Are South African Medical Schemes Efficient? A Longitudinal Analysis

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Abstract

This study assessed the efficiencies of South African private medical schemes for the period 2011 to 2017. There are two types of medical schemes in the private medical scheme sector. First, there are open medical schemes which are legally required to accept any individual who would want to join. Second, there are restricted medical schemes which are attached to a specific group such as an employer, industry or union and these schemes are open only to the members of the association. The study estimated efficiency scores using first, the Data Envelope Analysis (DEA) technique which is a non-parametric procedure that uses linear programming in order to formulate efficient frontiers which envelop all input-output combinations of firms within a sample. Second, the study employed the Stochastic Frontier Analysis (SFA) technique which is an econometric technique which postulates a functional relationship amongst outputs and inputs and thus employs statistical procedures in order to determine parameters for the function. The empirical findings of both the DEA and SFA approaches suggest that open medical schemes tend to be more efficient than restricted medical schemes in terms of technical, scale and pure technical efficiency over the sample period.

Keywords: Healthcare Insurance, DEA, SFA, Efficiency, Technical Efficiency, Pure Technical Efficiency, Scale Efficiency, South Africa

JEL Classification: L00, L11, L22

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1. Introduction

There is a viewpoint that healthcare financing is an important element of a well-functioning healthcare system, which in turn further contributes to the economic well-being of individuals and socio-economic development. Indeed, the World Health Organization (2007) submits that a well-functioning healthcare financing system should be able to raise sufficient funds for health, such that individuals can access the needed healthcare services and are protected from financial catastrophe or impoverishment associated with having to pay.

Given this, there have been attempts across the globe to find a balance between affordability and efficiency goals. According to the Competition Commission's ("the Commission") Health Market Inquiry (HMI), this has led to different sources of healthcare financing across nations which "combines out-of-pocket spending, supplementary health insurance and collective funding such as tax-based financing or social health insurance".[2]

In the South African context, a combination of publicly available services and regulated private medical scheme markets exists. The regulated private medical scheme markets include medical schemes which offer healthcare financing in the private healthcare sector. In return, medical scheme members pay monthly contributions to their desired medical schemes. Medical schemes are then responsible for financing their members' healthcare expenses as part of their benefit package.

There are two types of medical schemes in the private medical scheme sector. First, there are open medical schemes which are legally required to accept any individual who would want to join. Second, there are restricted medical schemes which are attached to a specific group such as an employer, industry or union and these schemes are open only to the members of the association. According to the HMI, open and restricted medical schemes compete in separate markets.[3]

Both open and restricted medical schemes are regulated by the Council for Medical Scheme (CMS), which is a statutory body established in terms of the Medical Schemes Act of 1998. The CMS statutory responsibilities include protecting the interests of medical scheme members, overseeing and coordinating the running of medical schemes, monitoring their financial soundness, and investigating complaints against medical schemes.

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[2] See Competition Commission Health Market Inquiry provisional report, para 2, page 76.
[3] See Competition Commission Health Market Inquiry provisional report, para 12, page 78.

Medical schemes are not-for-profit entities[4], which according to the HMI has meant that there hasn't been any meaningful entry within these markets since 2002 and 2007 as there is a lack of incentive for firms to enter into the not-for-profit market.[5]

Accordingly, both the open and restricted medical scheme markets are highly concentrated. Tables 1 and 2 below reflect the historic market shares for open and restricted medical schemes for the period 2011 to 2017.

Table 1: Open scheme market share

Medical Scheme	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Discovery Medical Scheme	49%	52%	53%	54%	55%	55%	56%
Bonitas Medical Fund	13%	13%	13%	13%	13%	15%	15%
Medihelp	5%	5%	5%	5%	4%	4%	4%
Medshield Medical Scheme	5%	4%	4%	3%	3%	3%	3%
Momentum Health	4%	4%	4%	5%	5%	5%	6%
Other	24%	23%	21%	20%	20%	17%	16%

Table 2: Restricted scheme market share

Medical Scheme	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Government Employees Medical Scheme (GEMS)	44%	46%	47%	47%	46%	47%	46%
South African Police Service Medical Scheme (POLMED)	13%	13%	13%	13%	13%	13%	13%
Bankmed	5%	5%	5%	5%	6%	5%	6%
LA Health Medical Scheme	2%	3%	3%	3%	4%	4%	4%
Other	35%	34%	32%	32%	32%	31%	31%

As reflected from the above tables, Discovery medical scheme has consistently been the largest open medical scheme enjoying a market share of between 49% and 56% for the period 2011 to 2017. Similarly, GEMS is the largest restricted medical scheme enjoying a market share of between 44% and 47% for the period 2011 to 2017. These, according to the HMI, are signs of uncompetitive market structures, as in competitive market structures the medical schemes should be competing to attract more business in the form of new members into the market as well as competing for members of other medical schemes.[6]

[4] See Competition Commission Health Market Inquiry final report, para 17, page 46.
[5] See Competition Commission Health Market Inquiry provisional report, para 48, page 85.
[6] See Competition Commission Health Market Inquiry final report, para 26, page 81

Much has been written regarding the effects of market structure and concentration on overall efficiency outcomes (Hicks, 1935; Demsetz, 1973; Smirlock, 1985; Boru & Kuhil, 2018). Given the structure of the medical scheme industry, the primary goal of this study was to assess efficiency for both open and restricted medical schemes. To do so, efficiency scores were estimated using both the data envelope analysis and stochastic frontier analysis techniques. The rest of the article is structured as follows: Section 2 is the literature review, Section 3 outlines the methodology used, Section 4 displays the results and the subsequent discussion of those results and Section 5 concludes the study.

2. Literature Review

2.1. Theoretical review

Cummins and Xie (2013) indicate that efficiency analysis attempts to separate firms that perform well from those that perform poorly. This is achieved through the estimation of best practice efficient frontiers which are taken from dominant firms, in terms of efficiency, in an industry and then used to compare all firms in the industry. There are two common approaches used in the estimation of efficiency frontiers, which are the Stochastic Frontier Analysis (SFA) and the Data Envelopment Analysis (DEA) (Battese & Coelli, 1995; Watkins et al., 2014).

The SFA approach postulates a functional relationship amongst outputs and inputs and thus employs statistical procedures in order to determine parameters for the function (Coelli, Perelman & Romano, 1999). According to the work of Coelli et al. (1999), the SFA includes an error composed of two additive components. First, it includes a symmetric component which considers statistical noise often associated with data measurement errors. Second, it includes a nonnegative component that estimates inefficiency in production. A drawback of the SFA approach is that it imposes specific assumptions on the functional form of the frontier and the distribution error term (Watkins et al., 2014).

The DEA approach is a non-parametric procedure that uses linear programming in order to formulate efficient frontiers which envelop all input-output combinations of firms within a sample (Luhnen, 2009). Accordingly, the input-output combinations of efficient firms are found on the envelope, the efficient frontier, whereas the input-output combinations of inefficient firms are found below the efficient frontier (Watkins et al., 2014). Given its nonparametric nature, the DEA approach does not need assumptions to be made regarding the functional form or distribution type and thus it is less sensitive to misspecification than the SFA approach

(Coelli et al., 1999). More so, the DEA approach can accommodate multiple input and output combinations (Barros et al., 2010). However, important to note is that the deterministic nature of the DEA approach implies that all deviations from the efficient frontier are caused by inefficiency and thus subject to statistical noises resulting from data measurement errors (Coelli et al., 1999).

Given the limitations of both approaches, this study employed both the DEA and SFA approaches to estimate the efficiency scores for South African medical scheme providers. The two approaches were then compared.

2.2. Empirical review

The literature contains a vast number of studies which adopted both the DEA and SFA approaches in order to estimate the efficiencies of insurance companies. To this score, Kaffash et al. (2020) found at least 132 articles between the years 1993 to 2018.

Using the DEA approach, Diacon and O'Brien (2002) estimated three different measures of value-based efficiency, namely pure technical efficiency, scale efficiency and mix efficiency. Using a dataset obtained from Standard & Poor's Eurothesys database which contains 450 insurance firms across 15 European nations, the authors estimated efficiency scores for the period 1996 to 1999.

For their input and output proxies, Diacon and O'Brien (2002) used staff and capital resources as the main input proxies and investment income and premiums as their proxies for outputs. After estimating the efficiency scores, Diacon and O'Brien (2002) found significant differences in average efficiency across 15 European countries.

Another study is the work of Brockett et al. (2004) which investigated the effect of Health Maintenance Organization ("HMO") arrangements on actual efficiency of healthcare delivery. Using the DEA methodology, the authors compared two major classes of HMO arrangements using game-theoretic data. To do so, the authors utilised data from the 1995 Series of HCIA's HMO Database which includes financial, enrolment and utilisation data. This dataset includes 538 HMOs from 46 American states.

In their work, Barros, Barroso and Borges (2005) used the DEA approach to assess the relative efficiencies of Portuguese insurance companies for the period 1995 to 2001. The authors used claims paid to policyholders and profits paid to owners as proxies for output. In addition, they used wages, capital, investment income and premiums paid as proxies for inputs. After

estimating the efficiency scores, the authors found that some insurance firms were able to achieve productivity growth while others experienced a decline in productivity.

Kasman and Turgutlu (2007) investigated the technical efficiency of a Turkish life insurance company by employing the deterministic data envelopment analysis, the chance-constrained data envelopment analysis and stochastic frontier analysis techniques for the period 1999 to 2005. For their output proxy, Kasman and Turgutlu (2007) used benefits incurred net of reinsurance plus additions to reserves. More so, Kasman and Turgutlu (2007) used three input proxies, namely labour, business services and financial capital. The empirical findings of all three techniques revealed that there are significant inefficiencies in the Turkish life insurance industry.

Cummins et al. (2010) used the DEA approach to assess economies of scope in the American insurance industry over the period 1993 to 2006. The authors employed a dataset which contains all diversified and specialist companies in the American insurance industry over the period 1993 to 2006. Using DEA, the authors estimated cost, revenue and profit efficiencies for both property-liability insurers and life-health insurers.

In regard to life-health insurers, the authors used six proxies for output: real invested assets and the real value of incurred benefits and additions to reserves for individual life, individual annuities, group life, group annuities and accident health insurance. For the property-liability insurers, the authors use five proxies for output, that being real invested assets and the present values of real losses incurred for short and long-tail personal and commercial lines.

Concerning input proxies, the same proxies are used for both property-liability and health-life insurers, which are administrative labour, agent labour, materials and business services and financial equity capital. The authors found that property-liability insurers have been able to achieve cost scope economies which are offset by revenue scope diseconomies where life-health insurers have achieved both cost and revenue scope diseconomies.

In terms of Asian insurance companies, Chen and Chang (2010) assessed the productive patterns of 24 Taiwanese life insurers for the period 1997 to 2006. Using the DEA approach, the authors estimated efficiency scores using equity capital and total expenses as proxies for inputs and premium income as a proxy for output. Through DEA, the authors were then able to estimate both technical and scale efficiency scores for 24 Taiwanese life insurance companies.

Barros, Nektarios and Assaf (2010) employed a two-stage procedure advocated by Simar and Wilson (2007) in order to assess the effects of deregulation on the efficiency of the Greek insurance industry. The authors used DEA in order to estimate the efficiency scores for 71 Greek insurance companies for the period 1994 to 2003. Using data obtained from the Association of Insurance companies of Greece, the authors were able to compile a panel dataset for the period 1994 to 2003.

The dataset contains 17 life insurers, 41 non-life insurers and 10 mixed insurance companies. As a proxy for inputs, the authors used labour costs, non-labour costs and equity capital. As a proxy for outputs the authors used invested assets losses incurred, reinsurance reserves and own reserves. After estimating the efficiency scores, the authors were able to rank the insurance companies according to their efficiency scores and find a decline in efficiency over the sample period.

Biener and Eling (2011) estimated the efficiencies of 20 Microinsurance programmes that span Africa, Asia and Latin America for the period 2004 to 2008 using DEA. These 20 Microinsurance programmes provide both life and health insurance services. Using data obtained from the Microinsurance Network which contains balance sheet and income statement data from 2004 to 2008, the authors were able to compile an unbalanced panel of 73 firm-years. Biener and Eling (2011) used labour, business services, debt capital and equity capital as proxies for inputs, where labour and business services were combined into operating expenses as a single variable due to data availability. Biener and Eling (2011) indicated that this is standard practice as seen in other international efficiency studies.

In addition, Biener and Eling (2011) use the value of current losses paid plus additions to reserves as a proxy for output. After estimating the efficiency scores Biener and Eling (2011) find that large Micro-insurers were able to improve performance during the sample period.

Biener and Eling (2012) employed a cross-frontier analysis based on DEA in order to investigate the relationship between organisation and efficiency in international insurance markets. The authors employed a dataset which contains 6000 insurers which translates to 23807 firm-years and 21 Northern American and European Union countries for the period 2002 to 2006. The authors employed labour, business services and material, debt capital and equity capital as inputs where labour and business services were combined as operating expenses. As a proxy for outputs, the authors employed a value-added approach and used current losses paid plus additions to reserves as a proxy for output. After calculating the efficiency scores, the

authors found evidence supporting the efficient structure hypothesis in selected markets but found no evidence supporting the expense preference hypothesis.

Bai-qing, Yi-Xing and Wen-Tao (2012) utilised a two-stage DEA approach to estimate technical, pure technical and scale efficiency for 34 property insurance companies in China. The authors used total assets, expenditure and the number of employees as proxies for inputs. The authors also used net premiums as a proxy for intermediate outputs. Further, final reserves, investment income and underwriting profit were used as proxies for final outputs. After estimating the efficiency scores, the authors found that the performance of China's property insurance companies has been unsatisfactory.

Another study which applied the SFA approach is that of Bhishma Rao and Venkateswarlu (2014) who employed the stochastic frontier technique to measure the relative efficiency of non-life insurance companies in India for the period 2008 to 2013. The empirical results revealed that the mean efficiency score for non-life insurance firms in India had been increasing year to year.

In terms of the African context, Barros and Dumbo (2014) estimated the efficiency scores for seven insurance companies from Angola for the period 2003 to 2012 using DEA. The authors used operating costs, the number of employees, wages and capital as proxies for inputs. The authors used claims paid, profits paid, premiums earned and ceded reinsurance as proxies for outputs. After estimating the efficiency scores, the authors found that older insurance companies with Portuguese origin tend to be more efficient.

Depotis, Koronakos and Sotiros (2016) employed a two-stage DEA approach in attempts to estimate efficiency scores for 24 Taiwanese non-life insurance companies from a dataset originally used in the work of Kao and Hwang (2008). As proxies for inputs the authors used operation expenses and insurance expenses. In addition, the authors used direct written premiums and reinsurance premiums as proxies for intermediate outputs. Further, the authors used underwriting profit and investment profit as proxies for output.

Biener, Eling and Wirfs (2016) adopted the DEA approach to analyse the efficiency and productivity of Swiss insurance companies in life, property/casualty, and reinsurance sectors for the period 1997 to 2003. Using data obtained from the Swiss regulator FINMA which contains data from all insurers operating in Switzerland, the authors were able to estimate technical, allocative, scale and revenue efficiency scores for the period 1997 to 2013.

Barros and Wanke (2017) describe a number of methodologies which could be used to assess the efficiency of major insurance companies based in Angola and Mozambique for the period 2003 to 2012. The authors obtained secondary data from 13 insurance companies in Angola and Mozambique. For inputs, the authors used operating costs, the number of employees, wages and capital as proxies.

For outputs, the authors used claims paid, profits paid, premiums earned and ceded reinsurance as proxies. After estimating the efficiency scores, the authors found a capacity shortfall in both Mozambique and Angola. Further, the authors found that the performance of insurance companies in both Angola and Mozambique is similar towards a common meta-frontier.

Akhtar (2018) assessed the performance of 30 Takaful and conventional insurance based in Saudi Arabia for the period 2010 to 2015. Using the DEA approach, the efficiency scores of six Takaful firms and 24 non-Takaful firms were estimated using secondary data published in company annual reports based on income statements and balance sheets. As proxies for inputs, Akhtar (2018) used financial capital, net claims incurred and general administrative expenses. As proxies for output, Akhtar (2018) used investment income, net premium earned and investment and management fee income. After estimating the efficiency scores, Akhtar (2018) found that the Saudi Arabian insurance market is characterised by large asymmetry among firms as average efficiency scores range from 0.18 to 1 for the period 2010 to 2015.

3. Methodology and Data

3.1. Data envelopment analysis

In order to estimate medical scheme efficiencies this paper uses a technique coined as Data Envelopment Analysis (DEA). This technique was proposed by Charnes, Copper and Rhodes (1978) and is based on the work of Farrell (1957) which sought to identify an empirical efficient frontier which is formed by a set of real units and is based on observed best practice (Dyson & Shale, 2010).

The DEA technique estimates the relative performance of firms through comparing multiple inputs and outputs and thus gives out an efficiency score. This efficiency score is the estimated ratio of the weighted sum of outputs to weighted sum of inputs. It seeks to analyse a set of decision-making units (DMUs) for the purpose of identifying efficient DMUs in order for them to become benchmarks for inefficient DMUs. DEA encompasses a range of inputs and outputs and utilises linear programming in order to establish a frontier of efficient DMUs and envelopes

inefficient DMUs (Dyson & Shale, 2010). Figure 1 below is a graphical illustration of such a frontier. The line on the graph represents the efficiency frontier. A, B, C, D, and E, which are found on the efficiency frontier are considered best practice DMUs and efficient firms. In contrast, firms which are found to be under the efficiency frontier are considered to be inefficient. Further, below is a brief discussion on technical efficiency, scale efficiency and pure technical efficiency.

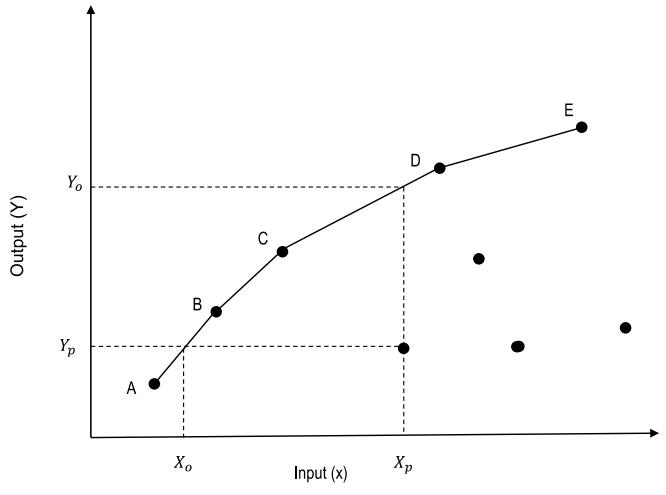

Figure 1: Efficiency frontier

3.2. Technical efficiency

The Farrell efficiency measure developed by Farrell (1957) can be understood as the inverse of the Shephard (1953) distance function. Given this, the efficiency problem can be understood as:

$$F^t(y_i^t, x_i^t) = [D^t(y_i^t, x_i^t)]^{-1} = \min [\lambda_i^t : \lambda_i^t x_i^t \epsilon L^t(y^t)] \qquad (1)$$

Where $D^t(y_i^t, x_i^t)$, the distance function, defines the contraction of x^t that would take an inefficient observation for any firm i, to a point on the frontier, and the minimised parameter λ, determines the factor in which the observed input combination can be reduced. It is understood that the efficiency measure takes a value of 1 for efficient firms which will be on the frontier, and between 0 and 1 for less efficient firms off the frontier.

For clear illustration of the above, assume that there are K inputs and corresponding M outputs for each of N firms. X would be the matrix of inputs and would have size $(K \times N)$. Further, Y would be the matrix of outputs and would have size $(M \times N)$.

Given this, for the ith firm, the input and output data can be represented by column vectors, xi and yi. Thus, the technical efficiency score (θ) for the ith can be estimated by solving the following linear programming problem:

$$\begin{aligned} & Min_{\theta,\lambda^{\lambda}} \\ & subject\ to\ -y_i + Y\lambda \geq 0 \\ & \qquad\qquad \theta x_i - X\lambda \geq 0 \\ & \qquad\qquad N1'\lambda = 1 \\ & \qquad\qquad \lambda \geq 0 \end{aligned} \tag{2}$$

Where $N1$ can be understood as a $(N \times 1)$ vector of ones and λ can be understood as $(N \times 1)$ vector of constants. Furthermore, it is indicated that the linear programming must be solved N times in order to get a value for each firm in the sample. As already indicated, the value of each θ must be less than 1, suggesting a point on the frontier and thus a technically efficient firm (Farrell, 1957).

3.3. Scale efficiency

The linear programming problem outlined above allows for the constructed production frontier to possess increasing, constant or decreasing returns to scale. If it is found that the convexity constraint $(N1'\lambda = 1)$ is omitted from equation 2 above, then the technical efficiency estimate can be calculated under the assumption of constant returns to scale allowing the decomposition of the technically efficiency measure into two measures of pure technical and scale efficiency.

3.4. Pure technical efficiency

Pure technical efficiency can be estimated by dividing technical efficiency by scale efficiency. Pure technical efficiency can be understood to represent efficiency regardless of scale of firms and reflects management skills and the technology applications of firms.

3.5. Stochastic frontier analysis

In addition to DEA, this study employed a stochastic production frontier model similar to that of Battese and Coelli (1995) and Ogloblin (2011). This model was derived as follows:

$$y_{it} = x'_{it}\beta + v_{it} - u_{it} \tag{3}$$

Where y_{it} represents the logarithm of net contribution income for medical scheme i at time t. x_{it} represents the vector in inputs for medical scheme i at time t. β is the vector of parameters

to be estimated. v_{it} represents the random component which is assumed to be independently distributed with a mean of zero and σ_v^2. Furthermore, u_{it} represents the non-negative random component associated with production inefficiency and is assumed to be independently distributed, such that, u_{it} is obtained by truncation at zero of the normal distribution with the mean $z_{it}'\delta$ and variance σ_u^2.

Further, the production inefficiency for medical scheme i at time t, can be illustrated by the following:

$$u_{it} = z\delta + w_{it} \quad (4)$$

Where w_{it} represents the random variable which defined by the truncation of the normal distribution with a zero mean and variance σ_u^2, where the point of truncation is -$z_{it}'\delta$. Given this, it is believed that the parameters δ show how the z variables influence the inefficiency term. Furthermore, in estimating the stochastic production frontier, this study employed the true fixed effects and true random effects models advocated by Greene (2005). These are briefly described below.

3.6. True fixed effects

According to Greene (2005), the inefficiency effect and time invariant firm-specific effect should be accounted for separately when estimating a stochastic frontier model. Greene (2005) stated that if firm-specific heterogeneity is not controlled, this will lead to the estimated inefficiency picking up firm-specific heterogeneity in addition to or even inefficiency. Given this, the possibility exists of a model not being able to estimate the individual effects in addition to the inefficient effects. Given this, Greene advocated the use of the true fixed effects model which accounts for unobserved firm specific heterogeneity and the time varying inefficiency. This model can be derived as follows:

$$y_{it} = \alpha_i + \beta' x_{it} + v_{it} + u_{it} \quad (5)$$

Given the above, it is assumed that the inefficiency term u_{it} is half normally distributed, that being, $u_{it} \sim N^+(O, \sigma^2)$, the log likelihood function for the fixed effects stochastic frontier model can be derived as follows:

$$logL \tag{6}$$
$$= \sum_{i=1}^{N}\sum_{t=1}^{T} \log\left[\frac{2}{\sigma}\Phi(-\lambda(\frac{y_{it}-\sigma_i-x_{it}\beta}{\sigma}))\phi(\left(\frac{y_{it}-\sigma_i-x_{it}\beta}{\sigma}\right))\right]$$

Where $\phi(.)$ and $\Phi(.)$ represents the probability and cumulative density functions of a standard normal distribution respectively. Further, $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$ represents the standard deviation of the composite error term $\varepsilon_{it} = v_{it} - u_{it}$. More so, $\lambda = \frac{\sigma_u}{\sigma_v}$ represents the ratio of inefficiency standard deviation to the noise standard deviation.

3.7. True random effects

The true random effects model is motivated by the same reasons as the true fixed effects model. Given this, the true random effects model can be derived as follows:

$$y_{it} = \alpha_i + \beta' x_{it} + w_i + v_{it} \pm u_{it} \tag{7}$$

Where w_i represents the random firm specific effect. More so, the above equation can be further derived as follows given that the model has a two-part composed error:

$$y_{it} = \alpha_i + \beta' x_{it} + w_i + \varepsilon_{it} \tag{8}$$

Which resembles an ordinary random effects model which contains a time varying component that has an asymmetric distribution as reflected in equation 9 below.

$$f(\varepsilon_{it}) = \frac{\Phi(-\varepsilon_{it}\lambda/\sigma)}{\Phi(0)}\,\frac{1}{\sigma}\phi(\frac{\varepsilon_{it}}{\sigma}) \tag{9}$$

Where $\lambda = \frac{\sigma_u}{\sigma_v}$ represents the ratio of inefficiency standard deviation to the noise standard deviation and $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$ represents the standard deviation of the composite error term $\varepsilon_{it} = v_{it} - u_{it}$. Moreover, the log likelihood function for the stochastic frontier model can be written as follows:

$$logLs = \sum_{i=1}^{N}\frac{1}{R}\sum_{r=1}^{R}\{\sum_{t=1}^{T} ln\Phi(\frac{\mu_{ir/(\sigma_{uir}/\sigma_v)]\pm[(y_{it}-\propto_{ir}-\beta'_{ir}x_{it})(\sigma_{uir}/\sigma_v)]}}{\sqrt{\sigma_{uir}^2+\sigma_v^2}}) \tag{10}$$

$$-ln\Phi\left[\frac{\mu_i}{\sigma_{uir}}\right] - ln\sqrt{\sigma_{uir}^2 + \sigma_v^2}\}$$

$$= \sum_{i=1}^{N} \frac{1}{R} \sum_{r=1}^{R} \sum_{t=1}^{T} log\ P_{itr}$$

Where α_{ir}, β_{ir}, μ_{ir} and σ_{uir} represent the technology parameters.

3.8. Input and output variables

Based on the services provided by medical schemes in the form of real services, risk pooling, risk bearing and intermediation functions, the input variables used in this study were labour and capital inputs. Due to data availability, these inputs were Non-Relevant Healthcare Expenses, Relevant Healthcare Expenses and Medical Scheme Year-end reserve position.

In regards to the output variable, this study followed the suggestions of Leverty, Lin and Zhou (2004) and used Net Contribution Income which is the net premiums paid by members instead of using claims incurred as the choice output. This is because outputs need to be desirable and no medical scheme would want to maximise incurred losses. Therefore, the efficiency scores were estimated based on the assumption that medical schemes aim to maximise net contributions/premiums and profits to be able to provide cover for any incurred losses.

3.9. Data

This study used data for the period 2011 to 2017, obtained from the Council of Medical Schemes. The researcher was able to gather information on all South African medical schemes. This data was subject to the econometric analysis discussed above.

4. Results and Discussion

4.1. Efficiency scores

Tables 5 and 6 reflect the disaggregated medical scheme efficiency scores for both open medical and restricted medical schemes for the period 2011 to 2017. Tables 3 and 4 below reflect the industry aggregated efficiency scores for both open and restricted medical schemes for the period 2011 to 2017. As reflected in Tables 3 and 4 below, the overall efficiency scores for both the markets for open medical schemes and restricted medical schemes have been modest at best.

On average it appears that open medical schemes were more efficient than restricted medical schemes for the sample period.

Open medical schemes on average were able to achieve higher efficiency scores in regard to technical, scale and pure technical efficiency. For the period 2011 to 2017, open medical schemes were able to achieve an average technical efficiency score of 91.9% whereas restricted medical schemes achieved a lower average technical efficiency score of 84.9%. The scale efficiency scores were relatively similar with open medical schemes achieving on average scale efficiencies of 97.9%, whereas restricted medical schemes achieved a slightly lower average score of 97.8%. Furthermore, open medical schemes on average achieved higher pure technical efficiency scores obtaining an average score of 93.9%, whereas restricted medical schemes achieved an average score of 86.8% over the sample period. Furthermore, the SFA technical efficiency scores appear to be higher than those of the DEA technical efficiency scores for both open and restricted medical schemes. The average SFA technical efficiencies scores achieved were 99.8% and 97.8% for open and restricted schemes respectively. More so, similar to the DEA average technical efficiency scores, open medical schemes were able to reach higher scores than those of restricted medical schemes.

Table 3: Aggregated Efficiency results for open medical schemes

Year	Technical Efficiency	Scale Efficiency	Pure Technical Efficiency	SFA Technical Efficiency
2011	93,2%	97,6%	95,5%	99,8%
2012	92,0%	97,3%	94,6%	99,8%
2013	91,0%	97,7%	93,1%	99,8%
2014	90,8%	97,7%	92,9%	99,8%
2015	92,1%	98,2%	93,8%	99,8%
2016	91,8%	98,3%	93,5%	99,8%
2017	92,3%	98,5%	93,8%	99,8%
Average	91,9%	97,9%	93,9%	99,8%

Table 4: Aggregated Efficiency results for restricted medical schemes

Year	Technical Efficiency	Scale Efficiency	Pure Technical Efficiency	SFA Technical Efficiency
2011	85,0%	97,7%	87,0%	97,8%
2012	84,9%	97,6%	86,9%	97,8%
2013	85,1%	97,9%	86,9%	97,9%
2014	84,2%	97,9%	86,0%	97,6%
2015	85,2%	98,0%	87,0%	98,0%
2016	84,5%	97,9%	86,3%	97,8%
2017	85,3%	97,8%	87,3%	97,9%
Average	84,9%	97,8%	86,8%	97,8%

In addition to the above, Tables 11 and 12, presented in the Appendix, reveal the existence of best practice medical schemes. In regard to open medical schemes, the following medical schemes can be considered best practice firms: (i) Bonitas in 2017; (ii) Genesis Medical Scheme in 2013 and 2015; (iii)Keyhealth in 2011, 2012, 2016 and 2017; (iv) Medihelp in 2017; (v) Medimed in 2017; (vi) The National Independent Medical Aid Society (NIMSA) in 2011; (vii) Resolution Health Medical Scheme in 2012, 2013 and 2015; and (viii) Thebemed in 2011 and 2014.

In regard to restricted medical schemes, the following can be considered best practice firms: (i) BMW Employees Medical Aid in 2016 and 2017; (ii) Food Workers Medical Benefit Fund in 2015 and 2016; (iii) the Government Employees Medical Scheme (GEMS) in 2011, 2015, 2016 and 2017; (iv) Impala Medical plan in 2017; (v) Lonmin Medical Scheme in 2011; (vi) Platinum Health in 2011; (vii) Rand Water Medical Scheme in 2017; (viii) TFG Medical Aid Scheme in 2014; and (ix) Umvuzo Health Medical Scheme in 2011.

4.2. Stochastic frontier production function estimates

Tables 5 and 6 below reflect the stochastic frontier production function for open medical schemes. The medical scheme production function variables were estimated in logarithmic form as this allows the interpretation of the marginal effects of the explanatory variables. Table 5 reveals the true fixed effects model whereas Table 6 shows the true random effects model. In Table 5, the true fixed effects model, the coefficients of the inputs in the production function illustrate their output elasticities. The output elasticities of all the inputs appear to be positive and statistically significant at a 1% level. Further, net relevant healthcare expenditure appears to be the most important factor of production. Similar results are found in Table 6, the true random effects model. The output elasticities of all the inputs appear to be positive and statistically significant at a 1% level. More so, net relevant healthcare expenditure appears to be the most important factor of production.

Table 5: Open medical scheme stochastic frontier production function estimates true fixed effects

Variable	Coefficient	Standard Error
Production Function		
Net Contributions		
Net relevant healthcare expenditure	0.873***	(0.0268)
Net non-relevant healthcare expenditure	0.0846***	(0.0256)
Year-end reserve position	0.0807***	(0.0144)

Year	-0.00883***	(0.00216)
Constant	-2.250	(39.73)
Observations	161	
Prob > chi2	0.0000	
σ_u	-5.628	(22.13)
σ_v	-6.949***	(0.132)
Wald chi2(4)	5875.96	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Open medical scheme stochastic frontier production function estimates true random effects

Variable	**Coefficient**	Standard Error
Production Function		
Net Contributions		
Net relevant healthcare expenditure	0.862***	(0.0128)
Net non-relevant healthcare expenditure	0.221***	(0.0139)
Year-end reserve position	0.0386***	(0.00599)
Year	-0.0138***	(0.000199)
Constant	30.11***	(0.444)
Observations	162	
Prob > chi2	0.0000	
σ_u	-1.952***	(0.209)
σ_v	-6.655***	(0.269)
θ	7.033***	(0.820)
Wald chi2(4)	9685.88	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Furthermore, Tables 7 and 8 display the stochastic frontier production function for restricted medical schemes. Similar to open medical schemes, the medical scheme production function variables were estimated in logarithmic form as this enables the interpretation of the marginal effects of the explanatory variables. Table 7 reveals the true fixed effects model whereas Table 8 shows the true random effects model. Similar to open medical schemes, Table 7 below reveals that the output elasticities of all the inputs appear to be positive and statistically significant at a 1% level where net relevant healthcare expenditure appears to be the most important factor of production. The same conclusions are drawn from Table 8 below.

Table 7: Restricted medical scheme stochastic frontier production function estimates true fixed effects

Variable	Coefficient	Standard Error
Production Function		
Net Contributions		
Net relevant healthcare expenditure	0.683***	(0.0218)
Net non-relevant healthcare expenditure	0.135***	(0.0157)
Year-end reserve position	0.146***	(0.0133)
Year	0.00190	(0.00224)
Constant	-0.398	(3.340)
Observations	435	
Prob > chi2	0.0000	
σ_u	-4.632	(6.797)
σ_v	-6.775***	(0.432)
Wald chi2(4)	8835.41	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Restricted medical scheme stochastic frontier production function estimates true random effects

Variable	**Coefficient**	Standard Error
Production Function		
Net Contributions		
Net relevant healthcare expenditure	0.864***	(0.00354)
Net non-relevant healthcare expenditure	0.200***	(0.00197)
Year-end reserve position	0.0724***	(0.00140)
Year	-0.000263***	(1.22e-05)
Constant	2.505***	(0.0295)
Observations	439	
Prob > chi2	0.0000	
σ_u	-1.704*	(0.930)
σ_v	-5.173***	(0.196)
θ	7.234	(0)
Wald chi2(4)	757838.71	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.3. Hausman test

In considering the most appropriate efficient estimators, the Hausman (1978) specification test was employed. The results of this test are shown below in Tables 9 and 10. As reflected below,

the Hausman test favoured the fixed effects model for both open and restricted medical scheme models. The null hypothesis, which suggests that the random effects model is the most appropriate model, can be rejected for both open and restricted medical schemes as the P-value for both is significantly less than 5%.

Table 9: Open medical scheme Hausman test

	Coefficients			
	(b)	**(B)**	**(b-B)**	**sqrt(diag(V_b-V_B))**
	Fixed Effects	**Random Effects**	**Difference**	**S.E.**
Net relevant healthcare expenditure	0.87322	0.8617721	0.0114559	0.0235281
Net non-relevant healthcare expenditure	0.0846136	0.2209387	-0.1363251	0.0215632
Year-end reserve position	0.0807357	0.0385716	0.0421641	0.0131066
Year	-0.0088337	-0.0138432	0.0050095	0.0021495
chi2(4)	27.01			
Prob>chi2	0.0000			

Table 10: Restricted medical scheme Hausman test

	Coefficients			
	(b)	**(B)**	**(b-B)**	**sqrt(diag(V_b-V_B))**
	Fixed Effects	**Random Effects**	**Difference**	**S.E.**
Net relevant healthcare expenditure	0.6826199	0.8637419	-0.181122	0.0214621
Net non-relevant healthcare expenditure	0.1351976	0.2001287	-0.0649311	0.0155604
Year-end reserve position	0.1457066	0.0724366	0.07327	0.0132685
Year	0.0018982	-0.0002632	0.0021614	0.0022431
chi2(4)	255.29			
Prob>chi2	0.0000			

5. Conclusion

This article adopted both the DEA and SFA approaches to estimate the efficiency scores of both open and restricted medical schemes for the period 2011 to 2017 based on data obtained from the Council of Medical Schemes. The DEA empirical findings suggest that open medical schemes tend to be more efficient than restricted medical schemes in terms of technical, scale and pure technical efficiency over the sample period. The same conclusions are found when assessing the SFA technical efficiency scores, whereby open medical schemes are seen to be more efficient than restricted medical schemes. More so, the SFA technical efficiency scores

are significantly higher than the DEA technical efficiency scores for both open and restricted medical schemes.

Further, the stochastic production frontier estimates reveal that the chosen input proxies, namely net relevant healthcare expenditure, non-relevant healthcare expenditure and Year-end reserve position are positive and statistically significant at a 1% level in regard to the chosen output variable, namely net contribution income. This is true for both the true fixed effect model and true random effect model. Furthermore, the empirical results show that input proxy, net relevant healthcare expenditure is the most important factor of production for both open and restricted medical schemes. The next viable step for future research would be extending the methodology in order to estimate, in addition to efficiency, the productivity and returns to scale economies of South African medical schemes.

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Appendix

Table 11: Efficiency results for open medical schemes

Year	Medical Schemes	Technical Efficiency	Scale Efficiency	Pure Technical Efficiency	SFA Technical Efficiency
2011	Bestmed Medical Scheme	73,04%	97,61%	93,68%	99,84%
2012	Bestmed Medical Scheme	74,76%	97,69%	93,59%	99,84%
2013	Bestmed Medical Scheme	77,81%	98,02%	93,97%	99,84%
2014	Bestmed Medical Scheme	80,82%	97,82%	94,72%	99,84%
2015	Bestmed Medical Scheme	86,06%	99,40%	95,32%	99,84%
2016	Bestmed Medical Scheme	86,64%	97,81%	98,46%	99,85%
2017	Bestmed Medical Scheme	86,30%	97,91%	99,68%	99,85%
2011	Bonitas Medical Fund	73,78%	95,66%	96,06%	99,84%
2012	Bonitas Medical Fund	73,08%	95,58%	94,23%	99,83%
2013	Bonitas Medical Fund	74,68%	95,40%	95,57%	99,84%
2014	Bonitas Medical Fund	77,39%	95,80%	94,64%	99,84%
2015	Bonitas Medical Fund	84,40%	96,52%	93,11%	99,84%
2016	Bonitas Medical Fund	88,49%	97,23%	97,43%	99,84%
2017	Bonitas Medical Fund	92,67%	100,00%	100,00%	99,85%
2011	Cape Medical Plan	58,87%	98,73%	86,79%	99,85%
2012	Cape Medical Plan	57,47%	98,76%	84,49%	99,85%
2013	Cape Medical Plan	55,41%	98,91%	77,49%	99,82%
2014	Cape Medical Plan	58,48%	99,09%	81,39%	99,84%
2015	Cape Medical Plan	58,90%	99,22%	79,63%	99,83%
2016	Cape Medical Plan	61,07%	99,24%	86,47%	99,86%
2017	Cape Medical Plan	57,86%	99,25%	79,83%	99,84%
2011	Community Medical Aid Scheme (COMMED)	76,80%	98,27%	93,56%	99,84%
2012	Community Medical Aid Scheme (COMMED)	72,18%	98,92%	92,78%	99,85%
2013	Community Medical Aid Scheme (COMMED)	69,13%	99,01%	88,81%	99,84%
2014	Community Medical Aid Scheme (COMMED)	67,80%	98,28%	85,53%	99,83%
2011	Compcare Wellness Medical Scheme	69,91%	98,83%	94,33%	99,85%
2012	Compcare Wellness Medical Scheme	68,31%	98,87%	94,92%	99,85%
2013	Compcare Wellness Medical Scheme	65,34%	98,81%	88,17%	99,83%
2014	Compcare Wellness Medical Scheme	66,94%	98,60%	89,69%	99,84%
2015	Compcare Wellness Medical Scheme	74,09%	99,66%	87,61%	99,83%
2016	Compcare Wellness Medical Scheme	79,28%	99,93%	88,19%	99,84%
2017	Compcare Wellness Medical Scheme	79,08%	99,87%	90,77%	99,85%
2011	Discovery Health Medical Scheme	71,45%	92,58%	99,49%	99,84%
2012	Discovery Health Medical Scheme	72,54%	92,87%	100,00%	99,84%

2013	Discovery Health Medical Scheme	73,86%	94,56%	100,00%	99,85%
2014	Discovery Health Medical Scheme	73,42%	93,81%	100,00%	99,84%
2015	Discovery Health Medical Scheme	78,92%	93,97%	100,00%	99,84%
2016	Discovery Health Medical Scheme	78,42%	93,07%	100,00%	99,84%
2017	Discovery Health Medical Scheme	79,14%	94,72%	100,00%	99,84%
2011	Fedhealth Medical Scheme	74,30%	98,12%	96,83%	99,85%
2012	Fedhealth Medical Scheme	73,59%	98,26%	97,13%	99,85%
2013	Fedhealth Medical Scheme	71,24%	98,22%	91,80%	99,83%
2014	Fedhealth Medical Scheme	71,22%	97,88%	90,47%	99,83%
2015	Fedhealth Medical Scheme	77,92%	98,19%	92,82%	99,84%
2016	Fedhealth Medical Scheme	76,80%	98,08%	90,19%	99,83%
2017	Fedhealth Medical Scheme	77,64%	97,98%	95,68%	99,85%
2011	Genesis Medical Scheme	65,52%	99,71%	98,61%	99,84%
2012	Genesis Medical Scheme	66,24%	99,76%	99,85%	99,84%
2013	Genesis Medical Scheme	65,72%	100,00%	100,00%	99,85%
2014	Genesis Medical Scheme	65,10%	99,93%	98,91%	99,84%
2015	Genesis Medical Scheme	65,72%	100,00%	100,00%	99,84%
2016	Genesis Medical Scheme	65,23%	99,98%	99,01%	99,84%
2017	Genesis Medical Scheme	64,44%	99,28%	99,17%	99,84%
2011	Hosmed Medical Aid Scheme	86,63%	98,47%	99,87%	99,85%
2012	Hosmed Medical Aid Scheme	83,98%	98,26%	98,55%	99,84%
2013	Hosmed Medical Aid Scheme	79,57%	97,94%	94,47%	99,84%
2014	Hosmed Medical Aid Scheme	81,77%	98,32%	96,13%	99,84%
2015	Hosmed Medical Aid Scheme	85,83%	99,59%	94,82%	99,84%
2016	Hosmed Medical Aid Scheme	87,29%	99,94%	92,99%	99,83%
2017	Hosmed Medical Aid Scheme	85,04%	99,49%	96,45%	99,84%
2011	Keyhealth	95,58%	100,00%	100,00%	99,85%
2012	Keyhealth	94,16%	100,00%	100,00%	99,85%
2013	Keyhealth	87,73%	99,73%	99,44%	99,85%
2014	Keyhealth	84,10%	99,58%	96,53%	99,84%
2015	Keyhealth	85,38%	99,91%	98,15%	99,82%
2016	Keyhealth	87,87%	100,00%	100,00%	99,83%
2017	Keyhealth	87,28%	100,00%	100,00%	99,84%
2011	Liberty Medical Scheme	72,97%	97,97%	90,22%	99,83%
2012	Liberty Medical Scheme	71,53%	96,90%	90,09%	99,84%
2013	Liberty Medical Scheme	72,22%	96,48%	92,39%	99,84%
2014	Liberty Medical Scheme	77,36%	94,91%	92,30%	99,84%
2015	Liberty Medical Scheme	93,78%	99,98%	100,00%	99,85%
2011	Makoti Medical Scheme	63,10%	89,03%	100,00%	99,83%
2012	Makoti Medical Scheme	55,01%	81,81%	100,00%	99,83%
2013	Makoti Medical Scheme	59,87%	90,05%	95,63%	99,84%

2014	Makoti Medical Scheme	59,82%	94,00%	90,71%	99,84%
2015	Makoti Medical Scheme	62,59%	93,70%	96,34%	99,85%
2016	Makoti Medical Scheme	65,12%	94,28%	97,06%	99,85%
2017	Makoti Medical Scheme	60,37%	95,49%	89,30%	99,84%
2011	Medihelp	84,81%	97,43%	98,08%	99,84%
2012	Medihelp	77,08%	97,59%	91,18%	99,83%
2013	Medihelp	75,85%	97,12%	91,72%	99,83%
2014	Medihelp	74,41%	95,99%	91,47%	99,84%
2015	Medihelp	81,90%	97,33%	95,89%	99,85%
2016	Medihelp	84,39%	97,90%	93,24%	99,84%
2017	Medihelp	89,22%	100,00%	100,00%	99,85%
2011	Medimed Medical Scheme	69,89%	98,21%	99,49%	99,84%
2012	Medimed Medical Scheme	67,21%	98,43%	95,45%	99,84%
2013	Medimed Medical Scheme	65,50%	98,64%	90,38%	99,82%
2014	Medimed Medical Scheme	70,20%	98,92%	97,69%	99,85%
2015	Medimed Medical Scheme	74,21%	98,97%	96,81%	99,84%
2016	Medimed Medical Scheme	76,62%	99,16%	100,00%	99,84%
2017	Medimed Medical Scheme	77,98%	100,00%	100,00%	99,85%
2011	Medshield Medical Scheme	76,97%	98,25%	91,68%	99,84%
2012	Medshield Medical Scheme	74,09%	98,25%	95,70%	99,85%
2013	Medshield Medical Scheme	73,40%	98,03%	94,49%	99,85%
2014	Medshield Medical Scheme	70,56%	98,05%	91,49%	99,84%
2015	Medshield Medical Scheme	77,40%	97,99%	94,44%	99,84%
2016	Medshield Medical Scheme	74,51%	98,51%	90,80%	99,84%
2017	Medshield Medical Scheme	74,32%	98,33%	88,16%	99,83%
2011	Momentum Health	76,74%	96,50%	99,59%	99,85%
2012	Momentum Health	75,72%	97,90%	100,00%	99,85%
2013	Momentum Health	73,69%	97,42%	98,45%	99,85%
2014	Momentum Health	71,90%	97,17%	95,82%	99,84%
2015	Momentum Health	75,69%	96,92%	94,82%	99,83%
2016	Momentum Health	76,05%	95,78%	94,11%	99,83%
2017	Momentum Health	76,80%	95,44%	96,25%	99,84%
2011	National Independent Medical Aid Society (NIMAS)	92,76%	100,00%	100,00%	
2011	Pharos Medical Plan	78,74%	98,91%	92,17%	99,83%
2012	Pharos Medical Plan	78,98%	98,73%	94,42%	99,84%
2013	Pharos Medical Plan	75,94%	97,83%	95,27%	99,85%
2011	Pro Sano Medical Scheme	81,84%	99,56%	92,50%	99,84%
2012	Pro Sano Medical Scheme	76,13%	97,94%	90,86%	99,84%
2011	Resolution Health Medical Scheme	86,47%	99,98%	92,83%	99,83%
2012	Resolution Health Medical Scheme	100,00%	100,00%	100,00%	99,84%

2013	Resolution Health Medical Scheme	99,51%	100,00%	100,00%	99,85%
2014	Resolution Health Medical Scheme	95,31%	99,94%	97,89%	99,84%
2015	Resolution Health Medical Scheme	98,71%	100,00%	100,00%	99,84%
2016	Resolution Health Medical Scheme	95,92%	99,78%	98,94%	99,84%
2017	Resolution Health Medical Scheme	90,10%	99,98%	96,66%	99,84%
2011	Selfmed Medical Scheme	65,20%	99,83%	94,43%	99,86%
2012	Selfmed Medical Scheme	61,28%	99,78%	85,48%	99,83%
2013	Selfmed Medical Scheme	59,99%	99,71%	84,76%	99,84%
2014	Selfmed Medical Scheme	60,57%	99,76%	86,17%	99,84%
2015	Selfmed Medical Scheme	66,54%	99,86%	91,95%	99,85%
2016	Selfmed Medical Scheme	62,73%	99,84%	83,19%	99,83%
2017	Selfmed Medical Scheme	61,91%	99,82%	80,85%	99,83%
2011	Sizwe Medical Fund	76,83%	97,39%	91,18%	99,83%
2012	Sizwe Medical Fund	80,64%	97,62%	93,24%	99,84%
2013	Sizwe Medical Fund	80,21%	98,36%	99,37%	99,85%
2014	Sizwe Medical Fund	75,76%	98,88%	100,00%	99,85%
2015	Sizwe Medical Fund	76,79%	98,33%	95,21%	99,84%
2016	Sizwe Medical Fund	72,62%	98,39%	93,40%	99,84%
2017	Sizwe Medical Fund	72,14%	98,20%	93,92%	99,84%
2011	Spectramed	74,28%	98,21%	100,00%	99,86%
2012	Spectramed	66,69%	97,76%	96,02%	99,85%
2013	Spectramed	60,15%	95,96%	93,16%	99,84%
2014	Spectramed	58,74%	95,95%	88,61%	99,83%
2015	Spectramed	59,42%	98,39%	79,12%	99,81%
2016	Spectramed	70,30%	99,48%	84,77%	99,84%
2017	Spectramed	74,91%	99,97%	86,76%	99,84%
2011	Suremed Health	60,88%	88,33%	100,00%	99,83%
2012	Suremed Health	64,60%	94,40%	100,00%	99,85%
2013	Suremed Health	75,43%	95,66%	93,88%	99,84%
2014	Suremed Health	75,33%	95,92%	91,07%	99,84%
2015	Suremed Health	68,96%	93,22%	100,00%	99,85%
2016	Suremed Health	70,49%	95,83%	100,00%	99,85%
2017	Suremed Health	66,99%	94,95%	96,66%	99,84%
2011	Thebemed	89,19%	100,00%	100,00%	99,86%
2012	Thebemed	89,88%	96,33%	100,00%	99,84%
2013	Thebemed	87,22%	98,57%	100,00%	99,84%
2014	Thebemed	83,47%	100,00%	100,00%	99,85%
2015	Thebemed	77,78%	99,39%	93,87%	99,83%
2016	Thebemed	79,42%	100,00%	91,44%	99,83%
2017	Thebemed	87,92%	98,17%	94,67%	99,83%
2011	Topmed Medical Scheme	55,24%	99,98%	82,36%	99,84%

2012	Topmed Medical Scheme	53,11%	99,97%	78,16%	99,82%
2013	Topmed Medical Scheme	52,74%	99,82%	76,34%	99,82%
2014	Topmed Medical Scheme	59,99%	99,02%	84,61%	99,85%
2015	Topmed Medical Scheme	63,07%	99,99%	84,62%	99,85%
2016	Topmed Medical Scheme	63,67%	99,98%	83,61%	99,85%
2017	Topmed Medical Scheme	65,37%	99,97%	84,11%	99,85%

Table 12: Efficiency results for restricted medical schemes

Year	Medical Schemes	Technical Efficiency	Scale Efficiency	Pure Technical Efficiency	SFA Technical Efficiency
2011	AECI Medical Aid Society	63,27%	99,25%	90,28%	98,80%
2012	AECI Medical Aid Society	60,91%	98,93%	87,11%	98,26%
2013	AECI Medical Aid Society	61,75%	98,67%	91,04%	98,65%
2014	AECI Medical Aid Society	60,22%	98,72%	91,50%	98,29%
2015	AECI Medical Aid Society	63,28%	98,28%	92,77%	98,28%
2016	AECI Medical Aid Society	59,56%	97,38%	85,77%	95,74%
2017	AECI Medical Aid Society	61,75%	96,75%	89,66%	97,23%
2011	Afrox Medical Aid Society	46,94%	99,51%	70,23%	97,43%
2012	Afrox Medical Aid Society	47,52%	99,20%	68,53%	97,45%
2013	Afrox Medical Aid Society	51,68%	99,38%	74,13%	98,89%
2011	Alliance Midmed Medical Scheme	55,30%	97,01%	81,41%	94,50%
2013	Alliance Midmed Medical Scheme	62,39%	97,83%	91,87%	98,70%
2014	Alliance Midmed Medical Scheme	60,02%	96,53%	84,30%	96,92%
2015	Alliance Midmed Medical Scheme	66,79%	97,31%	89,73%	98,54%
2016	Alliance Midmed Medical Scheme	65,15%	97,29%	90,53%	98,72%
2017	Alliance Midmed Medical Scheme	64,35%	97,26%	86,51%	98,36%
2011	Altron Medical Aid Scheme	64,30%	96,74%	89,53%	97,81%
2012	Altron Medical Aid Scheme	66,71%	98,58%	92,32%	98,44%
2013	Altron Medical Aid Scheme	65,22%	98,84%	93,25%	98,25%
2011	Anglo Medical Scheme	42,44%	98,62%	73,20%	98,95%
2012	Anglo Medical Scheme	42,86%	98,61%	74,29%	99,02%
2013	Anglo Medical Scheme	40,99%	98,58%	72,14%	98,45%
2014	Anglo Medical Scheme	38,51%	98,40%	68,58%	97,20%
2015	Anglo Medical Scheme	39,25%	98,16%	65,88%	96,14%
2016	Anglo Medical Scheme	38,92%	98,21%	65,07%	95,08%
2017	Anglo Medical Scheme	41,62%	98,04%	69,80%	98,03%
2011	Anglovaal Group Medical Scheme	52,61%	99,75%	80,49%	98,48%
2012	Anglovaal Group Medical Scheme	54,05%	99,71%	84,24%	98,82%
2013	Anglovaal Group Medical Scheme	49,89%	99,81%	76,54%	97,13%
2014	Anglovaal Group Medical Scheme	49,78%	99,83%	76,02%	96,95%

2015	Anglovaal Group Medical Scheme	53,52%	99,99%	81,49%	98,54%
2016	Anglovaal Group Medical Scheme	51,67%	99,99%	75,24%	97,67%
2017	Anglovaal Group Medical Scheme	53,29%	99,80%	77,76%	98,38%
2011	BMW Employees Medical Aid Society	57,07%	97,44%	80,80%	90,79%
2012	BMW Employees Medical Aid Society	61,69%	98,66%	88,94%	97,01%
2013	BMW Employees Medical Aid Society	60,80%	98,99%	88,07%	97,40%
2014	BMW Employees Medical Aid Society	58,97%	98,75%	83,16%	95,60%
2015	BMW Employees Medical Aid Society	68,33%	99,85%	89,33%	98,25%
2016	BMW Employees Medical Aid Society	70,78%	100,00%	100,00%	99,20%
2017	BMW Employees Medical Aid Society	69,50%	100,00%	100,00%	99,08%
2011	BP Medical Aid Society	51,10%	98,06%	72,50%	98,50%
2012	BP Medical Aid Society	50,07%	98,65%	71,31%	98,21%
2013	BP Medical Aid Society	51,30%	98,06%	75,16%	98,70%
2014	BP Medical Aid Society	48,99%	98,93%	70,65%	97,69%
2015	BP Medical Aid Society	52,44%	98,98%	72,91%	97,85%
2016	BP Medical Aid Society	52,71%	99,05%	75,87%	98,43%
2017	BP Medical Aid Society	49,60%	99,03%	72,23%	97,34%
2011	Bankmed	56,19%	93,36%	88,71%	97,31%
2012	Bankmed	56,48%	93,83%	88,03%	97,37%
2013	Bankmed	57,15%	93,01%	90,40%	97,79%
2014	Bankmed	56,24%	93,72%	87,51%	97,38%
2015	Bankmed	60,71%	96,42%	86,13%	98,17%
2016	Bankmed	64,39%	97,97%	86,75%	98,64%
2017	Bankmed	70,88%	96,32%	93,00%	99,05%
2011	Barloworld Medical Scheme	66,03%	99,64%	92,09%	99,04%
2012	Barloworld Medical Scheme	63,49%	99,21%	89,49%	98,74%
2013	Barloworld Medical Scheme	64,20%	98,92%	94,50%	98,95%
2014	Barloworld Medical Scheme	57,04%	98,71%	82,39%	96,00%
2015	Barloworld Medical Scheme	61,43%	98,78%	86,21%	96,98%
2016	Barloworld Medical Scheme	61,20%	98,69%	84,98%	96,59%
2017	Barloworld Medical Scheme	61,10%	98,56%	84,65%	96,50%
2011	Building & Construction Industry Medical Aid Fund	57,96%	99,50%	93,77%	98,79%
2012	Building & Construction Industry Medical Aid Fund	58,55%	99,79%	96,58%	98,87%
2013	Building & Construction Industry Medical Aid Fund	55,61%	99,92%	91,32%	98,09%

2014	Building & Construction Industry Medical Aid Fund	56,91%	99,96%	94,48%	98,53%
2015	Building & Construction Industry Medical Aid Fund	57,89%	99,92%	93,43%	98,50%
2016	Building & Construction Industry Medical Aid Fund	50,96%	99,96%	80,93%	91,75%
2017	Building & Construction Industry Medical Aid Fund	53,03%	99,78%	85,03%	95,29%
2011	Chartered Accountants (SA) Medical Aid Fund (CAMAF)	58,22%	93,98%	93,49%	98,48%
2012	Chartered Accountants (SA) Medical Aid Fund (CAMAF)	57,33%	94,29%	91,49%	98,23%
2013	Chartered Accountants (SA) Medical Aid Fund (CAMAF)	57,43%	94,66%	90,96%	98,25%
2014	Chartered Accountants (SA) Medical Aid Fund (CAMAF)	55,90%	94,48%	88,31%	97,68%
2015	Chartered Accountants (SA) Medical Aid Fund (CAMAF)	56,35%	96,88%	84,25%	97,24%
2016	Chartered Accountants (SA) Medical Aid Fund (CAMAF)	58,13%	96,74%	86,68%	98,11%
2017	Chartered Accountants (SA) Medical Aid Fund (CAMAF)	60,40%	96,34%	90,85%	98,72%
2011	De Beers Benefit Society	54,33%	98,57%	84,43%	98,71%
2012	De Beers Benefit Society	52,33%	98,93%	82,03%	98,33%
2013	De Beers Benefit Society	52,93%	98,85%	83,15%	98,49%
2014	De Beers Benefit Society	51,86%	98,38%	80,34%	98,09%
2015	De Beers Benefit Society	52,21%	98,64%	81,23%	98,34%
2016	De Beers Benefit Society	52,03%	98,57%	79,48%	97,66%
2017	De Beers Benefit Society	50,69%	98,51%	77,19%	96,79%
2011	Edcon Medical Aid Scheme	56,54%	98,63%	86,66%	
2011	Engen Medical Benefit Fund	61,54%	99,25%	87,02%	97,83%
2012	Engen Medical Benefit Fund	61,59%	99,60%	88,17%	98,01%
2013	Engen Medical Benefit Fund	58,94%	99,26%	81,93%	95,86%
2014	Engen Medical Benefit Fund	58,49%	99,42%	82,69%	96,46%
2015	Engen Medical Benefit Fund	70,33%	99,79%	91,27%	98,68%
2016	Engen Medical Benefit Fund	69,90%	99,72%	88,38%	98,34%
2017	Engen Medical Benefit Fund	72,44%	99,40%	97,56%	99,08%
2011	Eyethumed Medical Scheme	49,01%	96,22%	80,18%	98,87%
2012	Eyethumed Medical Scheme	45,79%	93,38%	75,49%	95,86%
2011	Fishing Industry Medical Scheme (Fishmed)	46,08%	77,53%	100,00%	89,40%
2012	Fishing Industry Medical Scheme (Fishmed)	48,51%	81,43%	100,00%	94,00%
2013	Fishing Industry Medical Scheme (Fishmed)	51,62%	86,22%	100,00%	97,48%
2014	Fishing Industry Medical Scheme (Fishmed)	53,74%	89,16%	100,00%	98,49%

2015	Fishing Industry Medical Scheme (Fishmed)	54,03%	88,84%	98,23%	98,52%
2016	Fishing Industry Medical Scheme (Fishmed)	55,53%	91,09%	96,52%	98,90%
2017	Fishing Industry Medical Scheme (Fishmed)	56,19%	92,86%	95,17%	99,01%
2011	Food Workers Medical Benefit Fund	53,40%	95,90%	97,95%	98,30%
2012	Food Workers Medical Benefit Fund	54,10%	97,56%	97,12%	97,94%
2013	Food Workers Medical Benefit Fund	53,85%	98,36%	94,80%	97,79%
2014	Food Workers Medical Benefit Fund	52,22%	98,78%	91,95%	96,36%
2015	Food Workers Medical Benefit Fund	58,63%	100,00%	100,00%	98,92%
2016	Food Workers Medical Benefit Fund	57,68%	100,00%	100,00%	98,59%
2017	Food Workers Medical Benefit Fund	54,76%	97,90%	96,03%	97,89%
2014	Glencore Medical Scheme	65,46%	99,68%	89,46%	98,01%
2015	Glencore Medical Scheme	71,40%	98,58%	86,93%	97,41%
2016	Glencore Medical Scheme	73,48%	98,36%	94,50%	98,58%
2017	Glencore Medical Scheme	72,13%	98,00%	94,01%	98,42%
2011	Gold Fields Medical Scheme	55,96%	99,49%	84,95%	98,05%
2012	Gold Fields Medical Scheme	57,72%	99,35%	87,64%	98,55%
2013	Gold Fields Medical Scheme	55,85%	99,26%	84,70%	97,85%
2012	Golden Arrow Employees Medical Benefit Fund	33,41%	93,89%	54,39%	
2011	Golden Arrows Employees Medical Benefit Fund	33,14%	92,53%	54,18%	98,74%
2013	Golden Arrows Employees Medical Benefit Fund	32,26%	94,58%	51,90%	98,00%
2014	Golden Arrows Employees Medical Benefit Fund	32,26%	96,33%	51,56%	97,89%
2015	Golden Arrows Employees Medical Benefit Fund	33,71%	94,62%	51,80%	97,96%
2016	Golden Arrows Employees Medical Benefit Fund	33,87%	96,36%	52,95%	98,25%
2017	Golden Arrows Employees Medical Benefit Fund	33,37%	96,96%	53,15%	98,04%
2011	Government Employees Medical Scheme (GEMS)	93,05%	100,00%	100,00%	98,49%
2012	Government Employees Medical Scheme (GEMS)	93,91%	100,00%	99,30%	98,36%
2013	Government Employees Medical Scheme (GEMS)	82,67%	98,77%	99,67%	97,55%
2014	Government Employees Medical Scheme (GEMS)	83,08%	97,34%	97,73%	96,92%
2015	Government Employees Medical Scheme (GEMS)	96,50%	100,00%	100,00%	98,35%
2016	Government Employees Medical Scheme (GEMS)	100,00%	100,00%	100,00%	98,65%
2017	Government Employees Medical Scheme (GEMS)	86,57%	100,00%	100,00%	98,19%

2011	Grintek Electronics Medical Aid Scheme	50,79%	94,82%	78,72%	97,41%
2012	Grintek Electronics Medical Aid Scheme	55,98%	95,79%	87,91%	98,79%
2013	Grintek Electronics Medical Aid Scheme	54,13%	95,00%	88,12%	98,07%
2014	Grintek Electronics Medical Aid Scheme	49,92%	93,24%	78,39%	93,85%
2015	Grintek Electronics Medical Aid Scheme	54,74%	91,66%	82,18%	97,25%
2016	Grintek Electronics Medical Aid Scheme	57,52%	92,53%	85,19%	98,56%
2017	Grintek Electronics Medical Aid Scheme	59,05%	93,26%	86,37%	98,97%
2011	Horizon Medical Scheme	52,24%	95,02%	89,60%	96,80%
2012	Horizon Medical Scheme	54,69%	95,74%	93,43%	98,15%
2013	Horizon Medical Scheme	54,52%	96,62%	91,62%	98,22%
2014	Horizon Medical Scheme	51,60%	97,21%	83,29%	96,86%
2015	Horizon Medical Scheme	59,42%	98,03%	98,03%	99,12%
2016	Horizon Medical Scheme	52,65%	98,01%	83,17%	97,36%
2017	Horizon Medical Scheme	54,80%	97,87%	85,46%	98,53%
2011	IBM (SA) Medical Scheme	55,99%	96,98%	87,73%	98,49%
2012	IBM (SA) Medical Scheme	54,14%	96,86%	84,73%	97,80%
2011	Impala Medical Plan	88,14%	98,46%	99,66%	97,78%
2012	Impala Medical Plan	94,77%	99,52%	100,00%	98,31%
2013	Impala Medical Plan	97,09%	99,58%	100,00%	98,52%
2014	Impala Medical Plan	89,02%	99,43%	99,38%	97,65%
2015	Impala Medical Plan	89,47%	99,62%	98,04%	97,66%
2016	Impala Medical Plan	93,89%	99,77%	98,63%	98,19%
2017	Impala Medical Plan	100,00%	100,00%	100,00%	98,72%
2011	Imperial Group Medical Scheme	55,06%	99,12%	80,05%	95,86%
2012	Imperial Group Medical Scheme	57,31%	99,14%	82,71%	97,51%
2013	Imperial Group Medical Scheme	58,59%	99,31%	83,66%	98,02%
2014	Imperial Group Medical Scheme	58,80%	99,05%	84,72%	98,18%
2015	Imperial Group Medical Scheme	61,53%	98,37%	88,67%	98,67%
2016	Imperial Group Medical Scheme	60,91%	98,29%	87,99%	98,53%
2017	Imperial Group Medical Scheme	61,35%	97,66%	90,29%	98,72%
2011	LA Health Medical Scheme	59,91%	92,74%	96,12%	98,16%
2012	LA Health Medical Scheme	59,92%	91,81%	97,22%	98,28%
2013	LA Health Medical Scheme	61,18%	91,67%	100,00%	98,60%
2014	LA Health Medical Scheme	60,39%	91,24%	100,00%	98,41%
2015	LA Health Medical Scheme	60,00%	93,19%	96,47%	98,01%
2016	LA Health Medical Scheme	59,23%	92,14%	96,69%	97,75%
2017	LA Health Medical Scheme	59,56%	90,42%	99,59%	97,92%

2011	Libcare Medical Scheme	55,47%	99,07%	85,94%	98,06%
2012	Libcare Medical Scheme	57,03%	98,88%	90,91%	98,61%
2013	Libcare Medical Scheme	57,76%	98,69%	92,96%	98,78%
2014	Libcare Medical Scheme	55,63%	98,62%	89,36%	98,26%
2015	Libcare Medical Scheme	56,61%	99,16%	88,58%	98,29%
2016	Libcare Medical Scheme	55,40%	99,20%	86,22%	97,69%
2017	Libcare Medical Scheme	53,81%	98,40%	80,59%	96,16%
2011	Lonmin Medical Scheme	67,27%	100,00%	100,00%	99,22%
2012	Lonmin Medical Scheme	59,44%	99,79%	88,52%	97,77%
2013	Lonmin Medical Scheme	57,94%	99,91%	86,31%	96,97%
2014	Lonmin Medical Scheme	57,86%	99,63%	86,70%	96,94%
2015	Lonmin Medical Scheme	62,91%	98,63%	80,17%	94,49%
2016	Lonmin Medical Scheme	71,27%	95,99%	84,99%	98,07%
2017	Lonmin Medical Scheme	72,86%	98,87%	91,09%	98,85%
2011	MBMed Medical Aid Fund	61,38%	99,32%	88,29%	98,56%
2012	MBMed Medical Aid Fund	57,78%	99,14%	82,21%	97,06%
2013	MBMed Medical Aid Fund	58,63%	99,62%	84,21%	97,70%
2014	MBMed Medical Aid Fund	60,41%	99,84%	87,78%	98,48%
2015	MBMed Medical Aid Fund	64,48%	99,98%	91,29%	98,94%
2016	MBMed Medical Aid Fund	60,12%	99,88%	84,02%	97,90%
2017	MBMed Medical Aid Fund	59,57%	99,77%	81,77%	97,28%
2011	Malcor Medical Scheme	59,36%	99,01%	80,43%	96,30%
2012	Malcor Medical Scheme	65,49%	98,66%	82,66%	97,81%
2013	Malcor Medical Scheme	66,05%	98,84%	82,65%	98,02%
2014	Malcor Medical Scheme	67,18%	98,70%	82,40%	98,04%
2015	Malcor Medical Scheme	69,97%	99,58%	83,24%	98,23%
2016	Malcor Medical Scheme	73,16%	99,88%	85,10%	98,56%
2017	Malcor Medical Scheme	75,52%	99,91%	88,02%	98,90%
2011	Massmart Health Plan	60,64%	99,42%	92,77%	97,87%
2012	Massmart Health Plan	59,65%	99,75%	92,48%	97,57%
2013	Massmart Health Plan	56,48%	99,77%	86,49%	95,07%
2014	Massmart Health Plan	60,27%	99,25%	91,16%	98,23%
2015	Massmart Health Plan	64,05%	99,77%	90,01%	98,75%
2016	Massmart Health Plan	61,28%	99,71%	87,26%	98,45%
2017	Massmart Health Plan	62,44%	99,62%	88,84%	98,79%
2011	Medipos Medical Scheme	60,92%	98,31%	93,83%	99,11%
2012	Medipos Medical Scheme	57,64%	97,80%	88,71%	98,52%
2013	Medipos Medical Scheme	57,17%	97,61%	88,80%	98,36%
2014	Medipos Medical Scheme	53,22%	97,63%	81,58%	96,43%
2015	Medipos Medical Scheme	56,31%	96,99%	84,21%	97,28%
2016	Medipos Medical Scheme	56,52%	95,94%	83,87%	97,02%

2017	Medipos Medical Scheme	58,57%	96,17%	85,31%	98,15%
2011	Metrocare	39,43%	93,73%	64,74%	
2011	Metropolitan Medical Scheme	56,19%	100,00%	82,35%	98,58%
2012	Metropolitan Medical Scheme	56,02%	99,97%	82,25%	98,62%
2013	Metropolitan Medical Scheme	56,24%	99,82%	82,95%	98,68%
2014	Metropolitan Medical Scheme	55,01%	99,99%	80,37%	98,40%
2015	Metropolitan Medical Scheme	56,89%	99,81%	76,56%	97,07%
2016	Metropolitan Medical Scheme	53,92%	99,49%	74,47%	95,00%
2011	Minemed Medical Scheme	75,45%	98,41%	94,55%	98,09%
2012	Minemed Medical Scheme	75,32%	99,18%	100,00%	98,30%
2011	Motohealth Care	55,91%	95,78%	87,98%	98,65%
2012	Motohealth Care	54,11%	95,01%	86,22%	98,20%
2013	Motohealth Care	54,29%	95,00%	86,45%	98,22%
2014	Motohealth Care	53,66%	96,86%	82,68%	97,68%
2015	Motohealth Care	57,33%	98,70%	82,97%	98,21%
2016	Motohealth Care	56,91%	98,64%	82,36%	98,14%
2017	Motohealth Care	57,28%	99,09%	80,68%	98,04%
2011	Nampak SA Medical Scheme	62,18%	99,65%	81,68%	98,47%
2012	Nampak SA Medical Scheme	57,35%	99,58%	82,31%	97,82%
2011	Naspers Medical Fund	55,14%	99,15%	86,28%	98,34%
2012	Naspers Medical Fund	54,82%	99,02%	86,09%	98,29%
2013	Naspers Medical Fund	52,67%	99,27%	80,74%	97,25%
2014	Naspers Medical Fund	55,72%	98,66%	86,70%	98,56%
2015	Naspers Medical Fund	58,17%	99,57%	85,18%	98,63%
2016	Naspers Medical Fund	55,91%	99,76%	80,93%	97,93%
2017	Naspers Medical Fund	55,94%	99,66%	80,86%	97,76%
2011	Nedgroup Medical Aid Scheme	57,54%	99,11%	81,60%	97,36%
2012	Nedgroup Medical Aid Scheme	59,26%	98,85%	84,39%	98,15%
2013	Nedgroup Medical Aid Scheme	58,72%	98,44%	84,37%	98,11%
2014	Nedgroup Medical Aid Scheme	58,30%	98,83%	81,79%	97,80%
2015	Nedgroup Medical Aid Scheme	62,22%	99,25%	85,47%	98,58%
2016	Nedgroup Medical Aid Scheme	61,27%	99,53%	82,51%	98,25%
2017	Nedgroup Medical Aid Scheme	63,93%	99,89%	83,83%	98,62%
2011	Netcare Medical Scheme	60,27%	99,83%	80,89%	95,25%
2012	Netcare Medical Scheme	66,38%	99,89%	89,23%	98,40%
2013	Netcare Medical Scheme	67,50%	99,98%	91,44%	98,63%
2014	Netcare Medical Scheme	64,48%	99,97%	86,16%	97,67%
2015	Netcare Medical Scheme	73,75%	97,22%	91,72%	98,12%
2016	Netcare Medical Scheme	74,54%	96,91%	93,42%	98,35%
2017	Netcare Medical Scheme	77,67%	95,49%	97,58%	98,71%
2011	Old Mutual Staff Medical Aid Fund	60,03%	98,72%	90,08%	98,69%

2012	Old Mutual Staff Medical Aid Fund	58,07%	98,66%	86,75%	98,16%
2013	Old Mutual Staff Medical Aid Fund	57,21%	98,27%	85,67%	97,93%
2014	Old Mutual Staff Medical Aid Fund	56,86%	98,21%	84,69%	97,76%
2015	Old Mutual Staff Medical Aid Fund	60,84%	99,25%	87,95%	98,54%
2016	Old Mutual Staff Medical Aid Fund	58,14%	99,50%	82,16%	97,58%
2017	Old Mutual Staff Medical Aid Fund	59,69%	99,46%	83,83%	98,24%
2011	PG Bison Medical Aid Society	48,41%	91,17%	83,93%	99,15%
2012	PG Bison Medical Aid Society	41,05%	86,37%	69,44%	94,07%
2013	PG Bison Medical Aid Society	43,34%	85,38%	77,53%	97,16%
2011	PG Group Medical Scheme	50,69%	96,34%	83,32%	98,47%
2012	PG Group Medical Scheme	46,18%	95,69%	74,31%	95,09%
2013	PG Group Medical Scheme	48,50%	95,51%	77,74%	97,26%
2014	PG Group Medical Scheme	47,33%	95,73%	73,65%	96,15%
2015	PG Group Medical Scheme	52,47%	95,89%	78,62%	98,44%
2016	PG Group Medical Scheme	53,59%	97,21%	78,21%	98,65%
2017	PG Group Medical Scheme	55,11%	97,36%	79,85%	99,06%
2011	Parmed Medical Aid Scheme	66,18%	99,98%	88,21%	98,21%
2012	Parmed Medical Aid Scheme	66,48%	99,93%	90,98%	98,57%
2013	Parmed Medical Aid Scheme	65,78%	99,74%	89,50%	98,31%
2014	Parmed Medical Aid Scheme	66,50%	99,33%	92,67%	98,77%
2015	Parmed Medical Aid Scheme	67,94%	99,51%	93,21%	98,67%
2016	Parmed Medical Aid Scheme	62,51%	99,52%	81,13%	94,58%
2017	Parmed Medical Aid Scheme	65,74%	98,07%	85,59%	96,81%
2011	Pick & Pay Medical Scheme	49,29%	98,98%	79,51%	96,98%
2012	Pick & Pay Medical Scheme	51,22%	98,86%	83,72%	98,10%
2013	Pick & Pay Medical Scheme	50,46%	98,69%	82,55%	97,80%
2014	Pick & Pay Medical Scheme	47,77%	98,62%	76,22%	95,59%
2015	Pick & Pay Medical Scheme	48,17%	99,12%	73,78%	95,26%
2016	Pick & Pay Medical Scheme	55,25%	98,82%	87,05%	99,00%
2017	Pick & Pay Medical Scheme	56,83%	98,60%	92,97%	99,17%
2011	Platinum Health	73,61%	100,00%	100,00%	98,92%
2012	Platinum Health	67,60%	99,86%	86,99%	96,26%
2013	Platinum Health	65,77%	100,00%	84,73%	95,19%
2014	Platinum Health	70,99%	99,99%	89,31%	98,02%
2015	Platinum Health	70,97%	99,90%	87,74%	98,24%
2016	Platinum Health	73,02%	99,97%	91,43%	98,69%
2017	Platinum Health	70,75%	99,84%	90,42%	98,53%
2011	Profmed	58,65%	94,15%	94,13%	98,86%
2012	Profmed	56,13%	94,31%	89,91%	98,27%
2013	Profmed	56,02%	93,64%	90,69%	98,25%
2014	Profmed	56,03%	93,19%	91,26%	98,28%

2015	Profmed	54,92%	94,61%	87,13%	97,75%
2016	Profmed	54,26%	94,38%	86,51%	97,35%
2017	Profmed	55,26%	94,67%	87,08%	97,89%
2011	Quantum Medical Aid Society	46,21%	99,66%	75,26%	97,02%
2012	Quantum Medical Aid Society	43,79%	99,50%	69,28%	94,45%
2013	Quantum Medical Aid Society	45,96%	99,33%	72,17%	97,15%
2014	Quantum Medical Aid Society	47,84%	99,49%	76,38%	98,01%
2015	Quantum Medical Aid Society	51,27%	99,68%	77,91%	98,65%
2016	Quantum Medical Aid Society	52,05%	99,66%	78,89%	98,80%
2017	Quantum Medical Aid Society	53,12%	99,62%	82,57%	98,98%
2011	Rand Water Medical Scheme	61,70%	99,69%	86,39%	96,61%
2012	Rand Water Medical Scheme	63,07%	99,91%	86,69%	97,22%
2013	Rand Water Medical Scheme	66,79%	99,99%	94,51%	98,75%
2014	Rand Water Medical Scheme	64,27%	99,89%	91,65%	98,25%
2015	Rand Water Medical Scheme	66,54%	99,95%	94,49%	98,27%
2016	Rand Water Medical Scheme	65,73%	99,98%	93,39%	97,97%
2017	Rand Water Medical Scheme	69,90%	100,00%	100,00%	98,78%
2011	Remedi Medical Aid Scheme	66,52%	98,58%	96,49%	99,05%
2012	Remedi Medical Aid Scheme	63,24%	98,26%	93,24%	98,62%
2013	Remedi Medical Aid Scheme	57,56%	98,64%	83,34%	95,66%
2014	Remedi Medical Aid Scheme	59,76%	98,75%	85,99%	97,34%
2015	Remedi Medical Aid Scheme	63,73%	97,72%	90,81%	98,34%
2016	Remedi Medical Aid Scheme	62,54%	97,72%	88,47%	97,85%
2017	Remedi Medical Aid Scheme	62,79%	97,65%	88,60%	97,90%
2011	Retail Medical Scheme	50,46%	99,63%	82,19%	97,01%
2012	Retail Medical Scheme	51,98%	99,34%	85,30%	98,01%
2013	Retail Medical Scheme	52,89%	97,70%	88,19%	98,44%
2014	Retail Medical Scheme	54,25%	96,01%	94,04%	98,72%
2015	Retail Medical Scheme	51,32%	98,70%	79,33%	96,46%
2016	Retail Medical Scheme	55,11%	98,53%	86,30%	98,50%
2017	Retail Medical Scheme	55,30%	98,38%	86,43%	98,58%
2011	Rhodes University Medical Scheme	61,76%	95,66%	98,80%	98,96%
2012	Rhodes University Medical Scheme	61,34%	96,38%	99,69%	98,94%
2013	Rhodes University Medical Scheme	56,35%	96,09%	89,98%	97,44%
2014	Rhodes University Medical Scheme	54,92%	96,05%	86,55%	96,32%
2015	Rhodes University Medical Scheme	59,65%	94,35%	94,02%	98,26%
2016	Rhodes University Medical Scheme	59,49%	94,95%	93,83%	98,22%
2017	Rhodes University Medical Scheme	55,76%	95,91%	85,43%	95,59%
2011	SABC Medical Aid Scheme	61,07%	99,63%	86,76%	98,11%
2012	SABC Medical Aid Scheme	61,90%	99,78%	87,27%	98,28%
2013	SABC Medical Aid Scheme	61,65%	99,89%	87,93%	98,31%

2014	SABC Medical Aid Scheme	64,09%	99,54%	91,63%	98,76%
2015	SABC Medical Aid Scheme	65,08%	99,10%	94,35%	98,74%
2016	SABC Medical Aid Scheme	61,36%	99,01%	88,40%	97,55%
2017	SABC Medical Aid Scheme	59,12%	98,93%	83,07%	94,95%
2011	SAMWUMed	63,01%	97,74%	93,55%	98,07%
2012	SAMWUMed	57,56%	98,47%	84,13%	94,62%
2013	SAMWUMed	60,79%	99,06%	84,36%	96,62%
2014	SAMWUMed	69,46%	98,60%	100,00%	99,17%
2015	SAMWUMed	68,49%	97,41%	100,00%	98,95%
2016	SAMWUMed	61,94%	97,22%	90,07%	97,00%
2017	SAMWUMed	62,86%	96,10%	93,99%	97,84%
2011	Sappi Medical Aid Scheme	60,69%	98,59%	83,48%	97,42%
2012	Sappi Medical Aid Scheme	64,65%	98,74%	87,03%	98,63%
2011	Sasolmed	65,48%	99,05%	88,52%	97,63%
2012	Sasolmed	65,09%	99,01%	87,10%	97,38%
2013	Sasolmed	66,53%	99,25%	89,20%	98,17%
2014	Sasolmed	67,16%	99,06%	91,82%	98,42%
2015	Sasolmed	72,86%	93,98%	96,47%	98,19%
2016	Sasolmed	74,30%	93,33%	99,42%	98,52%
2017	Sasolmed	74,55%	93,06%	99,73%	98,55%
2011	Sedmed	71,36%	92,70%	100,00%	99,08%
2012	Sedmed	59,17%	83,17%	91,58%	96,62%
2014	Sedmed	52,85%	90,89%	80,28%	95,47%
2015	Sedmed	55,75%	91,20%	82,65%	97,45%
2016	Sedmed	61,40%	85,34%	89,20%	98,17%
2017	Sedmed	63,70%	88,37%	89,14%	98,80%
2011	Siemens Medical Scheme	57,33%	97,91%	82,93%	
2014	Sisonke Health Medical Scheme	56,31%	99,30%	84,60%	98,15%
2015	Sisonke Health Medical Scheme	59,84%	99,64%	84,81%	98,38%
2016	Sisonke Health Medical Scheme	58,52%	99,66%	82,21%	97,86%
2017	Sisonke Health Medical Scheme	59,32%	99,72%	83,44%	98,33%
2011	South African Breweries Medical Aid Scheme (SABMAS)	56,52%	98,43%	85,67%	98,30%
2012	South African Breweries Medical Aid Scheme (SABMAS)	56,23%	98,47%	83,71%	98,12%
2013	South African Breweries Medical Aid Scheme (SABMAS)	57,18%	98,46%	85,28%	98,42%
2014	South African Breweries Medical Aid Scheme (SABMAS)	56,63%	98,36%	85,58%	98,30%
2015	South African Breweries Medical Aid Scheme (SABMAS)	57,22%	98,40%	82,24%	98,11%
2016	South African Breweries Medical Aid Scheme (SABMAS)	57,86%	98,65%	82,38%	98,27%

2017	South African Breweries Medical Aid Scheme (SABMAS)	56,96%	99,37%	78,66%	97,75%
2011	South African Police Service Medical Scheme (POLMED)	71,94%	96,37%	100,00%	98,98%
2012	South African Police Service Medical Scheme (POLMED)	67,64%	96,43%	93,29%	98,15%
2013	South African Police Service Medical Scheme (POLMED)	67,16%	96,94%	91,23%	97,77%
2014	South African Police Service Medical Scheme (POLMED)	66,50%	96,78%	90,41%	97,38%
2015	South African Police Service Medical Scheme (POLMED)	72,46%	92,57%	98,67%	98,20%
2016	South African Police Service Medical Scheme (POLMED)	69,97%	94,14%	93,99%	97,59%
2017	South African Police Service Medical Scheme (POLMED)	76,39%	90,61%	100,00%	98,31%
2011	TFG Medical Scheme	62,87%	97,53%	90,41%	97,93%
2012	TFG Medical Scheme	62,34%	98,45%	92,83%	98,38%
2013	TFG Medical Scheme	61,10%	98,70%	90,66%	97,91%
2014	TFG Medical Scheme	66,64%	100,00%	100,00%	98,97%
2015	TFG Medical Scheme	65,77%	99,64%	98,18%	98,50%
2016	TFG Medical Scheme	63,76%	99,65%	95,01%	97,83%
2017	TFG Medical Scheme	60,76%	99,68%	89,77%	95,83%
2011	Tiger Brands Medical Scheme	64,26%	99,64%	86,40%	97,82%
2012	Tiger Brands Medical Scheme	62,77%	99,63%	83,60%	97,00%
2013	Tiger Brands Medical Scheme	65,06%	99,81%	88,29%	98,23%
2014	Tiger Brands Medical Scheme	63,46%	99,78%	84,71%	97,42%
2015	Tiger Brands Medical Scheme	71,53%	99,21%	89,99%	98,42%
2016	Tiger Brands Medical Scheme	73,19%	99,38%	86,84%	98,22%
2017	Tiger Brands Medical Scheme	76,27%	99,40%	92,93%	98,97%
2011	Transmed Medical Fund	76,30%	99,86%	96,07%	99,05%
2012	Transmed Medical Fund	71,01%	98,84%	99,33%	99,02%
2013	Transmed Medical Fund	64,63%	98,73%	90,92%	97,46%
2014	Transmed Medical Fund	63,14%	98,59%	89,57%	96,55%
2015	Transmed Medical Fund	66,45%	99,95%	82,96%	94,88%
2016	Transmed Medical Fund	73,06%	99,18%	97,06%	98,78%
2017	Transmed Medical Fund	63,86%	99,94%	84,96%	94,34%
2011	Tsogo Sun Group Medical Scheme	56,53%	99,53%	93,29%	98,71%
2012	Tsogo Sun Group Medical Scheme	56,91%	99,92%	91,63%	98,88%
2013	Tsogo Sun Group Medical Scheme	54,20%	100,00%	86,52%	98,21%
2014	Tsogo Sun Group Medical Scheme	51,67%	100,00%	81,60%	96,88%
2015	Tsogo Sun Group Medical Scheme	54,34%	99,96%	82,55%	97,62%
2016	Tsogo Sun Group Medical Scheme	53,55%	99,76%	81,02%	97,23%
2017	Tsogo Sun Group Medical Scheme	55,66%	99,57%	86,32%	98,31%

2011	Umvuzo Health Medical Scheme	68,54%	100,00%	100,00%	98,79%
2012	Umvuzo Health Medical Scheme	67,79%	99,47%	98,71%	98,67%
2013	Umvuzo Health Medical Scheme	66,68%	99,59%	100,00%	98,82%
2014	Umvuzo Health Medical Scheme	63,60%	96,75%	97,24%	98,18%
2015	Umvuzo Health Medical Scheme	63,59%	96,43%	96,44%	97,75%
2016	Umvuzo Health Medical Scheme	61,30%	96,53%	92,87%	96,16%
2017	Umvuzo Health Medical Scheme	61,07%	96,61%	91,63%	95,91%
2011	University of KwaZulu-Natal Medical Scheme	52,05%	99,75%	80,54%	97,17%
2012	University of KwaZulu-Natal Medical Scheme	50,51%	99,72%	76,47%	95,15%
2013	University of KwaZulu-Natal Medical Scheme	57,17%	99,98%	87,96%	98,81%
2014	University of KwaZulu-Natal Medical Scheme	55,75%	99,93%	87,68%	98,51%
2015	University of KwaZulu-Natal Medical Scheme	54,87%	99,75%	80,82%	97,79%
2016	University of KwaZulu-Natal Medical Scheme	56,90%	99,94%	85,97%	98,61%
2017	University of KwaZulu-Natal Medical Scheme	56,53%	99,95%	84,44%	98,51%
2011	University of the Witwatersrand Staff Medical Aid Scheme	60,79%	99,07%	86,38%	98,60%
2012	University of the Witwatersrand Staff Medical Aid Scheme	61,20%	99,36%	87,16%	98,65%
2013	University of the Witwatersrand Staff Medical Aid Scheme	62,29%	99,76%	88,92%	98,78%
2014	University of the Witwatersrand Staff Medical Aid Scheme	59,55%	99,78%	86,50%	98,17%
2015	University of the Witwatersrand Staff Medical Aid Scheme	59,49%	99,93%	84,58%	97,60%
2016	University of the Witwatersrand Staff Medical Aid Scheme	61,30%	99,85%	86,19%	97,59%
2017	University of the Witwatersrand Staff Medical Aid Scheme	58,19%	99,95%	82,67%	96,14%
2011	Witbank Coalfields Medical Aid Scheme	50,73%	98,90%	75,77%	96,02%
2012	Witbank Coalfields Medical Aid Scheme	53,59%	98,31%	81,77%	98,14%
2013	Witbank Coalfields Medical Aid Scheme	57,83%	98,18%	89,51%	99,08%
2014	Witbank Coalfields Medical Aid Scheme	54,92%	98,28%	84,96%	98,67%
2015	Witbank Coalfields Medical Aid Scheme	54,56%	97,93%	84,54%	98,50%
2016	Witbank Coalfields Medical Aid Scheme	51,69%	98,21%	80,08%	97,45%
2017	Witbank Coalfields Medical Aid Scheme	49,88%	98,62%	77,87%	95,87%

2011	Wooltru Healthcare Fund	55,88%	98,95%	84,28%	98,17%
2012	Wooltru Healthcare Fund	55,93%	98,92%	83,79%	98,08%
2013	Wooltru Healthcare Fund	54,61%	98,80%	81,57%	97,27%
2014	Wooltru Healthcare Fund	52,49%	99,40%	77,99%	96,47%
2015	Wooltru Healthcare Fund	58,24%	99,70%	82,31%	98,42%
2016	Wooltru Healthcare Fund	58,99%	99,85%	82,29%	98,61%
2017	Wooltru Healthcare Fund	59,51%	99,65%	84,44%	98,81%
2011	Xstrata Medical Aid Scheme	68,59%	99,41%	93,07%	97,99%
2012	Xstrata Medical Aid Scheme	71,26%	99,93%	98,86%	98,70%
2013	Xstrata Medical Aid Scheme	66,55%	99,75%	94,11%	97,53%