Efficiency, risk and productivity patterns in South African development finance institutions

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Abstract

Like most commercial banks that needs to convert deposit (input) into loans (outputs) efficiently, the cost of bringing about the developmental mandate for the DFIs needs to be kept at the minimum, whilst producing maximum output. Whilst there is a wide literature on a traditional measure of efficiencies from the credit allocation perspective, few or no studies are available in linking the risk incurred by DFIs - due to their operational mandate- to their relative efficiencies and productivity patterns. The paper assessed the relationship between efficiency, risk and productivity patterns, within the DFIs. Principally the main area of interest is understanding the relationship between risks that DFIs are mandated to take and their effect on efficiency levels. The results firstly indicated that operational inefficiencies resulting from inability to allocate resources and cost were the primary source behind the DFIs inefficiencies. Turning to the second objective, the analysis reveals that the nexus between risk and efficiency does not exists for the South African DFIs. The majority of the DFI in SA are government funded to assume a certain risk in an effort to achieve the developmental goal.

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Chapter One: Introduction and background

1.1. Introduction

The deterioration in the global economy; dried-up international capital market; below sub-investment African credit rating grade and increasing developmental needs, widens the gap between private and public funding in most African economies. Therefore the role of the Development Finance Institutions (DFIs) in addressing market failures within the credit market is more crucial than ever before in facilitating a countercyclical role, whilst still promoting financial access for non-bankable market.

Thus the mission of the DFIs lies in servicing the investment shortfalls of the host countries and bridging the gap between commercial investment and state development aid. Khadiagala, (2011) argues that DFIs are typically policy tools in the hands of states to forge developmental objectives by addressing imperfections in markets for finance and investment capital, assisting markets to foster growth, and contributing to the public goods.

DFIs have for several decades been important intermediaries for donors aiming to channel financial resources to priority groups and to fill the long-term credit gap (McKean, 1990). African DFIs in particular, have assumed historically an important role of taking a higher than average risk which in turn translate to higher than average non-performing loans ratio in their pursuit to perform their mandates and reduce the pro cyclicality (Calice, 2013). However, the developmental contribution is usually associated with a cost of relatively low efficiency and effectiveness of the DFIs.

A stable and efficient financial system is important for economic growth. The credit allocation efficiency in the DFIs is seen as bridging the gap between public sector spending and private spending. That is an efficient DFI maximizes the development objective with minimal resource while at the same time remaining financially sustainable. Abrahams (2015) concluded that value is destroyed in the deployment of capital resources as a results and the development impact value is not maximized.

The contribution of directed credit to growth of output can be measured relative to the policy environment that ensures specifically that capital is put into its most productive use (McKean (1990). Directed credit has more positive impact on growth in economies with stable macroeconomic and political environment than in countries characterized by lack of (World Bank paper, 1989b). For example, Malawi has been identified by BAR (2006) as fundamentally flawed on the basis of development finance due to poor economic prospects, high levels of corruption and limited political will to foster good governance.

Therefore the nexus between credit allocation, developmental objective, and sustainability has proved to be challenging for most advanced and emerging markets especially African economies. In South Africa, the DFIs are government controlled institutions with different operational mandates and mostly seen as catalyst for job creation and industrial development. Like most commercial banks that needs to convert deposit (input) into loans (outputs) efficiently, the cost of bringing about the developmental mandate for the DFIs needs to be kept at the minimum, whilst producing maximum output. Therefore the operational efficiency and sustainability depends upon the DFIs ability to manage the resources and convert them into output with minimum cost and without waste.

1.2. Problem Statement

Whilst there is a wide literature on a traditional measure of efficiencies from the credit allocation perspective, few or no studies are available in linking the risk incurred by DFIs - due to their operational mandate- to their relative efficiencies and productivity patterns. Considering the market where the DFIs operate, measuring efficiency without understanding the risks that DFIs are mandated to take, might produce inconclusive results. Sarmiento and Galan (2015), argues that the failure to account for risk taking might led to biased estimation of bank efficiency.

Having in view the importance of the DFIs in credit allocation and the mandated risks they undertake in their pursuit of the developmental mandates, the aim of the study is to identify the influence of the DFI risk-taking on their efficiency levels. Further, the relationship between efficiency and change in productivity patterns is explored to understand the sources of productivity growth.

1.3. Research Objective

The aim of the study is to analyze the nexus between efficiency, risk and productivity patterns of the DFI's in SA. This will be assessed by following a three-stage analysis:

i. Firstly, to understand the causes of inefficiencies, data envelopment analysis (DEA) will be used to obtain the efficiency scores, which will be further decomposed into technical, scale and cost efficiencies.
ii. Secondly the determinants of efficiency will be evaluated to assess the influence of risk-taking on the levels of efficiencies.
iii. Thirdly, to understand the sources of growth, productivity changes are evaluated through an index approach which breaks down total factor productivity into technological and managerial efficiency.

The relationship between cost efficiency, risk and productivity patterns using DEA in South African DFIs has never been covered in the literature before. The majority of existing literature that employs the DEA to measure efficiency in SA covers the financial institution (see Mlambo and Ncube (2002), Van Heerden and Van der Westhuizen. (2008), Erasmus and Makina (2014)). Hence the study aims to contribute to such a literature.

The rest of the paper is organized as follows: Section 2 explores the existing literature on the efficiency. Section 3 sets out the methodological framework on the efficiency classification, data analysis and measurement. Section 4 present the results, while section 5 concludes.

Chapter Two: Literature review

The chapter begins by introducing efficiency and productivity concepts from the basic microeconomic theory and measurement perspective. Then an evolution of the seminal work on productivity from origin to recent developments is covered. The intension is to cover the literature that informs the modelling approach.

From the microeconomic theory, the performance of firm is defined through the production function. This function describes the relationship between the maximum production output of a commodity and the inputs used in production process. Therefore productivity of the firm can be defined as the ratio of output to its input (Lovell, 1993).

Efficiency on the other hand is described as a distance between the quantity of outputs and inputs that defines the best possible frontier for the firm (Daraio et. al. (2007). Lovell (1993) defines the efficiency of the production unit in terms of the comparison between the observed and optimal values of output and inputs. Therefore, efficiency is the measure of the distance between a given output-input combination and the optimum point on the frontier.

The comparison of the ratio of the observed to the maximum potential output obtainable from the given input is defined in terms of the production possibilities. Daraio, et.al. (2007) argued that the measures of efficiency are more accurate than those of productivity in the sense that they involve a comparison with the most efficient frontier and for that, they complete those of productivity which are based on the ratio of outputs on inputs. Therefore the measures of efficiency are more accurate than those of productivity in that they involve a comparison with the most efficient frontier (See Coelli et al., 2005; Daraio and Simar, 2007).

2.1. Measures of efficiency

The importance of efficiency measurement in the financial sector is related to the substantial impact that an efficient financial system has on the microeconomic as well as the macroeconomic level of the economy (Zuzana and Havránek, 2010).

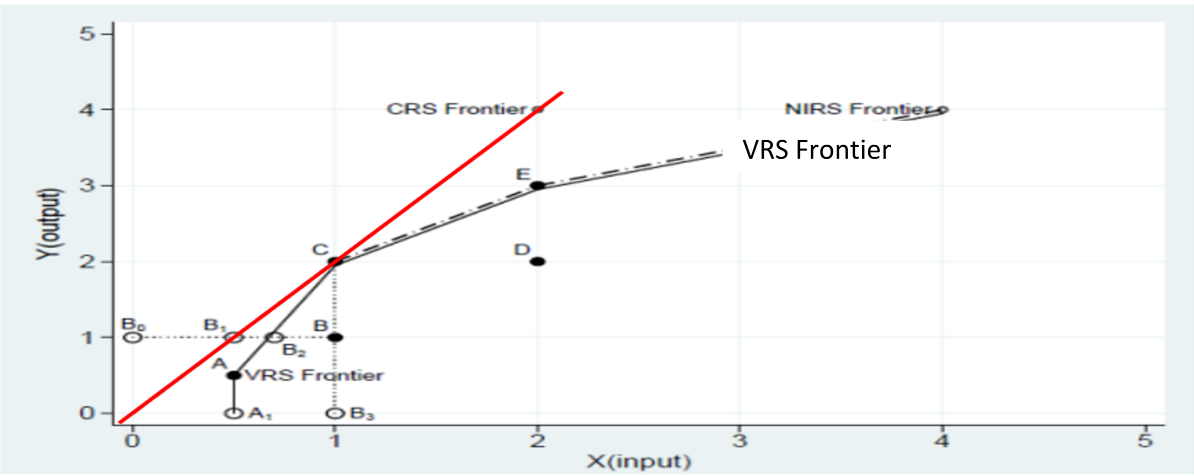
The measurement of productivity and efficiency in the literature dates as early as 1950's. Koopmans (1951); Debreu (1951) and Farell (1957). Farrell introduced the method of decomposing the overall efficiency into technical and allocative components.

Technical efficiency (TE) is the ability of a firm to obtain maximal output from a given set of inputs. A firm is considered technically efficient if it operates along the production possibility frontier. The TE measure that corresponding to constant returns to scale, represents an overall technical efficiency (OTE). The OTE determines inefficiency due to input-output configuration as well as the size of the operation (Kumar and Gulati, 2008).

The overall efficiency can be decomposed into pure technical (PTE) and scale efficiencies (SE) which are non-additive and mutually exclusive. PTE is the efficiency measures corresponding to variable returns to scale and reflects the managerial competence for proper allocation of resources (Roy, 2014). Thus mostly used as an index to measure managerial performance.

The SE reflects the management ability to choose optimum size of resources and is measured as the ratio OTP to PTE. This reflects the management ability to choose the scale of production that will attain the desired level of production. The SE can either follow a decreasing returns to scale which implies that the bank is too large to take full account of scale or increasing returns to scale where a bank is too small for its scale of operations.

Figure 1: Technical and Scale Efficiency



Source: Adapted and sourced from Lee, 2013

From the above graph, the ratio $\frac{B_0\,B_1}{B_0\,B}\frac{B_0\,B_1}{B_0\,B}$ and $\frac{B_0\,B_2}{B_0\,B}\frac{B_0\,B_2}{B_0\,B}$ represents TE and PTE respectively. The scale efficiency being the ratio TE/PTE.

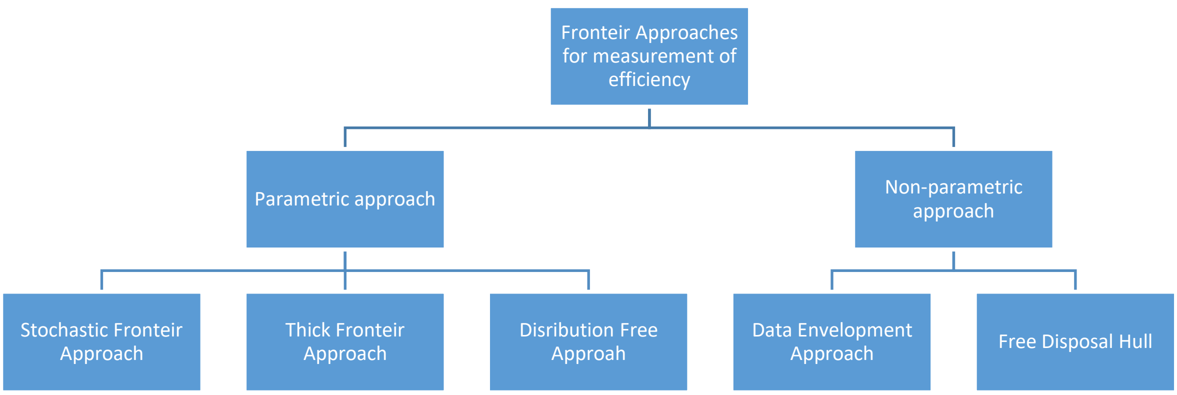
Allocative efficiency (AE) on the other hand involves a selection on input mixes that produce a given level of output at minimum cost. This is the efficiency that occurs when firm's inputs are allocated in a way to maximize the benefits, given their prices and production technology. The concepts are based on the economic foundation from efficiency due to economic optimization in response to market prices (Moffat, 2008). Berger and Mester, (1997) further decomposes AE into CE and PE.

According Kocisova (2014), the overall economic efficiencies can either be examined from the input based perspective (cost efficiency (CE)) or output perspective (profit efficiency (PE)). CE relates to a measure of how close the banks costs are to the best practice banks cost for producing the same output under the same costs. Whilst PE indicates how well a bank is predicted to perform in terms of revenue relative to other banks in the same period for producing the same set of outputs.

2.1.1. Efficiency frontier selection approaches and their evolution

In the literature, two main methodologies that dominate the efficiency frontier measurement are econometric (parametric) and mathematical programming (non-parametric) approach. The econometric approaches specifies production, cost, revenue or profit functions with specific shape and makes assumptions about the error term. Figure 2 below depicts the classification as follows;

Figure 2: Frontier approaches for efficiency



The parametric approaches have been critiqued in the literature for their lack of consistency with the economic definition of production functions. Schmidt (1986) argues that the estimated functions results in the mean output rather than the optimum output. Farrell (1957) suggested that a production function should be estimated as an envelope function associated with combinations of observed inputs. The estimated functions proposed by Ferrell had no statistical properties upon which inferences can be drawn. Charnes et.al. (1978) and Banker et al. (1984) extended the work of Farrell by developing a DEA to overcome lack of statistical inference.

2.1.1.1. Parametric approach

Under the parametric approach literature, there exist three main types of efficiency. The stochastic frontier analysis (SFA) originally development by Aigner et.al (1977). This approach specifies a particular form for the production/cost function allowing the error term. Therefore the approach parameterize the relationship between the level of inputs and efficient level of outputs.

The canonical formulation that is the foundation for other variations is given by $y = \boldsymbol{\beta}'x + v - u$. Where y is the observed outcome and $\boldsymbol{\beta}'x + v$ is the optimal with the $\boldsymbol{\beta}'x$ as the deterministic part and v is the deterministic part of the frontier. Many varieties of the SFA exist in the literature, see Kumbhakar and Lovell (2000) for survey that present major variations. Mostly, the variants are based on different assumptions about the distribution of the inefficiency term.

The distribution free approach (DFA) also specifies a functional form for the frontier but separates the inefficiencies from a random error. DFA was initially developed by Schmidt and Sickled (1984) and later by Berger (1993). The approach does not make strong assumption regarding the specific distributions of the inefficiencies or random errors. The approach assumes that inefficiency remain constant over time and the random error averages out over time. DeYoung (1997) argues that by averaging the residuals, DFA estimate the relative efficiencies relative to its competitors over a range of conditions across time rather than its relative efficiency at any point in time. Thus the approach gives a better indication of the firm's long term performance (Berger and Humphrey, 1997).

The thick frontier approach (TFA) identifies thick frontier of decision marking units that are close to the frontier, minimizing the impact of outliers. The approach was developed by Berger and Humphrey (1991) to estimate the thick frontier by estimating both the lowest cost quartile and highest average quartile of firms. The difference between the highest and the lowest quartile reflect a combination of inefficiencies. TFA provides an estimate of the overall level of efficiency. According to Zheng (2015), the assumptions of the approach do not hold as a result, TFA might yield imprecise estimates of general level of overall efficiency.

2.1.1.2. Non parametric approach

Popular in the non-parametric approach and central to this study is the data envelopment analysis (DEA) based on the linear programming techniques. The approach does not make any assumption about the functional form of the frontier but empirically builds a function from the observed inputs and outputs

(Favero and Papi, 1995). Roy (2014) summaries the advantages of the DEA as a preferred approach in measuring various efficiency scores based on the following reasons;

- First, it allows the estimation of overall OTE and decomposes it into two mutually exclusive and non-additive components, namely, PTE and scale efficiency SE. Further, it identifies the banks that are operating under decreasing or increasing returns-to-scale.
- Second, in DEA, there is no need to select a priori functional form relating to inputs and outputs like Cobb-Douglas and Translog production/cost functions (Banker, 1984).
- Third, DEA easily accommodates multiple-inputs and multiple-outputs of the banks.
- Fourth, it provides a scalar measure of relative efficiency, and the areas for potential addition in outputs and reduction in inputs.
- Fifth, in DEA, it is not necessary to provide values for weights associated with input and output factors, although the user may exert influence in the selection of weight values.
- Sixth, DEA works particularly well with small samples (Evanroff and Israilevich, 1991).

Unlike the parametric approach, that is based on the production function, which determines the relationship between a company's inputs and outputs; the non-parametric approaches to efficiency analysis are based on linear programming methods. The approach does not require specifying a functional relationship between inputs and outputs of a company. The DEA ignores the random component and assumes that any deviation from the efficiency frontier is associated with inefficiencies. Therefore the current study adopts a non-parametric DEA approach to estimate efficiency amongst the DFIs.

The choice of the best frontier boils down to the difference of opinion regarding the lesser of evils (Berger and Humbery, 1997). The parametric approach imposes a functional form that presupposes the shape of the frontier and if the functional form is mis-specified, measured efficiency is clouded by errors. That is the main problem is the identification of noise from inefficiency. Non-parametric approaches have been critiqued for not making allowance for random error terms and lack of statistical inference. Berger and Humery, argues that the solution to determine which approach is more robust lies in addressing the drawbacks of the two approaches.

Whilst the parametric and non-parametric approach to frontier estimation are very old measurement criteria, subsequent development have been made to address the challenges behind this approaches. Much of recent literature revolves around the assumptions that seeks to address the shortcomings, rather than alternative approaches to frontier modelling. Therefore it is safe to conclude that the frontier approaches for measurement of efficiency are still appropriate in this day and age.

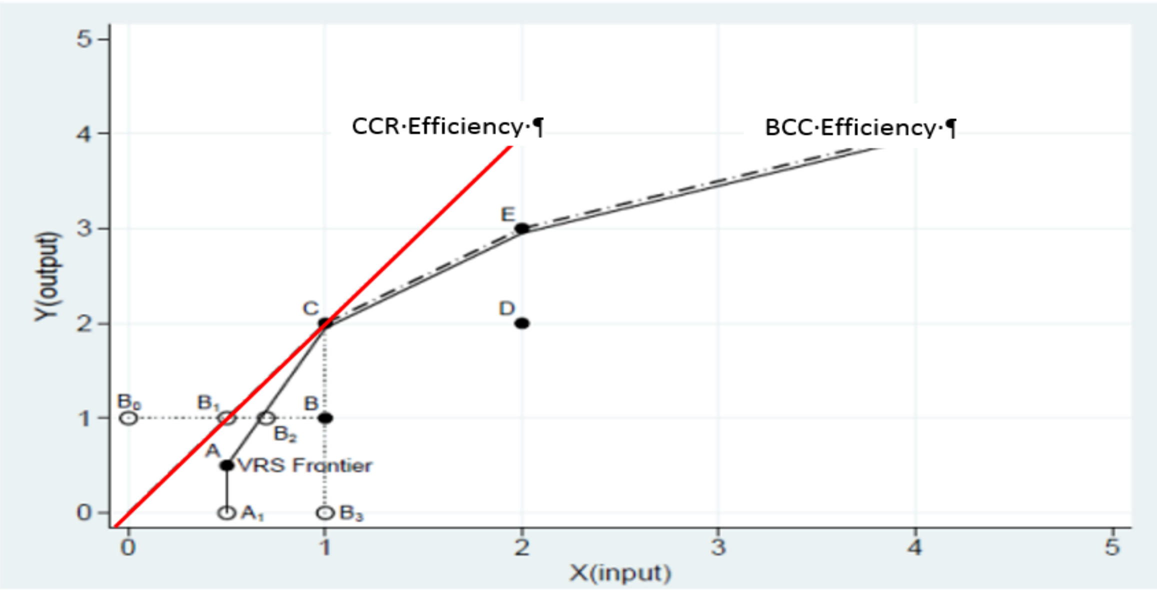
2.1.2. Functional forms of DEA

The DEA has two functional forms; CCR (Charnes, Cooper, and Rhodes) and BCC (Banker, Charnes, Cooper). The CCR assumes the frontier to have a constant returns to scale in line with the pure technical efficiency whilst BCC introduces a variable returns to scale frontier which added convexity condition$\sum_{j=1}^{n} \lambda_j = 1$ to capture the input excess and output shortfalls. CCR model simply measures technical efficiency and BCC models measures pure technical efficiency (Eken and Kale, 2013)

Katib and Yadav (2015) maintains that the CRS is acceptable when all decision making units (DMUs) are functioning at an optimal scale. The assumption of full optimal scale is unrealistic for most firms, hence Banker et al. (1984) proposed an extension to take into account variable returns to scale (VRS), which allows for the calculation of the pure technical efficiency score.

The illustration in Figure 3 uses one-input and one-output. The straight line represent the CRS assumption and the VRS is shown by the convex curve. The firms operating along the frontier (convex) are deemed efficient but are not equally productive due to the scale effects (Moffat, 2008). Firm A is operating at an increasing returns to scale and can increase its production by moving towards point C. Whereas firm E is operating at decreasing returns to scale, and can be more productive by decrease its production to point C. Point B and D are inefficient.

Figure 3: Production frontier based on CCR and BCC



Source: Adapted and sourced from Lee, 2013

In a multiple outputs and inputs, the DEA is formulated as either a constraint maximization or minimization objective function under the framework of linear programming. The solution is obtained by solving the simplex algorithm to estimate the efficiency score per DMU as a ratio.

According to Heerden and Westhuizen (2008) CRS efficiency score represents technical efficiency that measures the inefficiencies due to the size of operations and the organization's input/output combination. CRS evaluates efficient and non-efficient DMUs and determines how far from the efficient frontier are the non-efficient units. While VRS is the disproportional increase or decrease in outputs when the inputs are increased (Avkiran, 1999) and the scores represent pure technical efficiency without scale efficiency.

2.2. Determinants of efficiency

Understanding the level of inefficiency and identifying the sources can help in formulating the appropriate policies. Within the efficiency analysis, the majority of studies employ a two stage analysis to estimate the level of inefficiencies and secondly determine the factors that lead to such inefficiencies. In an effort to understand the determinants of efficiencies, the literature employs a regression analysis or its variations such as the tobit, probit and logistic regressions to estimate the effect of environmental variables on the TE and CE scores (see Han et al, 2012; Fang et al., 2011; Abu-Alkheil et al., 2012). Usually the explanatory variables takes the banks own characteristics, environmental, geographical, and or regulatory factors.

In their study, Nitoi and Spulbar (2016) assessed the nexus between efficiency and risk. As a results the study included risk based factors such as concentration index, the Z-score, equity to total asset ratios, liquidity ratios, return of equity, net interest margin, and loans to customer deposit ratio. The chosen variables were risk based in nature, i.e. the concentration index captures efficiency brought by the external market factors; and internally, factors such as the failure risk, the solvency risk, and the liquidity risk were used. Their results were rather mixed, suggesting that in order to increase CE the targeting of resource should be made towards riskier assets, whilst at same the Z-score suggests that banks with lower risk appetite and lower risk of failure were more efficient. However in terms of the link, the study found that lower failure risk and higher liquidity are positively associated with cost efficiencies. Therefore the implication for policy makers is to target a counter cyclical policy in order to mitigate banks risk in periods of high economic growth, which will ultimately increase the cost efficiency.

In the second stage of their analysis, Mathew and Sangeetha (2016) applied a Tobit regression in analyzing the determinants of TE and CE by considering operating variables (such as investment, advances, fixed assets, loanable funds). In terms of the models applied for estimation purposes, Simar and Willson (2007) argues that the use of the Tobit model has a potential bias in efficiency estimates because of the serial correlation problem. McDonald (2009), maintains that the score from the DEA are not censored but are fractional hence the logit is an appropriate model. The hypothesis used was as follows;

H0: Technical efficiency (TE) of Public sector banks is not influenced by primary operating variables
H1: Technical efficiency (TE) of Public sector banks is influenced by primary operating variables

Interestingly, their study found that an increase in investment and advances increase the TE and TE decrease for an increase in fixed assets, loanable funds and employee costs. Thus the null was rejected and the study concluded that TE is influenced by operating factors. This indicates to the policy makers that the loanable funds i.e., deposits and borrowings, should be deployed in the form of loans & advances first and then as investments. Second hypothesis was tested to assess the influence of operating variables on CE scores. The price of inputs factors have no influence CE scores. Therefore being a deposit taking institution, the price of funds are not significant in explain the cost inefficiencies.

Gulati and Kumar (2008) defines the dependent variable on the basis of OTE and employ the logistic regression as the scores are bounded between 0 and 1. Where the independent variables are market share, assets quality, exposure to off-balance sheet activities, profitability and size. These sets of factors were termed as environmental variables, and poor asset quality is expected to have a negative influence of TE score. The study concludes that the efficiency of PSBs is positively influenced by their exposure to off-balance sheet activities. Therefore this suggest that the efficiency of these PSBs in India are brought by activities that are non-core to banks activities.

Katib and Yadav (2015) used and OLS method with TE scores as the response variable and bank specific factors such as loan intensity, total assets, credit risk, diversification, capitalization and profitability were used as explanatory variables in a multivariate analysis. Loan intensity, DFI diversification and profitability were found to be positively correlated with the TE. That is banks with higher loans to asset ratio reveal greater ratio. Interestingly, their study added the size factor and found that larger banks tend to exhibit lower efficiency levels. In terms of risk as measured by net interest income to total assets, a significant negative relationship was observed. This relationship implies that DFI which tend to derive higher proportion of income from non-interest income tend to report lower efficiency. However equity to total assets was found to be positively related to efficiency. The implication of their finding is that sustainability not profitability is important for DFI to function efficiently.

According to Ekan and Kale (2005) banks risk taking activities have an effect on the banks performance; therefore the relationship between risks is deemed important as banks face not only credit but also operational and other key risks. Their study benchmarked performance of banks in comparison to risk taking preferences and found that profitability is not parallel with risk taking preferences.

Central to this analysis is the relationship between efficiency, risk, productivity and therefore the analysis will focus on the risk based factors. However there is no consensus in the literature of what variables should be used in analysis. Shen (2009) found out that the common factors that are usually include in this kind of analysis are usually bank size, ROA, ROE, equity ratio, non-performing loan ratio and ownership dummies. In line with Nitoi and Spulbar (2016) and in an effort to understand the relationship between CE, risks and productivity patterns, the bank characteristics with emphasis on the risk elements applicable to the DFIs will be considered in this analysis.

2.3. Development financial institutions efficiency analysis

A wide literature considering efficiency of banks using non-parametric approach has been comprehensively researched and covered in studies such as Berger and Humphery (1997), Gulati and Kumar (2008) and for application in insurance sector see Eling and Luhnen (2008). The section below covers efficiency across development finance institutions, sometime in the literature referred to as socially responsible banks. Alharthi (2016) found that socially responsible banks are more efficient than conventional, hence the focus for this sections will be on efficiency studies pertaining to non-conventional financial banks. For completeness purposes, Appendix 6.1 contains a summary of input and output variables used for the selected studies of DFIs efficiencies below.

Katib and Yadav (2015) analysed the intermediary role of the DFIs in Malaysia by applying the DEA. They found that the DFI were operating at the TE score of 78 percent which implies that DFI could have saved 22 percent of inputs to produce the same output. Further decomposition of the TE indicates that inefficiencies are brought by managerial underperformance. Important finding is that the DFI;s are scale inefficient and not operating at optimal scale; that is some DFIs needs to reduce the proportion of deposit and expenses to outputs in order to function optimally.

Gulati and Kumar (2008) also measured the extent of TE, PTE and SE in India for 27 public sector banks (PSBs). In their study, the inputs used to estimate the efficiency scores capture the ability of the banks to generate interest and non-interest incomes using the inputs of physical capital, labour and loanable funds. Their analysis found that the inputs of the PSBs can be reduced by 11.5 percent which indicates 88.5 percent level of TE. Moreover, their analysis revealed that the exposure to off-balance sheet activities has a strong and positive impact on TE while assessing the determinants of inefficiencies. Mathew and Sangeetha (2016) on the other hand attempts to measure the impact of financial crisis on efficiency of public sector banks (PSB) in India by classifying the study period into pre and post crisis. The study found that the scores reduced, which indicates a downward shift in efficiency level during the post period. The major driver behind TE was influence more by investment than advances. This implies that loanable funds should be deployed in the form of loans and advance first and then as investments.

In Africa region, Kariuki (2017) examines the financial intermediation efficiency of deposit saving and credit cooperative societies using the DEA for the period 2011-2014. On average the results indicates an increase in efficiency from 64.6 to 70.7 percent which was attributed to stronger regulatory compliance. Therefore important consideration is that compliance is efficient enhancing. The analysis reveals that over the years, scale efficiencies was higher than pure technical efficiencies implying inefficiencies are due to managerial underperformance rather than suboptimal size. Further the Malmquist productivity Index pointed to the fact that there was a limited growth in technological advancement, hence the level of inefficiencies.

In Tanzania Aziakpono and Marwa (2015) examines efficiency of savings and credit cooperatives using non-parametric DEA. The technical efficiency score on average for 103 savings and cooperative banks was 42% which indicates that the majority of the firms are inefficient in the utilisation of inputs. That is the same output could have been produced by saving 58% of the inputs. To reduce this high level of inefficiency, the authors are recommending increased regulatory measures be introduced.

It is evident from the literature that DEA has been applied over the years to study efficiencies from non-conventional banking institutions and the common threat to efficiency is the managerial and scale inefficiencies. However no studies were found in South Africa to assess the level efficiencies within the DFIs. Therefore the study not only contributes to the sparsely researched literature in this area, but also serves to inform needed policy changes within the DFIs.

2.4. Productivity measures

As highlighted above, productivity is measured as a ratio of output to input. For a firm that has multiple input and output, an index that aggregates the input and output needs to be developed. Though productivity and efficiency are different concept, Berg et al. (1992) found that the source of productivity growth are efficiency improvement.

Likewise the approaches of measuring productivity are categorised throughout the literature into non-parametric and parameter techniques under the frontier approach. The latter approach results production, cost or revenues functions, whereas non parametric approach follows the index number approach. In terms of simplicity, computational ease and minimal specification error, the former approach is seen as advantageous within the literature.

Under parametric approach, the productivity change is measured by differentiating the production function in terms of the time trend variable. That is productivity change is measured for the whole sample period. Under the index number approach, productivity is measured in discrete time which allows comparison from period to period.

2.4.1. Parametric approach to productivity change

Nishimizu and Page (1982) showed that productivity growth could also be estimated in the parametric frontier framework based on Solow growth model. In their model, Nishimizu and Page used time derivatives to estimate and decompose productivity growth into two elements: Technical change corresponding to shifts at the frontier level and, efficiency change corresponding to individual productivity displacements with respect to the frontier.

Within the parametric index estimation, the models based on a translog form of the production technology are widely applied. Kumbhakar et al. (1999) argues that the two widely used specifications, the time trend model and the general index model, their difference lies in the way time enters the production function. The majority of parametric studies use variations of time trend approach to estimate technological change and productivity growth (see Williams (2001), and Battese et al. (2000)). Therefore econometric approaches are generally used to estimate the interactions between time and other explanatory variables (Heshmati, 2001).

Berger and Mester (2001) used cost and profit functions estimates to decompose productivity growth into changes in business conditions and another portion due to changes in productivity. They further decomposed productivity change due to best practice and changes due to inefficiency components. Casu et.al. (2003) used the decomposed parameters when examining the productivity change in European banking system. The study applied both parametric and non-parametric approach which generally yield markedly similar results.

Kumbhakar et.al (1999) on the other hand assessed the consistency across parametric models such as time trend, general index model and their variations by estimating firm specific technical changes. The results of their analysis revealed inconsistency across different model approaches which suggested that there is a risk of model selection bias amongst this approaches parametric approaches to productivity measurement.

2.4.2. Non-parametric approach to productivity change

The operationalization of the indices using non-parametric approach is usually based on the DEA approach to measurement of efficiencies. Metter et al. (2016) explains that the technology estimated by DEA can be used to provide relative efficiency measures (distance functions), which are subsequently used to compute the index. Popular DEA based index in the literature is the Malmaquist productivity index (MPI) which was first initiated by Caves et al. (1982) to measure total factor productivity (TFP) change and later by Fare et al. (1994). The index analyses the relationship between productivity and efficiency and uses the distance function approach to measure productivity improvements. The distance function describes the multi-input and output production technology.

According to Ondrej et al. (2012), the index based on distance function require larger sets of cross-sectional data and are theoretical in nature. The other measures of productivity based on price aggregation are the Tornquist productivity index and Fisher productivity index. This by contrast to the former, requires minimum number of observations and are quite straight forward. The Tornquist index of productivity change between year t and year T is the share-weighted logarithmic change in outputs minus the share-weighted logarithmic change in inputs given as;

$$\ln TFP = \sum_{j}^{T} \frac{1}{2}\left(RS_{j,T} + RS_{j,t}\right) \ln \frac{Y_{j,T}}{Y_{j,T}} - \sum_{i}^{T} \frac{1}{2}\left(CS_{i,T} + CS_{i,t}\right) ln \frac{X_{i,T}}{X_{i,t}}$$

Where $RS_{j,t}$ is the share of output j in year t revenue and $CS_{i,t}$ is the share of input in year t costs and the exponential change yields an index number. This index can be used to combine indices of defined inputs such as capital, labour and intermediates inputs into indices of total input.

Another preferred index in the literature is the Fisher index which is the geometric mean of the Laspeyres and Paashe quantity indices. The Fisher index is less preferred in the literature of productivity given that it does not reveal any information regarding the source of productivity change. The above mentioned approaches are not central to the objective of this study, a further and detailed explanation on theoretical properties and issues in the measurement of the productivity through the Indices can be found in Diewert (1978, 1980); Christensen (1975); Capalbo and Antle (1988) and Coelli et al., (2005). The majority of non-parametric approach to productivity in the literature where assessed using the Fischer (1922) index and later Malmquist (1953) index. The Malmquist index (MI) gained more popularity since it was used to combine inputs and output to measure changes in productivity.

$$M^t = \frac{D_o^t(X^{t+1}, Y^{t+1})}{D_o^t(X^t, Y^t)}$$

The MI measures the total factor productivity change between two data points over time, by calculating the ratio of distances of each data points relative to a common technology. With the numerator as the output distance function at time $\mathrm{t} + 1$ bassed on period t technology and the denominator is the output distance function at time t based on period t technology. Fare et al. (1994) later specifies the index as a geometric mean that attributes productivity change (shift in technology) between the two periods. The index decomposes total factor productivity (TFP) change into efficiency change and technological change presented as follows:

$$MI^{t+1} = (y^{t+1}, x^{t+1}, y^t, x^t) = \left[\frac{D^t(y^{t+1}, x^{t+1})}{D^t(y^t, x^t)} \times \frac{D^{t+1}(y^{t+1}, x^{t+1})}{D^t(y^t, x^t)}\right]^{0.5}$$

Where MI is the productivity of the most recent production point $(t + 1)$ relative to earlier production point (t) and D's are the input/output distance functions depending on model orientation. A value of MI greater than 1 indicates a growth in total productivity over the two periods and the value less than 1 indicates a regress in productivity change.

Chang et al (2012) argues that the index is aggregative in nature. That is, the MPI lacks insights into disaggregating the impact of a single input factor into the total productivity change amongst all other factors. Chang et al. (2012) proposed an input slack based productivity index (ISP) to measure productivity. The index is computed using the input oriented directional distance function Fare-Lovell efficiency measure and calculates the total factor productivity change of an individual input under total factor concern as follows:

$$ISP_i = \frac{1}{2}\Big[\Big(\overrightarrow{D_{\iota(t)}}\,(x^t, y^t) - \overrightarrow{D_{\iota(t)}}\,(x^{t+1}, y^{t+1})\Big) + \Big(\overrightarrow{D_{\iota(t+1)}}\,(x^t, y^t) - \overrightarrow{D_{\iota(t+1)}}\,(x^{t+1}, y^{t+1})\Big)\Big]$$

The ISP based index is considered a better approximation given that it does not only calculates the total factor productivity change, but also productivity change of the individual input under the total factor concern simultaneously. However the index does not estimate or indicate the sources of change directly, therefore the index is further decomposed into efficiency change and technical change based on the Luenberger productivity index.

A recent extension/adjustment to the traditional DEA based Malmquist index is presented in Mette et al. (2016) where the efficiencies score are estimated using the multi-dimensional efficiency analysis. The existing traditional MPI mentioned above do not consider variable-specific analysis since they all use one-dimensional indices for overall efficiency. Therefore this technique enables estimation of variable specific production changes as well as its components. In their study, the results revealed that differences in variable specific performance of firms can be hidden when using conventional MPI. From the above reviewed literature, different variations in productivity estimation methods exists and the choice of approach depends on the objective and the efficiency technique applied.

Chapter Three: Methodology and Data

3.1 Methodological Frameworks

In line with the objective of the research, a three stage analysis will be employed to assess the objective of the study. The first stage will estimate the efficiency scores using DEA and secondly, the determinants of efficiency will be assessed with particular risk factors taken into account. Lastly the productivity patterns will be assessed using the Malmaqvist productivity index.

3.1.1 Specification: DEA

As mentioned in the literature, DEA is based on the concept of productivity, defined as the ratio of a single output to a single input, but it is applied to multidimensional situations where there is more than one input and more than one output (Moffat, 2008). The approach compares the productive efficiency of the similar peer entities referred as the Decision Making Units (DMUs). This implies that the unit of assessment has control over the process it employs. The method constructs a frontier based on actual data, where firms along the frontier are considered efficient and firms off the frontier are inefficient. Efficiency in this case, implies the firm is the best practice firm in a sample (Talluri, 2000). The mathematical approach to DEA was first introduced by Charnes et al. (1978) and Coelli (1996) computed a dual solution using duality as follows:

$$\begin{gathered} min\theta \\ subject\ to \\ -y_{ik} + \sum_{n=1}^{N} \lambda_n\ \gamma_n \geq 0, \\ \theta x_{jk} - \sum_{n=1}^{N} \lambda_n\ \gamma_{jn} \geq 0, \\ \lambda_n \geq 0, \end{gathered}$$

Where θ_k represents the technical efficiency of the ith DMU and y_{ik} and x_{jk} are the observed output and input for the firm. The λ_n is used as weights in the linear combination of other efficient DMU's for an inefficient DMU. The restriction $\lambda_n \geq 0$ limits the intensity variables to be non-negative. This model represent envelopment form of CCR model and provides TE under the assumption of CRS (Kumar and Gulati, 2008). Similar to Nitol and Spulbar (2016), the input prices are used and the cost minimization DEA becomes:

$$\begin{gathered}\min w_{jk}x_{jk}\\ subjecy\ to\\ -y_{ik}+\sum_{n=1}^{N}\lambda_n y_{in}\ \geq 0\\ x_{jk}-\sum_{n=1}^{N}\lambda_n x_{jn}\geq 0,\\ \lambda_n\geq 0\end{gathered}$$

Where $\mathrm{w_{jk}}$ and $\mathrm{x_{jk}}$ are input prices and cost minimizing input prices. By adding additional constraint $\sum_{\mathrm{j=1}}^{\mathrm{n}}\lambda_{\mathrm{n}}=1$ to the above specification represents the VRS. Under this restriction the model specified above represent a measure known as PTE. The overall CE is defined as the ratio of minimum cost of producing the outputs to observed cost of producing the outputs for the DMU (Coelli and all, 2005):

$$CE=\frac{\sum_{n=1}^{N}w_{jk}x_{jk}{}^{*}}{\sum_{n=1}^{N}w_{jk}x_{jk}}$$

The overall CE can be expressed as a product of TE and AE measures. Therefore, the AE of the DMU can be calculated as ratio of overall CE to input-oriented technical efficiency (Kocisova, 2014). An input orientation of the DEA will be adopted in this analysis to estimate the efficiency scores under CRS and VRS assumptions.

3.1.2 Specification: Determinants of efficiency

To estimate the effect of bank specific risk factors on efficiency, the study employs a tobit model as the distribution of scores are confined on the interval (0,1].

$$y_i=\begin{cases}x_i\beta+e_i & if\ x_i\beta+e_i<1\\ 1 & otherwise\end{cases}$$

The dependent variable is defined as efficiency scores (both TE and CE) with the independent variables (x_i) taken as vector that includes the explanatory variable, β is the estimated parameters and e_i is the distributed error term. The functional form is deemed appropriate as dependent variables are constrained between 0 and 1 in line with McDonald (2009) argument that efficiency scores are not censored but are fractional.

3.1.3 Specification: Productivity patterns

The DEA is a measure of relative efficiency which represent static efficiency. While productivity is measured by dynamic efficiency patterns, that is, absolute change in efficiency from one period to the next. According to Moffat (2008), productivity movement overtime maybe either due to technical efficiency, that is the movement along the frontier or technological improvements, which represent an upward shift of the frontier. To measure productivity the analysis makes use of the Malmquist index that uses distance functions to measure productivity change.

3.2 Data

Academia reveals that the majority of studies in efficiency analysis employ inputs and outputs in accordance with the intermediation and production approaches. The production approach considers banks as providers of a service to the consumer's whilst the intermediation approach views financial institutions as the intermediary between savers and borrowers.

Given that the production approach considers banks as producers of financial services (Benston, 1965), the inputs typically include physical variables, such as labour and raw materials, which are needed to produce the outputs, such as services provided to customers and number of deposit and loan accounts can be used assess the level of services provided (Moffat, 2008). The intermediation approach on the other hand considers banks as a financial intermediaries that buys inputs, in order to generate earning assets. Therefore the approach includes operating and interest expense as inputs whilst loans and other major assets count as outputs.

In this approach the intermediation approach will be adopted, with output vector comprising; (i) total loans and advances (ii) investment. The input vectors includes; (i) physical capita- fixed asset, and (ii) labour – number of employees. A vector consisting of prices of; (i) labour and (ii) capital was added to estimate cost efficiency. These output variables are commonly applied in other literature, (See Berger et.al (2009) Chang et al. (2012) and Nitoi et al. (2016).

In line with best practice and to get a good discriminatory power, Boussofiane et al. (1991) argues the lower bound on the number of DMU should be a multiple of a number of the number of inputs and outputs. This enables flexibility in the selection of weights assigned in input and output values in determining the efficiency of each DMU. Therefore the analysis employs 2 inputs x 2 outputs < 5 DMU's.

The samples focus on five DFIs-the Industrial Development Corporation (IDC), the Development Bank of Southern Africa (DBSA), SEFA, the Land Bank, and the National Housing Finance Corporation (NHFC)—which have the mandates to contribute to the construction of a developmental state (Khadiagala, 2011). Data is extracted from the annual financial statements with the chosen period selected based on the availability of the statements. According to the descriptive statistics in Table 1, all variable present a clear pattern of differences in line with their respective mandates and development objective.

3.2.1 Input and output variables

The choice of output and input is the most challenging across the literature and there is no consensus that exists. The task becomes more daunting than in case of conventional banking given a limited number of efficiency studies within a non-deposit taking DFIs. The associated measure of success within the DFIs is the achieved development and measured mostly by the number of firms and jobs created successfully. However the numbers on their own present a further challenge as the lower number of jobs in the NHFC case is not indication of bad outcome given its mandate, whilst the same lower number in IDC's case represent a bad developmental outcome.

Table 1: Descriptive statistics in Rand million (2010-2017)

	Loans and advance	**Investments**	**Physical Capital**	**Labour**	**Price capital**	**Price labour**
DBSA	47 797	4 633	463	552	0,45	1,13
IDC	14 208	42 353	323	794	10,38	1,00
SEFA	302	31	181	166	0,32	0,50
Land bank	25 800	430	189	555	2,89	0,60
The NHFC	1 621	5	1	77	18,90	0,58

In their analysis, Fu and Heffernan (2007) exclude non-performing loans in the cost function as they argue that they are caused endogenously due to a poor risk management framework, cutting back on screening and monitoring, or making loan decisions without anticipating changes in the business cycle. The developmental agenda necessitate the deduction of non-performing loans from loans and advances as lending decisions are made based on the mandate not the conventional credit assessment. Therefore for the purpose of this study, non-performing loans were deducted from loans and advances.

Pasiouras (2006) rightly argues that comparison of bank's performance should be conducted among banks with the same output quality. However, it is possible to have unmeasured differences in quality because the banking data may not fully capture the heterogeneity in bank output. These differences may not be captured by the output quantity in the model. Mester (1996) suggest that quality and risk should be controlled otherwise the level of inefficiencies might be miscalculate. Banks scrimping on credit evaluations or producing excessively risky loans might be labelled as efficient when compared to banks spending resources to ensure their loans are of higher quality (Mester, 1996). The majority of studies uses investment and loans & advances as output factors in determining efficiencies, however for the DFIs in SA the investment is used mainly as a source for sustainability or strategic investment decision. The inputs selected are consistent with the intermediation approach and are deemed appropriate for the DFIs. Further the price of input factors were added to measure the cost efficiencies.

3.2.2 Risk factors that affect efficiencies

Another important task in this analysis is to assess the factors driving the cost and technical inefficiencies of the DFIs. The assumption in efficiency studies is that producers share the same technology and face the same environmental factors (Shen, 2009). However the assumption might not hold, especially for DFIs where their mandate are driven by completely different developmental agendas. Although no consensus exist in the literature about the choice of variables, the common risk specific factors are considered for this analysis in line with the objective of the study. These includes the Z-score, profitability indicators, loan to deposit ratio and credit risk quality factors.

Table 2: Descriptive statistic: Explanatory variables (Averages)

	Z Score	**ROA**	**ROE**	**NIM**	**Loan/deposit**
DBSA	22,1	1,1%	2,8%	45,2%	2,1
IDC	67,9	1,6%	1,6%	65,2%	0,7
SEFA	3,2	-9,8%	-22,3%	64,3%	0,7
Land bank	42,5	0,9%	5,1%	37,4%	1,1
NHFC	60,8	0,3%	0,5%	90,2%	31,7

The Z-score is the most applied accounting based measure of the bank risk and this measure according to Boyd et al. (1993) has been conceived from the concept of banks probability of default. The principal of the measure is to relate capital level to variability as measured by the standard deviation of returns and the returns as follows;

$$Z - Score = \ ROA + EQ/TASD(ROA)$$

Hakennes et al. (2015) used z-score as a bank efficiency proxy and found that high risk taking banks corresponding to lower z-score and thus are less efficient in capital allocation. The banks performance is measured by ROE, NIM and loans to deposit ratio (short term funding used as a proxy for deposit). Banks with high profitability rate are deemed more efficient as reflected by high ROE. Alharthi (2016) found a positive significant relationship of profitability on efficiency of Islamic, conventional and socially responsible banks. The loans to deposit ratio considers the efficiencies of the intermediation process (Fries and Taci, 2005). Therefore a low ratio indicates banks' inability to transform deposit into loans and a higher ratio indicates efficiency. Banks with higher ratio are usually associated with higher risk and according to Angelidis and Lyroudi (2006) they are the most efficient. That is, the higher the ratio, the better could the banks carry there intermediation optimally. Williams and Nguyen (2005) defines the ratio as a measure of liquidity risk. Higher ratios indicates increased liquidity risk for banks but positive relation with liquidity. Given that the South African DFIs are non-deposit taking, short term funding was used as a proxy for deposit in this analysis. The majority of the literature under efficiency have either assessed the determinants of CE or TE, few attempts have been made to study both like in Mathew and Sangeetha (2016). Therefore the study intends to examine the efficiency by testing the hypothesis that both TE and CE scores of the South African DFI is influenced by selected risk factors.

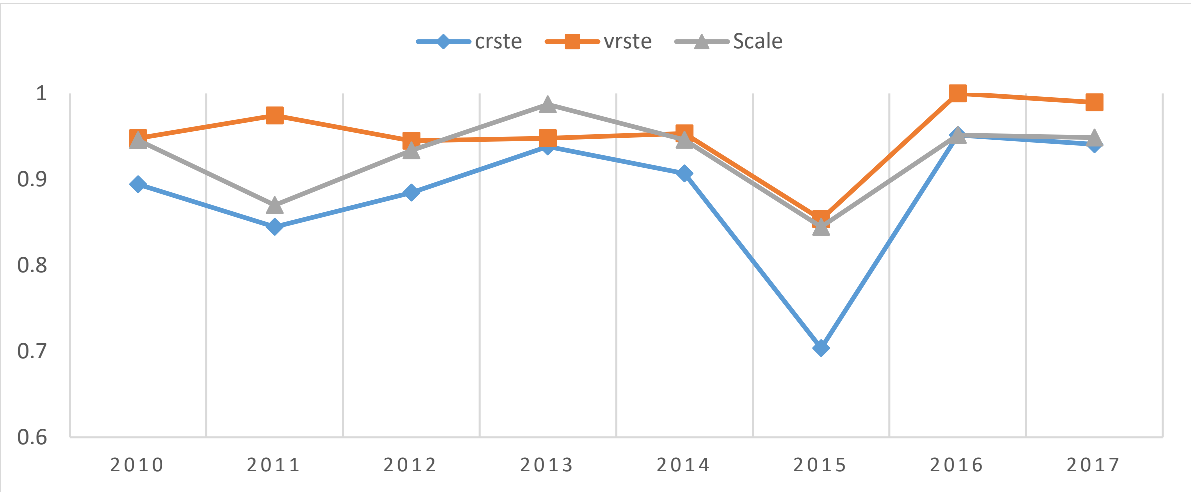
Chapter Four: Results and discussions

The following section presents the results of the analysis based on the principles of the methodological framework set above and in line with the reviewed literature. The first section presents the efficiency scores, followed by analysis on the determinants of efficiency. The last section of the results present the findings regarding the productivity analysis.

4.1 Technical efficiency under multi-stage method

The results are based on an input oriented DEA model under VRS using slacks calculated using multi-stage method. The input orientation is deemed appropriate as the managers have more freedom to change input factors of production than changing the outputs. To understand the causes of inefficiencies, the CRSTE scores are decomposed into VRSTE and SE. As indicated in the above literature, the efficiency corresponding to VRSTE indicates technical inefficiency emanating from non-scale factors, also referred to as PTE.

Figure 4: Efficiency scores



The average CRTSE scores of the South African DFIs have been stable across the years with the least score observed in 2015 and the most in 2016. The stability of the scores over time implies that effort has been made across the DFIs on average to decrease the levels of inefficiencies by employing best practice technology.

On average the PTE and SE has maintained a score of 95% and 93% respectively across the years. Therefore the level of inefficiencies is mostly attributable to the size of the DFIs more than the managerial inefficiencies. The mean scores dropped to their lowest in 2015 under CRTSE and the DBSA and NHFC being the major contributor. According to Table 3 the observed decline in 2015 was mainly attributable to DBSA's managerial competencies where the VRSTE declined to 26%.

Table 3: Variable Returns to Scale Technical Efficiency

	2010	2011	2012	2013	2014	2015	2016	2017
DBSA	0,740	1,000	1,000	1,000	1,000	0,268	1,000	0,948
IDC	1,000	0,872	1,000	0,739	0,768	1,000	1,000	1,000
SEFA	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Land bank	1,000	1,000	0,725	1,000	1,000	1,000	1,000	1,000
NHFC	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000

Table 4 below highlight the results under input oriented VRS assumption. The results shows that for the period 2015 SEFA and NHFC exhibit decreasing returns to scale while DBSA showed increasing returns to scale. The implication for SEFA and NHFC is that a reduction in scale or size would increase the efficiency whilst DBSA can gain efficiency by increasing production.

Table 4: Scale efficiencies

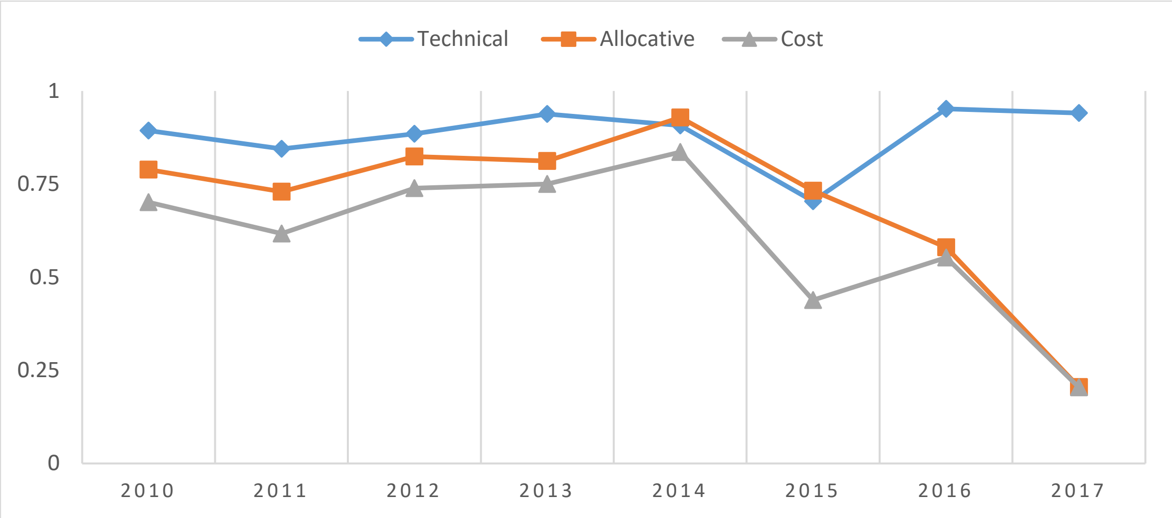
	2010	2011	2012	2013	2014	2015	2016	2017
DBSA	0,99 (irs)	1,00	1,00	1,00	1,00	0,964 (irs)	0,758 (drs)	0,744 (irs)
IDC	1,00	0,994 (irs)	0,777 (drs)	0,936 (irs)	0,843 (irs)	1,00	1,00	1,00
SEFA	0,74 (irs)	0,616 (irs)	1,00	1,00	1,00	0,977 (drs)	1,00	1,00
Land bank	1,00	0,741 (drs)	0,891 - (irs)	1,00	1,00	1,00	1,00	1,00
NHFC	1,00	1,00	1,00	1,00	0,887 (drs)	0,283 (drs)	1,00	1,00

The results above indicate that the DFIs inefficiencies are attributable to the scale of operations more than managerial capabilities over the years of consideration. The lowest seen average was observed in 2015 for NHFC at 28% implying that inefficiencies across the industry was driven by NHFC.

4.2 Cost efficiency DEA

The TE of the DFIs are estimated using the input oriented DEA model and Figure 4 present the results. From 2014 there has been substantial decline in CE and AE levels for the period considered. This indicates an increasing level of allocative and costs inefficiencies across DFIs in SA. Since 2010, the mean CE reduced from 70% to 20% on average and the AE levels reduced from 79% to 20% over the same period. The inefficiency levels increased from almost 20% to 80% over the considered period. This implies that the DFIs have not employed the best practices in the intermediation operations to achieve the maximum outputs with minimum input costs. However, the DFIs could have achieved considerable cost savings with proper allocation and efficient use of resources.

Figure 5: Mean efficiency scores



Further analysis of the mean scores reveal that IDC and SEFA from 2015 could not allocate resources optimally. The worst scores were observed for all the DFIs with the exception of IDC in 2017. This implies that the DFIs on average needs to minimize the inputs costs to achieve allocative efficiency.

Table 5: Allocative efficiency scores over time

	2010	2011	2012	2013	2014	2015	2016	2017
DBSA	0,661	0,563	0,542	0,597	0,645	1,000	0,549	0,015
IDC	0,840	0,805	1,000	1,000	1,000	0,444	0,188	1,000
SEFA	1,000	1,000	1,000	1,000	1,000	0,214	0,161	0,001
Land bank	0,443	0,284	0,580	1,000	1,000	1,000	1,000	0,002
NHFC	1,000	1,000	1,000	0,461	1,000	1,000	1,000	0,008
Mean	**0,789**	**0,730**	**0,824**	**0,812**	**0,929**	**0,732**	**0,580**	**0,205**

The overall mean score suggest that the DFIs have been cost inefficient since 2010. The lower levels could be attributed to inappropriate selection of the optimal combination of inputs given the prices, technology and wastage of resources. The DFIs have not employed best practice in intermediation operations to achieve maximum input with minimum costs inputs. Therefore with proper allocation of resources and efficient use of resources, the DFI can achieve considerable cost savings.

Table 6: Cost efficiency score over time

	2010	2011	2012	2013	2014	2015	2016	2017
DBSA	0,485	0,563	0,542	0,597	0,645	0,258	0,417	0,010
IDC	0,840	0,698	0,777	0,692	0,648	0,444	0,188	1,000
SEFA	0,737	0,616	1,000	1,000	1,000	0,209	0,161	0,001
Land bank	0,443	0,210	0,374	1,000	1,000	1,000	1,000	0,002
NHFC	1,000	1,000	1,000	0,461	0,887	0,283	1,000	0,008
Mean	**0,701**	**0,617**	**0,739**	**0,750**	**0,836**	**0,439**	**0,553**	**0,204**

The overall results indicate the allocation of resources efficiently and maintaining the minimum cost in the intermediation process, both needs to be maintained in order for DFIs to be technically efficient. Consistently across the years of analysis, the cost efficiency has been the lowest, implying increased focus/policy needs to be devoted in the way resources are distributed.

4.3 Determinants of efficiency

The important second objective of the paper is to emphasize the link between risk and efficiency in the DFI space. In addition to the risk factors, the operating variables were also used in estimating the factors that determine efficiencies. The operating variables such as investment, loans and advances, physical capital, labour and their prices were used in the analysis.

The results suggests no link exists between efficiency and the chosen risk factors. Only the loan-to-deposit ratio was significant with positive coefficient. This implies that the efficiency, both TE and CE, increases with an increase in loan-to-deposit ratio. The finding suggests that liquidity is important in facilitating efficiency within the DFIs. The insignificant profitability parameters, as measured by the ROE, ROA and NIM, implies that the profitability is not important in facilitating efficiency but might be important for sustainability. Turning to the risk of failure as measured by the Z-score, the evidence of no link to efficiency asserts the developmental mandate of the DFIs as a state instrument to forge the needs.

Table 7: Determinants of the CE scores using risk factors (Refer to Appendix for TE results)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LOAN_DEPOSIT	0.007574	0.004321	1.753057	0.0796
NIM	-0.381567	0.362713	-1.051981	0.2928
ROA	-0.684299	1.457064	-0.469643	0.6386
ROE	-0.992569	0.690622	-1.437211	0.1507
Z_SCORE	0.003521	0.002169	1.623597	0.1045
C	0.610937	0.170066	3.592347	0.0003

Further, according to Table 8 below, the analysis using the operating variables suggests the link between cost efficiencies and capital, short-term funding and their respective prices. An increase in capital and its price increases with inefficiencies. Thus CE reduces for an extra unit of capital and its price while funds and their prices increases with CE. A positive relationship between the funds implies that DFI should direct their focus in increasing funding for loans and advances so as to improve efficiencies.

Table 8: Determinants of CE scores using operating factors

Variable	Coefficient	Std. Error	z-Statistic	Prob.
INVESTMENTS_SHARES	0.000692	0.000649	1.065648	0.2866
LABOUR	-0.023781	0.047817	-0.497332	0.6190
LOANS_N_ADVANCE	-0.000959	0.000786	-1.220014	0.2225
PHYSICAL_CAPITAL	-0.192931	0.083301	-2.316058	0.0206
PRICE_CAPITAL	-0.026310	0.011395	-2.308939	0.0209
PRICE_FUNDS	0.960117	0.428754	2.239320	0.0251
PRICE_LABOUR	0.376040	0.256702	1.464892	0.1430
ST_FUND	0.002015	0.000833	2.418010	0.0156
C	0.656814	0.191753	3.425303	0.0006

The determinant of TE are represented in Table 9 below. The results indicate that TE has been determined by all variables expect for short term funding, fixed assets and their prices. Furthermore the price of funds and labour contributed positively towards TE and negatively to investment and loans. That is the development institutions with higher loans and advances and investment tend to exhibit lower technical efficiencies scores.

Table 9: Determinants of the TE scores using operating variables

Variable	Coefficient	Std. Error	z-Statistic	Prob.
INVESTMENTS	-0.000951	0.000359	-2.652996	0.0080
LABOUR	0.072239	0.026410	2.735352	0.0062
LOANS_N_ADVANCE	-0.001226	0.000434	-2.823547	0.0047
PHYSICAL_CAPITAL	0.001021	0.046008	0.022188	0.9823
PRICE_CAPITAL	-0.003377	0.006293	-0.536598	0.5915
PRICE_FUNDS	0.396756	0.236803	1.675474	0.0938
PRICE_LABOUR	0.279136	0.141777	1.968837	0.0490
ST_FUND	-0.000130	0.000460	-0.282787	0.7773
C	0.669641	0.105906	6.322966	0.0000

Based on the above findings, it can be stated that the both CE and TE are influenced by operating variables. The price of funds influence TE more than the price of labour which implies that the price of funds is important than labour for a firm to obtain maximal output from a given set of inputs. In terms of the positive relationship with liquidity, the DFIs needs to increase and maintain acceptable levels to drive cost and technical efficiencies

4.4 Malmaquist Productivity Index

This section looks at the changes in productivity, efficiency and technology for DFIs over the period 2010-2017. A balance panel data with 240 observation over 8 years were employed to calculate the MPI index which is based on a DEA technique. The change in TFP entails the change in technical efficiency change, referred to as catching-up effect and frontier shift effect referred to as a change in technology. Technical efficiency change (TEC) is further decomposed into PE and SE which aids in providing information on the overall sources of efficiencies. Therefore a value greater than one indicates improvement/progression while a value less than one indicates deterioration.

Table 10: Malmquist index summary of annual means

	effch	techch	pech	sech	tfpch
2011	0,939	1,178	1,033	0,909	1,107
2012	1,049	1,073	0,964	1,088	1,125
2013	1,066	0,904	1,004	1,062	0,964
2014	0,963	0,550	1,008	0,956	0,530
2015	0,659	0,897	0,810	0,813	0,591
2016	1,604	1,402	1,301	1,233	2,249
2017	0,986	3,823	0,989	0,996	3,768
mean	**1,008**	**1,171**	**1,007**	**1,001**	**1,180**

Based on the results presented in Table 10, on average there is an overall improvement TFP across the DFIs. For 2013-2015 period, there was a deterioration in TFP change and this was mainly driven mainly by technological regress. Thereafter there was an increase which reflects that DFIs were now embarking on the use of technology to deliver services. This finding is supported by Deliktas (2002) that total factor productivity depends on improvement of both efficiency change and technological change to achieve optimal levels.

Table 11: Malmquist index summary of firm means

	effch	techch	pech	sech	tfpch
DBSA	0.994	0.910	1.036	0.960	0.905
IDC	1.000	2.319	1.000	1.000	2.319
SEFA	1.045	1.371	1.000	1.045	1.432
Land bank	1.000	0.765	1.000	1.000	0.765
NHFC	1.000	0.995	1.000	1.000	0.995
mean	**1.008**	**1.171**	**1.007**	**1.001**	**1.180**

Turning to the individual changes, Table 6 above shows improvement in productivity change across the industry was mainly driven by IDC and SEFA. Whilst NHFC, Land bank and DBSA shows loss in productivity. Still the major factor affecting the loss in productivity is found to be lack of improvement in technological change. The majority of the institutions have not embarked on the use of new technologies in their delivery of services. In terms of the catching up effect measured by efficiency change, only DBSA is failing behind and the rest of the DFIs are neither improving nor deteriorating.

Figure 6: Malmaquist Index of firms

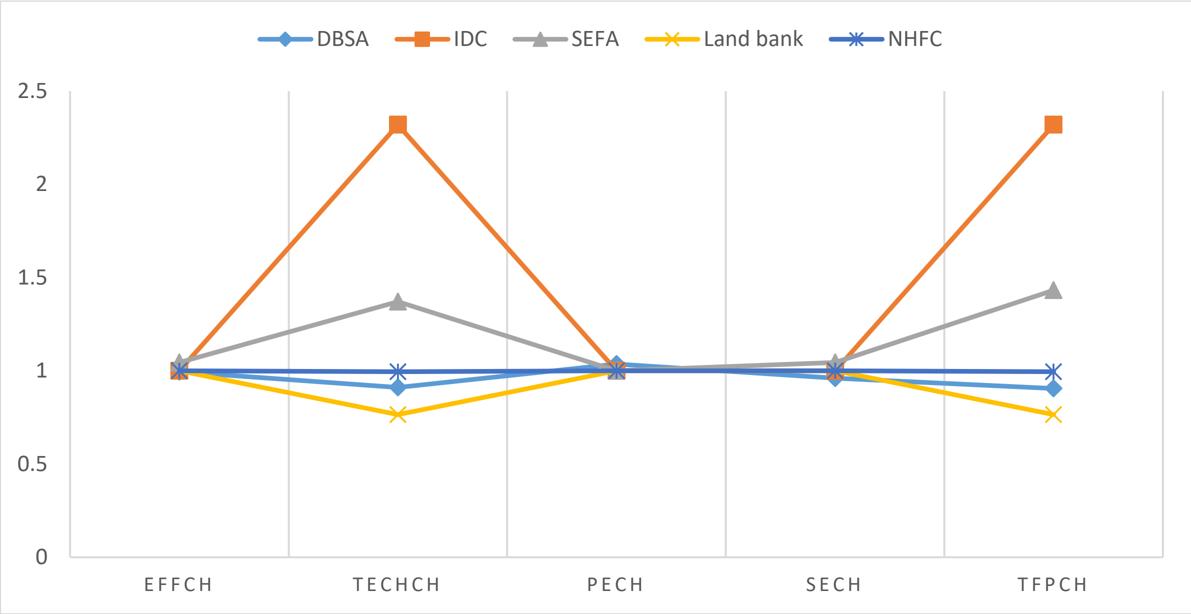


Figure 5 above shows that movements in total factor productivity change are highly influenced by technological change. Therefore, despite the caution in generalizing, technological adoption may prove to be a vital source of productivity gain across the DFIs. Land bank has shown technological regress which ultimately resulted to TFP loss.

Chapter Five: Conclusion

The paper assessed the relationship between efficiency, risks and productivity patterns, within the DFIs. Principally the main area of interest is understanding the relationship between risk that DFIs are mandated to take and their effect on efficiency levels. In an effort to assess this relationship, significant amount of literature was explored on the measurement of efficiency and productivity across the banking sector. Through literature, evidence was found that supports the link between efficiencies and risk particularly in the banking sector.

Turning to empirical results, the analysis revealed firstly that cost and the ability to allocate resources were the major sources of inefficiencies. Operational inefficiencies, poor procurement practices, weak corporate governance and failures to abide by fiduciary obligations have plagued DFIs into serious financial difficulty. This was mostly the case in 2015, where economy slumped in the second quarter to negative growth, the cost inefficiencies were mainly exacerbated by the counter cyclical role of the DFI. From the analysis of returns-to-scale, it has been noticed that SEFA and NHFC were operating in the zone of decreasing returns-to-scale implying a need to downsize in their operations to observe an efficiency gains during the same period.

The second objective of the paper emphasize the determinants of CE and TE using the risk based factors. The analysis reveals that the nexus between risk and efficiency does not exists for the South African DFIs. The finding is not surprising as the majority of the DFI in SA are government funded to assume a certain risk in an effort to achieve the developmental goal. Therefore the assumption that risk is an important factor when evaluating efficiencies does not hold for the SA DFIs.

Exploring the second set of variables, which were not even core of this analysis, we found that both inefficiencies are influenced by choosing inappropriate mix of inputs and output.. The finding that TE and CE are both positively influenced more by the price of funds than the price labour, implies that policy makers should deploy resources in obtaining cheaper source of funds first than employing labour to be efficient. Therefore, it is clear that development objectives comes at the cost and the cheaper sources of funding should be priority in order to increases efficiency.

In terms of productivity patterns, most DFIs have been stagnant and operate without an improvement in efficiency change in terms of management ability and technological advancement. The major driver behind the improvement in productivity was technological improvement. IDC and SEFA outperformed all other DFIs in total factor productivity changes, brought by changes in best practice given that SEFA is a subsidiary of the IDC.

A number of important policy implications arise from the results of the study. Firstly, the price of funds more than the price of labour influences efficiencies across the DFIs. As a consequence, directed efforts to source cheaper funding should be put in place by policy makers in order for the DFIs to perform at their optimal levels to achieve on their mandates. Secondly, productivity performance constrain DFIs ability to function at an optimum potential to achieve their developmental mandate. As a consequence, policy marker will need to rethink ways to improve technological advancement within the DFIs.

The study has made a major contribution in the analysis of efficiency and productivity, whilst taking risk into account, in South African DFIs using the DEA and Malmauist productivity indices. However, the study can be improved by employing firstly the multi-dimensional efficiency index to measure productivity; and lastly incorporate inputs that assess the efficiency in relation to sustainability of the DFI.

Reference

Abu Alkhail, A.M., Burghof, H., Khan, W. A., (2012). Islamic commercial banking in Europe: a cross country and interbank analysis of efficiency performance. International Business and Economics Research Journal, 11(6), 647-676

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

Alharthi, M. (2016). A comparative study of efficiency and its determinants in Islamic, conventional, and socially responsible banks. Corporate Ownership & Control. Volume 13, Issue 4.

Angelidis, D and Lyroudi, K. (2006). Measuring banking productivity of the most recent European Union member countries; a non-parametric approach. Journal of Economics and Business Vol. IX – 2006, No 1 (37-57)

Aziakpono, M. & Marwa, N. (2015). Efficiency and sustainability of Tanzanian saving and credit cooperatives. PhD candidate in Development Finance at University of Stellenbosch Business School, South Africa

Banker, R. D., Charnes, R. F., & Cooper, W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science, 30, 1078–1092.

BAR (Benefit Advisory Research). (2006). Generic development finance institutional framework. Paper prepared for the Development Bank of Southern Africa.

Boussofiane A, Dyson RG and Thanassoulis (1991). Applied data envelopment analysis. European Journal of Operational Research 52(1); 1-15

Berg, S. A., F. Forsund, and E. Jansen, (1992). Malmquist Indices of Productivity Growth during the Deregulation of Norwegian Banking, 1980-89. Scandinavian Journal of Economics,94: S211-S228

Berger and Humbery, (1997). Efficiency of Financial Institutions: International Survey and Directions for Future Research. Forthcoming in European Journal of Operational Research, 1997, Special Issue on “New Approaches in Evaluating the Performance of Financial Institutions”

Berger, A.N., Mester, L.J., (1997). Inside the black box: what explains differences in the efficiencies of financial institutions? J. Bank. Finance 21 (7), 895-947.

Caves, D., Christensen, L. Diewert, W.E., (1982). The economic theory of index numbers and measurement of input, output, and productivity. Econometrica, 50 (6), 1393-414

Calice, P. (2013). African Development Finance Institutions: Unlocking the Potential, Working Paper Series N0 174 African Development Bank, Tunis, Tunisia.

Chang, T.P. Hu, J. L. Chou, R.Y. and Sun, L., (2012). The sources of bank productivity growth in China during 2002–2009: A disaggregation view. Journal of Banking and Finance, 36, pp. 1997-2006.

Coelli, T., Rao, D., O'Donnell, C., & Battese, G. (2005). An Introduction to Efficiency and Productivity Analysis. Springer Science & Business Media.

Daraio, C., & Simar, L. (2007). The measurement of efficiency. In advanced robust and non-parametric methods in efficiency analysis. Springer.

Denizer, C., Dinc, M., Tarimcilar, M., (2007). Financial liberalization and banking efficiency: evidence from Turkey. Prod. Anal 27, 177-195.

DeYoung, R. (1997) A diagnostic test for the distribution-free efficiency estimator: An example using U.S. commercial bank data, European Journal of Operational Research, 98, 243- 249.

Dipasha Sharma Anil K. Sharma and Mukesh K. Barua (2013) Efficiency and Productivity of Banking sector A critical analysis of literature and design of conceptual model. Qualitative Research in Financial Markets Vol. 5 No. 2, 2013 pp. 195-224

Diewert W.E. 1976, "Exact and Superlative Index Numbers", Journal of Econometrics, Vol. 4 pp.114 - 145

Evanoff, D. D., &. Israilevich, P.R (1991). Productive efficiency in banking, Economic Perspectives. Federal Reserve Bank of Chicago, 11-32.

Eken, M. & Kale, S. (2013). Evaluating the efficiency of Turkish banks: A risk and profitability approach. The Business and Economics Research Journal, Volume 6, Issue 1, 2013, 53- 68

Favero, C., & Papi, L. (1995). Technical efficiency and scale efficiency in the Italian banking sector: a non-parametric approach. Applied Economics, 27, 385-395.

Farrell, M. J. (1957). The Measurement of Productive Efficiency. Journal of the Royal Statistical Society, Series ACXXPart3:253-290

Favero, C., & Papi, L. (1995). Technical efficiency and scale efficiency in the italian banking sector:a non-parametric approach. Applied Economics, 27, 385-395.

Fischer, I. (1922). The making of Index numbers. Houghton-Miflin. Boston, MA

Fries, S. and Taci, A., (2005). Cost efficiency of banks in transition: Evidence from 289 banks in 15 post-communist countries. Journal of Banking and Finance, 29, pp. 55–81.

Färe, R., Grosskopf, S., Norris, M. and Zhang, Z. (1994b). Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries. The American Economic Review, vol. 84, no. 1, pp. 66-83.

Fu, X. and Heffernan, S. (2007). Cost X-Efficiency in China's Banking Sector. China Economic Review, vol. 18, no. 1, pp. 35-53.

Galbis, V., (1977). Financial intermediation and economic growth in less developed countries: A theoretical approach. Journal of Development Studies, 13 – 2: 58-72.

Guzowska, M., Strak T., (2010). An examination of the efficiency of Polish Public Sector Entities based on Public Prosecutor Offices. Operations Research and Decisions, 2(1), 41-47.

Han, Y., Kim, H.M., Kim, W. Joong, (2012). Determinants of profit efficiency: Evidence from Korean savings banks. Applied Financial Economics, 22(12), 1003-1016

Hakan, G. & Yildirim, D. (2016). Estimating cost efficiency of Turkish commercial banks under unobserved heterogeneity with stochastic frontier models. Central Bank Review 16 (2016) 127e136 https://www.journals.elsevier.com/central-bank-review/

Hakennes, H., Hasan, I., Molyneux, P., and Xie, R. (2015). Small banks and local economic development. Review of Finance, 19(2), 653-683.

Heshmati, A., (2001). Productivity Growth, Efficiency and Outsourcing in Manufacturing and Service Industries. SSE/EFI Working Paper, No. 394, October.

Kariuki, P.W. (2017). Financial intermediation efficiency and productivity of deposit taking Savings and Credit Cooperative Societies in Kenya: A Data Envelopment Analysis. Journal of Emerging Issues in Economics, Finance and Banking. An Online International Research Journal (ISSN: 2306-367X) 2017 Vol: 6 Issue: 1

Kočišová, K. (2014). Application of Data Envelopment Analysis to Measure Cost, Revenue and Profit Efficiency. Statistika, 94(3), 47-57.

Kumar, S., & Gulati, R. (2008). An Examination of Technical , Pure Technical , and Scale Efficiencies in Indian Public Sector Banks using Data Envelopment Analysis. Eurasian Journal of Business and Economics, 1(2), 33–69.

Katib, M and Yadav, R., (2015). Technical Efficiency of Malaysia's Development Financial Institutions: Application of Two-Stage DEA Analysis. Asian Social Science; Vol. 11, No. 16;

Koopmans, T. (1951). Analysis of Production as An Efficient Combination of Activities" in Activity Analysis of Production and Allocation, ed. T.C. Koopmans, Cowles Commission for Research in Economics, Monograph no. 13, New York, pp. 33-97.

Kumbhakar, S.C., Lozano-V., Lovell,C. and Hasan, I. (2001). The Effects of Deregulation on the Performance of Financial Institutions: The Case of Spanish Savings Banks. Journal of Money, Credit and Banking, vol. 33, no. 1, pp. 101-20.

Lee, C. & Ji, Y. (2013). Data Envelopment Analysis in Stata: User written commands. Available online at http://sourceforge.net/projects/deas/files/dea/

Leibenstein, H. (1966). Allocative Efficiency Vs. X- Efficiency. The American Economic Review, Volume 56, Issue 3 (June 1966), pp 392 -415.

Lewin, A., & Lovell, C. (1990). Editor's introduction. Journal of Econometrics, 46 (1-2), 3-5.

Luccheti, R., Papi, L., & Zazzaro, A. (2000). Banks' efficiency and economic growth: a micro-macro approach. Italy: Universita di Ancona.

Lepetit, L. Nys, E. Rous, P. and Tarazi, A., (2008b). The expansion of services in European banking: Implications for loan pricing and interest margins. Journal of Banking and Finance, 32, pp. 2325-35.

Malmquist, S. (1953). Index numbers and indifference surfaces. Trabajos de Estadistica Y de Investigacion Operativa, 4(2), 209–242.

Mathew, J. & Sangeetha, R., (2016). Impact of Financial Crisis on the Sustainability of Public Sector Banks in India - A Data Envelopment Analysis. Journal of Economics and Finance. Volume 7, Issue 2. Ver. II (Mar. - Apr. 2016), PP 32-38.

Mette, A., Baležentis, T., Leth Hougaard, J., (2016). Multi-directional productivity change: MEA-Malmquist. Journal of Productivity Analysis. December 2016, volume 46, Issue 2-3, pp 109-119.

McDonald, J., (2009). Using least squares and tobit in second stage DEA efficiency analyses. European Journal of Operational Research, 197, pp. 792-798.

Mckean, S. (1990). Development Finance Institutions: a discussion of donor experience, A.I.D. program evaluation discussion paper no. 31. Washington, D.C.: A.I.D. February 1990.

Moffat, B.D. (2008). 'Efficiency and productivity in Botswana's Financial Institutions'. PhD Thesis presented at University of Wollongong.

Moffat, B.D. & Valadkhani, A. (2008). Technical efficiency in Botswana's Financial Institutions: a DEA approach. University of Wollongong, WP 08-14.

Maudos, J. and de Guevara, J. F., (2004). Factors explaining the interest margin in the banking sectors of the European Union. Journal of Banking and Finance, 28, pp. 2259-2281.

Nishimizu, M., Page, J,. (1982). Total factor productivity growth, technological progress and technical efficiency change: Dimensions of productivity change in Yugoslavia, Economic Journal pp. 920-936

Ondrej, M., Jiri, H (2012). Total factor productivity approach in competitive and regulated world. Procedia Soc. Behav. Science 57, pp223-230

Qunta, N.Z. (2015). A review of the effectiveness of development finance institutions in KwaZulu-Natal, Wits School of Governance. http://hdl.handle.net/10539/21577

Rikhotso K (2016). Assessing the Financial Sustainability of South African Development Finance Institutions: Stellenbosch University https://scholar.sun.ac.za

Roy, D. (2014). Analysis of technical efficiency of Indian banking Sector: An Application of Data Envelopment Analysis. International Journal of Finance & Banking Studies. Vol.3 No.1, 2014. Available online at www.ssbfnet.com

Sarmiento, M ., & Jorge, E. (2015). The influence of risk-taking on bank efficiency: evidence from Colombia. The Working Paper Series No 1537, banco de España, Madrid, 2015.

Simar, L. & Wilson, P.W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. Journal of econometrics, 136, pp. 31-64.

Schmidt, P. and Sickles, R. (1984) Production frontiers and panel data. Journal of Business and Economic Statistics, 2, 367-374.

Spulbar, C. & Nitoi, M. (2014). Determinants of bank cost efficiency in transition economies: evidence for Latin America, Central and Eastern Europe and South East Asia.

Shen Zhi (2009) Efficiency and Productivity Analysis in Ten

The World Bank, (1989a). The Sustainability of Development Finance Institutions in an Evolutionary Environment. Vol. 1 and 2. Washington, D.C.: World Bank. May 15.

The World Bank, (1989b). World Development Report 1989. Washington D.C.: Oxford University Press.

Talluri, S. (2000). Data Envelopment Analysis. Silberman College of Business. Decision Line, 31(3), 8–11.

Vanheerden and Van erwesthuizen, C (2008). The cost of banking services and the technical efficiency of a South African bank: The Journal for Trans disciplinary Research in Southern Africa, Vol. 4 no. 2, December 2008, pp. 401-417.

Williams, J. (2012). Efficiency and market power in Latin American banking. J. Financ Stab. 8 (4), 263e276

Yadav, R., & Katib, M. N. (2015). Technical Efficiency of Malaysia's Development Financial Institutions : Application of Two-Stage DEA Analysis. Asian Social Science, 11(16), 175–182

Zheng, W. (2015). Efficiency measurement. A methodological comparison of parametric and non-parametric approaches. University of Bradford, online publication URI http://hdl.handle.net/10454/7294

Zuzana, I., & Havránek, T. (2010). Measuring Bank Efficiency: A Meta-Regression Analysis. Prague Economic Papers, University of Economics, Prague, vol. 2010(4), pages 307-328.

Appendix

6.1. Input and output variables used in DFIs

	Output	**Inputs**
Mathew and Sangeetha (2016)	Loans and advance Investment	Physical capital Labour Loanable funds
Gulati and Kumar (2008)	Net-interest income Non-interest income	Physical capital Labour Loanable funds
Katib and Yadav (2015)	Loans and advance Investment	Total deposit Total expenses
Kariuki (2017)	gross loans investments	total deposits, labour cost core capital
Aziakpono and Marwa (2015)	Total Loan Portfolio	Total Cost Total Fixed Asset Total Deposit

6.2. Efficiency results

Technical efficiency scores over time

	2010	2011	2012	2013	2014	2015	2016	2017
DBSA	0,734	1,000	1,000	1,000	1,000	0,258	0,758	0,705
IDC	1,000	0,867	0,777	0,692	0,648	1,000	1,000	1,000
SEFA	0,737	0,616	1,000	1,000	1,000	0,977	1,000	1,000
Land bank	1,000	0,741	0,646	1,000	1,000	1,000	1,000	1,000
NHFC	1,000	1,000	1,000	1,000	0,887	0,283	1,000	1,000
Mean	**0,894**	**0,845**	**0,885**	**0,938**	**0,907**	**0,704**	**0,952**	**0,941**

Allocative efficiency scores over time

	2010	2011	2012	2013	2014	2015	2016	2017
DBSA	0,661	0,563	0,542	0,597	0,645	1,000	0,549	0,015
IDC	0,840	0,805	1,000	1,000	1,000	0,444	0,188	1,000
SEFA	1,000	1,000	1,000	1,000	1,000	0,214	0,161	0,001
Land bank	0,443	0,284	0,580	1,000	1,000	1,000	1,000	0,002
NHFC	1,000	1,000	1,000	0,461	1,000	1,000	1,000	0,008
Mean	**0,789**	**0,730**	**0,824**	**0,812**	**0,929**	**0,732**	**0,580**	**0,205**

CE score over time

	2010	2011	2012	2013	2014	2015	2016	2017
DBSA	0,485	0,563	0,542	0,597	0,645	0,258	0,417	0,010
IDC	0,840	0,698	0,777	0,692	0,648	0,444	0,188	1,000
SEFA	0,737	0,616	1,000	1,000	1,000	0,209	0,161	0,001
Land bank	0,443	0,210	0,374	1,000	1,000	1,000	1,000	0,002
NHFC	1,000	1,000	1,000	0,461	0,887	0,283	1,000	0,008
Mean	**0,701**	**0,617**	**0,739**	**0,750**	**0,836**	**0,439**	**0,553**	**0,204**

6.3. Tobit model results: Operating factors

Dependent Variable: CE_SCORE
Method: ML - Censored Normal (TOBIT) (Quadratic hill climbing)
Date: 01/27/18 Time: 20:20
Sample: 2010 2017
Included observations: 40
Left censoring (value) at zero
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
INVESTMENTS_SHARES	0.000692	0.000649	1.065648	0.2866
LABOUR	-0.023781	0.047817	-0.497332	0.6190
LOANS_N_ADVANCE	-0.000959	0.000786	-1.220014	0.2225
PHYSICAL_CAPITAL	-0.192931	0.083301	-2.316058	0.0206
PRICE_CAPITAL	-0.026310	0.011395	-2.308939	0.0209
PRICE_FUNDS	0.960117	0.428754	2.239320	0.0251
PRICE_LABOUR	0.376040	0.256702	1.464892	0.1430
ST_FUND	0.002015	0.000833	2.418010	0.0156
C	0.656814	0.191753	3.425303	0.0006
Error Distribution				
SCALE:C(10)	0.290959	0.032529	8.944589	0.0000

Mean dependent var	0.604900	S.D. dependent var	0.343529
S.E. of regression	0.336487	Akaike info criterion	0.868728
Sum squared resid	3.396702	Schwarz criterion	1.290948
Log likelihood	-7.374563	Hannan-Quinn criter.	1.021390
Avg. log likelihood	-0.184364		
Left censored obs	0	Right censored obs	0
Uncensored obs	40	Total obs	40

Dependent Variable: TE_SCORE
Method: ML - Censored Normal (TOBIT) (Quadratic hill climbing)
Date: 01/27/18 Time: 20:28
Sample: 2010 2017
Included observations: 40
Left censoring (value) at zero
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
INVESTMENTS_SHARES	-0.000951	0.000359	-2.652996	0.0080
LABOUR	0.072239	0.026410	2.735352	0.0062
LOANS_N_ADVANCE	-0.001226	0.000434	-2.823547	0.0047
PHYSICAL_CAPITAL	0.001021	0.046008	0.022188	0.9823
PRICE_CAPITAL	-0.003377	0.006293	-0.536598	0.5915
PRICE_FUNDS	0.396756	0.236803	1.675474	0.0938
PRICE_LABOUR	0.279136	0.141777	1.968837	0.0490
ST_FUND	-0.000130	0.000460	-0.282787	0.7773
C	0.669641	0.105906	6.322966	0.0000
Error Distribution				
SCALE:C(10)	0.160698	0.017966	8.944589	0.0000

Mean dependent var	0.883150	S.D. dependent var	0.192377
S.E. of regression	0.185558	Akaike info criterion	-0.318585
Sum squared resid	1.032949	Schwarz criterion	0.103635
Log likelihood	16.37170	Hannan-Quinn criter.	-0.165924
Avg. log likelihood	0.409293		
Left censored obs	0	Right censored obs	0
Uncensored obs	40	Total obs	40

6.4. Tobit model results: Risk factors

Dependent Variable: CE_SCORE
Method: ML - Censored Normal (TOBIT) (Quadratic hill climbing)
Date: 01/27/18 Time: 20:31
Sample: 2010 2017
Included observations: 40
Left censoring (value) at zero
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LOAN_DEPOSIT	0.007574	0.004321	1.753057	0.0796
NIM	-0.381567	0.362713	-1.051981	0.2928
ROA	-0.684299	1.457064	-0.469643	0.6386
ROE	-0.992569	0.690622	-1.437211	0.1507
Z_SCORE	0.003521	0.002169	1.623597	0.1045
C	0.610937	0.170066	3.592347	0.0003
Error Distribution				
SCALE:C(7)	0.299297	0.033462	8.944328	0.0000

Mean dependent var	0.604900	S.D. dependent var	0.343529
S.E. of regression	0.329395	Akaike info criterion	0.775239
Sum squared resid	3.580546	Schwarz criterion	1.070793
Log likelihood	-8.504776	Hannan-Quinn criter.	0.882102
Avg. log likelihood	-0.212619		

Left censored obs	0	Right censored obs	0
Uncensored obs	40	Total obs	40

Dependent Variable: CE_SCORE
Method: ML - Censored Normal (TOBIT) (Quadratic hill climbing)
Date: 01/27/18 Time: 20:31
Sample: 2010 2017
Included observations: 40
Left censoring (value) at zero
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LOAN_DEPOSIT	0.007574	0.004321	1.753057	0.0796
NIM	-0.381567	0.362713	-1.051981	0.2928
ROA	-0.684299	1.457064	-0.469643	0.6386
ROE	-0.992569	0.690622	-1.437211	0.1507
Z_SCORE	0.003521	0.002169	1.623597	0.1045
C	0.610937	0.170066	3.592347	0.0003
Error Distribution				
SCALE:C(7)	0.299297	0.033462	8.944328	0.0000

Mean dependent var	0.604900	S.D. dependent var	0.343529
S.E. of regression	0.329395	Akaike info criterion	0.775239
Sum squared resid	3.580546	Schwarz criterion	1.070793
Log likelihood	-8.504776	Hannan-Quinn criter.	0.882102
Avg. log likelihood	-0.212619		

Left censored obs	0	Right censored obs	0
Uncensored obs	40	Total obs	40