Determinants of bank technical efficiency: A South African study.

By

Jared Abels (ABLJAR001)

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Department of Finance and Tax
Faculty of Commerce
University of Cape Town

Supervisor: Dr. Edward Chamisa (A/Professor)

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Abstract

The purpose of this study is to investigate the determinants of technical efficiency, using data envelopment analysis and the Tobit regression model, of the six largest listed South African banks for the years 2008-2018. An input-oriented intermediary constant-return-to-scale approach was followed to determine technical efficiency scores. After technical efficiency scores were obtained, a binary data set was created by assigning a score of 1 to all observations that were regarded as technical efficient, whereas all observations that were regarded as technically inefficient were assigned a score of 0. Thereafter, a Tobit regression analysis was performed to test the following hypotheses: skimping hypothesis, diversification hypothesis, bad management hypothesis and the funding hypothesis. The results of the regression analysis show that the skimping, diversification, and bad management hypotheses were not relevant for the six largest South African banks over the period under review. Regression results pointed towards the funding hypothesis being applicable to the six largest listed banks over the review period. It can therefore be suggested that the banks under review were generally well managed with a keen focus on expense control and thorough underwriting. To ensure the efficiency of large listed banks, it is proposed that regulators continue to monitor large banks as evidence of the study suggests that as deposit bases grow, a deterioration in technical efficiency is experienced. Generally, the results of the study indicate that the six large listed banks are overall relatively efficient over the review period.

Keywords: Data envelopment analysis, input-oriented, technical efficiency, listed banks, skimping hypothesis, diversification hypothesis, bad management hypothesis, funding hypothesis

1. **Introduction**

As many participants in a modern economy are dependent on bank credit, a well-functioning and productive banking sector is an important imperative to ensure sustainable economic growth. Many economists subscribe to the money supply multiplier effect theory. Fractional reserve banking implies that commercial banks take on surplus savings from the public, with a certain percentage of received funds placed as prescribed reserves with the central bank, while the balance is used to make loans to those who are in need of liquidity (Rossouw et al., 2015). The requirement that only a portion of deposits is placed as prescribed reserves leads to a multiplier effect as to the supply of credit or lending in an economy. Therefore, assuming this theory holds true, a well-performing bank sector should translate into positive externalities in the real economy such as increased lending and increased aggregate output. A virtuous cycle can be created if this transmission mechanism operates efficiently. Although measuring, evaluating and assessing the performance of the banking industry is an area of interest for all stakeholders in an economy, it is of significant interest to regulators especially since they are tasked with ensuring the stability and prosperity of the entire financial system.

It is reasonably well accepted by industry participants to analyse bank performance utilising ratio analysis. Various ratios are typically used by buy-side/sell-side analysts to highlight the risk characteristics and financial performance of banks. These ratios include but are not limited to: return-on-equity (ROE), return-on-assets (ROA), non-performing loans as a percentage of gross loan book (NPL%), cost-to-income, net interest margin, percentage of non-interest income of total income metrics. However, no consensus exists as to which measure is the superior indicator of bank performance as even viewing credit rating agency methodologies (credit ratings) reflect both qualitative and quantitative views on creditworthiness and therefore is dependent, to some degree, on value judgements (Packer and Tarashev, 2011).

Financial ratio analysis does not allow for independent measures to be objectively combined into a single measure, as one bank might have strong results for some ratios and poor results for other ratios, making it difficult to judge whether a bank is on average performing ideally (Paradi et al., 2011). Viewing performance measures in isolation limits circumspect analysis as they are calculated using only a subset of data available on the firm (Van der Westhuizen, 2014). The use of financial ratios is only meaningful when compared to a benchmark and finding a suitable benchmark may be difficult (Yeh, 1996). The predictability power of ratios is also not clear. Trend and peer analyses are more important to infer performance using financial ratios than their absolute values (Peterson and Peterson, 1996). However, ratios are easy to compute, the information required to produce ratios are easily available and ratios are easy to interpret making them the most preferred analytical tool (Oberholzer, 2012).

This research piece seeks to answer the following questions: how efficient are listed South African banks and can the determinants of efficiency measures be specified in a statistically significant manner? Understanding these issues will provide authorities with the ability to identify inefficient banks and highlight variables which can assist in improving efficiency. This, over time, should lead to an improvement in the transmission mechanism of the financial sector in general and may lead to improved economic growth. To prevent subjective judgments from impeding circumspect analysis an analytical tool was sought where relative performance is inferred from the data set. Such a tool is technical efficiency produced by Data Envelopment Analysis (DEA). This study contributes to the literature by expanding the knowledge on efficiency studies of the large South African banks, through utilising non-parametric methods to investigate bank efficiency and utilising linear regression techniques to identify the determinants of efficiency.

This study is organised as follows. In the section that follows an overview of the South African banking sector between 2008-2018 will be presented. This is followed by a discussion of the efficiency studies found in literature. After that, the methodology employed in the study will be discussed. The results and discussion of the results will be discussed in the final section.

2. Background to the study

2.1 Overview of the banking sector in SA

South Africa is considered to have a relatively well-developed financial sector and compares well with countries such as Brazil, Russia, India and China (Mlambo and Ncube, 2011). South Africa has one of the largest capital markets among emerging economies, with the market capitalisation to Gross Domestic Product amounting to 178% in 2008 (Mlambo and Ncube, 2011). The number of registered banks and local branches of foreign banks remained relatively stable over the period 2007-2017, increasing from 33 in 2007 to 34 in 2017 (SARB, 2018).

The South African Reserve Bank (SARB) is tasked with ensuring a sound, well-functioning and internationally competitive banking system (SARB, 2018). It is the mandate of the Bank Supervision Department located within the SARB to promote the safety and soundness of the banking system (SARB, 2018). However, the Financial Sector Regulation Act 9 of 2017 being signed into law on 21 August 2017 created specialist peaks for prudential and conduct regulation. Therefore, since 21 August 2017, it is the Prudential Authority that is tasked with promoting the safety and soundness of individual financial institutions (SARB, 2018).

The balance sheet structure of the South African banking sector is dominated by five large banks. As at 31 December 2017 the largest five banks held 90.5% of the total banking sector assets (SARB, 2018). These banks are: Absa Group Ltd (31 December 2017 Total Assets: R914bn), Capitec Bank Holdings Ltd (31 December 2017 Total Assets: R72bn), FirstRand Ltd (31 December 2017 Total Assets: R1,000bn), Nedbank Group Ltd (31 December 2017 Total Assets: R869bn) and The Standard Bank Group Ltd (31 December 2017 Total Assets: R1,235bn). Local branches of foreign banks held 5.9% of banking sector assets as at 31 December 2017, while other registered banks made up the balance (SARB, 2018). Total South African banking sector assets amounted to R5,157bn in 2017 (SARB, 2018). Furthermore, in 2017 total gross loans and advances amounted to R3,802bn, average cost-to-income amounted to 56.65%, average ROE amounted to 15.96%, while average ROA amounted to 1.31% (SARB, 2018), from a capital adequacy perspective the average common equity tier 1 capital ratio amounted to 12.88%, the average capital adequacy ratio amounted to 16.22% and average leverage amounted to 6.62 times (SARB, 2018). Impaired advances as a percentage of gross loans and advances were relatively muted in 2017 at 2.84% (SARB, 2018).

Overall, the banking sector in South Africa reflected resilient financial profiles and robust metrics despite trading in a difficult economic environment characterised by low economic growth. It is therefore no surprise that external rating agencies have continually, in their sovereign reviews of the South African government’s credit rating, cited the banking sector’s resilience as the key pillar of the sovereign’s credit rating underpin, in the sense that a well-funded financial sector lowered event risk susceptibility. Considering the size of the largest listed banks it is important that these institutions function optimally and efficiently.

2.2 The concept of efficiency

Burger and Moormann (2009) expressed the need for productivity measures to have a strong relatedness to the production process, measuring the success of transforming inputs into outputs. Although in many business journals and scholarly articles productivity and efficiency are synonymously used, no precise definition or measurement for efficiency could be found by the preceding authors in extant literature. Instead, the authors themselves defined efficiency as a comparative concept, where the transformation of inputs into outputs are evaluated against best practise. Farrell (1957) in his seminal research paper proposed a measure of productive efficiency which considers a multiple input/output process. Farrell (1957) argued that specifying a theoretically efficient production function, such as those used in parametric methods, is difficult when the process evaluated is complex and therefore advocated for the use of empirical data to estimate a production function. It therefore follows that when evaluating the efficiency of banks, which is considered a complex process, parametric methods should be avoided. Charnes et al. (1978) formulated a non-parametric approach called DEA, which extended the approach espoused by Farrell (1957). The approach championed by Charnes et al. (1978) is ideally suited to evaluate and assess the efficiency of banks. The model developed by Charnes et al. (1978) is commonly referred to as the technical efficiency (TE) model and this is also the model that was utilised in this research piece.

TE is a multi-input/output efficiency measure and can be described as a position where output cannot be improved, or inputs cannot be reduced without reducing other outputs or increasing other inputs (Yue, 1992). If one can identify certain desirable measures as outputs using certain inputs, this model can be used to identify efficient banks. Significant extant literature exists on the study of TE of commercial banks (Aikaeli, 2008; Assaf et al., 2011; Saka et al., 2012; Banya and Biekpe, 2018). To my knowledge the following studies on bank TE in South Africa focusing on of listed banks include: Banya and Biekpe (2018). The approach in this paper differs in terms of the regression method employed and the period considered. Banya and Biekpe (2018) evaluated a bank-level panel data set over the period 2008-2012 and used a truncated bootstrapping approach to analyse the determinants of banking efficiency.

3. Literature review

3.1 Introduction

There is no doubt that research regarding the determinants of bank TE is gathering pace internationally (Aikaeli, 2008; Hauner and Peiris, 2008; Assaf et al., 2011; Kiyota, 2011; Saka et al., 2012). However, in the South African context research has remained scant on exploring the determinants of bank TE, specifically evaluating whether certain theories of bank efficiency hold true in the South African context.

In the next sections theories of bank efficiency determinants will be discussed individually together with results of studies that pertain to that theory. A summary of bank efficiency studies related to the South African banking sector will also be discussed. The literature review section will conclude with a foundation of support for this study, namely to expand the current literature by providing an empirical linkage between DEA TE and theories of bank efficiency determinants.

3.2 Theories of bank efficiency determinants and related empirical studies

Efficient structure hypothesis: Formulated by Demsetz (1973) the hypothesis postulates that a market becomes more efficient the more concentrated it becomes. Girardone et al. (2004) attempted to determine the main cost efficiency drivers of Italian banks over the period 1993-1996 using a stochastic cost frontier. The data from the preceding exercise was pooled and a logistic regression model was estimated. The results showed that there was no clear relationship between asset size and bank efficiency. Hauner and Peiris (2008) studied the effect of banking sector reforms undertaken in Uganda on bank efficiency for the period 1999-2004, using the non-parametric DEA approach to estimate TE. Tobit regression analysis was utilised to identify the determinants of TE. The study found that smaller banks' TE regressed with the increase in competitiveness. Assaf et al. (2011) evaluated the TE of Saudi Arabian banks using a two-stage DEA approach, during the first stage of analysis a DEA variable-return-to-scale model was used to identify efficiency scores, whereas in the second stage a bootstrapped truncated regression model was used to identify the drivers of TE. The regression model showed that TE scores increased with assets, implying larger sizes contributed to higher TE scores. Tochkov and Nenovsky (2011) examined the efficiency of Bulgarian banks and the determinants thereof over the 1999-2007 period. The levels of technical, allocative, and cost efficiency were first estimated using DEA, thereafter the results were regressed using Tobit regression upon several bank-specific, institutional, and EU-related factors. It was found that market share was all positively correlated with efficiency. Homma et al. (2014) using data from Japan found the market to be consistent with the efficient structure hypothesis. Singh and Fida (2015) investigated whether differences between technical and scale efficiencies of commercial banks in Oman, using the DEA approach, exist. Once efficiency scores were obtained, scores were regressed on a set of explanatory variables, i.e.: bank size, profitability, capital adequacy and liquidity, using the Tobit regression model. The study revealed that bank size was insignificant. Alhassan et al. (2016) tested whether the market power, relative market power and efficient structure frameworks were relevant in the Ghanaian banking sector, using the Herfindahl-Hirschmann Index and concentration ratio as proxies to test the market power hypothesis, while efficiency scores from DEA analysis were used as proxies to test the efficient structure hypothesis. TE was found to have a positive relationship with profitability, supporting the efficient structure hypothesis, whereas a negative relationship was found to exist between scale efficiency and profitability. Řepková (2014) and Al-Gasaymeh (2016), found no significant effect of bank size on bank TE.

Quiet-life hypothesis: This theory postulates that in a concentrated market, for example where banks have high market power, efforts to reduce costs are lax due to ineffective managerial effort and lack of entrepreneurial flair. This leads to the incurrence of wasteful expenditure to maintain monopoly power (Homma et al., 2014). Kiyota (2011) utilised the stochastic frontier approach to perform a comparative analysis of profit efficiency and cost inefficiency of commercial banks operating in 29 sub-Saharan Africa focusing on bank ownership and bank size during 2000-2007. Key findings suggest that smaller banks were more profit efficient. Saka et al. (2012) evaluated TE in the Ghanaian banking sector over the period 2000-2008, using the DEA approach and the Tobit regression technique. The authors argued that using the Tobit model in establishing the determinants of TE was ideal as it is a truncated regression model where a dependent variable can take on values between 0 and 1 just like TE scores. The regression model was specified using TE scores as dependent variables while using foreign share of total banking assets, Herfindahl-Hirschmann Index scores, ROE ratios, loan ratios (total loans/total assets), bank capitalisation ratios (total equity/total assets) and inflation as independent variables. Their study found that TE scores were positively affected by a reduction in the concentration of the banking sector. Homma et al. (2014) found that market concentration reduces bank efficiencies, the authors pointed out that the finding implies an intriguing growth-efficiency dynamic throughout a bank’s life cycle. Banya and Biekpe (2018) investigated the determinants of banking efficiency in ten frontier African countries based on bank-level panel data over the period 2008-2012, utilising a two-stage procedure. During the first stage of analysis the DEA technique was used to estimate technical, pure technical and scale bank efficiency. Thereafter, a truncated bootstrapping approach was used to analyse the determinants of efficiency. The results of their analysis showed that banks in the subject countries were reasonably efficient. The results of the truncated regression indicated that bank size was negatively related to banking sector efficiency.

Structure-conduct-performance hypothesis: This theory postulates that the structure of a market influences firms pricing conduct and ultimately market efficiency (Alhassan et al., 2016). In the study performed by Alhassan et al. (2016) the structure-conduct-performance hypothesis for the Ghanaian market was rejected.

Skimping hypothesis: This theory developed by Berger and DeYoung (1997) postulates that a bank seeking cost efficiency enhancement to maximise profits may decide to lower spending on operating expenditure in the short run by spending less resources on loan underwriting and credit risk monitoring, which may result in a bank incurring larger bad debt losses in the future. The hypothesis suggests a negative relationship between TE and credit risk exists. Girardone et al. (2004) found that inefficiencies in Italian banks were positively related to the level of non-performing loans on the balance sheet. Sufian (2009) investigated the efficiency of the Malaysian banking sector around the Asian financial crisis of 1997. The DEA approach was utilised to determine efficiency estimates of individual banks. The author also analysed the variation in calculated efficiencies by regressing efficiency scores against a set of explanatory variables, i.e.: bank size, profitability and ownership using the standard Tobit regression model. Evidence in support of the skimping hypothesis was found where a negative statistically significant relationship between credit risk and bank TE was found. However, Řepková (2014) found no significant relationship between credit risk and TE exists. Saka et al. (2012) found a negative relationship between credit risk and TE exists, albeit statistically insignificant. Banya and Biekpe (2018) also found credit risk to be negatively related to TE, although statistically insignificant.

Diversification hypothesis: As with Harry Markowitz's modern portfolio theory, which theorises a quantified approach can be utilised to build a portfolio of assets that maximises return while accepting a reasonable amount of risk, the diversification theory posits that an increase in revenue diversification enhances TE. Sufian (2009) found a positive relationship between firm diversification and TE.

Bad management hypothesis: Berger and DeYoung (1997) argued that weak management effectiveness negatively affects TE, as weak managerial oversight leads to ineffective monitoring and inefficient expense control. Sufian (2009) found that management quality, using non-interest expenses over total assets as a proxy, had a negative statistically significant relationship with TE.

Funding hypothesis. Köhler (2015) developed a theory which argued that the greater the bank's ability to raise deposits, the greater the chance exists for managerial laxity to set in which could lead to deteriorating TE. Saka et al. (2012) found a negative statistically significant relationship exists between funding quality and TE.

3.3 South African studies on bank efficiency

Oberholzer and Van der Westhuizen (2004) and O'Donnell and Van der Merwe (2002) performed studies on bank performance on branch level and found that there was no significant relationship between TE, conventional profitability and general balance sheet/income statement measures.

Cronjé (2007) investigated the relative efficiency of South African banks and applied DEA to 13 South African banks. The author approached the research piece from the view that banks perform complex functions within an economy, beyond that of acting only as financial intermediaries or institutions that only produce various loans and other investments from deposits, labour and material. Due to this view the study used the Du-Pont system of financial ratio analysis. The findings of the study showed that a total of seven banks could be classified as inefficient.

Mlambo and Ncube (2011) analysed the evolution of competition and efficiency of the banking sector in South Africa for the period 1999-2008. A three-step estimation approach was adopted. First, efficiency was measured using the DEA methodology. In the second step the Panzar-Rosse approach was used to derive the H-statistic, which served as a measure for gauging competitiveness in the banking market. Whereas in the third state, management's ability to remain competitive was considered by re-estimating the Panzar-Rosse model using the DEA efficiency scores as an explanatory variable. The results showed that average efficiency increased over the years, however the number of efficient banks decreased over the same period.

Erasmus and Makina (2014) evaluated the efficiency of the banks in South Africa using both the standard and alternative approaches to DEA. Under both approaches the authors found most of the South African banks were efficient.

Branken (2019) used the input-oriented, intermediation approach DEA method to estimate TE of medium-sized banks in South African for the 13-year period 2004-2017. The study found that medium-sized banks exhibited technical and scale inefficiency. The study also found that no clear correlation between technical and scale efficiency scores, and business cycle phases could be identified.

3.4 Literature review summary

What is clear from the above is that there is no single universally accepted theory that explains all determinants of TE. Given the lack of extant literature on this subject in the South African context, an investigation as to the determinants of TE is warranted, providing the motivation for this study. Although no previous studies could be found on the determination of TE in South Africa focusing on the six largest listed banks. The two-stage analysis method between TE and the Tobit model is not new, albeit applied in different disciplines. Tasnim and Afzal (2018), in investigating the country level efficiency and national system of entrepreneurship, used the DEA and Tobit model to explain efficiency.

Simar and Wilson (2007) emphasised that as efficiency scores generated by DEA are strongly related, careful consideration should be given when TE scores are used in a second stage regression analysis. Simar and Wilson (2007) and Assaf et al. (2011) highlighted the statistical limitations of TE scores due to the nature of TE scores being strongly dependent on each other (i.e. TE scores are relative efficiency measures). They argued that given the strong dependency, assumptions required for specifying a linear regression model may be violated. The authors also argued that as DEA efficiency scores are calculated rather than estimated, one cannot obtain the statistical properties of DEA scores.

Tobit regression is used in this study as, despite its limitations, it remains a popular procedure in literature (Sufian, 2009; Assaf et al., 2011; Saka et al., 2012; Adusei 2016). Sufian (2009), Tochkov and Nenovsky (2011), Saka et al. (2012) and Adusei (2016) investigated the determinants of TE by employing DEA to calculate TE scores and Tobit regression models. This shows that sufficient academic literature exists to pursue a Tobit regression model in examining the determinants of the TE scores for the six largest listed South African banks.

4. Research methodology

4.1 Introduction

As alluded to earlier, to estimate efficiency, both parametric and non-parametric approaches can be utilised. Parametric approaches involve the estimation of a production function, i.e. an economic function that provides linkage between production, cost or profit (Delis et al., 2009). With non-parametric approaches objective functions are defined in such a way that it envelops the data set, the metrics that ensure the observed data set is enveloped are calculated by using linear programming techniques (Delis et al., 2009). Efficiency scores can then be used to estimate how far an observation is positioned from the 'envelope' or frontier (Delis et al., 2009). DEA is such a non-parametric method and when it was first developed by Charnes et al. (1978) it was proposed under the constant-return-to-scale assumption. The model as espoused by Charnes et al. (1978) is generally referred to the TE model and is formulated as the production of outputs using the smallest possible number of inputs, also called the input-oriented approach.

DEA identifies those input-output weights that maximise the efficiency of each decision-making unit or unit of interest (UOI), while maintaining that no other UOI can exceed an efficiency rating of 1, using the same weights (Cronjé, 2007). Where efficiency, by way of a ratio, represents the rate by which inputs are transformed into outputs. In solving the equation for a target UOI, the linear programme will attempt to maximize the efficiency of the target UOI and the search procedure will terminate when either the efficiency of the target UOI or the efficiency of one or more other UOIs hit the upper limit of 1 (Cronjé, 2007). For each inefficient UOI at least one other UOI will be efficient with the target UOIs set of weights (Cronjé, 2007). These efficient UOIs are referred to as the peer group for the inefficient UOI and can be used as a benchmark for efficiency improvement. This procedure produces efficiency ratings for each UOI. DEA can also provide a set of target inputs and outputs weights that will deem an inefficient UOI to be efficient using the identified efficient UOIs. These target weights provide information on the extent to which inputs can be decreased without decreasing outputs (Cronjé, 2007).

As previously mentioned, DEA models can be specified as having constant-returns-to-scale, i.e. with an increase in input there is an expectation of a proportionate rise in output. DEA models can also be specified as having variable-returns-to-scale, which implies a non-commensurate rise or fall in outputs when inputs are adjusted. Avkiran (1999) suggests that both constant-returns-to-scale and variable-returns-to-scale models be explored and if efficiency scores differ between the two approaches, it can be said that variable-returns-to-scale model can be assumed. Cronjé (2007) argued that imperfect competition between banks, due to size differences and specialisation in segments, may result in differences between constant-returns-to-scale and variable-returns-to-scale approaches. However, Assaf et al. (2011) argued that the constant-return-to-scale is appropriate if banks are operating at an optimal level of scale.

In this study the DEA method is adopted to compute the TE scores of the six largest listed banks in South Africa, using the constant-return-to-scale model, given the banking sector's highly concentrated market structure. A number of previous studies utilised the DEA method to study bank or bank-branch efficiency, these include: O'Donnell and Van der Merwe (2002), Oberholzer and Van der Westhuizen (2004), Cronjé (2007), Ncube (2009), Mlambo and Ncube (2011). In this study TE scores obtained from a DEA model are used to formulate Tobit regression model to help determine the drivers of TE.

Berger and Humphrey (1997) evaluated 130 studies that utilised frontier efficiency analysis to analyse financial institution efficiency in 21 countries to arrive at a consensus view on the most appropriate approach. The authors found that approaches focusing on parametric analysis, extant literature mostly favours stochastic frontier analysis, whereas in non-parametric analysis DEA is favoured. The DEA method is used in this study to determine TE and its drivers.

4.2 Selection of inputs and outputs

The input and output factors utilised in DEA analysis has been a subject of debate among researchers for some time. Input and output factor selection is extremely important as it is widely acknowledged that factor selection in efficiency studies have a profound effect on analysis results (Saka et al., 2012).

In TE bank analysis traditionally the banking function has been modelled as using inputs to produce outputs or as intermediating funds from the surplus accounts of savers to deficit accounts of borrowers in need of liquidity (Saka et al., 2012). These approaches are respectively referred to as the production and intermediation approaches. Identifying inputs and outputs primarily depend on the approach followed. The production approach focuses on the commercial activities that banks perform, such as accepting deposits and the granting of loans. The approach therefore views banks as using labour and physical capital to deliver services to account holders, one proxy for this is approximating the number of transactions facilitated (Saka et al., 2012). A drawback of the production approach is that it does not consider the economic function a bank fulfils by intermediating savings and making it available to those who require it (Saka et al., 2012). The intermediation approach, which views banks as intermediating funds between surplus liquidity to liquidity deficit users, is used in this study. There is also growing support in academic literature to utilise this approach (Oberholzer and Van der Westhuizen, 2004; Hauner and Peiris, 2008; Mlambo and Ncube, 2011; Branken, 2019).

Yue (1992) used a variant of the intermediary approach in the efficiency analysis of sixty Missouri banks, output factors considered were as follows: interest income, total loans and non-interest income, while interest expenses, non-interest expenses and deposits were used as inputs. Alhassan et al. (2016) and Khankhoje and Sathye (2009) utilised: customer deposits, assets and operating expenses as inputs, and loans, investments assets and commission income as output variables. Adusei (2016) used deposits, and shareholders' equity as inputs, whereas loans, investments, and profit before interest and tax were used as outputs. Banya and Biekpe (2018) used deposits and labour as inputs, whereas total assets were used as outputs. In this study the following inputs and outputs are evaluated:

Table 1: Input and output variables used in study

Inputs	Outputs
Customer Deposits	Loans
Total Assets	Net Interest Income
Operating Expenses	Non-interest Revenue
Total Equity	

4.3 Sample selection procedure and data sources

The sample covers the six largest listed South African banks for the period 2008-2018. It was decided not to include data points for the 2019 financial year due to the introduction of IFRS 16. As the introduction of IFRS 16 impacts leased assets, financial liabilities and income statement line items, comparisons with unadjusted prior year figures should be carefully considered, as in essence figures are not comparable. In total, a panel of 66 data points were used for the regression analysis to identify the determinants of TE.

4.4 The DEA Model

Charnes et al. (1978) formulated the model as follows:
Objective function:

Max $E_r = \frac{\sum_{i=1}^{k} u_i y_{ir}}{\sum_{j=1}^{m} v_j x_{jr}}$

where:

E_r = the efficiency score of an UOI from the set of r = 1, 2, ..., n;

k = the number of outputs of UOIs;

m = the number of inputs of UOIs;

y_{ir} = observed output i of UOI r;

x_{jr} = observed input j of UOI r.

Subject to the following constraints:

$\frac{\sum_{i=1}^{k} u_i y_{ir}}{\sum_{j=1}^{m} v_j x_{jr}} \leq 1$, r= 1,…,n

u_i, $v_i \geq 0$, i = 1,…,k and j = 1,…,m and respectively represent the output and input weights;

The above analysis is performed repetitively, with each UOI becoming the subject of interest in the objective function. As previously mentioned, the linear programme identifies those input-output weights that maximise the efficiency of each UOI, while maintaining that no other UOI can exceed an efficiency rating of 1, using the same weights (Cronjé, 2007).

Advantages of utilising DEA (Thanassoulis, 1993) includes:

1. No functional form needs to be specified that relates how inputs inform outputs, as it uses linear programming techniques to identify weights which optimises the efficiency score for a particular UOI;
2. The solution provides a relative efficiency measure for each UOI, and a subset of peers for inefficient UOIs and target measures for each inefficient UOI;
3. DEA offers more accurate estimates of efficiencies.

DEA is however not without its shortcomings. As the data informs efficiency scores, it is assumed that it contains no measurement error and is free from any statistical noise. The linear programming technique is also a relative assessment of efficiency and does not reflect absolute efficiency, i.e. it provides a measure of comparison between different UOIs analysed, however little can be said about the absolute efficiency of an UOI relative to a wider population. The DEA model assumes that outputs and inputs are perfectly substitutable (Erasmus and Makina, 2014).

4.5 The regression model

The regression model specified in this study takes on a similar structure to the regression model specified in Saka et al. (2012), where independent variables: foreign share of total banking assets, Herfindahl-Hirschmann Index, ROA, loan ratio, bank capitalisation ratio and inflation were regressed on TE scores. However, as the focus of this study is on the six largest listed South African banks, the foreign share of total banking assets is excluded as a variable. As many of the banks have significant market share, the Herfindahl-Hirschmann Index variable is also excluded. The altered model explored therefore looks as follows:

$$TE_{i,t} = \beta_1 DEP_{i,t}/TA_{i,t} + \beta_2 TL_{i,t}/TA_{i,t} + \beta_3 NII_{i,t}/TA_{i,t} + \beta_4 NIE_{i,t}/TA_{i,t} + \varepsilon_{i,t}$$

Where $TE_{i,t}$ is the binary TE score computed by an intermediary input-oriented DEA model for bank *i* at time *t*; β_1,…,β_4 are the regression variable coefficients and $\varepsilon_{i,t}$ the error term, for *i* = 1,…..,6 at year *t* = 2008,…..,2018.

The hypotheses for the explanatory variables are presented below:

$DEP_{i,t}/TA_{i,t}$ = Deposit ratio (total deposits over total assets). The funding hypothesis posits that the greater the bank's ability to raise deposits, the greater the chance exists for managerial laxity to set in, it is therefore expected that a negative relationship exists between funding quality and TE;

$TL_{i,t}/TA_{i,t}$ = Credit risk (total loans over total assets). According to the skimping hypothesis, a negative relationship exists between TE and credit risk, as a higher ratio would point towards greater potential for future losses, a negative sign is therefore expected;

$NII_{i,t}/TA_{i,t}$ = Non-interest income over total assets. This serves as a proxy measure to gauge the diversification strategy into non-traditional activities. In line with the diversification hypothesis it is expected that it will be positively related to TE; and

$NIE_{i,t}/TA_{i,t}$ = Non-interest expenditure over total assets. The bad management hypothesis posits that weak management oversight will result in inefficient expense management control; therefore, it is expected that a negative relationship exists between higher expenses incurred and TE.

The Tobit model can be described as a statistical model that attempts to define a relationship between a non-negative dependent variable and independent variables (Saka et al., 2012). The model hypothesizes that a variable depends on a vector of variables linearly by way of a parameter vector of coefficients (Saka et al., 2012). To capture random effects of this relationship a normally distributed error term is added (Saka et al., 2012).

5. Data analysis and results

For purposes of this study, annual data covering the period 2008-2018 was obtained from a Bloomberg L.P. terminal. Income statement data and statement of financial position (balance sheet) data were available to calculate DEA measures over the period concerned. Banks included in the study are: Capitec Bank Holdings Ltd; The Standard Bank Group Ltd; FirstRand Ltd; Absa Group Ltd; Investec Ltd and Nedbank Group Ltd. However, for ethical reasons and consistent with similar prior studies (e.g., Sake et al., 2012), the results of the TE analysis do not identify the banks by their names, instead pseudonyms are used (e.g., Bank 1).

5.1 Results of technical efficiency analysis

The first objective of this study is to perform an efficiency evaluation for the six largest listed South African banks over the period of 2008-2018, using an input-oriented intermediary constant-return-to-scale DEA model as explained in Sections 3 and 4.

5.1.1 Descriptive statistics for variables used in the TE analysis

Table 2 below shows the descriptive statistics of the variables used in the TE analysis. These variables include input variables under Panel A (i.e., total deposits, total assets, operating expenses and total equity) and output variables under Panel B (i.e., total loans, net interest income and total non-interest income).

Table 2: Descriptive statistics for variables used in the TE analysis

Variables	**Mean**	**Minimum**	**Maximum**	**Standard deviation**
Panel A: Input variables:				
Total Deposits (R millions)	518 856.9	1 528.1	1 248 114.0	320 625.2
Total Assets (R millions)	864 243.9	2 936.4	2 126 962.0	534 002.2
Operating Expenses (R millions)	27 492.1	763.1	62 693.0	16 337.7
Total Equity (R millions)	74 758.0	1 217.4	199 063.0	47 470.1
Panel B: Output variables:				
Total Loans (R millions)	497 462.1	2 192.1	1 140 062.0	289 002.6
Net Interest Income (R millions)	25 838.9	654.0	79 285.0	17 285.7
Total Non-Interest Income (R millions)	23 584.9	754.1	57 361.0	14 298.1

The disparity in observations, as evidenced by the differences in minimum and maximum values, can mainly be ascribed to one bank experiencing rapid growth over the period under review.

5.1.2 Correlation matrix of variables used in the TE analysis

To ascertain the validity of the DEA model specification an isotonicity test was performed on the data. This test involves calculating the inter-correlations between inputs and outputs to identify whether increasing amounts of inputs lead to greater outputs, meaning positive statistically significant correlations exist between inputs and outputs (Adusei, 2016).

The sample correlations of the various inputs and outputs are summarised in Table 3.

Table 3: Correlation matrix for inputs and outputs variables

Sample Correlations (r)	**Total Deposits**	**Total Assets**	**Operating Expenses**	**Total Equity**	**Total Loans**	**Net Interest Income**	**Total Non-Interest Income**
Total Deposits	1.00000						
Total Assets	0.93791	1.00000					
Operating Expenses	0.93004	0.96335	1.00000				
Total Equity	0.94462	0.98235	0.96002	1.00000			
Total Loans	0.97379	0.90988	0.93013	0.90940	1.00000		
Net Interest Income	0.86325	0.88634	0.93537	0.89220	0.86734	1.00000	
Total Non-Interest Income	0.90195	0.89685	0.88376	0.91108	0.88514	0.72564	1.00000

The test-statistics of the sample correlations, calculated as test statistic $= \frac{r\sqrt{n-2}}{\sqrt{1-r^2}}$, where *r* denotes the sample correlation and n denotes the sample size, are summarised in Table 4.

Table 4: Test statistics for sample input and output variable correlations

Test Statistics	**Total Deposits**	**Total Assets**	**Operating Expenses**	**Total Equity**	**Total Loans**	**Net Interest Income**	**Total Non-Interest Income**
Total Deposits							
Total Assets	21.63120						
Operating Expenses	20.24872	28.73178					
Total Equity	23.02804	42.01019	27.43426				
Total Loans	34.25418	17.54578	20.26241	17.49149			
Net Interest Income	13.68123	15.31388	21.15797	15.80330	13.94132		
Total Non-Interest Income	16.70926	16.22033	15.10912	17.68127	15.21729	8.43676	

The critical value of the t-distribution at a confidence level 95% with 64 degrees of freedom is approximately 1.671 (Pardoe, 2006), therefore there is sufficient evidence to conclude that there is a significant linear relationship between all variables due to the correlation coefficients being significantly different from zero, as all the sample test statistics far exceed the critical value.

The results therefore confirm the validity of the input and output selection for the DEA model.

5.1.3 Results of the TE analysis of South African banks (2008-2018)

Table 5 below shows the estimated TE scores of the six banks included in this study over the period 2008-2018 using the DEA method as discussed in the previous sections.

Table 5: Year-by-year TE scores of six largest listed banks (2008-2018)

Bank number	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**Min**	**Max**	**Standard Deviation**
Bank 1	1.0000	0.8400	0.9306	1.0000	0.9517	0.9482	0.9798	0.9811	0.9838	0.9564	1.0000	**0.8400**	**1.0000**	**0.04**
Bank 2	1.0000	1.0000	0.9923	0.9696	0.9059	0.9133	0.9396	0.8940	0.8966	0.9152	0.9067	**0.8940**	**1.0000**	**0.04**
Bank 3	1.0000	1.0000	0.9990	1.0000	1.0000	1.0000	1.0000	0.9876	1.0000	0.9784	0.9999	**0.9784**	**1.0000**	**0.01**
Bank 4	1.0000	1.0000	0.9713	0.8869	0.8547	0.8625	0.8617	0.8303	0.8717	0.8433	0.8716	**0.8303**	**1.0000**	**0.06**
Bank 5	1.0000	0.8179	0.9114	0.7588	0.7480	0.7536	0.7543	0.7835	0.8053	0.8337	0.8181	**0.7480**	**1.0000**	**0.07**
Bank 6	0.9442	0.8642	0.8594	0.7495	0.9364	0.8446	0.8311	0.8220	0.7542	0.7368	0.7811	**0.7368**	**0.9442**	**0.07**
Mean	***0.9907***	***0.9203***	***0.9440***	***0.8941***	***0.8995***	***0.8870***	***0.8944***	***0.8831***	***0.8853***	***0.8773***	***0.8962***			
Standard Deviation	***0.0208***	***0.0808***	***0.0492***	***0.1060***	***0.0808***	***0.0790***	***0.0868***	***0.0786***	***0.0883***	***0.0824***	***0.0833***			
Number of efficient banks	***5***	***3***	***0***	***2***	***1***	***1***	***1***	***0***	***1***	***0***	***1***			

It is interesting to note that the number of efficient banks recorded in 2008 and 2009 amounted to 5 and 3, respectively. It was expected that TE scores would be negatively affected by the fallout from the global financial crisis. This is not evident from the efficiency scores recorded in these two years and can be indicative of the insulated nature of the South African banking system, with relatively low cross exposure to international bank risk factors. An adverse impact is only recorded in 2010, with none of the banks registering as being technically efficient in this year. The early 2000s was characterised by high economic growth recorded in the South African economy which averaged 4% over the period 2000-2008, this compares starkly with an average economic growth rate of 1.12% over the period 2014-2018. This can potentially point towards economic growth having a lagged impact on efficiency scores.

Average TE was the highest in 2008, declining in subsequent years. In terms of TE score dispersion Bank 3 showed significantly less dispersion than the other banks as evidenced by TE scores ranging between 0.9784-1, whereas Bank 5 and Bank 6 showed greater dispersion with regards to the TE scores recorded as evidenced by TE scores ranging between 0.748-1 and 0.7368-0.9442 respectively.

In the study performed by Cronjé (2007) efficiency results were anonymised making direct comparisons with the results obtained from this study impossible, however an extract of the input-oriented TE scores indicate that efficiency scores ranged from 0.073 to 1. In the study performed by Oberholzer et al. (2010) efficiency results were anonymised making direct comparisons with the results obtained from this study impossible. Mlambo and Ncube (2011) found that the mean TE scores for the banks evaluated in their study between 1999-2008 to be 0.672. In the study performed by Oberholzer (2012) the efficiency study was centred around listed manufacturing companies and therefore does not allow for direct comparison with the results obtained from this study. In the study performed by Saka et al. (2012) average bank TE scores varied considerably ranging from 0.339 to 0.904 over the period of interest, the analysis was performed per bank over the period of interest. An emphasis should be made that results from different studies can significantly be influenced by the specific banks evaluated, the choice of input/output variables and the period under consideration, therefore direct comparisons should be done with caution.

Table 6 shows the ranking according to the average TE scores recorded over the period under review.

Table 6: Banks ranked by average TE scores, 2008-2018

Bank number	Average TE score	Rank
Bank 1	0.9611	2
Bank 2	0.9394	3
Bank 3	0.9968	1
Bank 4	0.8958	4
Bank 5	0.8168	6
Bank 6	0.8294	5

Overall, relatively little scope exists for banks to increase their output by optimising inputs. Based on average TE score rankings the banks under review can be grouped in two categories. Group one comprises of Bank 3, Bank 1 and Bank 2 which all have average TE scores above 0.9 and group two which comprises of Bank 4, Bank 5 and Bank 6 which all have average TE scores below 0.9.

5.2 Tobit regression analysis results

The aim of the Tobit regression model is to uncover, by means of a logit regression model, the underlying relationship between TE banks and a variety of factors. To run the regression a binary data set was created by assigning a code of 1 to each of the TE observations, while for each of the technically inefficient banks a code of 0 was assigned. A multi-linear regression analysis was then performed in Microsoft® Excel® for Microsoft 365.

5.2.1 Descriptive statistics of regression variables

A summary of the descriptive statistics of the regression variables is given in table 7 below.

Table 7: Descriptive statistics of regression variables

Variable*	Mean	Standard Deviation	Min	Max
DEP/TA	59%	13%	32%	82%
TL/TA	61%	13%	38%	80%
NII/TA	5%	5%	1%	26%
NIE/TA	5%	4%	2%	26%
*figures shown as percentages				

Deposits on average made up 59% of bank liabilities, whereas total loans on average comprised about 61% of total assets. Average non-interest income only amounted to 5% relative to total assets, however there is significant disparity in the data as evidenced by the minimum percentage of 1% and the maximum percentage of 26% recorded. Average non-interest expenditure also amounted to 5% relative to total assets, a similar disparity is observed compared to non-interest income expressed as a percentage of total assets.

5.2.2 Multi-collinearity of regression variables

The existence of multi-collinearity was investigated to ascertain whether two or more explanatory variables in the regression model were highly linearly related. The results of the explanatory variable correlation matrix are summarised in Table 8 below:

Table 8: Independent variable correlation matrix

Variable	**DEP/TA**	**TL/TA**	**NII/TA**	**NIE/TA**
DEP/TA	1			
TL/TA	0.540058	1		
NII/TA	-0.304019	0.27092078	1	
NIE/TA	-0.305112	0.265219058	0.981691	1

Multi-collinearity may be a problem if correlation coefficients exceed 0.80 (Gujarati, 1995). Given that all but one of the correlation coefficients are less than the 0.80 threshold, it is considered that multi-collinearity is not a major problem.

5.2.3 Results of regression analysis

Parameter coefficients and the significance of variables are presented in Table 9.

Table 9: Regression output summary

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.663563
R Square	0.440316
Adjusted R Square	0.403615
Standard Error	0.326111
Observations	66

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	5.103656967	1.275914	11.99749	2.96159E-07
Residual	61	6.487252124	0.106348		
Total	65	11.59090909			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.15755	0.219616702	-0.717387	0.475874	-0.5967009	0.281601	-0.5967	0.281600576
DEP/TA	-1.649176	0.427535572	-3.8574	0.000279	-2.50408582	-0.79427	-2.50409	-0.794265391
TL/TA	2.205411	0.434060039	5.08089	3.81E-06	1.337454776	3.073368	1.337455	3.073368158
NII/TA	3.286903	4.457586923	0.737373	0.463723	-5.62659268	12.2004	-5.62659	12.20039921
NIE/TA	-2.822159	5.094248269	-0.553989	0.581611	-13.008738	7.36442	-13.0087	7.364419951

The coefficient of determination indicates that 44% of the variability of the dependent variable can be explained by the explanatory variables. The p-value of the F-test is less than the 5% significance level therefore the null-hypothesis, that the fit of the intercept-only model and the specified model are equal, can be rejected.

Two variables have statistically significant coefficients at a 5% significance level, these variables are DEP/TA and TL/TA, while the other two variable coefficients were found to be statistically insignificant at a 5% significance level. It can therefore be concluded that the diversification and bad management hypotheses are both not relevant for the six largest South African banks over the period under review.

In terms of the skimping hypothesis, the results obtained from the study is in contrast with Sufian (2009) and Saka et al. (2012) where it was found that credit risk negatively impacted bank TE. The results also contrast with Řepková (2014) where it was found that no statistically significant relationship between credit risk and bank TE exists. The positive coefficient may point towards greater emphasis being applied by management teams to credit risk underwriting and monitoring as loan books increase in size.

In terms of the diversification hypothesis the results obtained from this study is in contrast with Sufian (2009) where a positive relationship between firm diversification and TE was found to exist. It can therefore be said that no discernible TE benefit can be obtained by the banks evaluated in this study by increasing revenue generating avenues.

In terms of the bad management hypothesis the results obtained from the study is in contrast with results obtained by Sufian (2009), where a negative statistically significant relationship was found to exist between expense control and TE. It can therefore be said that management teams of banks under review seem to apply effective oversight on the monitoring of expense control.

In terms of the funding hypothesis, the results obtained from this study is consistent with results obtained by Saka et al. (2012) where a negative statistically significant relationship was found to exist between the size of the deposit base and TE. An argument can therefore be made that management teams may be prone to lose focus as deposit bases increase.

6. Summary and conclusions

The primary objective of the study was to establish the determinants of bank TE of the six largest listed South African banks for the period 2008-2018. To accomplish the objective of this study, TE scores were calculated using the DEA method based on the input-oriented intermediary constant-return-to-scale approach. After the TE scores were obtained a binary data set was created by assigning a score of 1 to all observations that were regarded as TE, whereas all observations that were regarded as technically inefficient were assigned a score of 0. These observations were then regressed using Microsoft® Excel® for Microsoft 365 against explanatory variables to test for consistency against the skimping, diversification, bad management and funding hypotheses.

From the results obtained from the regression analysis only the funding hypothesis was relevant for the six largest listed South African banks for the period under review. The bad management hypothesis, which postulates that ineffective management oversight will lead to poor expense control and negatively affect TE was rejected. The diversification hypothesis, which posits that an increase in revenue diversification has a favourable impact on TE was rejected, indicating no favourable efficient effect is obtained by an increase in revenue generation. The skimping hypothesis which posits that the focus on profit maximisation activities will lead to poor underwriting and an increase in credit risk, which in turn negatively affects TE, was rejected. Although it was found that the proxy for skimping hypothesis was statistically significant, the positive sign of the coefficient was in contrast with what the hypothesis supposes and therefore an increase in the loan book size did not negatively impact TE. Generally, the conclusions that may be drawn include: the large listed banks are overall effectively managed, these banks exhibit effective expense control (by virtue of the bad management hypothesis being rejected) and thorough credit underwriting seems to be applied (by virtue of the skimping hypothesis showing a positive coefficient instead of a negative sign). To ensure the ongoing efficiency of large listed banks, it is proposed that regulators continue to monitor large banks as evidence of the study suggests that as deposit bases grow, a deterioration in TE is experienced.

As this study has highlighted that enhanced prudential oversight may be warranted in instances where deposit bases grow over time, it would be interesting to see whether the deposit base growth dynamics in the years building up to the collapse of VBS Mutual Bank and Saambou Bank could have been used as an early warning mechanism for the prudential authorities to prevent their downfall. This study can also be revisited should alternative proxies be identified to test the skimping, bad management, diversification and funding hypotheses.

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