.

Musonda [46] applied a single-stage maximum likelihood estimation procedure to a stochastic frontier cost function to measure the efficiency of commercial banks in Zambia between 1998 and 2006. The results revealed an upward trajectory of cost efficiency scores and suggested that regulatory reforms did not impact efficiency. Instead, macroeconomic uncertainty and bank-specific factors influenced banking cost efficiency performance. However, on the contrary, in the aftermath of the 1997 financial crisis, Manlagnit [41] observed that the ensuing regulatory reforms and bank mergers and acquisitions had a significant impact on cost efficiency in the Philippine banking industry.

Kofi et al. [35] using fixed effects and dynamic generalised method of moments to analyse the Ghanaian banking efficiency between 2001-2010, established that well-capitalised banks were less cost-efficient than their counterparts. In addition, the results indicated that bank size did not influence the cost efficiency, implying that larger banks had no cost advantages over their smaller counterparts. Similarly, the loan loss provision ratio was insignificant in influencing bank efficiency, while the GDP growth rate negatively impacted cost efficiency.

Abel [1] analysed, by DEA and Tobit regression methods, the cost efficiency of commercial banks in Zimbabwe stretching from 2009-2014. The findings were that bank size, capital adequacy, profitability, economic stability and credit risk were significant cost efficiency determinants. Similarly, a stable macroeconomic environment was found to be critical to cost-efficiency improvement by banks. A follow-up study [2] based on the SFA method covering the same jurisdiction for 2009-2017 returned a lower cost inefficiency score of 17% than 35.3% obtained earlier.

The independent cross-country studies of Čihák & Podpiera [14], and Hauner & Peiris [29] on banking efficiency in East Africa, observed a significant relationship between bank competition and bank efficiency. The two studies concurred that increased bank competition leads to higher efficiency. However, this was disputed by Beck & Hesse [7], who found banking spreads to be significantly high in Uganda, suggesting reduced efficiency. The differences in these studies could be ascribed to differences in estimation methods.

Regarding asset concentration, Hauner [28], through his study on a few developing and developed countries, found that domestic government debt raised to finance fiscal gaps had significant and adverse effects on banking efficiency. The result implied that rising domestic credit to the government by banks pointed to macroeconomic uncertainty, operational and competitive slackness that could further impair efficiency performance.

The preceding insights may not explain the evolution and determinants of banking efficiency in developing countries, where the local socio-economic and political fabric is fundamentally different. Most African countries lurch from one political crisis to another and suffer from chronic macroeconomic instability, high inflation and slower economic growth. Put together, these factors distort the banking sector incentives underpinning efficient resource allocation in an economy notwithstanding the positive reforms implemented in the financial sector.

3. Methodology

3.1. The Stochastic Cost Frontier Function

Aigner et al. [3] and Meesen and van den Broeck [44] are credited with simultaneously developing the stochastic cost frontier model based on the cost function proposed by Shepherds [52]. The stochastic cost frontier model includes a composite error term to represent measurement errors and statistical noise. The use of SFA is supported because departure from the cost or production frontier may invariably not be under the firm's direct control. In light of this, the stochastic cost frontier is given as:

$$ln\,T\,C_{it} = f(Q_{it}, W_{it}; \beta) + \varepsilon_{it} \quad (1)$$

$$\varepsilon_{it} = v_{it} + u_{it},\ i = 1, \ldots., N,\ t = 1, \ldots., T$$

where TC_{it} is the total cost of bank i at time t expressed in natural logs; Q_{it} and W_{it} are output and input prices respectively expressed in natural logs; $f(Q_{it}, W_{it}; \beta)$ is the deterministic kernel of the model; β denotes unknown parameters for output, Q_{it} and input and output prices, W_{it} variables; $N$and T represent the total number of banks and period considered in the study respectively; ε_{it} is the composite error term; v_{it} denotes random and uncontrollable variables which are assumed to be independent and identically distributed as $N(0, \delta_v^2)$, and captures the effects of measurement errors; u_{it} denotes non-negative, $u_{it} > 0$, effects of inefficiency and is assumed to be independent and identically distributed as half-normal distribution, $N^+(0, \delta_u^2)$ and captures the deviation of actual cost from the optimal cost level given by the stochastic cost frontier.

The one-sided error term, u_{it} obtained from estimating (1) is modelled against variables representing bank-level and industry-specific characteristics, and economic conditions to ascertain the determinants of cost inefficiency. According to Battese and Coelli [5], the inefficiency effects model is expressed as:

$$u_{it} = z_{it}\theta + \varepsilon_{it} \quad (2)$$

where u_{it} are the mean inefficiency scores obtained using the stochastic frontier function, z_{it} is the vector of explanatory variables that may cause cost inefficiency, and θ is the corresponding vector of coefficients relating cost inefficiency to its determinants. Random error terms are represented by ε_{it}.

The estimation of the exact cost inefficiency for a firm is given by the conditional mean distribution of u_{it} following Jondrow et al. [31] within the framework of the normal-half normal stochastic frontier model:

$$E(u_{it}|\varepsilon_{it}) = \frac{\delta}{1+\gamma^2}\left[\frac{f\left(\frac{\varepsilon_{it}\gamma}{\delta}\right)}{1-F\left(\frac{\varepsilon_{it}\gamma}{\delta}\right)} + \frac{\varepsilon_{it}\gamma}{\delta}\right] \quad (3)$$

where $E(u_{it}|\varepsilon_{it})$ is an unbiased estimator of inefficiency effects u_{it}; $F(.)$ and $f(.)$ represent the standard normal cumulative distribution function (CDF) and standard normal density function respectively evaluated at $\frac{\varepsilon_{it}\gamma}{\delta}$; $\gamma = \frac{\delta_u}{\delta_v}$ and $\delta = [\delta_v^2 + \delta_u^2]^{\frac{1}{2}}$ where the composite error term, $\varepsilon_{it} = u_{it} + v_{it}$. γ has a value between 0 and 1 such that the composite error term (ε_{it}) is dominated by effects of pure noise term (v_{it}) as $\gamma \rightarrow 0$. In this case, stochastic inefficiency effects are nonexistent, and deviation from the frontier is explained by pure noise. On the other hand, as $\gamma \rightarrow 1$, the cost inefficiency effects are more significant in the composite error term causing deviations from the frontier function.

3.2. Empirical Model Specification

The empirical specification is expressed as a translog cost function which is general and appropriate for the frontier estimation. The translog model is flexible, does not impose any restrictions on the cost function, and accommodates multiple complementary links between the explanatory variables [27].

Following Coelli et al. [15], Wang and Kumbhakar [54], and Mathews and Thompson [43] the general translog cost frontier model is thus given as:

$$\begin{aligned}\ln C_{it} = {} & \theta_0 + \sum_{m=1}^{M}\theta_m \ln y_{mit} + \sum_{n=1}^{N}\beta_n \ln w_{nit} + \frac{1}{2}\sum_m\sum_k \theta_{m.k}\ln y_{mit}\ln y_{kit} \\ & + \frac{1}{2}\sum_n\sum_j \beta_{n.j}\ln w_{nit}\ln w_{jit} + \sum_m\sum_n \partial_{mn}\ln y_{mit}\ln w_{nit} \\ & + \delta_0 t + \frac{1}{2}\delta_{00}t^2 + \sum_m \delta_{m.t}\ln y_{mit}t + \sum_n \delta_{nt}\ln w_{nit}t \\ & + \sum_q^{Q}\psi_q z_{qit} + \varepsilon_{it}.\end{aligned} \tag{4}$$

$$m,k = 1,\ldots\ldots,M;\ n,j = 1,\ldots\ldots,N;\ i = 1,\ldots\ldots.,I;\ t = 1,\ldots\ldots,T$$

where C_{it} is the observed cost of firm i; y_{mit} is the m-th output; w_{nit} is the n-th input price; z_{qit} is the q-th control variables that affect the total cost; *t* is time trend to account for technological change; θ, β, δ, ∂, and ψ are vectors of unknown parameters; ε_{it} is the composite error term comprising of cost inefficiency, u_{it}, and random error, v_{it}.

To satisfy the duality theorem properties, the cost function must be positively linearly homogenous in input prices. Thus, the assumption of homogeneity of degree one in input prices, $\sum_{n=1}^{N}\beta_n = 1$, is imposed on total costs and input prices by the input price of funds, w_3. This adjustment does not affect the outcome of the estimates obtained using the maximum likelihood method but ensures the degrees of freedom are gained. Indeed, Mester [45] further accredit such normalisation for resolving instances of heteroscedasticity. Similarly, the symmetry constraints condition is imposed on parameters in the cost function such that $\theta_{mk} = \theta_{km}$ and $\beta_{nj} = \beta_{jn}$. Hence, the empirical model is transformed as:

$$\begin{aligned}\ln\left(\frac{TC_{it}}{w_{3it}}\right) = {} & \beta_0 + \beta_1\ln\left(\frac{w_{1it}}{w_{3it}}\right) + \frac{1}{2}\beta_{11}\left[\ln\left(\frac{w_{1it}}{w_{3it}}\right)\right]^2 + \beta_2\ln\left(\frac{w_{2it}}{w_{3it}}\right) + \frac{1}{2}\beta_{22}\left[\ln\left(\frac{w_{2it}}{w_{3it}}\right)\right]^2 \\ & + \beta_{12}\ln\left(\frac{w_{1it}}{w_{3it}}\right)\ln\left(\frac{w_{2it}}{w_{3it}}\right) + \theta_1\ln Y_{it} + \frac{1}{2}\theta_{11}\left(\ln Y_{it}\right)^2 + \theta_2\ln SEC_{it} + \frac{1}{2}\theta_{22}\left(\ln SEC_{it}\right)^2 \\ & + \theta_{12}\ln Y_{it}\ln SEC_{it} + \partial_{12}\ln\left(\frac{w_{1it}}{w_{3it}}\right)\ln Y_{it} + \partial_{22}\ln\left(\frac{w_{2it}}{w_{3it}}\right)\ln Y_{it} + \partial_{11}\ln\left(\frac{w_{1it}}{w_{3it}}\right)\ln SEC_{it} \\ & + \partial_{12}\ln\left(\frac{w_{2it}}{w_{3it}}\right)\ln SEC_{it} + \delta_1 T + \delta_2 1/2(T)^2 + \delta_3 T\ln(w_1/w_3) + \delta_4 T\ln(w_2/w_3) \\ & + \delta_5 T\ln Y + \delta_6 T\ln SEC + \psi\ln FUNDRISK + \psi\ln HHI + \varepsilon_{it}\end{aligned} \tag{5}$$

where TC_{it} is a dependant variable representing total cost. The various input and output prices, and control variables are represented by $w_1, w_2, w_3, ln\,Y, ln\,SEC, ln\,FUNDRISK, ln\,HHI$ and further explained below; $\beta, \theta, \partial, \psi$ represent parameter estimates for inputs and outputs prices and control variables vectors, and; ε_{it} is composite error term containing random noise and the non-negative inefficiency term.

The efficiency determinants model is given as follows:

$$(1 - u_{it}) = \varphi_0 + \varphi_1 INFR_t + \varphi_2 CONTASS_{it} + \varphi_3 MS_{it} + \varphi_4 CA_{it} + \varphi_5 CLR_{it} + \varepsilon_{it} \tag{6}$$

where $(1 - u_{it})$ represents the unobserved efficiency score of bank i at time period t; $INFR, CONTASS, MS, EQ, CLR$ are the explanatory variables further explained below; φ_0 the intercept term for the explanatory variables; $\varphi_1, \varphi_2, \varphi_3, \varphi_4, \varphi_5,$ represents the parameters of the various variables of the determinants of bank cost efficiency.

The cost frontier model (5) and the efficiency model (6) coefficients are estimated in one step using the method of maximum likelihood (ML) and the Tobit regression model, respectively. Regarding the composition of the frontier and efficiency models, Battese and Coelli [5] allow both models to have common (all or some) variables because cost drivers may impact efficiency performance.

3.3. Empirical Model Specification

3.3.1. Data Sources

This study uses annual data for nine commercial banks for the ten years, 2010-2019. The sample data were collected from audited balance sheets and income statements published by the commercial banks and supplemented by the central bank, RBM's Financial Institutions Supervision Annual Reports. The annual inflation rate was sourced from RBM. The data panel is reasonably long to reflect the situation of the banking sector in Malawi. The sample period was characterised by increased bank mergers and acquisitions, Basel II implementation, IFRS 9 adoption and a spate of liquidity crises. All model estimations are performed using STATA 16 software, from which the cost efficiency results are calculated.

3.3.2. Input and Output Variables

There are divergent views on the definition and measurement of inputs and outputs in the banking sector. However, the bank production process is commonly defined using the intermediation approach suggested by Sealey and Lindley [51], which postulates that banks are generally price takers in input markets. This study has prices for three inputs: price of funds, price of labour and price of physical capital, and; two outputs: total loans and securities. Positive parameters are expected for input prices and outputs, implying a direct relationship between the use of input and production on the one hand, and total bank costs on the other.

Price of funds (w_3) is measured as the proportion of total interest expenses to gross deposits and other interest-bearing liabilities. Price of funds measures the cost of obtaining funding to support the lending business and reflects interest rate risk and liquidity risk associated with different sources of funds.

Price of labour (w_1) relates to the cost of employees.

Specific staff costs are, however, not available. Thus, the cost-to-income ratio is proxied as the price of labour as it measures staff productivity in generating revenue.

Price of physical capital (w_2) measures the proportion of all other expenses to all the fixed and other assets. Physical capital includes book values of property plant and equipment and other assets. Because banks do not publish data on depreciation, total other expenses are used instead, as its proxy.

Loans (Y) sum up all types of loans, overdrafts and interbank placements extended by banks to their clientele and the market. The use of net amounts ensures the quality of credit exposure on bank outputs is taken into consideration. In contrast, gross amounts assume there is no damage to the portfolio book exacted by bad debts.

Securities (SEC) capture output from investments in risk-free assets such as government treasury bills, bonds and other risk-free investments. It includes all banking and trading instruments and balances with related parties.

3.3.3. Determinants of Bank Efficiency

The motivation for the inclusion of explanatory variables in (6) is to capture the systematic effects these may have on inefficiency distribution u_{it}.

Herfindahl-Hirschman Index HHI_t is the banking industry level variable which measures market concentration as a prospective determinant of market power. In this study, HHI_t is calculated as the sum of squared individual bank's shares based on gross customer deposits.

$FUNDRISK_{it}$ is a bank-specific variable that measures liquidity risk associated with funding banks loans using customer deposits. $FUNDRISK_{it}$ is a rate calculated by dividing total funding (gross deposits only) by total customer loans. Funding risk rises with total cost performance.

CA_{it} measures the capital adequacy ratio. Capital adequacy is a proportion of the bank's total equity to total assets. Capital adequacy speaks to insolvency risk and banks' ability to absorb losses in the event of bankruptcy.

$CONTASS_{it}$ measures asset concentration as reflected by the intensity of banks' increased investment in risk-free government securities compared to traditional intermediation activities. It is measured as a ratio of total government securities to total loans.

CLR_{it} is used to measure banks' credit risk. The credit loss ratio is calculated as a proportion of credit loss provisions to total loans. This reflects the asset quality of the banks' investment portfolio such that higher credit risk losses lead to higher costs of production.

MS_{it}, market share based on customer loans captures the size effects of individual banks. Bank size determines economies of scale: larger banks have lower average transaction costs and tend to have market power over smaller banks [8].

$INFR_t$ is the annual inflation rate used to capture the effects of macroeconomic stability and government policy on bank efficiency in the host country. The inflation rate is used in this study because it is closely related to interest rates and exchange rates whose volatilities significantly impact the bank's total cost.

3.3.4. Descriptive Statistics

Table 2 below presents the summary descriptive statistics of the variables for the nine banks that are used in this study. The large SD on Total cost (TC), Loans (Y), and Securities (SEC) confirm considerable dispersion from the mean of the data across the banks. However, it may also be attributed to the natural heterogeneity of the variables from the banks varying in size and scope. In contrast, relatively lower SD reported for Capital adequacy (CA), and the price of labour (W1) points to the importance of regulatory stipulations and industry norms. The rest of the other variables in Table 2 are to be construed in a similar fashion.

Table 2. *Descriptive statistics for variables.*

	Obs	Mean	SD	Min	Max
Dependent variable					
TC (MK'm)	90	13 544	11 924	0.000	45 687
Input variables					
W3	90	0.073	0.084	0.000	0.505
W2	90	1.841	1.457	0.000	7.359
W1	90	0.092	0.050	0.000	0.257
Output variables					
Y (MK'm)	90	35 966	39 165	0.000	188 324
SEC (MK'm)	90	40 215	53 968	0.000	221 681
Control variables					
HHI	90	1 955	195	1634	2 291
FUNDRISK	90	0.471	0.439	0.000	2.315
Explanatory variables					
CONTASS	90	1.036	1.058	0.000	5.483
MS	90	0.111	0.103	0.000	0.348
CLR	90	0.029	0.062	-0.084	0.405
CA	90	0.127	0.066	0.000	0.290
INFR	90	0.161	0.075	0.074	0.286

4. Results and Discussion

4.1. Stochastic Cost Frontier Estimates

The parameters and scores of the stochastic cost frontier function are estimated by one stage maximum likelihood method developed by Battese and Coelli [5] using STATA 16. The generalised likelihood ratio (LR) test was conducted to ascertain if the stochastic cost frontier model is correctly specified. Results rejected the null hypothesis of no technical inefficiency with LR test statistic of 49.605 at a 1% significance level implying that explanatory/control variables statistically improve the fit of the SFA model.

Table 3 below shows that the overall outcome supports the theoretical requirements that the cost function should be positively linear homogenous in input and output prices. The empirical results are consistent with the a priori hypotheses as input and output price variables have positive signs. Similarly, the empirical estimates of the cost function are not plagued by the problem of multicollinearity.

The coefficient estimate for lnY, θ_1 is positive but statistically insignificant. In other words, customer loans on their own do not influence total cost at conventional levels of significance. However, the quadratic form of customer loans is statistically significant and depicts an increasing cost structure associated with a growing customer loan book: θ_{11} shows that a 5% increase in customer loans yields a 21.9% growth in total cost. The implication is that cost growth associated with customer loans has a floor, having a minimum limit beyond which it increases at an increasing rate. Similarly, the parameters for loans augmented with labour (∂_{12}) and loans augmented with physical capital investment (∂_{22}) are significant and bear cost elasticity of 10.4% and -15.4% respectively. The implication is that if the right investment in physical assets is made and adequately skilled staff are employed, writing customer loans will significantly influence a bank's total cost base. Otherwise, customer loans have no bearing on the cost base at less than 10% significance level. Although aligned to general cost function properties, this finding contradicts Abel et al. [2] observations.

The coefficient estimate for securities θ_2 shows that on average, a 10% increase in risk-free investment securities leads to an 83.3% growth in total costs. In other words, the cost elasticity concerning government securities acquired by banks is 0.833. Compared to the parameter estimate for customer loans, the estimated coefficient of risk-free investment securities is relatively higher, implying that disintermediation, as measured by banks' unwillingness to lend to customers, is costly to banks. By opting to invest in risk-free government securities, banks are forgoing higher returns (from customer loans) needed to compensate for the general business risk assumed and the higher operating costs incurred.

Table 3. *Maximum likelihood estimates for stochastic frontier cost function.*

	Parameters		Std error	t-statistic	p-value
Frontier variables					
Intercept	β_0	0.756	1.111	0.680	0.496
$ln(w_1/w_3)$	β_1	0.322	0.280	1.153	0.249
$\frac{1}{2}(ln(w_1/w_3))^2$	β_{11}	-0.064	0.067	-0.955	0.340
$ln(w_2/w_3)$	β_2	1.237	0.375	3.304	0.001***
$\frac{1}{2}(ln(w_2/w_3))^2$	β_{22}	0.012	0.130	0.093	0.926
$ln(w_1/w_3)\,ln(w_2/w_3)$	β_{12}	0.107	0.091	1.185	0.236
$ln\,Y$	θ_1	0.072	0.452	0.160	0.873
$\frac{1}{2}(ln\,Y)^2$	θ_{11}	0.219	0.105	2.079	0.038**
$ln\,Y\,ln(w_1/w_3)$	∂_{12}	0.104	0.051	2.040	0.041**
$ln\,Y\,ln(w_2/w_3)$	∂_{22}	-0.154	0.056	-2.766	0.007***
$ln\,SEC$	θ_2	0.833	0.471	1.768	0.077*
$\frac{1}{2}(ln\,SEC)^2$	θ_{22}	0.064	0.078	0.827	0.408
$ln\,SEC\,ln(w_1/w_3)$	∂_{11}	-0.093	0.062	-1.502	0.133
$ln\,SEC\,ln(w_2/w_3)$	∂_{12}	0.017	0.060	0.287	0.774
$ln\,SEC\,ln\,Y$	θ_{12}	-0.123	0.091	-1.348	0.178
T	δ_1	0.043	0.183	0.234	0.815
$\frac{1}{2}(T)^2$	δ_2	-0.029	0.009	-3.192	0.001***
$T\,ln(w_1/w_3)$	δ_3	0.007	0.022	0.314	0.753
$T\,ln(w_2/w_3)$	δ_4	0.008	0.023	0.346	0.729
$T\,ln\,Y$	δ_5	-0.020	0.030	-0.689	0.491
$T\,ln\,SEC$	δ_6	0.0297	0.024	1.257	0.209
Control variables					
$ln\,FUNDRISK$	ψ_1	3.425	0.973	3.520	0.000***
$ln\,HHI$	ψ_2	-13.680	10.180	-1.344	0.179
Diagnostics					
Log-likelihood	74.120				
Wald Chi-square	16 044				
LR test	49.605				
Sigma-squared $\sigma^2 = \sigma_u{}^2 + \sigma_v{}^2$	5.921				
Gamma $\gamma = \frac{\sigma_u{}^2}{\sigma_u{}^2+\sigma_v{}^2}$	1.005				
Observations	82				

Significance level: * p<0.10, ** p<0.05, *** p<0.01.

The coefficient for normalised input price for labour β_1 is statistically insignificant, implying that changes in labour costs do not impact total operating expenses at conventional significance levels. Labour costs constitute a significant component of banks' costs and are generally rigid to restructure because of strict labour laws. On the other hand, the price of fixed assets is observed to be positive and significant. Cost elasticity with respect to the price of physical capital $\beta_2$is 1.237. This implies that expenditure on physical capital raises total cost more than those associated with unit labour expenses. Banks require constant investment in physical and technology to maintain their competitiveness.

Time trend is included in the stochastic cost frontier function to capture the impact of technological progress and learning by doing on total costs. A significant downward nonlinear effect is indicated by the quadratic time trend coefficient (δ_2) of 2.9%. Over time, banks' total costs have decreased at an increasing rate, lending credence to the hypothesis of learning by doing. New bank entrants will face mounting cost pressures while existing banks enjoy cost reduction associated with learning by doing.

Table 4. *Average efficiency scores per year.*

Year	Mean	SD	Min	Max
2010	0.808	0.184	0.539	0.971
2011	0.812	0.158	0.545	0.944
2012	0.897	0.162	0.509	0.988
2013	0.905	0.166	0.500	0.996
2014	0.900	0.100	0.715	0.996
2015	0.940	0.101	0.679	0.995
2016	0.932	0.082	0.740	0.992
2017	0.961	0.039	0.884	0.996
2018	0.965	0.026	0.908	0.992
2019	0.984	0.011	0.962	0.992
Total	0.915	0.122	0.500	0.996

Table 5. *Average efficiency scores per bank.*

Bank	Mean	SD	Min	Max
CDH	0.888	0.087	0.740	0.974
Ecobank	0.717	0.190	0.500	0.962
FCB	0.957	0.045	0.854	0.989
FDH	0.942	0.041	0.878	0.992
MyBucks	0.972	0.020	0.946	0.995
NBM	0.967	0.028	0.905	0.993
NBS	0.960	0.034	0.887	0.988
NedBank	0.903	0.179	0.550	0.996
SBM	0.949	0.040	0.871	0.990
Total	0.915	0.122	0.500	0.996

4.2. Analysis of Efficiency Scores

Table 4 and Table 5 show cost efficiency scores of the banking industry over the ten years. The sector achieved mean cost efficiency of 91%, implying that banks lost up to 9% in operating costs per annum by not applying the best practice technology. Over the sample period, the sustained upward trajectory trend is observed (see Figure 2) coinciding with the significant interest rate reductions, the Malawi Kwacha devaluation, Basel II adoption and IFRS 9 implementation. These changes affected the economic and regulatory landscape and may have influenced Banks' performance responses. The lowest mean cost efficiency, 0.50 was registered by Ecobank in 2013, while the higher score, which was 0.996 came in 2017 on Nedbank results. The banks' efficiency scores are widely dispersed at the start of the period, but they tend to move towards convergence in the latter stages of the study period.

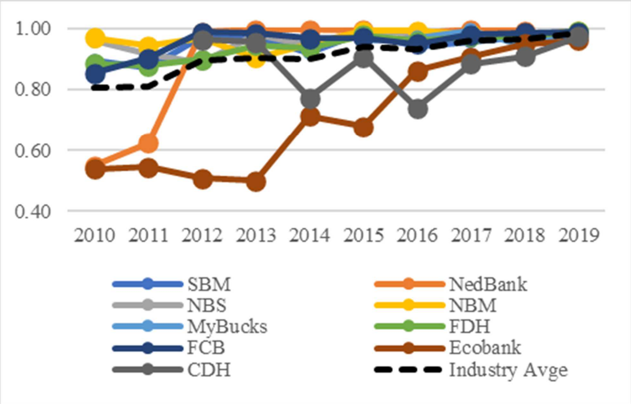

Figure 2. *Cost efficiency trends.*

4.3. Determinants of Cost Efficiency

Results of the multivariate censored Tobit regression model are presented in Table 6. The Tobit model was preferred to the conventional OLS model because it generates consistent estimates of regression coefficients. More importantly, the dependent variable (cost efficiency index) has a restricted range from 0 to 1. Therefore, we ran a regression of cost efficiency scores against set factors with a left-censored bound of 0 and a right-censored bound of 1. The regression coefficients listed in Table 6 carry mixed signs and significance levels and are interpreted as elasticities of change in cost efficiency relative to environmental factors.

First, the inflation rate exhibits a positive and significant influence on cost efficiency in banks with an estimated positive elasticity of 0.31. Clearly, inflationary environments force banks to be a lot more cost-conscious and to limit their appetite for credit lending in order to manage credit losses. According to Lu [40], in such environments, banks fully anticipate inflation rates and appropriately adjust interest rates faster than their costs to accord themselves a chance to earn higher economic profits.

Second, HHI is found to be significant and detrimental to bank efficiency. Thus, a 1% increase in market concentration results in a negligible reduction in bank efficiency. These findings are consistent with the Structure-Conduct-Performance (SCP) paradigm which postulates that an increase of the banks' market power contributes to inefficiency since dominant banks are not pressured to be innovative and offer cost-efficient products. Malawi banking sector is generally considered highly concentrated with the mean HHI of 1954 between 2010 and 2019 (see Figure 1) and offers mostly homogenous products.[1]

1 The general rule for interpreting HHI is that: HHI <1000 if concentration is low; HHI > 1800 if concentration is high; and 1000 < HHI <1800 if concentration is moderate [43].

Table 6. *Tobit degression of cost efficiency determinants.*

Coefficient	Parameter	SE	t-ratio	p-value	Coefficient
Intercept	φ_0	1.415	0.137	10.31	0.000***
INFR	φ_1	0.311	0.121	2.576	0.010**
HHI	φ_2	-0.001	0.000	-4.926	0.000***
FUNDRISK	φ_3	-0.210	0.050	-4.162	0.000***
CLR	φ_4	0.098	0.146	0.667	0.505
CONTASS	φ_5	0.065	0.020	3.301	0.001***
MS	φ_6	0.621	0.258	2.404	0.016**
CA	φ_7	-0.102	0.240	-0.427	0.670
LR test		15.47			
Log-likelihood (ll)		-86.97			
Chi2 (χ^2)		46.48			
N		82			

Significance level: * p<0.10, ** p<0.05, *** p<0.01.

Third, elasticity on FUNDRISK (-0.21) is statistically significant and negatively related to cost efficiency. Conversely, the loan to deposit ratio is positively related to cost efficiency. Thus, utilising cheap customer deposits to fund customer loans improves bank efficiency as opposed to funding loans by equity. Excess customer deposits not converted into customer loans, hurts cost efficiency. Thus, when the FUNDRISK increases by 1% for the period under review, the bank efficiency decreases by 21%.

Fourth, CONTASS coefficient is positive and statistically significant with the estimated elasticity of 0.07, suggesting that a high proportion of securities relative to gross loans influences bank efficiency. Financial disintermediation is cost beneficial to Malawi banks contrary to Hauner [28] who found that increased government borrowing dampens banks' efficiency performance in most developing countries.

Fifth, bank size influences cost efficiency. The parameter for MS is observed to be positive and significant, implying that large banks enjoy relatively higher cost efficiency scores because of large economies of scale and scope. Large banks attract highly qualified and experienced professionals and tend to have the financial capacity to hold an optimally diversified investment portfolio in an uncertain environment. In Table 6, when the MS increases by 1%, bank efficiency increases by 62.1%.

Sixth, the credit risk coefficient (CLR) is positive but statistically insignificant at all conventional levels. The finding can be attributable to the fact that bank managers have no incentive to report high credit provisions as it reflects poorly on their managerial ability. This outcome affirms the Williamson theory of the firm model [55] in which managers have the discretion to advance policies that maximise their utility rather than the utility of owners.

Finally, regarding the impact of regulatory conditions, we observe that the requirement of minimum capital adequacy (CA) ratio is statistically insignificant to cost efficiency at conventional levels. The findings are in stark contrast to Olaosebikan [47], whose study established that the introduction of a minimum capital requirement improved Nigerian banks' cost efficiencies. Therefore, it can be implied that the introduction of Basel II capital requirements in 2014 did not affect banks' efficiency scores.

5. Conclusion

The broad objective of this study was to evaluate the cost-efficiency of the Malawian banking sector using stochastic frontier analysis (SFA). The results indicate that the average cost efficiency level between 2010 and 2019 was 91.5% with the mean efficiency scores ranging from 50% to 99.6%. The results further indicate an upward trajectory for the average efficiency level with most of the banks operating close to the common frontier. Further analysis using the Tobit regression model, indicates that credit risk and capital adequacy were statistically insignificant in explaining cost-efficiency performance. On the other hand, inflation, market concentration, funding risk, asset concentration and size determine cost efficiency in the Malawi banking sector.

The policy implications of the results are the need for: the reduction of market concentration and improving competitiveness to ensure industry efficiency improvement; improve current credit risk assessment techniques by enforcing a common framework of reporting credit provisions and losses, and; ensuring an environment with macroeconomic policy certainty to enhance the industry-wide efficiency.

The study was limited by the lack of data on the number of branches maintained by banks and staff cost incurred over the period under study which are normally not published. Proxy measures associated with both size and labour costs were used instead. It is therefore possible that the results obtained using proxy measures reflect an element of aggregation bias compared to results based on exact variables. Furthermore, published financial statements are affected by accounting standards and policies adopted by different banks, such that inputs and output parameters estimates may differ from study to study.

Apart from the SFA technique used in this study, other techniques such as Thick Frontier Approach (TFA), Data Envelopment Analysis (DEA) and Distribution Free Approach (DFA) could also be adopted collectively or separately to analyse the nature of efficiency in banks. Using more than one approach to measure efficiency ensures that the results are robust and in-depth and that the parameters are analysed objectively.

References

[1] Abel, S. (2018). Evaluating the Cost Efficiency of Commercial Banks in Zimbabwe. MEFMI research and policy journal (1), 4-25.

[2] Abel, S., Bara, A., & le Roux, P. (2019). Evaluating Bank Cost Efficiency Using Stochastic Frontier Analysis. Journal of Economics and Behavioral Studies, 11 (3), 48-57.

[3] Aigner, D., Lovell, C., & Schmidt, P. (1977). Formulation and Estimation of Stochastic Frontier Production Function Models. Journal of Econometrics, 6, 21-37.

[4] Battese, G., & Coelli, T. J. (1993). A Stochastic Frontier Production Function Incorporating a Model for Technical Inefficiency Effects. Working papers in econometrics and applied statistics, No 69 (Armidale: Department of Economics, University of New England).

[5] Battese, G., & Coelli, T. J. (1995). A model for Technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics, 20, 325-332.

[6] Baumol, W. (1959). Business Behavior, Value and Growth (1st ed.). New York, USA: Macmillan.

[7] Beck, T., & Hesse, H. (2006). Bank Efficiency, Ownership, and Market Structure: Why are Interest Spreads so High in Uganda? World Bank Policy Research Working Paper WPS4027. Retrieved November 2020, from World Bank: http://www-wds.worldbank.org/servlet/WDSContentServer/WDSP/IB/2006/10/03/000016406_20061003154648/Rendered/PDF/wps4027.pdf

[8] Berger, A. N. (2007). International Comparisons of Banking Efficiency. Financial Markets, Institutions & Instruments, 16 (3), 119-144.

[9] Berger, A. N., & Humphrey, D. (1997). Efficiency of Financial Institutions: International Survey and Directions for Future Research. European Journal of Operational Research, 98 (2), 175-212.

[10] Bikker, J., & Haaf, K. (2003). Measures of Competition and Concentration in the Banking Industry: A Review of the Literature. Economic and Financial Modelling (Summer).

[11] Brewster, D. (1997). Business Economics - Decision-making and the Firm (1st ed.). London: The Dryden Press.

[12] Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. European Journal of Operational Research, 12, 429-444.

[13] Chirwa, E., & Mlachila, M. (2002). Financial Reforms and Interest Rate Spreads in the Commercial Banking System in Malawi. IMF Staff Papers, 55 (1), 5.

[14] Čihák, M., & Podpiera, R. (2005). Bank Behavior in Developing Countries: Evidence from East Africa. IMF Working Paper No.WP/05/129. Retrieved November 2020, from International Monetary Fund: http://www.imf.org/external/pubs/ft/wp/2005/wp05129.pdf

[15] Coase R. H. (1937). The Nature of The Firm, Economica, New Series, 4, 386-405.

[16] Coelli, T., Prasada Rao, D., O'Donnell, C., & Battese, G. (2005). An Introduction to Efficiency and Productivity Analysis (2nd ed.). Springer.

[17] Cohen, K. J. & Cyert, R. M. (eds) (1975). Theory of the Firm: Resource Allocation in a Market Economy (2nd ed.). New Jersey: Prentice-Hall.

[18] Cornwell, C., Schmidt, P., & Sickles, R. C. (1990). Production frontiers with cross-sectional and time-series variation in efficiency levels. Journal of Econometrics, 46 (1–2), 185-200. doi: 10.1016/0304-4076(90)90054.

[19] Cyert, R., & March, J. (1963). Behavioral Theory of the Firm (2nd ed.). Oxford, USA: Wiley-Blackwell.

[20] Debreu, G. (1951). The Coefficient of Resource Utilisation. Econometrica, 19, 273-292.

[21] Demsetz, H. (1997). The Firm in Economic Theory: A Quiet Revolution. American Economic Review, 87 (2), 426-429.

[22] Farrell, M. (1957). The Measurement of Productive Efficiency. Journal of the Royal Statistical Society, 120 (2), 252-290.

[23] FinMark Trust. (2014). FinScope Consumer Survey Malawi. Retrieved November 2020, from https://www.africanbondmarkets.org/fileadmin/uploads/afdb/Countries/Malawi/Reserve_Bank_of_Malawi/Malawi-FinScope-2014.pdf

[24] Fries, S., & Taci, A. (2005). Cost efficiency of banks in transition: evidence from 289 banks in 15 post-communist countries. Journal of Banking and Finance, 29 (1), 55-81.

[25] Greene, W. (1990). A Gamma-distributed Stochastic Frontier Model, Journal of Econometrics, 46 (1-2), 141-163.

[26] Greene, W. (2005). Reconsidering Heterogeneity in Panel Data Estimators of the Stochastic Frontier Model, Journal of Econometrics, 126 (2), 269-303.

[27] Hadhek, Z., Frifita, M., & Lafi, M. (2018). The Determinants of Profit Efficiency of Islamic Banks Using Stochastic Frontier Analysis Approach. International Journal of Economics and Financial Issues, EconEconjournals, 8 (6), 20-29.

[28] Hauner, D. (2008). Credit to Government and Banking Sector Performance. Journal of Banking and Finance, 53, 237-254.

[29] Hauner, D., & Peiris, S. J. (2005). Bank Efficiency and Competition in Low-Income Countries: The Case of Uganda. Working Paper, WP/05/240, Washington DC: International Monetary Fund.

[30] Idialu, J., & Yomere, G. (2010). Stochastic Frontier Analysis of the Efficiency of Nigerian Banks. Indian Journal of Economics and Business, 9 (1), 75.

[31] Jondrow, J., Knox Lovell, C., Materov, I., & Schmidt, P. (1982). On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model. Journal of Econometrics, 19 (2-3), 233-238.

[32] Kablan, S. (2007). Measuring Banking Efficiency in Developing Countries: The Case of the Western African Monetary Union (WAEMU). Retrieved November 2020, from African Development Bank: http://www.afdb.org/pls/portal/docs/PAGE/ADB_ADMIN_PG/DOCUMENTS/AEC/MESURE%20DE%20LA%20PERFORMANCE%20DES%20BANQUES%20UEMOA.PDF

[33] Khalil, S., Mehmood, B., & Ahmad, N. (2015). Cost Efficiency of Pakistani Banking Sector. A Stochastic Frontier Analysis. Journal of Commerce, 7 (3), 110-126.

[34] Kiyota, H. (2009). Efficiency of Commercial Banks in Sub-Saharn Africa: A Comparative Analysis of Domestic and Foreign Banks. Oxford: Economic Development in Africa.

[35] Kofi, A., Gan, C., & Hu, B. (2014). Cost Efficiency of Ghana’s Banking Industry: A Panel Data Analysis. The International Journal of Business and Finance Research, 8 (2), 69-86.

[36] Koopmans, T. (1951). An analysis of production as an efficient combination of activities. In T. C. Koopmans (Ed.), Activity Analysis of Production and Allocation (Vol. 13). New York: Wiley.

[37] Kumbhakar, S. (1990). Production Frontiers, Panel Data, and Time-Varying Technical Inefficiency, Journal of Econometrics, 46 (1-2), 201-211.

[38] Kumbhakar, S., & Lovell, C. (2000). Stochastic Frontier Analysis. Cambridge: Cambridge University Press.

[39] Kumbhakar, S., & Wang, D. (2007). Economic Reforms, Efficiency and Productivity in Chinese Banking, Journal of Regulatory Economics, 32 (2), 105-129.

[40] Lu, Y. F. (2020, November). Determinants of Foreign-Owned Banks’ Efficiency in New Zealand: A Stochastic Frontier Approach. Retrieved from Lincoln University: https://researcharchive.lincoln.ac.nz/handle/10182/6795

[41] Manlagñit, M. C. (2011). The Economic Effects of Foreign Bank Presence: Evidence from the Philippines. Journal of International Money and Finance, 30 (6), 1180-1194.

[42] Marris, R. (1964). The Economic Theory of Managerial Capitalism (1st ed.). New York, USA: Free Press of Glencoe.

[43] Mathews, K., & Thompson, J. (2014). The Economics of Banking (3rd ed.). Chichester, UK: Wiley.

[44] Meeusen, W., & van Den Broeck, J. (1977). Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error. International Economic Review, 18 (2), 435-444.

[45] Mester, L. (1997). Measuring Efficiency at U.S. Banks: Accounting for Heterogeneity is Important. European Journal of Operational Research, 98 (2), 230-242.

[46] Musonda, A. (2008). An Investigation into the Determinants of Cost Efficiency in the Zambian Banking Sector, 13th Annual African Econometric Society Conference, South Africa, 9-11 July 2008. Retrieved November 2020, from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.590.1459&rep=rep1&type=pdf

[47] Olaosebikan, B. (2009). Surveying Efficiencies of Nigerian Banks before and after the Minimum Capital Requirement Increase. Retrieved November 2020, from https://digitalcommons.iwu.edu/cgi/viewcontent.cgi?article=1019&context=busadmin_honproj

[48] Pitt, M., & Lee, L. (1981). The Measurement and Sources of Technical Inefficiency in the Indonesian Weaving Industry. Journal of Development Economics, 9 (1), 43-64.

[49] Reserve Bank of Malawi. (2019). Financial Institutions Supervision Annual Report. Retrieved November 2020, from https://www.rbm.mw/Home/GetContentFile/?ContentID=38601

[50] Schmidt, P. & Sickles, R. (1984), Production Frontiers and Panel Data, Journal of Business & Economic Statistics, 2 (4), 367-374.

[51] Sealey, C., & Lindley, J. (1977). Inputs, Outputs, and a Theory of Production and Cost at Depository Financial Institutions. Journal of Finance, 32 (4), 1251-66.

[52] Shephard, R. (1970). Theory of Cost and Production Functions. Princeton, USA: Princeton University Press.

[53] Simon, H. (1959). Theories of Decision-Making in Economics and Behavioural Science. The American Economic Review, 49 (3), 253-283.

[54] Wang, D., & Kumbhakar, S. C. (2009). Strategic groups and heterogeneous technologies: an application to the US banking industry. Macroeconomics and Finance in Emerging Market Economics, 2 (1), 31-57.

[55] Williamson, O. (1964). The Economics of Discretionary Behaviour: Managerial Objectives in a Theory of the Firm (1st ed.). Englewood Cliffs, USA: Prentice-Hall.