

Re-examining the ability to explain future South African banking share returns: A data envelopment analysis approach

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Background: Using financial ratios is considered to be important when making informed judgments about investment portfolios. However, the 'ideal' set of ratios is an elusive notion on which the literature has failed to reach any consensus.

Aim: This study attempts to identify to what extent so-called 'non-financial' measures can outperform 'traditional' financial and risk-adjusted performance ratios to explain future share returns for South African banks in a momentum investment strategy.

Method: A multi-stage data envelopment analysis model was used in the study.

Results: The results suggest that non-financial measures are able to explain up to 90% of banking shares' future returns, which is a 30% to 40% improvement on that of traditional financial and risk-adjusted performance ratios. In identifying the 'ideal' set of ratios for the South African banking industry, this study also found that pure technical efficiency, the price-to-earnings ratio and the static omega ratio were able to explain up to an average of 83% of future banking share returns.

Conclusion: The study contributes to the field of portfolio management in that both risk-adjusted performance ratios and non-financial measures can be used as short-term and long-term investment decision-making tools. Further to this, the ability to explain future returns to some extent implies that the South African banking industry may be time-varying-information efficient.

Keywords: Banking industry; data envelopment analysis; DEA; financial and non-financial measures; risk-adjusted performance ratios; South Africa.

Introduction

The capital asset pricing model (CAPM) has played a significant role in modern portfolio theory for decades. The innovative work of Sharpe (1964), Lintner (1965), Mossin (1966) and Black (1972) brought together a model that 'embodies a theory of what can be inferred about expected returns when markets are in equilibrium, homogeneous expectations prevail and when all investors pursue a mean-variance optimizing objective' (Van Rensburg & Robertson 2003:7). However, literature has shown that there are several empirical contradictions of the so-called Sharpe-Lintner-Black (SLB) model, brought about by the assumptions that expected returns are a positive linear function of market betas and that market betas are sufficient to describe the cross-section of expected returns (Fama & French 1992). The most prominent contradiction of the SLB model is reported by Banz (1981), who found that the size effect contributes to the ability of market betas to explain the cross-section of average returns. Another contradiction can be found in the work of Bhandari (1988), who reported a positive relationship between average returns and leverage. Although the SLB model assumes that leverage risk should already be captured by the market beta, Bhandari (1988) found that including leverage in a model (which already accounts for market size and beta) improves the explanation of average share returns. Further studies also found evidence to support the book-to-market ratio (B/M); the price-to-earnings ratio (P/E); the return-on-equity ratio (ROE); the DuPont model to overcome the shortcomings of the ROE ratio (Berzkalne & Zelgalve 2014; Traub 2001); the dividend yield (DY); the implied dividend growth rate; the cash-flow-to-price ratio; and the price-to-net asset value (NAV) ratio as additional 'blanket' proxies for unnamed risk factors that can enhance the explanation of average share returns (see, for example, Asness, Porter & Stevens 2000; Auret & Cline 2011; Auret & Sinclair 2006; Basiewicz & Auret 2010; Basu 1983; Chan, Hamao & Lakonishok 1991; Fama & French 2017; Hoffman 2012; Hou, Karolyi & Kho 2011; Johannes, Korteweg & Polson 2014; Lakonishok, Shleifer

& Vishny 1994; Litzenger & Ramaswamy 1979; Rosenberg, Reid & Lanstein 1985; Soliman 2008; Stattman 1980; Van Rensburg 2001; Van Rensburg & Robertson 2003; Zaremba & Czapkiewicz 2017).

However, the studies of Chen and Shimerda (1981) and Pech, Noguera and White (2015) argue that financial ratios tend to comprise overlapping information, which make the suitability of a small representative group of ratios possible, but to establish such an 'all-inclusive' group remains an enormous challenge. Delen, Kuzey and Uyar (2013) attempted to address this problem by evaluating the underlying dimensions of several ratios and found that the net profit margin and earnings before tax-to-equity ratio possess the most promise for predicting future performance. The results from surveys conducted by Gibson (1987) and Matsumoto, Shivaswamy and Hoban (1995) contradict these findings. They report that security analysts and financial analyst charter-holders consider profitability and valuation ratios to be more insightful. Conversely, Pech et al. (2015) reported a wider range of ratios, pointing out that the DY, P/E and the ROE ratio are some of the ratios that are more frequently used by equity analysts. Nevertheless, the study of Clark (1997) considers financial ratios as being backward-looking, lacking the ability to reflect long-term and future consequences of managerial actions. This may be due to: their reliability on internal historical data and the sensitivity to manipulation (Van Heerden & Heymans 2013), their being ineffective to represent the many facets of performance in general (Avkiran 1997), their inability to capture the interplay amongst the multiple resources and outputs of a company (Davenport & Sherman 1987), and their failure to explain the reasons for 'good' or 'bad' performances (Avkiran 1997). To overcome these shortcomings, investors could typically consider the use of non-financial ratios as they are less exposed to manipulation, a more reliable source of information on firm failure, and better predictors of long-term performance (Ames et al. 2012; Kaplan & Norton 1996; Johnson & Kaplan 1987; Singleton-Green 1993).

Given this background, the main objective of this study is to determine to what extent bank efficiency, as a non-financial measure, outperforms: (1) financial (or, traditional accounting) and (2) risk-adjusted performance ratios to explain ex-post future share returns for the six largest South African banks from a momentum investment strategy perspective. The study of Jegadeesh and Titman (1993) found that past 'winners' on average continued to outperform past 'losers', which implies that there is momentum in share returns, to some extent, which can be exploited as documented by Fama (1991). For this study, this implies that the year-end rankings of each ratio at time t is used to determine which of the top six South African banking shares will be more profitable over a one, three, and five year investment horizon. After each consecutive year the rankings of each ratio is compared to the ex-post realised and risk-adjusted banking share returns to determine which of the ratios is more efficient in explaining ex-post future performance and thus more ideal to utilise in a momentum investment strategy. Establishing which ratios

are more consistent in explaining future performance can enable investors and portfolio managers to make more informed ex-ante decisions, using the more 'ideal' set of ratios as identified in this article. The scope of this study will, however, not include a comparative study of alternative momentum investment strategies, as the focus will be directed to determine only the most insightful ratios to use in the South African banking industry as future decision-making tools. Also, this study will only consist of an ex-post analysis and will not include any form of forecasting (ex-ante analysis).

The modelling flexibility of data envelopment analysis (DEA) and its ability to address both quantitative and qualitative data, as well as discretionary and non-discretionary inputs (Golany & Storbeck 1999), makes it most suitable for this study. The significance of this study is further emphasised by the limited research in this field. Only an estimated 1.63% of all DEA application papers have been applied in the field of investment management (Liu et al. 2013). In this study the goal of the DEA model will be twofold. Firstly, it is utilised to estimate three different forms of bank efficiency scores from the historical DI900 reports that were converted to BA900 reports by the South African Reserve Bank (SARB 2017a). These efficiency scores incorporate the internal operations of a banks and entail pure technical efficiency, scale efficiency, and total technical efficiency (which is a combination of scale and pure technical efficiency). Secondly, the same non-parametric, non-stochastic, mathematical programming approach is used to determine the ability of these bank efficiency scores to explain ex-post future banking share returns, along with that of other selected financial and risk-adjusted performance ratios. The DEA model's ability to acknowledge the interdimensional relationships (Cooper, Seiford & Tone 2007) between the selected ratios and the ex-post future realised share returns for banks further reinforces its applicability as an investment decision-making tool and is therefore deemed appropriate for a study of this nature.

The structure of this article is as follows: section two provides a brief overview of the South African banking industry and, specifically, highlights the benefits of this industry as an investment option; section three provides an overview of the concept of relative bank efficiency and the general DEA model; section four provides a discussion on the methodology adopted in the study; section five reports the findings; finally, section six provides the conclusion and recommendations.

The South African banking industry Structure and performance

The South African banking industry has changed substantially since especially 2001, when the number of registered banks equalled 41, which has subsequently fallen to 17 by the end of 2016 (SARB 2016). After the September 2001 terrorist attacks in the United States (US), global uncertainty had a particularly profound impact on the South African banking industry, as many smaller banks either lost their licences or merged with larger South African universal banks (Stemmet 2016). As such,

as of 2017 the South African banking industry was characterised by having four dominant universal bank holding companies, namely Barclays Africa Group Ltd (functioning under ABSA bank), the FirstRand Group Ltd (which includes the banks First National Bank – FNB – Wesbank and Rand Merchant Bank – RMB), the Standard Bank Group Ltd, and the Nedbank Group Ltd. These so-called Big Four had a combined market share of approximately 83% in 2017 (SARB 2017b). Investec Bank Ltd, which has a dual listing on both the London Stock Exchange and the Johannesburg Stock Exchange (JSE), is a high net worth specialist bank and the fifth largest according to asset size. Capitec Bank Ltd has in recent years entered the retail banking environment and shown tremendous growth. In September 2017, it had surpassed Nedbank in size according to market capitalisation and held the second-largest number of retail clients of all South African banks (Bonorchis 2017b; Businesstech 2017). The growth of Capitec Bank Ltd has seen unprecedented levels since its February 2002 listing on the JSE, where it had gained over 50 000% as at August 2017 (Bonorchis 2017a).

Although the South African banking industry is highly concentrated with predominantly four large banks, by no means is the industry as a whole large in global terms. With total assets of approximately R4.9 trillion at the beginning of 2017 (SARB 2017b), the total assets-to-GDP-ratio has exceeded 100% consistently in recent years (Stemmet 2016). For banks individually, in 2014 it was estimated that the largest South African bank, the Standard Bank Group, was approximately 20 times smaller than the largest bank in the world (ICBC) according to assets, 18 times smaller according to equity, and employed almost ten times fewer the number of personnel (Coetzee 2016). Although small in global terms, the industry as a whole is, however, well capitalised. For example, due to strict compliance requirements to the Basel Capital standards, the average total capital adequacy ratio (CAR) as of January 2017 was 15.9% (SARB 2017b). On an individual bank level, the common equity tier one (CET1) CAR ratio and the total CAR ratios are provided in Table 1 for the six largest bank holding groups in South Africa. The table also provides the most recent Basel III requirements relating to the leverage ratio and the liquidity coverage ratio.

The CET1 ratios for all six banks are well above the minimum South African requirements of 6.88% for year-end 2016, and

the total capital ratios also exceed the minimum requirement of 10.38%. The leverage ratios also exceed the minimum of 4% set by the SARB and the liquidity coverage ratios (LCRs) are above the 2016 requirement of 70%. Overall, the South African banking industry is well capitalised and complies with the Basel III requirements driving the international regulatory agenda for banks (SARB 2017b).

The regulation and soundness of South African banks

The South African banking industry is regarded as one of the best regulated in the world. The World Economic Forum's Global Competitiveness Report (GCR), for example, rates the soundness of South African banks as consistently being in the top 10 globally since 2009. Table 2 reports the global competitiveness of five selected indicators provided by GCR that relate specifically to the South African banking industry and the JSE. Clearly, the banking industry is very competitive, and the soundness of banks in particular, suggests well-capitalised banks, that have been shown to be resilient to global systemic shocks, especially since the advent of the global financial crisis.

As of the end of 2017, South African banks were regulated by the Banking Supervision Department (BSD) at the South African Reserve Bank (SARB). However, the regulatory and supervisory environment is set to change in the next few years towards the so-called Twin Peaks Framework, which focuses on separating *prudential* and *market conduct* regulation and supervision: the former will be governed by the Prudential Authority (PA) and the latter by the Financial Sector Conduct Authority (FSCA) (Coetzee & De Beer 2016). The so-called Financial Stability Oversight Committee (FSOC) will also be established to provide systemic oversight in the financial sector at large. These changes have been proposed amid the regulatory challenges post the global financial crisis of 2007–2009 throughout the world. More specifically, Twin Peaks is 'intended to provide a streamlined system of licensing, regulating and supervising financial institutions, whilst at the same time providing a new approach to the enforcement of financial regulation, supervision, client complaints (including a revised ombud scheme), client advice and financial (literacy) education' (Coetzee & De Beer 2016:74).

The Financial Sector Regulation (FSR) Bill of 2015 is set to be the legislation used by regulators to enforce the Twin Peaks

TABLE 1: Selected regulatory indicators according to Basel III for the top six South African banks for year-end 2016.

Banks	Source	CET1 CAR (%)	Total CAR (%)	Leverage ratio (%)	Liquidity coverage ratio (%)
Barclays Africa Group Ltd	Barclays Africa Ltd 2016	12.10	14.80	7.10	98.00
Capitec Bank Holdings Ltd	Capitec Bank Ltd 2017	30.80	33.90	5.00	1152.00†
FirstRand Ltd	FirstRand Ltd 2016	13.90	16.90	8.40	96.00
Investec Ltd	Investec Ltd 2017	9.90	14.10	7.30‡	130.00§
Nedbank Group Ltd	Nedbank Ltd 2016	12.10	15.30	6.50	109.30
Standard Bank Group Ltd	Standard Bank Group Ltd 2016	13.90	16.60	6.90	117.10

Note: Please see the full reference list of the article, Van Heerden, C. & Coetzee, J., 2019, 'Re-examining the ability to explain future South African banking share returns: A data envelopment analysis approach', *South African Journal of Economic and Management Sciences* 22(1), a2852. <https://doi.org/10.4102/sajems.v22i1.2852>, for more information.

†, The value for Capitec Bank Ltd is substantially higher than that of the other banks due to the conservative liquidity management approach adopted by the bank. This is primarily due to the bank relying solely on retail deposit funding (Capitec Bank Ltd 2017); ‡, The group figures for Investec are not provided for this indicator. As such, the data for the South African operations is provided; §, This amount equals the three-month average for Investec Bank Ltd.

CET1, common equity tier; CAR, capital adequacy ratio.

TABLE 2: The global competitiveness of the South Africa's banking industry.

Year	Source	Availability of financial services	Affordability of financial services	Ease of access to loans	Soundness of banks	Regulation of securities exchanges
2008/2009 (out of 134)	World Economic Forum (2008)	12 [†]	-	31	15	5
2009/2010 (out of 133)	World Economic Forum (2009)	6 [†]	-	31	6	2
2010/2011 (out of 139)	World Economic Forum (2010)	7	43	41	6	1
2011/2012 (out of 142)	World Economic Forum (2011)	3	39	36	2	1
2012/2013 (out of 144)	World Economic Forum (2012)	2	22	30	2	1
2013/2014 (out of 148)	World Economic Forum (2013)	2	13	22	3	1
2014/2015 (out of 144)	World Economic Forum (2014)	6	21	32	6	1
2015/2016 (out of 137)	World Economic Forum (2015)	6	21	32	8	2
2016/2017 (out of 138)	World Economic Forum (2016)	2	27	12	2	3

Note: Please see the full reference list of the article, Van Heerden, C. & Coetzee, J., 2019, 'Re-examining the ability to explain future South African banking share returns: A data envelopment analysis approach', *South African Journal of Economic and Management Sciences* 22(1), a2852. <https://doi.org/10.4102/sajems.v22i1.2852>, for more information.

†, The indicator was labelled 'Financial market sophistication' for the respective year.

framework. The FSR is also set to provide clear guidelines for regulators regarding the systemic risk and financial stability facing South African banks (SARB 2017b). This macro-prudential approach to regulation is at the core of the future regulatory approach adopted by both the PA and the FSCA and is aligned to global best practices. Twin Peaks will therefore provide a total revamp of the regulatory environment for the South African financial sector. Overall, the South African banking industry is well regulated and capitalised and is regarded as one of the most sound in the world. These features suggest an environment that encourages future investment into the industry.

Relative efficiency and the general data envelopment analysis model

The literature provides no consensus regarding which method is more appropriate in measuring bank efficiency (Titko, Stankevičienė & Lāce 2014). The traditional approach mostly considered applying traditional financial ratios, but it is considered to provide unreliable results as these ratios are unable to capture the complex financial environment and all the activities of a bank (Arshinova 2011; Yang 2009). Despite that, the study of Mester (2003) also argues that efficiency measurement can be thought of as only one aspect of firm performance. Nevertheless, to overcome the shortcomings of using traditional financial ratios, frontier approaches were introduced which are able to incorporate multiple inputs and outputs (Titko et al. 2014). This new approach of measuring efficiency was initiated by studies like that of Debreu (1951), who demonstrated the comprehensive quality of using a resource utilisation coefficient, and Koopmans (1951), who introduced the concept of an efficient point. However, the novel work by Farrell (1957) demonstrated how to measure efficiency in practice and was the first to recommend that the level of efficiency be measured by means of an equi-proportionate reduction in current inputs to produce predetermined levels of outputs. This can be accomplished by means of either a non-parametric, non-stochastic, mathematical programming framework (Charnes, Cooper & Rhodes 1978), or a parametric, stochastic, statistical framework (Aigner, Lovell & Schmidt 1977; Meeusen & Van Den Broeck 1977). The latter includes the stochastic frontier analysis (SFA), which constructs a smooth parametric frontier that considers stochastic noise in the data and allows for hypothesis testing

regarding production structures and the degree of inefficiency (Hossain et al. 2012; Jacobs 2001). However, the need to impose an explicit parametric form for the underlying technology and an explicit distributional assumption for the inefficiency term makes this a less flexible model (Sharma, Leung & Zaleski 1999). To deal with this, Charnes et al. (1978) introduced a suitable alternative that entails a non-parametric, non-stochastic, mathematical programming framework called the DEA model. This model was originally introduced under a limited constant returns-to-scale (CRS) perspective, which generalises 'the single-output to single-input classical engineering-science ratio definition to multiple outputs and inputs without requiring preassigned weights' (Banker, Charnes & Cooper 1984:1078). Inspired by the work of Allen (1939) and Shephard (1953; 1970), which considered the possibility of increasing, decreasing or constant returns to scale in multiple input and output scenarios, Banker et al. (1984) improved on the CRS perspective by introducing a variable returns to scale (VRS) perspective, which accounts for possibilities such as capacity limitations on inputs. Under both CRS and VRS, the DEA model has the ability to solve linear programming (LP) problems that generate a non-parametric, piecewise-linear, convex frontier (Färe, Grosskopf & Lovell 1985). This enables the measurement of relative or comparative efficiency in terms of the inputs and outputs of a decision-making unit (DMU) (or in the case of this study, banks) by benchmarking the non-best practices with best practices in order to determine the extent of inefficiencies (Avkiran 1999; Jaforullah & Whiteman 1999). Although the DEA model does not address the problem of output assessment, it seeks to combine multiple inputs and outputs in a single, non-arbitrary, non-subjective manner via the criterion of Pareto efficiency without requiring specification of any a priori weights (Nunamaker 1985). Nevertheless, the results derived from the DEA model are still sensitive to the selection of inputs and outputs (Kumar & Singh 2014), emphasising the importance of selecting the correct inputs and outputs.

The significance of the DEA model can be emphasised by its vast application. For example, in the health care sector (Nunamaker 1983; Omrani, Shafaat & Emrouznejad 2018; Worthington 2004), in the agricultural sector (Iglesias, Castellanos & Seijas 2010; Kuhn et al. 2018), in the transportation sector (Azadeh, Ghaderi & Maghsoudi 2008;

Barak & Dahooei 2018; Schefczyk 1993), in the education sector (Aparicio et al. 2018; Bessent et al. 1982), in the tourism sector (Barros & Dieke 2008; Cheng, Lu & Chung 2010; Van Heerden & Saayman 2018), in the industrial sector (Fang, Wu & Zeng 2009; Sueyoshi, Goto & Ueno 2010; Wang & Zhang 2018), in the communication sector (Giokas & Pentzaropoulos 2008; Hu et al. 2018; Resende & Façanha 2005), in the energy sector (Azadeh et al. 2008; Shi, Bi & Wang 2010; Zurano-Cervelló et al. 2018), in local government (Afonso & Fernandes 2008; Van Heerden & Rossouw 2014; Xia et al. 2018), in the sport industry (Boscá et al. 2009; Roboredo, Aizemberg & Meza 2015), in the real estate sector (Anderson et al. 2002; Isik & Topuz 2017; Topuz, Darrat & Shelor 2005), in the construction industry (Hu & Liu 2018; Tsolas 2011; Xue et al. 2008), in the manufacturing sector (Halim 2010; Liu 2008; Mahadevan 2002), in the retail sector (Kahraman et al. 2018; Xavier, Moutinho & Moreira 2015), in the insurance sector (Barros, Nektarios & Assaf 2010; Eling & Jia 2018; Wanke & Barros 2016), and in the banking sector (Quaranta, Raffoni & Visani 2018; Sherman & Gold 1985; Van Heerden & Van Der Westhuizen 2008). However, the significance of this study can be emphasised by the limited research in investment management. The only existing literature in this field includes, amongst others, the use of DEA as a portfolio selection criterion (Dia 2009; Edirisinghe & Zhang 2008; Huang et al. 2015; Joro & Na 2006; Mashayekhi & Omrani 2016; Pätäri, Leivo & Honkapuro 2010, 2012), to measure portfolio efficiency in a mean-variance framework (Liu et al. 2015), to evaluate fund managers' efficiency (Banker, Chen & Klumpes 2016), as a mutual fund performance assessor (Abad, Thore & Laffarga 2004; Alexakis & Tsolas 2011; Basso & Funari 2016; Chen 2008; Kuosmanen 2007), to evaluate portfolio risk in the forex spot market (Amiri et al. 2010), to evaluate the link between bank efficiency and share performance (Beccalli, Casu & Girardone 2006; Sufian & Majid 2007), to evaluate the relationship between portfolio diversification and efficiency (Choi & Min 2017), as a complementary share performance tool to the traditional set of fundamental factors (Van Heerden & Heymans 2013), as an investment tool to predict Japanese bank share performance (Avkiran & Morita 2010), and to evaluate an investment fund's or portfolio's performance (Lim, Oh & Zhu 2014; Tarim & Karan 2001).

From the literature it is clear that the popularity of the DEA model can be motivated by its flexibility, as it is capable of handling non-commensurate multiple inputs and outputs simultaneously (Kirigia, Sambo & Scheel 2001; Nunamaker 1985). Its estimators are considered to be consistent, able to converge faster than estimators from other frontier methods, and unbiased, with the assumption of no underlying model or reference technology (Grosskopf 1996; Kittelsen 1999). The DEA model is also able to uncover relationships that are unknown to other methodologies (Kumar & Singh 2014). Furthermore, the efficiency scores generated from the DEA model enable the characterisation of resource utilisation (Førsund & Hjalmarsson 1974), which is grounded on an initial set of objectives (Mester 1993). The scope of this study

will, however, be limited to focusing on only two elements of X-efficiency, namely technical and scale efficiency. X-inefficiency as a whole implies that banks are either wasting their inputs (that is, they are technically inefficient), or using the wrong combination of inputs (they are allocatively inefficient), or both (Mester 2003). The inappropriate usage of the capacity size (too small or too large) can also be a contributing factor to total technical inefficiency. This is commonly referred to as scale inefficiency and can take on two forms, namely increasing returns to scale (IRS) or decreasing returns to scale (DRS). If the scale of the operation is considered to be too small and must be expanded in order to improve efficiency, the economies of scale are characterised as being IRS. However, when the scale of operation is too large and must decrease in order to improve efficiency, it is characterised as being DRS (Zere et al. 2006). In the estimation process an input-orientated or output-orientated approach can be executed under a CRS or a VRS perspective. The input-orientated approach will characterise the production technology of a DMU for producing a given output mix with the minimum inputs, whereas an output-orientated approach will characterise a DMU in pursuit of producing the maximum output bundle with the given inputs mix (Coelli, Rao & Battese 1998).

In order to determine the level of efficiency in which ratios explain future share returns, this study will adopt an input-orientated approach. Using this approach with a VRS perspective will result in outputs increasing or decreasing disproportionately when the inputs increase; conversely, with a CRS perspective, outputs will increase proportionally owing to an increase in inputs (Avkiran 1999). However, the CRS perspective will not function properly under conditions such as imperfect competition and constraints on finance that limit DMUs, and in this case banks, from operating at their optimal scale (Coelli et al. 1998). Despite this, it is still recommended that the DEA model be estimated separately under both the CRS and VRS perspectives and then compared in terms of the generated efficiency scores (Coelli et al. 1998): the efficiency scores generated from the VRS perspective represent pure technical efficiency that measures efficiency without scale efficiency, whereas the efficiency scores generated from the CRS perspective represent technical efficiency that measures the inefficiencies resulting from the size of operations and input-output combinations (Avkiran 1999). The difference between the VRS efficiency and CRS efficiency scores represents a potential scale inefficiency measurement. To determine the economies of scale, an additional model must be estimated with a non-increasing return to scale (NIRS) perspective. By comparing the technical efficiency scores of the NIRS perspective with those of the VRS perspective, it can be determined if banks are operating at decreasing or increasing returns to scale (Coelli et al. 1998). If these models generate efficiency scores that are the same, it will be an indication that banks are operating at decreasing returns to scale. However, if the efficiency scores of the VRS perspective and of the NIRS model differ, increasing returns to scale exist.

Methodology and data

The multi-stage DEA model

This study utilises the multi-stage DEA model, which is estimated using the DEAFrontier software, a DEA add-in for Microsoft Excel® developed by Zhu (2016). In this model, consider K to be the number of inputs and M the number of outputs on each of N banks, where for the i th banks these inputs and outputs are represented by the vectors x_i and y_i . The $M \times N$ output matrix is represented by Y , and the $K \times N$ input matrix by X . The constant returns to scale, input-orientated, multi-stage DEA model can thus be illustrated by the following steps provided by Coelli (1998), with minor changes to this approach when applying a variable returns to scale approach:

First, conduct a radial LP process with the following form:

$$\begin{aligned} & \min \theta \\ & \theta, \lambda \\ & \text{s. t. } -y_i + Y\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0, \\ & \lambda \geq 0, \end{aligned} \quad [\text{Eqn 1}]$$

θ is a scalar and λ denotes a $N \times 1$ vector of constants. This process is continued N times, generating a θ for each of the banks.

Second, this process is followed by a second-stage LP process in which the sum of any remaining slacks is maximised, illustrated as follows:

$$\begin{aligned} & \max (M1' OS + K1' IS) \\ & \lambda, OS, IS \\ & \text{s. t. } -y_i + Y\lambda - OS = 0 \\ & \theta x_i - X\lambda - IS = 0, \\ & \lambda \geq 0, OS \geq 0, IS \geq 0, \end{aligned} \quad [\text{Eqn 2}]$$

θx_i denotes the input vector of the i th banks, which has been multiplied by θ (being contracted) from Step 1; OS denotes the $M \times 1$ vector of output slacks; IS denotes the $K \times 1$ vectors of input slacks; and $K1$ and $M1$ are $K \times 1$ and $M \times 1$ vectors of ones. This process is continued N times, after which all the banks with no slacks and those who have a technical efficiency score of $\theta = 1$ are identified and classed as 'efficient banks'. This process is also duplicated for all banks with non-zero slack variables, after which they are classified as the 'banks with slacks' set. The 'banks with slacks' set is then used to estimate a sequence of radial movements based on projected points estimated in Step 1 in order to obtain the projected point on the efficient frontier. Conversely, the 'efficient banks' will be used only as a reference in the LP estimations from this stage forward.

Third, a sequence of K LPs is conducted in order to identify all input dimensions that consist of slacks of the i th banks in the 'banks with slacks' set. This step will, however, break down if some inputs are found to be zero. In this process, each LP will allow contractions in only one of the inputs, which will determine the presence of potential slacks within

these inputs. The LP for the j th input of the i th bank can be illustrated as follows:

$$\begin{aligned} & \min \theta \\ & \theta, \lambda \\ & \text{s. t. } -y_i + Y_e \lambda \geq 0, \\ & \theta c x_i^j - X_e^j \lambda \geq 0, \\ & c x_i^{\neq j} - X_e^{\neq j} \lambda \geq 0, \\ & \lambda \geq 0, \end{aligned} \quad [\text{Eqn 3}]$$

$c x_i^j$ denotes the j th input of the i th bank, which is multiplied by θ (being contracted) that is obtained from Step 1, X_e^j denotes the $1 \times N_e$ vector of the j th input of all the efficient banks, and $c x_i^{\neq j}$ denotes the $(K - 1) \times 1$ vector of inputs of the i th bank. This excludes the j th input, which is then contracted by being multiplied by θ , as obtained in Equation 1. $X_e^{\neq j}$ denotes the $(K - 1) \times N_e$ matrix of inputs of all the efficient banks, also excluding the j th input, N_e denotes the number of efficient banks as already identified in Step 2, Y_e denotes the matrix of outputs of the efficient banks, and λ has a dimension of $N_e \times 1$.

Fourth, an LP is estimated for the i th bank in the 'banks with slacks' set, which seeks a radial reduction in all inputs that have already been identified during Step 3 as having potential slacks. This estimation can be illustrated as follows:

$$\begin{aligned} & \min \theta \\ & \theta, \lambda \\ & \text{s. t. } -y_i + Y_e \lambda \geq 0, \\ & \theta c x_i^s - X_e^s \lambda \geq 0, \\ & c x_i^{ns} - X_e^{ns} \lambda \geq 0, \\ & \lambda \geq 0, \end{aligned} \quad [\text{Eqn 4}]$$

s denotes the subset of inputs that have potential slacks, and ns denotes the remainder of the inputs used. Remember that the radial reduction in this specific step starts by applying the projected point ($y_e, c x_i$) that has already been estimated during Step 1.

Fifth, it is still possible for some input slacks to remain after the radial reduction in the previous step. To overcome this problem, Steps 3 and 4 must be repeated with the projected point (which has already been identified during Step 4) until no remaining input slacks are present.

Finally, a radial expansion is conducted in the output slack dimensions until no output slacks remain. This can be accomplished by taking the projected points of the i th bank (as estimated in Step 5) and repeating Steps 3 through to 5. The final projected point from this step (which will be invariant to the units of measurements that were chosen) will be on the efficient surface. The slacks can then be estimated by subtracting the final projected point in this step from the projected point that was obtained in Step 1. Also, the peers of the i th bank can be identified from the λ vector of the final projected point.

The benefit of using a multi-stage DEA model is that it has the ability and advantage to focus on each bank individually,

relative to sample averages or parametric populations. The model can thus adjust for exogenous variables that are beyond the control of DMUs and accommodate multiple inputs and outputs without the need for homogeneous measurement units. It also does not require any assumptions of a functional form relating inputs to outputs and can focus on observed best-practice frontiers rather than on central tendency properties of frontiers. Furthermore, it provides insight into the input and output quantities that inefficient banks must achieve in order to operate on the efficient frontier and it produces a single efficiency estimate for each bank in terms of its respective input-output relationships (Charnes et al. 1978; Nunamaker 1985). The multi-stage DEA version is therefore appropriate for this study, as it overcomes two main shortcomings of the commonly used two-stage LP process (Coelli 1998; Lovell & Pastor 1995): firstly, the two-stage LP process maximises the sum of slacks, where it should minimise it, and it identifies the furthest efficient point, where it should identify the nearest point; secondly, the two-stage LP process is not invariant to the units of measurement.

Sampling and data selection

The data used for this study included annual financial ratios obtained from the IRESS INET (2017) database spanning from 2004 to 2016 (see Table 3). The implied dividend growth rate and the equally weighted DuPont were estimated in Microsoft Excel®. As the ROE fails to account for financial leverage, a DuPont index was constructed, where equal weights were assigned to financial leverage, return on assets, and the ROE. The implied dividend growth rate was estimated by multiplying the retention rate with the ROE, as obtained from the IRESS INET (2017) database. Furthermore, monthly closing prices for Barclays Africa Group Ltd (BGA), Capitec Bank Holdings Ltd (CPI), Firststrand Ltd (FSR), Investec Ltd (INL), Nedbank Group Ltd (NED) and Standard Bank Group Ltd (SBK) were sourced from the IRESS INET (2017) database for the period 31 January 2004 to 31 December 2016. This time span was determined by the data availability at the time of the study. The monthly share returns and market capitalisation derived from these closing prices were adjusted for splits and dividends, accordingly, before being converted to an annual average. The monthly returns were estimated as follows: $(Price_t - Price_{t-1}) \div Price_{t-1}$.

The JSE Bank index (J835) was utilised as the market proxy and was also sourced from the IRESS INET (2017) database. Based on the findings and arguments posed by Van Heerden (2016) and Grandes and Pinaud (2004), this study uses the 3-month Negotiable Certificates of Deposits (NCDs) rate as the risk-free rate proxy and the threshold proxy for the static Omega ratio, which was sourced from the SARB website (2017a). Owing to the unavailability of data, transaction costs were excluded.

A list of the typically most popular risk-adjusted performance ratios and measures used in this study is provided in Table 3. Jensen's alpha (Jensen 1968) is included to evaluate the predictive ability of the market beta over the time horizon under evaluation. Further to this, in order to account for higher moments and correlation in returns, the Sharpe ratio is adjusted to account for value-at-risk (VaR), conditional expectation of loss (CVaR), and the implementation of the Cornish-Fisher expansion (MVar). Finally, as with the works of Elyasiani and Mehdiian (1990), Kaparakis, Miller and Noulas (1994) and Wheelock and Wilson (1995), this study will adopt an intermediation approach (Sealey & Lindley 1977) in the selection of input and output variables for the estimation of pure technical (VRS), scale, and total technical efficiency (CRS). Listed in Table 4, these input and output variables for the period January 2004 to December 2016 were obtained from the historical D1900 reports that were converted to BA900 reports on the SARB website (2017a). The monthly total of each variable (which also forms the main entries in the financial return statements) is used as reported in the BA900 statements (see column 2 in Table 4), with the only exception being the deposits, loans and advances output variable which excludes SA group financing (item #111), and was used as an input variable.

Results

The results on the average ability of each ratio (across all six banks) to explain ex-post future share returns over a one-, three- and five-year investment horizon are depicted in Figure 1. On average, pure technical efficiency (VRS) was able to explain 94% (the highest) of the ex-post future share returns over all three investment horizons under evaluation.

TABLE 3: The financial, non-financial and risk-adjusted performance ratios and measures under evaluation.

Financial ratios	Non-financial measures	Risk-adjusted performance ratios
Dividend yield (%)	Pure technical efficiency (VRS)	Sharpe ratio (Sharpe 1966)
Earnings yield (%)	Scale efficiency	Treynor ratio (Treynor 1965)
Book-to-market ratio	Total technical efficiency (CRS)	Jensen's alpha (Jensen 1968)
Cash-flow-to-price ratio	-	Sortino ratio (Sortino & Van Der Meer 1991)
Price-to-earnings ratio	-	Calmar ratio (Young 1991)
Price-to-NAV ratio	-	VaR(99%)-Sharpe ratio (adapted from Dowd 1999, 2000)
Return-on-equity ratio (%)	-	Conditional [CVaR(99%)] Sharpe ratio (adapted from Artzner et al. 1997, 1999; Esfahanipour & Mousavi 2011)
Market capitalisation	-	Modified [MVar(99%)] Sharpe ratio (adapted from Favre & Galeano 2002; Gregoriou & Gueyie 2003)
Implied dividend growth rate	-	Static Omega ratio (Keating & Shadwick 2002)
Equally weighted DuPont	-	-

Note: Please see the full reference list of the article, Van Heerden, C. & Coetzee, J., 2019, 'Re-examining the ability to explain future South African banking share returns: A data envelopment analysis approach', *South African Journal of Economic and Management Sciences* 22(1), a2852. <https://doi.org/10.4102/sajems.v22i1.2852>, for more information.

VRS, variable returns to scale; CRS, constant returns to scale; NAV, net asset value; VaR, value at risk; CVaR, conditional value at risk; MVar, Modified value at risk.

Total technical efficiency (CRS) exhibited the second best performance in explaining an average of 91% of ex-post future share returns over the three- and five-year investment horizon. Scale efficiency exhibited the second best ability to explain one-year-ahead share returns (92%) and the third best ability to explain ex-post future share returns over the three- and five-year investment horizon (90% on average for both periods). Conversely, market capitalisation exhibited the poorest ability to explain ex-post future returns over all three investment horizons under evaluation (34% on average), followed by the equally weighted DuPont index (41% on average) and the VaR-Sharpe ratio (43% on average), with their poor ability to explain one-, three- and five-years-ahead share returns (ex-post). The financial ratio that exhibited the best performance over all three investment horizons under evaluation was the P/E ratio (82% on average), which supports the findings of Van Rensburg and Robertson (2003). Other top-performing financial ratios include the ROE ratio (76% on average), the EY (69% on average), and the implied dividend growth rate (65% on average).

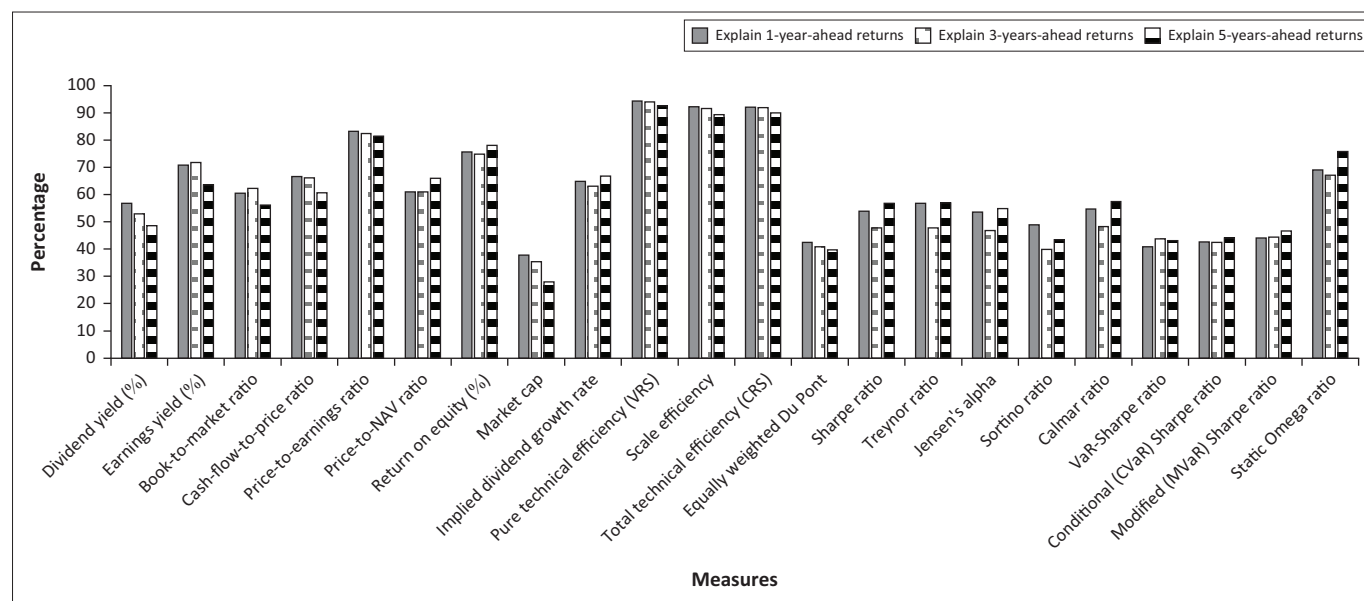
The results reported in Figure 1 (and Table 1-A1 in the appendix) contradict the findings of Fama and French (2017),

TABLE 4: Selected input and output variables for estimating technical and scale efficiency.

Variables	Item number
Input	
Total deposits	1
Central bank and money	103
SA group financing	111
Total equity	96
Output	
Deposits, loans and advances	110
Other liabilities	80
Investment and bills	195

Note: The scale of some of these variables had to be adjusted to accommodate negative values.

Muller and Ward (2013), and Van Rensburg and Robertson (2003) from a specifically banking industry point of view. More specifically, the EY (69% on average), cash-flow-to-price ratio (64% on average), B/M ratio (60% on average), and the market capitalisation (34% on average) performed relatively poorly and were inconsistent in explaining ex-post future returns over the different investment horizons. It is also interesting to note that the composition of the best performing financial ratios differed amongst the three investment horizons. Although the P/E and return-to-equity ratios exhibited the best performance throughout all three investment horizons, the rest of the composition for each investment horizon differed. The other three top-performing ratios over the one- and three-year investment horizon entailed the earnings yield, cash-flow-to-price ratio and the implied dividend growth rate, whereas the implied dividend growth rate, price-to-NAV ratio and the earnings yield were the other three top-performing ratios over the five-year investment horizon. These results imply that passive and active portfolio managers may consider different financial ratio compositions. The implication is that the most 'ideal' set of ratios will be influenced by the investment horizon, which to some extent may provide some explanation as to why past studies found different results (besides the fact that they might also be sector dependent). This time-dependency phenomenon was, however, not present with the evaluation of the risk-adjusted performance measures. The static Omega ratio exhibited the best performance in explaining ex-post future share returns over all three investment horizons under evaluation (71% on average), followed by the Treynor ratio (53% on average), the Sharpe ratio (53% on average), and the Jensen's alpha (52% on average). This implies that risk-adjusted performance ratios (including non-financial measures) can be used, to some extent, as a short- and long-term investment decision-making tool. However, the worst performing risk-adjusted



Note: See Table 1-A1 in Appendix 1 for a more detailed report.

FIGURE 1: Average ability to explain future returns (across all banks).

performance ratios over the three investment horizons consisted of the Sortino ratio (44% on average) and the different modified Sharpe ratios, which entailed the MVaR-Sharpe ratio (45% on average), the CVaR-Sharpe ratio (43% on average), and the VaR-Sharpe ratio (43% on average). Overall, the results suggest that non-financial measures exhibit the highest average ability (92%) to explain ex-post future share returns over all three investment horizons, followed by the financial ratios (61% on average) and risk-adjusted performance ratios (51% on average). Nevertheless, there is also consistency found in the top-ranked measures (per category) over all three investment horizons under evaluation. These ratios entailed pure technical efficiency (94% on average), the P/E ratio (82% on average), and the static Omega ratio (71% on average), where this group of measures would have enabled an investor to explain 82% (on average) of future returns over all three investment horizons.

Tables 5–7 further highlight the findings that non-financial measures had the highest success rate in explaining future returns of individual banking shares, over the one-, three-, and five-year investment horizons (83%, 83%, and 67% on average). Pure technical efficiency (VRS) exhibited the best performance, followed by scale efficiency and total technical efficiency (CRS). The financial ratios outperformed the risk-adjusted performance ratios, with the P/E ratio having the highest success rate followed by the ROE and price-to-NAV ratios. From the risk-adjusted performance ratios perspective, the

static Omega ratio exhibited the best success followed by the Treynor and the Sharpe ratios. Of interest to note is that market capitalisation exhibited the worst success rate in explaining the ex-post future share returns of Firststrand Ltd, Standard Bank Group Ltd, and Nedbank Ltd over all three investment horizons under evaluation, except for Nedbank Ltd over the five-year investment horizon. The Sortino and CVaR-Sharpe ratios exhibited the poorest success rate in explaining the ex-post future share returns of Capitec Bank Holdings Ltd and Investec Bank Ltd, over all three investment horizons (see Tables 3–5). The only noteworthy exception was for Barclays Africa Group Ltd, where the P/E ratio exhibited the best success rate (as opposed to pure technical efficiency), whereas the equally weighted DuPont (over the one-year horizon) and market capitalisation (over the three- and five-year horizons) exhibited the poorest success rate. Furthermore, over the five-year investment horizon, there was no significant difference between the different ratios in explaining the ex-post future share returns of Capitec Bank Holdings Ltd. Also, the price-to-NAV ratio exhibited the best success rate in explaining the ex-post future share returns of Firststrand Ltd over all three investment horizons (see Tables 5–7).

These findings suggest that the non-financial measures, namely pure technical efficiency (VRS), scale efficiency, and total technical efficiency (CRS), outperformed the ability of financial and risk-adjusted performance ratios to explain ex-post future share returns for the six individual South African banking shares. It is also noteworthy to report

TABLE 5: Average explanatory ability of ratios to explain one year ahead share returns per bank.

Ratios under evaluation	Barclays Africa Group Ltd (%)	Capitec Bank Holdings Ltd (%)	Firststrand Ltd (%)	Investec Ltd (%)	Nedbank Group Ltd (%)	Standard Bank Group Ltd (%)
Dividend yield (%)	41.76	95.41	48.95	46.33	45.75	62.50
Earnings yield (%)	59.17	92.35	63.50	84.05	58.00	67.60
Book-to-market ratio	51.19	92.49	69.58	49.79	44.06	56.23
Cash-flow-to-price ratio	59.99	92.22	66.82	65.00	59.44	56.54
Price-to-earnings ratio	92.41	81.58	83.35	74.49	87.49	80.05
Price-to-NAV ratio	30.31	64.61	66.30	93.21	38.48	72.47
Return-on-equity (%)	64.58	86.97	58.11	88.28	84.04	71.82
Market cap	18.61	95.81	15.98	66.90	14.43	14.92
Implied dividend growth rate	66.10	77.52	54.48	74.12	61.80	55.10
Pure technical efficiency (VRS)	91.58	96.75	92.78	95.13	99.09	90.56
Scale efficiency	89.81	100.00	89.87	92.43	90.34	90.82
Total technical efficiency (CRS)	88.27	98.67	89.43	92.41	95.87	87.89
Equally weighted DuPont	12.13	62.84	67.30	54.17	26.50	31.64
Sharpe ratio	43.51	68.90	47.90	60.62	56.16	45.89
Treynor ratio	44.67	68.29	53.81	68.78	52.15	53.39
Jensen's alpha	41.04	68.37	48.03	68.47	47.37	47.64
Sortino ratio	37.93	59.23	45.67	55.19	46.89	48.49
Calmar ratio	45.95	68.78	42.56	64.68	51.05	54.76
VaR-Sharpe ratio	18.55	77.64	27.60	46.98	43.11	31.35
Conditional (CVaR) Sharpe ratio	22.73	77.76	35.77	40.92	46.25	32.20
Modified (MVaR) Sharpe ratio	23.44	77.05	36.33	48.49	46.24	32.86
Static Omega ratio	66.25	72.34	64.76	76.33	68.53	65.94
Overall average	50.45	80.71	57.68	68.49	57.41	56.85
Overall minimum	12.13	59.23	15.98	40.92	14.43	14.92
Overall maximum	92.41	100.00	92.78	95.13	99.09	90.82
Average of traditional financial ratios	49.62	84.18	59.44	69.64	52.00	56.89
Average of non-financial measures	89.89	98.47	90.70	93.32	95.10	89.76
Average of risk-adjusted performance ratios	38.23	70.93	44.71	58.94	50.86	45.84

VaR, value at risk; CVaR, conditional value at risk; MVaR, Modified value at risk.

TABLE 6: Average explanatory ability of ratios to explain three years ahead share returns per bank.

Ratios under evaluation	Barclays Africa Group Ltd (%)	Capitec Bank Holdings Ltd (%)	Firststrand Ltd (%)	Investec Ltd (%)	Nedbank Group Ltd (%)	Standard Bank Group Ltd (%)
Dividend yield (%)	34.72	100.00	47.05	40.06	43.21	52.66
Earnings yield (%)	56.28	100.00	64.65	82.85	62.05	64.53
Book-to-market ratio	54.49	100.00	70.52	46.34	45.06	57.48
Cash-flow-to-price ratio	56.32	98.53	64.66	61.21	58.31	58.12
Price-to-earnings ratio	92.07	92.09	86.43	65.36	80.39	78.00
Price-to-NAV ratio	24.66	81.03	79.89	82.91	31.18	66.45
Return-on-equity (%)	60.51	89.09	63.75	83.44	84.31	67.98
Market cap	7.30	98.39	23.48	60.68	18.34	4.38
Implied dividend growth rate	59.80	86.00	59.13	65.10	59.81	48.57
Pure technical efficiency (VRS)	90.84	99.12	92.22	93.08	99.09	89.26
Scale efficiency	89.22	100.00	90.80	90.40	90.05	89.14
Total technical efficiency (CRS)	87.07	100.00	90.08	91.41	97.00	85.37
Equally weighted DuPont	13.98	80.00	68.05	44.57	11.37	26.69
Sharpe ratio	38.42	80.00	50.13	48.92	44.65	24.44
Treynor ratio	40.37	80.00	51.58	55.47	32.65	26.66
Jensen's alpha	36.67	80.00	49.89	56.34	31.79	25.82
Sortino ratio	34.11	70.66	38.11	41.76	28.02	26.78
Calmar ratio	39.73	80.23	43.68	51.63	39.59	34.66
VaR-Sharpe ratio	21.30	83.57	48.52	38.92	49.79	20.00
Conditional (CVaR) Sharpe ratio	21.30	83.71	48.41	38.44	47.54	15.73
Modified (MVaR) Sharpe ratio	21.84	84.14	48.49	47.86	47.65	16.31
Static Omega ratio	66.74	82.31	64.65	67.13	63.69	58.42
Overall average	47.63	88.58	61.10	61.54	52.98	47.16
Overall minimum	7.30	70.66	23.48	38.44	11.37	4.38
Overall maximum	92.07	100.00	92.22	93.08	99.09	89.26
Average of traditional financial ratios	46.01	92.51	62.76	63.25	49.40	52.49
Average of non-financial measures	89.04	99.71	91.03	91.63	95.38	87.92
Average of risk-adjusted performance ratios	35.61	80.51	49.27	49.61	42.82	27.65

VaR, value at risk; CVaR, conditional value at risk; MVaR, Modified value at risk.

TABLE 7: Average explanatory ability of ratios to explain five years ahead share returns per bank.

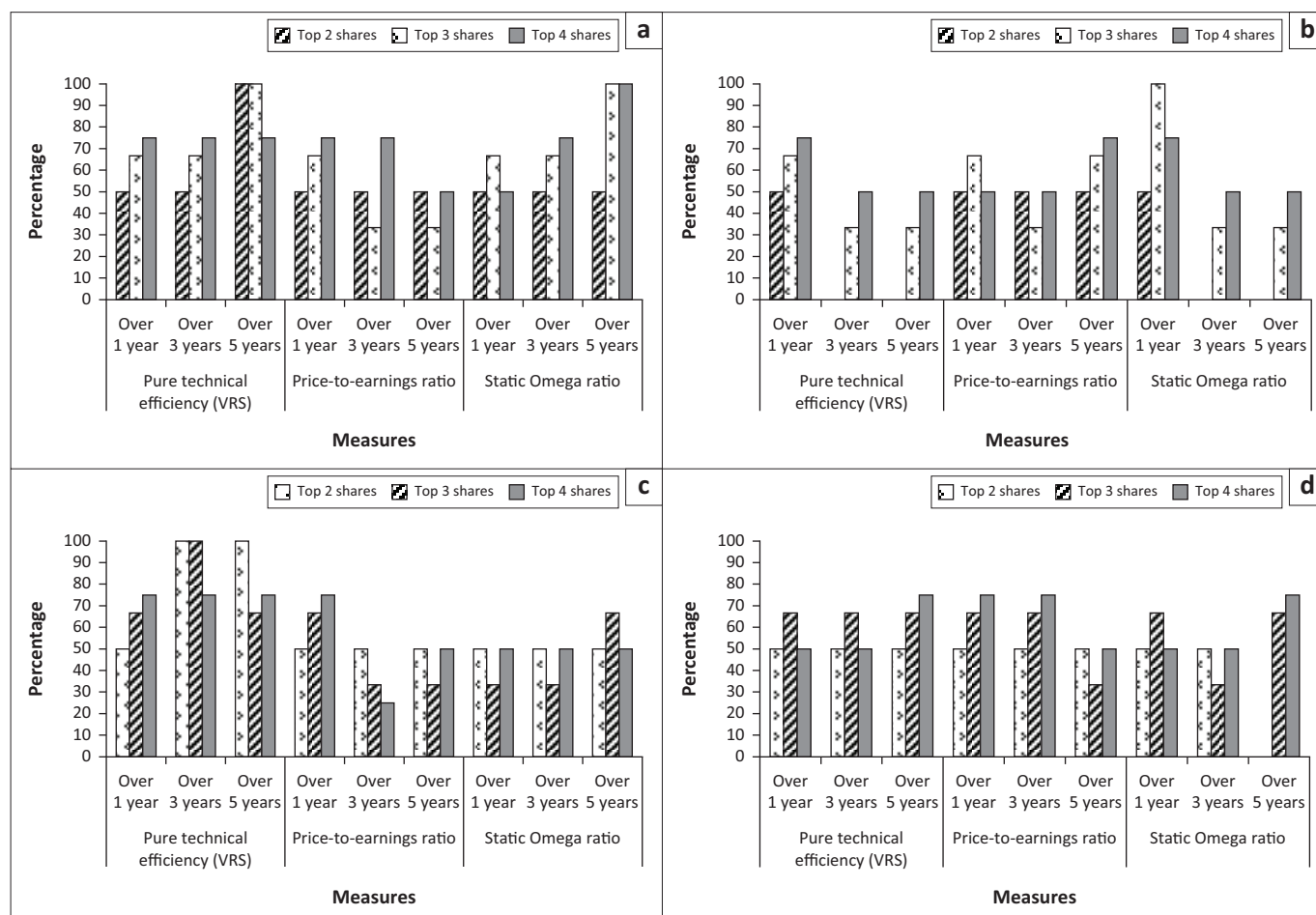
Ratios under evaluation	Barclays Africa Group Ltd	Capitec Bank Holdings Ltd	Firststrand Ltd	Investec Ltd	Nedbank Group Ltd	Standard Bank Group Ltd
Dividend yield (%)	33.73	100.00	35.88	36.22	36.51	48.66
Earnings yield (%)	48.50	100.00	51.29	73.66	52.56	55.63
Book-to-market ratio	48.30	100.00	51.69	49.31	37.16	50.21
Cash-flow-to-price ratio	47.61	100.00	52.67	60.30	48.75	54.34
Price-to-earnings ratio	91.31	100.00	83.40	63.54	76.31	74.26
Price-to-NAV ratio	23.59	100.00	98.07	78.25	30.20	65.24
Return-on-equity (%)	63.10	100.00	60.55	80.20	93.08	71.65
Market cap	5.48	100.00	4.60	46.47	7.88	3.25
Implied dividend growth rate	51.24	100.00	61.83	71.14	65.56	51.02
Pure technical efficiency (VRS)	86.80	100.00	91.16	91.96	99.78	85.82
Scale efficiency	87.06	100.00	86.78	88.19	86.83	86.95
Total technical efficiency (CRS)	83.96	100.00	86.60	89.87	96.44	83.01
Equally weighted DuPont	7.51	100.00	52.42	50.00	9.29	18.89
Sharpe ratio	38.49	100.00	59.88	59.15	52.64	30.35
Treynor ratio	40.88	100.00	61.86	68.58	37.92	32.46
Jensen's alpha	35.94	100.00	61.01	65.30	36.36	30.98
Sortino ratio	31.70	87.50	46.21	39.65	24.27	31.10
Calmar ratio	39.86	100.00	50.92	64.28	45.74	43.62
VaR-Sharpe ratio	15.21	100.00	51.67	22.56	59.90	9.36
Conditional (CVaR) Sharpe ratio	19.56	100.00	51.43	22.25	60.71	10.17
Modified (MVaR) Sharpe ratio	21.26	100.00	51.26	34.20	61.64	11.28
Static Omega ratio	64.68	100.00	73.51	76.68	76.92	62.80
Overall average	44.81	99.43	60.21	60.53	54.38	45.96
Overall minimum	5.48	87.50	4.60	22.25	7.88	3.25
Overall maximum	91.31	100.00	98.07	91.96	99.78	86.95
Average of traditional financial ratios	42.04	100.00	55.24	60.91	45.73	49.32
Average of non-financial measures	85.94	100.00	88.18	90.00	94.35	85.26
Average of risk-adjusted performance ratios	34.18	98.61	56.42	50.29	50.68	29.12

VaR, value at risk; CVaR, conditional value at risk; MVaR, Modified value at risk.

that the ex-post future returns of Capitec Bank Holdings Ltd (90% on average), Investec Ltd (64% on average) and Firstrand Ltd (60% on average) are best explained by all the measures over all three investment horizons under evaluation. On the other hand, the ex-post future share returns of Standard Bank Group Ltd is the poorest explained by all the measures (56% on average), where the risk-adjusted performance measures explained the least (34% on average). The ability to explain Barclays Africa Group Ltd's ex-post future share returns also ranked second last (58% on average), with risk-adjusted performance ratios being able to explain only 36% (on average) over all investment horizons under evaluation.

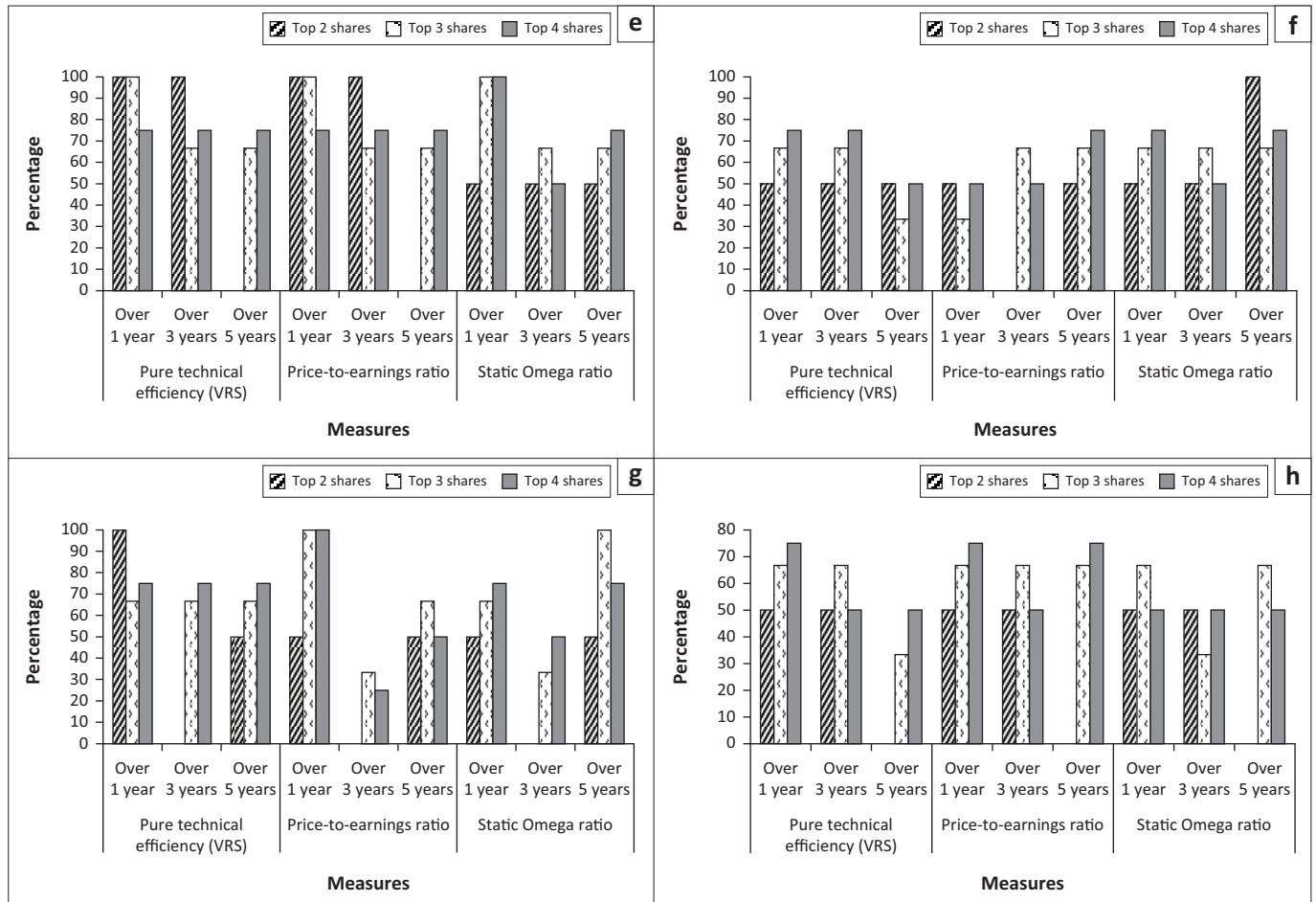
To conclude the empirical study, until this point pure technical efficiency (VRS), the price-to-earnings ratio and the static Omega ratio were identified as the top performing ratios. However, these measures were only credited with being able to explain ex-post future share returns, but not identified as selecting tools in establishing the ranking order of the top performing banking shares. For this reason, it is also useful from a risk-adjusted perspective, to evaluate the ability of these measures to select the top two, three and four banking shares over the three investment horizons under evaluation. This implies that the ranking orders of the different efficiency scores were compared to the ranking

orders derived from evaluating the realised risk-adjusted returns (average returns divided by the annualised standard deviation) over the three investment horizons. Over the one-year investment horizon, Figure 2 reports that pure technical efficiency (VRS) exhibited the greatest success rate, with an average ability to predict 63% of the top two banking shares (on an ex-post basis), followed by the P/E ratio (56% on average) and the static Omega ratio (50% on average). However, pure technical efficiency (VRS) and P/E ratio exhibited similar performance in being able to predict the top three and top four banking shares (71% and 72% on average). It is also noteworthy to report that pure technical efficiency (VRS) and the P/E ratio were able to predict 100% of the top two banking shares during 2008, and to predict 83% (VRS) and 67% (P/E ratio) of the top two banking shares over the global financial crisis (estimated from 2008 to 2010). Besides the poor ability of the Omega ratio to predict 66% (on average, from 2004 to 2011) of the top four banking shares, it exhibited similar performance to pure technical efficiency (VRS) and the P/E ratio in predicting the top three banking shares. Furthermore, the static Omega ratio outperformed in predicting 100% of the top four banking shares in 2008, and exhibited the greatest ability to predict the top four banking shares (83% on average) over the global financial crisis (estimated from 2008 to 2010). On the other hand, in



Note: See Table 2-A1 in Appendix 1 for a more detailed report.

FIGURE 2: Average ability of pure technical efficiency (VRS), the P/E ratio and static Omega ratio to select the top performing banking shares: (a) 2004; (b) 2005; (c) 2006; (d) 2007; (e) 2008; (f) 2009; (g) 2010 and (h) 2011.



Note: See Table 2-A1 in Appendix 1 for a more detailed report.

FIGURE 2 (Continues...): Average ability of pure technical efficiency (VRS), the P/E ratio and static Omega ratio to select the top performing banking shares: (a) 2004; (b) 2005; (c) 2006; (d) 2007; (e) 2008; (f) 2009; (g) 2010 and (h) 2011.

predicting the top three banking shares over the global financial crisis, all three measures exhibited similar performance (78% on average), and specifically in 2008 where 100% of the top three banking shares could be predicted by all three measures.

Over a three-year investment horizon, Figure 2 illustrates that pure technical efficiency (VRS) and the P/E ratio exhibited the greatest ability in predicting the top two and top four banking shares in 2008 (100% and 75%), whereas all three measures exhibited similar performance in being able to predict 67% of the top three banking shares in 2008. However, on average, pure technical efficiency (VRS) outperformed the P/E and static Omega ratio in predicting the top two, three and top four banking shares over the global financial crisis and over the entire horizon under evaluation (2004 to 2011). However, over the five year investing horizon the static Omega ratio was more dominant in predicting the top three and top four banking shares (71% and 69% on average). The only exception was in predicting the top two banking shares, where pure technical efficiency (VRS) was more dominant (44% on average). Nonetheless, the static Omega ratio was better at predicting the top two banking shares in 2008 and more dominant at predicting the top two, three and top four banking shares over the global financial

crisis (67%, 78% and 75% on average, respectively). There is only one exception to the former, where all three measures exhibited similar performance in predicting the top three and top four banking shares in 2008 (67% and 75% on average). Overall, from these results it is more conclusive that non-financial measures may have the tendency to better explain future returns and to select top performing banking shares. Although the results from this study may suggest that pure technical efficiency (VRS), the price-to-earnings ratio and the static Omega ratio are the more 'ideal' set of ratios to consult, it is evident from Figure 2 that there may be a tendency for risk-adjusted measures to be a better share selecting tools over a longer investment horizon.

Conclusion and recommendations

From the literature it is clear that there is no consensus on the choice of an 'all-inclusive' group of ratios that can be used as a basis to explain future returns. This leaves a gap in the literature to identify the true drivers that will ensure the creation of future portfolio wealth. This study fills this gap by comparing the abilities of financial, non-financial, and risk-adjusted performance ratios to explain ex-post future returns for banks in the South African context for a specifically momentum-based investment strategy over one-, three- and five-year investment horizons. The results find that non-financial measures exhibited

the overall highest average ability (92%) to explain ex-post future banking share returns over the three investment horizons, followed by the financial ratios (61% on average) and risk-adjusted performance ratios (51% on average). The most accurate non-financial measure was pure technical efficiency (VRS), because of its ability to incorporate the interdimensional relationships of banking operations and, in so doing, be less vulnerable to data manipulation. The financial and risk-adjusted performance ratios that exhibited the best performance included the P/E and the static Omega. However, with the evaluation of the five top-performing measures per investment horizon, evidence suggested that passive and active portfolio managers may consider different financial ratio compositions, as each investment horizon emphasised a different composition of more 'ideal' performing ratios. Nevertheless, the dominance of non-financial measures was further accentuated by demonstrating pure technical efficiency's (VRS) ability to predict the top performing banking shares over the one- and three-year investment horizons from a risk-adjusted perspective. The static Omega ratio, on the other hand, exhibited greater performance over the five-year investment horizon, in predicting the top three and top four banking shares. This implies that risk-adjusted performance ratios and non-financial measures can be used as a short-, and long-term investment decision-making tool, although the static Omega ratio tended to be a better share-selecting tool over a longer investment horizon.

This study raises a few opportunities for future research. Firstly, additional non-financial measures such as balanced scorecards and the stochastic frontier analysis can also be investigated to determine their ability to explain future share returns as compared to the efficiency ratios used in this study. Secondly, future studies can use the approach used in this study and apply it in other industries or sectors. These studies can also use a wider range of financial and risk-adjusted performance ratios. Finally, the ability to explain future returns to some extent may imply that the South African banking industry may be time-varying information efficient. Future studies can therefore determine whether or not rigorous regulation is a function of better share return predictability.

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Competing interests

The authors have declared that no competing interests exist.

Author's contributions

Prof. Chris van Heerden was responsible for the empirical study, whereas Dr Johan Coetzee was responsible for the literature study.

Ethical consideration

This article followed all ethical standards for carrying out research without direct contact with human or animal subjects.

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Data availability statement

Data sharing is not applicable to this article.

Disclaimer

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References

- Abad, C., Thore, S.A. & Laffarga, J., 2004, 'Fundamental analysis of stocks by two-stage DEA', *Managerial and Decision Economics* 25(5), 231–241. <https://doi.org/10.1002/mde.1145>
- Afonso, A. & Fernandes, S., 2008, 'Assessing and explaining the relative efficiency of local government', *The Journal of Socio-Economics* 37(5), 1946–1979.
- Aigner, D., Lovell, C.K. & Schmidt, P., 1977, 'Formulation and estimation of stochastic frontier production function models', *Journal of Econometrics* 6(1), 21–37. [https://doi.org/10.1016/0304-4076\(77\)90052-5](https://doi.org/10.1016/0304-4076(77)90052-5)
- Alexakis, P. & Tsolas, I.E., 2011, 'Appraisal of mutual equity fund performance using data envelopment analysis', *Multinational Finance Journal* 15(3–4), 273–296.
- Allen, R.G.D., 1939, *Mathematical analysis for economists*, New York, MacMillan.
- Ames, D., Brazel, J.F., Jones, K.L., Rich, J.S. & Zimbelman, M.F., 2012, 'Using nonfinancial measures to improve fraud risk assessments', *Current Issues in Auditing* 6(1), C28–C34. <https://doi.org/10.2308/ciaa-50168>
- Amiri, M., Zandieh, M., Vahdani, B., Soltani, R. & Roshanaei, V., 2010, 'An integrated eigenvector-DEA-TOPSIS methodology for portfolio risk evaluation in the FOREX spot market', *Expert Systems with Applications* 37(1), 509–516. <https://doi.org/10.1016/j.eswa.2009.05.041>
- Anderson, R.I., Fok, R., Springer, T. & Webb, J., 2002, 'Technical efficiency and economies of scale: A non-parametric analysis of REIT operating efficiency', *European Journal of Operational Research* 139(3), 598–612.
- Aparicio, J., Cordero, J.M., Gonzalez, M. & Lopez-Espin, J.J., 2018, 'Using non-radial DEA to assess school efficiency in a cross-country perspective: An empirical analysis of OECD countries', *Omega* 79, 9–20. <https://doi.org/10.1016/j.omega.2017.07.004>
- Arshinova, T., 2011, 'The banking efficiency measurement using the frontier analysis techniques', *Journal of Applied Mathematics* 4(3), 165–176.
- Artzner, P., Delbaen, F., Eber, J.-M. & Heath, D., 1997, 'Thinking coherently', *Risk* 10, 68–71.
- Artzner, P., Delbaen, F., Eber, J.M. & Heath, D., 1999, 'Coherent measures of risk', *Mathematical Finance* 9(3), 203–228. <https://doi.org/10.1111/1467-9965.00068>
- Asness, C., Porter, R. & Stevens, R., 2000, 'Predicting stock returns using industry-relative firm characteristics', viewed 03 November 2017, from <https://faculty.som.yale.edu/zhiwuchen/Investments/Predict.pdf>.
- Auret, C. & Cline, R., 2011, 'Do the value, size and January effects exist on the JSE?', *Investment Analysts Journal* 40(74), 29–37. <https://doi.org/10.1080/10293523.2011.11082539>
- Auret, C.J. & Sinclair, R.A., 2006, 'Book-to-market ratio and returns on the JSE', *Investment Analysts Journal* 35(63), 31–38. <https://doi.org/10.1080/10293523.2006.11082476>
- Avkiran, N.K., 1997, 'Models of retail performance for bank branches: Predicting the level of key business drivers', *International Journal of Bank Marketing* 15(6–7), 224–237. <https://doi.org/10.1108/02652329710184451>
- Avkiran, N.K., 1999, 'An application reference for data envelopment analysis in branch banking: Helping the novice researcher', *International Journal of Marketing* 17(5), 206–220. <https://doi.org/10.1108/02652329910292675>
- Avkiran, N.K. & Morita, H., 2010, 'Predicting Japanese bank stock performance with a composite relative efficiency metric: A new investment tool', *Pacific-Basin Finance Journal* 18(3), 254–271.
- Azadeh, A., Ghaderi, S.F. & Maghsoudi, A., 2008, 'Location optimization of solar plants by an integrated hierarchical DEA PCA approach', *Energy Policy* 36(10), 3993–4004.
- Banker, R., Chen, J.Y.S. & Klumpes, P., 2016, 'A trade-level DEA model to evaluate relative performance of investment fund managers', *European Journal of Operational Research* 225(3), 903–910. <https://doi.org/10.1016/j.ejor.2016.05.056>
- Banker, R.D., Charnes, A.W. & Cooper, W.W., 1984, 'Some models for estimating technical and scale efficiency in data envelopment analysis', *Management Sciences* 30(9), 1078–1092. <https://doi.org/10.1287/mnsc.30.9.1078>

- Banz, R.W., 1981, 'The relationship between return and market value of common stocks', *Journal of Financial Economics* 9(1), 3–18. [https://doi.org/10.1016/0304-405X\(81\)90018-0](https://doi.org/10.1016/0304-405X(81)90018-0)
- Barak, S. & Dahooei, J.H., 2018, 'A novel hybrid fuzzy DEA-Fuzzy MADM method for airlines safety evaluation'. *Journal of Air Transport Management* 73, 134–149. <https://doi.org/10.1016/j.jairtraman.2018.09.001>
- Barclays Africa Ltd, 2016, *Barclays Africa Group Limited integrated report*, Barclays Africa Ltd, Johannesburg.
- Barros, C.P. & Dieke, P.U., 2008, 'Technical efficiency of African hotels', *International Journal of Hospitality Management* 27(3), 438–447. <https://doi.org/10.1016/j.ijhm.2007.11.004>
- Barros, C.P., Nektarios, M. & Assaf, A., 2010, 'Efficiency in the Greek insurance industry', *European Journal of Operational Research* 205(2), 431–436.
- Basiewicz, P.G. & Auret, C.J., 2010, 'Feasibility of the Fama and French three factor model in explaining returns on the JSE', *Investment Analysts Journal* 39(71), 13–25.
- Basso, A., Funari, S., 2016, 'DEA performance assessment of mutual funds', *Data Envelopment Analysis* 2016, 229–287. https://doi.org/10.1007/978-1-4899-7684-0_8
- Basu, S., 1983, 'The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence', *Journal of Financial Economics* 12(1), 129–156. [https://doi.org/10.1016/0304-405X\(83\)90031-4](https://doi.org/10.1016/0304-405X(83)90031-4)
- Beccalli, E., Casu, B. & Girardone, C., 2006, 'Efficiency and stock performance in European banking', *Journal of Business Finance & Accounting* 33(1–2), 245–262. <https://doi.org/10.1111/j.1468-5957.2006.01362.x>
- Berzkalne, I. & Zelgalve, E., 2014, 'Return on equity and company characteristics: An empirical study of industries in Latvia', *The 8th International Days of Statistics and Economics, Prague*, September, pp. 94–103, viewed 03 November 2017, from https://msed.vse.cz/msed_2014/article/253-Berzkalne-Irina-paper.pdf.
- Bessent, A., Bessent, W., Kennington, J. & Reagan, B., 1982, 'An application of mathematical programming to assess productivity in the Houston independent school district', *Management Science* 28(12), 1355–1367.
- Bhandari, L.C., 1988, 'Debt/equity ratio and expected common stock returns: Empirical evidence', *Journal of Finance* 43(2), 507–528. <https://doi.org/10.2307/2328473>
- Black, F., 1972, 'Capital market equilibrium with restricted borrowing', *Journal of Business* 45(3), 444–455.
- Bonorchis, R., 2017a, 'Capitec's stock price has jumped 50 000% since 2002', *Moneyweb*, viewed 10 October 2017, from <https://www.moneyweb.co.za/news/companies-and-deals/capitecs-stock-price-has-jumped-50-000-since-2002/>.
- Bonorchis, R., 2017b, 'Capitec overtakes Nedbank, now SA's fourth-largest bank by value', *Fin24*, viewed 10 October 2017, from <https://www.fin24.com/Companies/Financial-Services/capitec-overtakes-nedbank-now-sas-fourth-largest-bank-by-value-20170908>.
- Boscá, J.E., Liern, V., Martínez, A. & Sala, R., 2009, 'Increasing offensive or defensive efficiency? An analysis of Italian and Spanish football', *Omega* 37(1), 63–78.
- Businessstech, 2017, 'Capitec is now the second biggest bank in South Africa', *Business Tech*, viewed 10 October 2017, from <https://businessstech.co.za/news/banking/189420/capitec-is-now-the-second-biggest-bank-in-south-africa/>.
- Capitec Bank Ltd., 2017, *Capitec Bank Holdings Ltd integrated annual report*, viewed 10 October 2017, from https://commondatastorage.googleapis.com/capitecbank-co-za/integrated_annual_report.pdf.
- Chan, L.K., Hamao, Y. & Lakonishok, J., 1991, 'Fundamentals and stock returns in Japan', *Journal of Finance* 46(5), 1739–1764. <https://doi.org/10.1111/j.1540-6261.1991.tb04642.x>
- Charnes, A.W., Cooper, W.W. & Rhodes, E., 1978, 'Measuring the efficiency of decision making units', *European Journal of Operational Research* 2(6), 429–444. [https://doi.org/10.1016/0377-2217\(78\)90138-8](https://doi.org/10.1016/0377-2217(78)90138-8)
- Chen, H.H., 2008, 'Stock selection using data envelopment analysis', *Industrial Management & Data Systems* 108(9), 1255–1268. <https://doi.org/10.1108/02635570810914928>
- Chen, K. & Shimerda, T., 1981, 'An empirical analysis of useful financial ratios', *Financial Management* 10(1), 51–60.
- Cheng, H., Lu, Y.C. & Chung, J.T., 2010, 'Improved slack-based context-dependent DEA – A study of international tourist hotels in Taiwan'. *Expert Systems with Applications* 37(9), 6452–6458. <https://doi.org/10.1016/j.eswa.2010.02.142>
- Choi, H.S. & Min, D., 2017, 'Efficiency of well-diversified portfolios: Evidence from data envelopment analysis', *Omega* 73(December), 104–113. <https://doi.org/10.1016/j.omega.2016.12.008>
- Clark, P., 1997, 'The balanced scorecard', *Accountancy Ireland* 29(6), 25–26.
- Coelli, T., 1998, 'A multi-stage methodology for the solution of orientated DEA models', *Operations Research Letters* 23(3), 143–150.
- Coelli, T., Rao, D.S.P. & Battese, G., 1998, *An introduction to efficiency and productivity analysis*, Boston, MA, Kluwer Academic.
- Coetzee, J., 2016, 'Financial intermediation theory', in J. Coetzee (ed.), *Bank management in South Africa: A risk-based perspective*, pp. 3–28, Cape Town, Juta.
- Coetzee, J. & De Beer, J., 2016, 'Financial regulation in the South African banking industry', in J. Coetzee (ed.), *Bank management in South Africa: A risk-based perspective*, pp. 63–94, Cape Town, Juta.
- Cooper, W.W., Seiford, L.M. & Tone, K., 2007, *Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software*, 2nd edn., New York, Springer.
- Davenport, T.O. & Sherman, H.D., 1987, 'Measuring branch profitability', *The Banker's Magazine* 170(5), 37–38.
- Debreu, G., 1951, 'The coefficient of resource utilization', *Econometrica* 19(3), 273–292. <https://doi.org/10.2307/1906814>
- Delen, D., Kuzey, C. & Uyar, A., 2013, 'Measuring firm performance using financial ratios: A decision tree approach', *Expert Systems with Applications* 40(10), 3970–3983. <https://doi.org/10.1016/j.eswa.2013.01.012>
- Dia, M., 2009, 'A portfolio selection methodology based on data envelopment analysis', *INFOR: Information Systems and Operational Research* 47(1), 71–79. <https://doi.org/10.3138/infor.47.1.71>
- Dowd, K., 1999, 'A value at risk approach to risk-return analysis', *The Journal of Portfolio Management* 25(4), 60–67. <https://doi.org/10.3905/jpm.1999.319755>
- Dowd, K., 2000, 'Adjusting for risk: An improved Sharpe ratio', *International Review of Economics and Finance* 9(3), 209–222.
- Edirisinghe, N.C. & Zhang, X., 2008, 'Portfolio selection under DEA-based relative financial strength indicators: Case of US industries', *Journal of the Operational Research Society* 59(6), 842–856. <https://doi.org/10.1057/palgrave.jors.2602442>
- Eling, M. & Jia, R., 2018, 'Business failure, efficiency, and volatility: Evidence from the European insurance industry', *International Review of Financial Analysis* 59, 58–76. <https://doi.org/10.1016/j.irfa.2018.07.007>
- Elyasiani, E. & Mehdi, S.M., 1990, 'A non-parametric approach to measurement of efficiency and technological change: The case of large US commercial banks', *Journal of Financial Services Research* 4(2), 157–168.
- Esfahanipour, A. & Mousavi, S., 2011, 'A genetic programming model to generate risk-adjusted technical trading rules in stock markets', *Expert Systems with Application* 38(7), 8438–8445. <https://doi.org/10.1016/j.eswa.2011.01.039>
- Fama, E.F., 1991, 'Efficient capital markets: II', *Journal of Finance* 46(5), 1575–1617. <https://doi.org/10.1111/j.1540-6261.1991.tb04636.x>
- Fama, E.F. & French, K.R., 1992, 'The cross-section of expected stock returns', *Journal of Finance* 47(2), 427–465. <https://doi.org/10.1111/j.1540-6261.1992.tb04398.x>
- Fama, E.F. & French, K.R., 2017, 'International tests of a five-factor asset pricing model', *Journal of Financial Economics* 123(3), 441–463.
- Fang, H., Wu, J. & Zeng, C., 2009, 'Comparative study on efficiency performance of listed coal mining companies in China and the US', *Energy Policy* 37(12), 5140–5148. <https://doi.org/10.1016/j.enpol.2009.07.027>
- Färe, R., Grosskopf, S. and Lovell, C.A.K., 1985, *The measurement of efficiency of production*, Boston, MA, Kluwer-Nijhoff.
- Farrell, M.J., 1957, 'The measurement of productive efficiency', *Journal of the Royal Statistical Society. Series A (General)* 120(3), 253–290. <https://doi.org/10.2307/2343100>
- Favre, L. & Galeano, J.-A., 2002, 'Mean-modified value-at-risk optimization with hedge funds', *The Journal of Alternative Investments* 5(2), 21–25. <https://doi.org/10.3905/jai.2002.319052>
- Firststrand Ltd, 2016, *Firststrand Group annual integrated report*, Firststrand Ltd, Johannesburg.
- Førsund, F.R. & Hjalmarsson, L., 1974, 'On the measurement of productive efficiency', *The Swedish Journal of Economics* 76(2), 141–154.
- Gibson, C., 1987, 'How chartered financial analysts view financial ratios', *Financial Analysts Journal* 43(3), 74–76.
- Giokas, D.I. & Pentzaropoulos, G.C., 2008, 'Efficiency ranking of the OECD member states in the area of telecommunications: A composite AHP/DEA study', *Telecommunications Policy* 32(9–10), 672–685.
- Golany, B. & Storbeck, J., 1999, 'A data envelopment analysis of the operational efficiency of bank branches', *Interfaces* 29(3), 14–26.
- Grandes, M. & Pinaud, N., 2004, 'Which policies can reduce the cost of capital in Southern Africa?' *OECD Policy Brief No. 25*, viewed 03 November 2017, from <http://search.oecd.org/countries/swaziland/33722694.pdf>.
- Gregoriou, G.N. & Gueyie, J.P., 2003, 'Risk-adjusted performance of funds of hedge funds using a modified Sharpe ratio', *The Journal of Wealth Management* 6(3), 77–83. <https://doi.org/10.3905/jwm.2003.442378>
- Grosskopf, S., 1996, 'Statistical inference and nonparametric efficiency: A selective survey', *Journal of Productivity Analysis* 7(2), 161–176. <https://doi.org/10.1007/BF00157039>
- Halim, E.R., 2010, 'Marketing productivity and profitability of Indonesian public listed manufacturing firms: An application of data envelopment analysis (DEA)', *Benchmarking: An International Journal* 17(6), 842–857. <https://doi.org/10.1108/14635771011089755>
- Hoffman, A.J., 2012, 'Stock return anomalies: Evidence from the Johannesburg stock exchange', *Investment Analysts Journal* 2012(75), 21–41. <https://doi.org/10.1080/10293523.2012.11082542>
- Hossain, M.K., Kamil, A.A., Baten, M.A. & Mustafa, A., 2012, 'Stochastic frontier approach and data envelopment analysis to total factor productivity and efficiency measurement of Bangladeshi rice', viewed 31 October 2017, from <http://journals.plos.org/plosone/article/file?id=10.1371/journal.pone.0046081&type=printable>.
- Hou, K., Karolyi, G.A. & Kho, B.C., 2011, 'What factors drive global stock returns?' *The Review of Financial Studies* 24(8), 2527–2574. <https://doi.org/10.1093/rfs/hhr013>
- Hu, J.L., Hsu, H.H., Hsiao, C. & Tsao, H.Y., 2018, 'Is mobile jumping more efficient? Evidence from major Asia-Pacific telecommunications firms', *Asia Pacific Management Review* 11, 1–10. <https://doi.org/10.1016/j.apmr.2018.04.001>
- Hu, X. & Liu, C., 2018, 'Measuring efficiency, effectiveness and overall performance in the Chinese construction industry', *Engineering, Construction and Architectural Management* 25(6), 780–797. <https://doi.org/10.1108/ECAM-06-2016-0131>

- Huang, C.Y., Chiou, C.C., Wu, T.H. & Yang, S.C., 2015, 'An integrated DEA-MODM methodology for portfolio optimization', *Operational Research* 15(1), 115–136. <https://doi.org/0.1007/s12351-014-0164-7>
- Iglesias, G., Castellanos, P. & Seijas, A., 2010, 'Measurement of productive efficiency with frontier methods: A case study for wind farms', *Energy Economics* 32(5), 1199–1208.
- Investec Ltd., 2017, *Investec Group integrated annual report: Risk and basel pillar III disclosures*, vol. 2.
- IRESS INET BFA, 2017, 'Data source', viewed 10 October 2017, from <https://www.secure.mcgbfa.com/>.
- Isik, I. & Topuz, J.C., 2017, 'Meet the "born efficient" financial institutions: Evidence from the boom years of US REITs', *The Quarterly Review of Economics and Finance* 66, 70–99. <https://doi.org/10.1016/j.qref.2017.07.017>
- Jacobs, R., 2001, 'Alternative methods to examine hospital efficiency: Data envelopment analysis and stochastic frontier analysis', *Health Care Management Science* 4(2), 103–115. <https://doi.org/10.1023/A:1011453526849>
- Jaforullah, M. & Whiteman, J., 1999, 'Scale efficiency in the New Zealand dairy industry: A non-parametric approach', *The Australian Journal of Agricultural and Resource Economics* 43(4), 523–541. <https://doi.org/10.1111/1467-8489.00093>
- Jegadeesh, N. & Titman, S., 1993, 'Returns to buying winners and selling losers: Implications for stock market efficiency', *Journal of Finance* 48(1), 65–91. <https://doi.org/10.2307/2328882>
- Jensen, M.C., 1968, 'The performance of mutual funds in the period 1945–1964', *Journal of Finance* 23(2), 389–416.
- Johannes, M., Korteweg, A. & Polson, N., 2014, 'Sequential learning, predictability, and optimal portfolio returns', *Journal of Finance* 69(2), 611–644. <https://doi.org/10.1111/jofi.12121>
- Johnson, H.T. & Kaplan, R.S., 1987, *Relevance Lost: The rise and fall of management accounting*, Boston, MA, Harvard Business School.
- Joro, T. & Na, P., 2006, 'Portfolio performance evaluation in a mean–variance–skewness framework', *European Journal of Operational Research* 175(1), 446–461. <https://doi.org/10.1016/j.ejor.2005.05.006>
- Kahraman, C., Uluğ, İ., Othan, C.B., Özkan-Özen, Y.D. & Kazançoğlu, Y., 2018, 'Efficiency analysis in retail sector: Implementation of data envelopment analysis in a local supermarket chain', in *The International Symposium for Production Research*, Cham, Springer.
- Kaparakis, E.I., Miller, S.M. & Noulas, A.G., 1994, 'Short-run cost inefficiency of commercial banks: A flexible stochastic frontier approach', *Journal of Money, Credit and Banking* 26(4), 875–893. <https://doi.org/10.2307/2077953>
- Kaplan, R.S. & Norton, D.P., 1996, 'Using the balanced scorecard as a strategic management system', *Harvard Business Review* 74(1), 75–85.
- Keating, C. & Shadwick, W.F., 2002, 'A universal performance measure', *Journal of Performance Measurement* 6(3), 59–84.
- Kirigia, J. M., Sambo, L.G. & Scheel, H., 2001, 'Technical efficiency of public clinics in Kwazulu-Natal province of South Africa', *East-African Medical Journal* 78(3), 1–13. <https://doi.org/10.4314/eamj.v78i3.9070>
- Kittelsen, S.A., 1999, *Monte Carlo simulations of DEA efficiency measures and hypothesis tests (No. 1999, 09)*, Memorandum, Department of Economics, University of Oslo, viewed 31 October 2017, <https://www.econstor.eu/bitstream/10419/63113/1/323421636.pdf>.
- Koopmans, T. C., 1951, 'An analysis of production as an efficient combination of activities', in T.C. Koopmans (ed.), *Activity analysis of production and allocation*, John Wiley and Sons, New York.
- Kuhn, L., Balezentis, T., Hou, L. & Wang, D., 2018, 'Technical and environmental efficiency of livestock farms in China: A slacks-based DEA approach', *China Economic Review* 1–14. <https://doi.org/10.1016/j.chieco.2018.08.009>
- Kumar, N. & Singh, A., 2014, 'Efficiency analysis of banks using DEA: A review', *International Journal of Advance Research and Innovation* 1, 120–126.
- Kuosmanen, T., 2007, 'Performance measurement and best-practice benchmarking of mutual funds: Combining stochastic dominance criteria with data envelopment analysis', *Journal of Productivity Analysis* 28(1–2), 71–86. <https://doi.org/10.1007/s1123-007-0045-7>
- Lakonishok, J., Shleifer, A. & Vishny, R.W., 1994, 'Contrarian investment, extrapolation, and risk', *Journal of Finance* 49(5), 1541–1578. <https://doi.org/10.1111/j.1540-6261.1994.tb04772.x>
- Lim, S., Oh, K.W. & Zhu, J., 2014, 'Use of DEA cross-efficiency evaluation in portfolio selection: An application to Korean stock market', *European Journal of Operational Research* 236(1), 361–368. <https://doi.org/10.1016/j.ejor.2013.12.002>
- Lintner, J., 1965, 'The valuation of risk assets and the selection of risky investments in stock portfolios and capital assets', *Review of Economics and Statistics* 47(1), 13–37. <https://doi.org/10.2307/1924119>
- Litzenberger, R.H. & Ramaswamy, K., 1979, 'The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence', *Journal of Financial Economics* 7(2), 163–195. [https://doi.org/10.1016/0304-405X\(79\)90012-6](https://doi.org/10.1016/0304-405X(79)90012-6)
- Liu, J.S., Lu, L.Y., Lu, W.M. & Lin, B.J., 2013, 'A survey of DEA applications', *Omega* 41(5), 893–902. <https://doi.org/10.1016/j.omega.2012.11.004>
- Liu, S.T., 2008, 'A fuzzy DEA/AR approach to the selection of flexible manufacturing systems', *Computers & Industrial Engineering* 54(1), 66–76. <https://doi.org/10.1016/j.cie.2007.06.035>
- Liu, W., Zhou, Z., Liu, D. & Xiao, H., 2015, 'Estimation of portfolio efficiency via DEA', *Omega* 52(April), 107–118. <https://doi.org/10.1016/j.omega.2014.11.006>
- Lovell, C.A.K. & Pastor, J.T., 1995, 'Units invariant and translation invariant DEA models', *Operations Research Letters* 18(3), 147–152. [https://doi.org/10.1016/0167-6377\(95\)00044-5](https://doi.org/10.1016/0167-6377(95)00044-5)
- Mahadevan, R., 2002, 'A DEA approach to understanding the productivity growth of Malaysia's manufacturing industries', *Asia Pacific Journal of Management* 19(4), 587–600. <https://doi.org/10.1023/A:1020577811369>
- Mashayekhi, Z. & Omrani, H., 2016, 'An integrated multi-objective Markowitz–DEA cross-efficiency model with fuzzy returns for portfolio selection problem', *Applied Soft Computing* 38(January), 1–9. <https://doi.org/10.1016/j.asoc.2015.09.018>
- Matsumoto, K., Shivaswamy, M. & Hoban, J., 1995, 'Security analysts' views of the financial ratios of manufacturers and retailers', *Financial Practice and Education* 5(2), 44–55.
- Meeusen, W. & Van Den Broeck, J., 1977, 'Efficiency estimation from Cobb–Douglas production functions with composed error', *International Economic Review* 18(2), 435–444. <https://doi.org/10.2307/2525757>
- Mester, L.J., 1993, 'Efficiency of banks in the third Federal Reserve district', Working paper 94–13, viewed 25 October 2017, from <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.36.3776&rep=rep1&type=pdf>.
- Mester, L.J., 2003, 'Applying efficiency measurement techniques to central banks', Working paper 03–13, viewed 25 October 2017, from <https://philadelphiafed.org/-/media/research-and-data/publications/working-papers/2003/wp03-13.pdf>.
- Mossin, J., 1966, 'Equilibrium in a capital asset market', *Econometrica* 34(4), 768–783. <https://doi.org/10.2307/1910098>
- Muller, C. & Ward, M., 2013, 'Style-based effects on the Johannesburg Stock Exchange: A graphical time-series approach', *Investment Analysts Journal* 2013(77), 1–16.
- Nedbank Ltd, 2016, *Basel III public disclosure report: Pillar 3 risk and capital management report*, Nedbank Ltd, Johannesburg.
- Nunamaker, T.R., 1983, 'Measuring routine nursing service efficiency: A comparison of cost per patient day and data envelopment analysis models', *Health Services Research* 18, 183–208.
- Nunamaker, T.R., 1985, 'Using data envelopment analysis to measure the efficiency of non-profit: A critical evaluation', *Managerial and Decision Economics* 6(1), 50–58. <https://doi.org/10.1002/mde.4090060109>
- Omrani, H., Shafaat, K. & Emrouznejad, A., 2018, 'An integrated fuzzy clustering cooperative game data envelopment analysis model with application in hospital efficiency', *Expert Systems with Applications* 114, 615–628. <https://doi.org/10.1016/j.eswa.2018.07.074>
- Pätäri, E., Leivo, T. & Honkapuro, S., 2012, 'Enhancement of equity portfolio performance using data envelopment analysis', *European Journal of Operational Research* 220(3), 786–797.
- Pätäri, E.J., Leivo, T.H. & Honkapuro, S., 2010, 'Enhancement of value portfolio performance using data envelopment analysis', *Studies in Economics and Finance* 27(3), 223–246. <https://doi.org/10.1108/10867371011060036>
- Pech, C.O.T., Noguera, M. & White, S., 2015, 'Financial ratios used by equity analysts in Mexico and stock returns', *Contaduría y Administración* 60, 578–592. <https://doi.org/10.1016/j.cya.2015.02.001>
- Quaranta, A.G., Raffoni, A. & Visani, F., 2018, 'A multidimensional approach to measuring bank branch efficiency', *European Journal of Operational Research* 266(2), 746–760. <https://doi.org/10.1016/j.ejor.2017.10.009>
- Resende, M. & Façanha, L.O., 2005, 'Price-cap regulation and service-quality in telecommunications: An empirical study', *Information Economics and Policy* 17(1), 1–12.
- Roboredo, M.C., Aizemberg, L. & Meza, L.A., 2015, 'The DEA game cross efficiency model applied to the Brazilian football championship', *Procedia Computer Science* 55, 758–763. <https://doi.org/10.1016/j.procs.2015.07.161>
- Rosenberg, B., Reid, K. & Lanstein, R., 1985, 'Persuasive evidence of market inefficiency', *The Journal of Portfolio Management* 11(3), 9–16. <https://doi.org/10.3905/jpm.1985.409007>
- Schefczyk, M., 1993, 'Operational performance of airlines – An extension of traditional measurement paradigms', *Strategic Management Journal* 14, 301–317.
- Sealey, C.W. & Lindley, J.T., 1977, 'Inputs, outputs and a theory of production and cost as depositary financial institutions', *Journal of Finance* 32(4), 1251–1266.
- Sharma, K.R., Leung, P. & Zaleski, H.M., 1999, 'Technical, allocative and economic efficiencies in swine production in Hawaii: A comparison of parametric and nonparametric approaches', *Agricultural Economics* 20(1), 23–35. [https://doi.org/10.1016/S0169-5150\(98\)00072-3](https://doi.org/10.1016/S0169-5150(98)00072-3)
- Sharpe, W., 1964, 'Capital asset prices: A theory of market equilibrium under conditions of risk', *Journal of Finance* 19(3), 425–442. <https://doi.org/10.2307/2977928>
- Sharpe, W.F., 1966, 'Mutual fund performance', *Journal of Business* 39(1), 119–138.
- Shephard, R.W., 1953, *Cost and production functions*, Princeton, NJ, Princeton University Press.
- Shephard, R.W., 1970, *Cost and production functions*, Princeton, NJ, Princeton University Press.
- Sherman, G. & Gold, F., 1985, 'Bank branch operating efficiency – Evaluation with data envelopment analysis', *Journal of Banking & Finance* 9, 297–315. [https://doi.org/10.1016/0378-4266\(85\)90025-1](https://doi.org/10.1016/0378-4266(85)90025-1)
- Shi, G.M., Bi, J. & Wang, J.N., 2010, 'Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs', *Energy Policy* 38(10), 6172–6179. <https://doi.org/10.1016/j.enpol.2010.06.003>

- Singleton-Green, B., 1993, 'If it matters, measure it', *Accountancy* 111(1197), 52–53.
- Soliman, M.T., 2008, 'The use of Du Pont analysis by market participants', *The Accounting Review* 83(3), 823–853. <https://doi.org/10.2308/accr.2008.83.3.823>
- Sortino, F.A. & Van Der Meer, R., 1991, 'Downside risk', *Journal of Portfolio Management* 17(4), 27–31.
- South African Reserve Bank (SARB), 2016, *Bank Supervision Department, annual report*, viewed 10 October 2017, from <https://www.resbank.co.za/fastsearch/Pages/Results.aspx?sq=1&k=BankSupervision> Report.
- South African Reserve Bank (SARB), 2017a, 'Data source', viewed 13 October 2017, <https://www.resbank.co.za>.
- South African Reserve Bank (SARB), 2017b, 'Financial stability review', viewed 10 October 2017, from <https://www.rba.gov.au/publications/fsr/2016/oct/pdf/financial-stability-review-2016-10.pdf>.
- Standard Bank Group Ltd, 2016, *Risk and capital management report and annual financial statements*, Standard Bank Group Ltd, Johannesburg.
- Stattman, D., 1980, 'Book values and stock returns', *The Chicago MBA: A Journal of Selected Papers* 4(1), 25–45.
- Stemmet, K., 2016, 'The competitive and operating environment of the South African Banking Industry', in J. Coetzee (ed.), *Bank management in South Africa: A risk-based perspective*, pp. 3–62, Cape Town, Juta.
- Sueyoshi, T., Goto, M. & Ueno, T., 2010, 'Performance analysis of US coal-fired power plants by measuring three DEA efficiencies', *Energy Policy* 38(4), 1675–1688. <https://doi.org/10.1016/j.enpol.2009.11.017>
- Sufian, F. & Majid, M.Z.A., 2007, 'Singapore banking efficiency and its relation to stock returns: A DEA window analysis approach', *International Journal of Business Studies* 15(1), 83–106.
- Tarim, S.A. & Karan, M.B., 2001, 'Investment fund performance measurement using weight-restricted data envelopment analysis: An application to the Turkish capital market', *Russian & East European Finance and Trade* 37(5), 64–84.
- Titko, J., Stankevičienė, J. & Lāce, N., 2014, 'Measuring bank efficiency: DEA application'. *Technological and Economic Development of Economy* 20(4), 739–757.
- Topuz, J.C., Darrat, A.F. & Shelor, R.M., 2005, 'Technical, allocative and scale efficiencies of REITs: An empirical inquiry', *Journal of Business Finance & Accounting* 32(9–10), 1961–1994. <https://doi.org/10.1111/j.0306-686X.2005.00653.x>
- Traub, E., 2001, 'Using ROE to analyze stocks: What you need to know about', *American Association of Individual Investor Journal*, July, 4–7, viewed 13 October 2017, from <https://www.aail.com/journal/article/using-roe-to-analyze-stocks-what-you-need-to-know-about>.
- Treynor, J.L., 1965, 'How to rate management investment funds', *Harvard Business Review* 43(1), 63–75. <https://doi.org/10.1002/9781119196679.ch10>
- Tsolas, I.E., 2011, 'Modelling profitability and effectiveness of Greek-listed construction firms: An integrated DEA and ratio analysis', *Construction Management and Economics* 29(8), 795–807. <https://doi.org/10.1080/01446193.2011.610330>
- Van Heerden, C., 2016, 'The eminence of risk-free rates in portfolio management: A South African perspective', *The Journal of Applied Business Research* 32(2), 569–596. <https://doi.org/10.19030/jabr.v32i2.9597>
- Van Heerden, C. & Heymans, A., 2013, 'A fundamental evaluation of the top five South African banks after the financial crisis', *Journal of Economic and Financial Sciences* 6(3), 731–762.
- Van Heerden, C. & Rossouw, R., 2014, 'Resource utilisation efficiency: A South African provincial evaluation', *South African Journal of Economics* 82(4), 475–492. <https://doi.org/10.1111/saje.12037>
- Van Heerden, C. & Saayman, M., 2018, 'Sustainability of a national arts festival: An application of a data envelopment analysis approach', *Tourism Economics* 24(5), 576–592. <https://doi.org/10.1177/1354816618762186>
- Van Heerden, C. & Van Der Westhuizen, G., 2008, 'The cost of banking services and the technical efficiency of a South African bank', *The Journal for Transdisciplinary Research in Southern Africa* 4(2), 401–417. <https://doi.org/10.4102/td.v4i2.160>
- Van Rensburg, P., 2001, 'A decomposition of style-based risk on the JSE', *Investment Analysts Journal* 30(54), 45–60. <https://doi.org/10.1080/10293523.2001.11082431>
- Van Rensburg, P.V. & Robertson, M., 2003, 'Size, price-to-earnings and beta on the JSE securities exchange', *Investment Analysts Journal* 32(58), 7–16. <https://doi.org/10.1080/10293523.2003.11082449>
- Wang, W. & Zhang, C., 2018, 'Evaluation of relative technological innovation capability: Model and case study for China's coal mine', *Resources Policy* 58, 144–149. <https://doi.org/10.1016/j.resourpol.2018.04.008>
- Wanke, P. & Barros, C.P., 2016, 'Efficiency drivers in Brazilian insurance: A two-stage DEA meta frontier-data mining approach', *Economic Modelling* 53, 8–22. <https://doi.org/10.1016/j.econmod.2015.11.005>
- Wheelock, D.C. & Wilson, P.W., 1995, 'Explaining bank failures: Deposit insurance, regulation, and efficiency', *Review of Economics and Statistics* 77(4), 689–700.
- World Economic Forum, 2008, *The Global Competitiveness Report, 2008–2009*, WEF, Coligny.
- World Economic Forum, 2009, *The Global Competitiveness Report, 2009–2010*, WEF, Coligny.
- World Economic Forum, 2010, *The Global Competitiveness Report, 2010–2011*, WEF, Coligny.
- World Economic Forum, 2011, *The Global Competitiveness Report, 2011–2012*, WEF, Coligny.
- World Economic Forum, 2012, *The Global Competitiveness Report, 2012–2013*, WEF, Coligny.
- World Economic Forum, 2013, *The Global Competitiveness Report, 2013–2014*, WEF, Coligny.
- World Economic Forum, 2014, *The Global Competitiveness Report, 2014–2015*, WEF, Coligny.
- World Economic Forum, 2015, *The Global Competitiveness Report, 2015–2016*, WEF, Coligny.
- World Economic Forum, 2016, *The Global Competitiveness Report, 2016–2017*, WEF, Coligny.
- World Economic Forum, 2017, *The Global Competitiveness Report, 2017–2018*, WEF, Coligny.
- Worthington, A.C., 2004, 'Frontier efficiency measurement in health care: A review of empirical techniques and selected applications', *Medical Care Research and Review* 61(2), 135–170. <https://doi.org/10.1177/1077558704263796>
- Xavier, J.M., Moutinho, V.F. & Moreira, A.C., 2015, 'An empirical examination of performance in the clothing retailing industry: A case study', *Journal of Retailing and Consumer Services* 25, 96–105. <https://doi.org/10.1016/j.jretconser.2015.04.002>
- Xia, Q., Jin, M., Wu, H. & Yang, C., 2018, 'A DEA-based decision framework to determine the subsidy rate of emission reduction for local government', *Journal of Cleaner Production* 202, 846–852. <https://doi.org/10.1016/j.jclepro.2018.08.171>
- Xue, X., Shen, Q., Wang, Y. & Lu, J., 2008, 'Measuring the productivity of the construction industry in China by using DEA-based Malmquist productivity indices', *Journal of Construction Engineering and Management* 134(1), 64–71.
- Yang, Z., 2009, 'Bank branch operating efficiency: A DEA approach', *Proceedings of the International MultiConference of Engineers and Computer Scientists* 2, 18–20.
- Young, T.W., 1991, 'Calmar ratio: A smoother tool', *Futures* 20(1), 40.
- Zaremba, A. & Czapkiewicz, A., 2017, 'Digesting anomalies in emerging European markets: A comparison of factor pricing models', *Emerging Markets Review* 31(June), 1–15. <https://doi.org/10.1016/j.ememar.2016.12.002>
- Zere, E., Mbeeli, T., Shangula, K., Mandlhate, C., Mutirua, K., Tjivambi, B. et al., 2006, 'Technical efficiency of district hospitals: Evidence from Namibia using data envelopment analysis', *Cost Effectiveness and Resource Allocation* 4(1), 1–9. <https://doi.org/10.1186/1478-7547-4-5>
- Zhu, J., 2016, 'DEAFrontier', viewed 27 June 2017, from <http://www.deafontier.net/deasupport/index.html>.
- Zurano-Cervelló, P., Pozo, C., Mateo-Sanz, J.M., Jiménez, L. & Guillén-Gosálbez, G., 2018, 'Electricity mix assessment of the EU member countries using DEA and EffMixF', *Computer Aided Chemical Engineering* 43, 445–450.

Appendix 1

TABLE 1-A1: Average ability to explain future returns (across all banks).

Ratios under evaluation	Explain 5 years ahead (%)	Explain 3 years ahead (%)	Explain 1 year ahead (%)
Dividend yield (%)	48.50	52.95	56.78
Earnings yield (%)	63.61	71.73	70.78
Book-to-market ratio	56.11	62.31	60.56
Cash-flow-to-price ratio	60.61	66.19	66.67
Price-to-earnings ratio	81.47	82.39	83.23
Price-to-NAV ratio	65.89	61.02	60.90
Return-on-equity (%)	78.10	74.85	75.63
Market capitalisation	27.95	35.43	37.78
Implied dividend growth rate	66.80	63.07	64.85
Pure technical efficiency (VRS)	92.59	93.94	94.31
Scale efficiency	89.30	91.60	92.21
Total technical efficiency (CRS)	89.98	91.82	92.09
Equally weighted DuPont	39.69	40.78	42.43
Sharpe ratio	56.75	47.76	53.83
Treynor ratio	56.95	47.79	56.85
Jensen's alpha	54.93	46.75	53.49
Sortino ratio	43.40	39.91	48.90
Calmar ratio	57.40	48.25	54.63
VaR-Sharpe ratio	43.12	43.68	40.87
Conditional (CVaR) Sharpe ratio	44.02	42.52	42.60
Modified (MVaR) Sharpe ratio	46.61	44.38	44.07
Static Omega ratio	75.77	67.16	69.02
Overall average	60.89	59.83	61.93
Overall minimum	27.95	35.43	37.78
Overall maximum	92.59	93.94	94.31
Average of traditional financial ratios	58.87	61.07	61.96
Average of non-financial measures	90.62	92.45	92.87
Average of risk-adjusted performance ratios	53.22	47.58	51.59

VaR, value at risk; CVaR, conditional value at risk; MVaR, Modified value at risk.

TABLE 2-A1: Average ability of pure technical efficiency (VRS), the P/E ratio and static Omega ratio to select the top performing banking shares.

Year	Shares	Pure technical efficiency (years)			Price-to-earnings ratio			Static omega ratio		
		Over 1 year (%)	Over 3 years (%)	Over 5 years (%)	Over 1 year (%)	Over 3 years (%)	Over 5 years (%)	Over 1 year (%)	Over 3 years (%)	Over 5 years (%)
2004	Top 2 shares	50.00	50.00	100.00	50.00	50.00	50.00	50.00	50.00	50.00
2005	Top 2 shares	50.00	0.00	0.00	50.00	50.00	50.00	50.00	0.00	0.00
2006	Top 2 shares	50.00	100.00	100.00	50.00	50.00	50.00	50.00	50.00	50.00
2007	Top 2 shares	50.00	50.00	50.00	50.00	50.00	50.00	50.00	50.00	0.00
2008	Top 2 shares	100.00	100.00	0.00	100.00	100.00	0.00	50.00	50.00	50.00
2009	Top 2 shares	50.00	50.00	50.00	50.00	0.00	50.00	50.00	50.00	100.00
2010	Top 2 shares	100.00	0.00	50.00	50.00	0.00	50.00	50.00	0.00	50.00
2011	Top 2 shares	50.00	50.00	0.00	50.00	50.00	0.00	50.00	50.00	0.00
2004	Top 3 shares	66.67	66.67	100.00	66.67	33.33	33.33	66.67	66.67	100.00
2005	Top 3 shares	66.67	33.33	33.33	66.67	33.33	66.67	100.00	33.33	33.33
2006	Top 3 shares	66.67	100.00	66.67	66.67	33.33	33.33	33.33	33.33	66.67
2007	Top 3 shares	66.67	66.67	66.67	66.67	66.67	33.33	66.67	33.33	66.67
2008	Top 3 shares	100.00	66.67	66.67	100.00	66.67	66.67	100.00	66.67	66.67
2009	Top 3 shares	66.67	66.67	33.33	33.33	66.67	66.67	66.67	66.67	66.67
2010	Top 3 shares	66.67	66.67	66.67	100.00	33.33	66.67	66.67	33.33	100.00
2011	Top 3 shares	66.67	66.67	33.33	66.67	66.67	66.67	66.67	33.33	66.67
2004	Top 4 shares	75.00	75.00	75.00	75.00	75.00	50.00	50.00	75.00	100.00
2005	Top 4 shares	75.00	50.00	50.00	50.00	50.00	75.00	75.00	50.00	50.00
2006	Top 4 shares	75.00	75.00	75.00	75.00	25.00	50.00	50.00	50.00	50.00
2007	Top 4 shares	50.00	50.00	75.00	75.00	75.00	50.00	50.00	50.00	75.00
2008	Top 4 shares	75.00	75.00	75.00	75.00	75.00	75.00	100.00	50.00	75.00
2009	Top 4 shares	75.00	75.00	50.00	50.00	50.00	75.00	75.00	50.00	75.00
2010	Top 4 shares	75.00	75.00	75.00	100.00	25.00	50.00	75.00	50.00	75.00
2011	Top 4 shares	75.00	50.00	50.00	75.00	50.00	75.00	50.00	50.00	50.00

VRS, variable returns to scale.