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Essays on Competition and Technical Efficiencies in South Africa's Medical Scheme Industry

by

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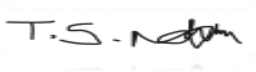
DECLARATION

I hereby declare that:

This PhD thesis titled, "***Essays on Competition and Technical Efficiencies in South Africa's Medical Scheme Industry***", submitted to the University of the Witwatersrand, is my own original work. It has not been submitted before for any other degree or examination at any other university. All sources of material have been fully acknowledged by means of a comprehensive bibliography.



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ABSTRACT

According to existing economic literature there are idiosyncratic elements within healthcare markets that prevent normal market forces, such as competition, to shape the healthcare industry in the same manner as other industries. The reasons for this are regulatory barries to entry, fixed costs, the role of insurance, information frictions and asymmetries. More so, the healthcare sector is comprised of various interconnected sub-sectors that all have their own institutions and nuances. In the South African Context, the Health Market Inquiry, which was conducted by the Competition Commission of South Africa, submit that the South African healthcare sector comprises a complex set of interrelated stakeholders that interact in markets that are not transparent and not quite understood. Given this, the primary objective of conducting this doctoral study was to understand the competition and efficiency dynamics within South African healthcare insurer markets through a collection of related empirical papers on competition and efficiency. Annual firm level data on South African medical schemes was used to study various economic theories using panel data econometric techniques.

The results suggest that open medical schemes tended to be more efficient than restricted medical schemes in terms of technical, scale and pure technical efficiency over the sample period. More so, the empirical results reveal that there is room for improvement in terms of efficiencies for both open and restricted medical schemes. This is specifically true for restricted medical schemes. In addition, the empirical results seem to support the view that firms with market power, operating in highly concentrated markets, will limit competition and will operate under a reduced efficiency level. Further, the empirical results revealed that both the structure-conduct-performance and efficient structure hypotheses can be rejected in relation to South African medical schemes. The empirical evidence further suggests support for differing hypotheses for open and restricted medical schemes when traditional structural approaches to assessing competition are employed. Moreover, the empirical evidence suggests that the market for restricted medical schemes is highly concentrated and operating under a reduced efficiency level which produces less than desirable outcomes. These findings are supported when non-structural approaches to competition are employed as the empirical results from the non-structural approaches to assessing competition suggest that both open and restricted medical schemes are operating under conditions of monopolistic competition. Furthermore, once efficiency is incorporated in the model, the empirical findings still reveal conditions of monopolistic competition.

DEDICATION

I dedicate this thesis to God, my parents, wife, grandmother, daughter, family and friends.

ACKNOWLEDGEMENTS

First, all thanks goes to God for providing me the strength and patience to be able to complete my Doctoral Degree. Special thanks is due to my supervisor, Prof Liberty Mncube, your guidance is much appreciated. To my loving parents, Gugu and Zimele, this would not have been possible without the both of you. To the love of my life, my wife Nozibusiso Ndlovu, your continuous support and encouragement are highly appreciated. To my daughter Nokuphila, your father loves you. To my grandmother Margaret, you continue to be my inspiration. To all my siblings, I love you. Special thanks also goes to my family and friends.

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1 Chapter One: Introduction

1.1 Introduction to Study

Arrow (1963) indicates that there are idiosyncratic elements within healthcare markets that prevent normal market forces, such as competition, to shape the healthcare industry in the same manner as other industries.[1] Cutler (2010), Skinner (2011), Chan (2016) and Chandra et al. (2016) suggest that the reasons for this are: (i) regulatory barriers to entry; (ii) high fixed costs; (iii) the role of insurance; and (iv) information frictions and asymmetries. Moreover, Eliason (2018) submits that the healthcare sector is comprised of various interconnected sub-sectors that all have their own institutions and nuances. In the South African Context, the Health Market Inquiry (2019) (HMI), which was conducted by the Competition Commission of South Africa, submits that the South African private healthcare sector comprises a complex set of interrelated stakeholders that interact in markets that are not transparent and not quite understood.[2]

Futher, the HMI finds that the South African private healthcare market is characterised by "*high rising costs of healthcare and medical scheme cover, highly concentrated funders and facilities markets, disempowered and uninformed consumers, a general absence of value-based purchasing, ineffective constraints on rising volumes of care, practitioners that are subject to little regulation and failures of accountability at many levels*" (HMI, 2018, p.6). In addition, the HMI submits that the South African private healthcare sector has consistently rising medical scheme premiums which are accompanied by increasing out-of-pocket payments for the insured, almost stagnant growth in covered lives and a progressively decreasing range and depth of services covered by medical scheme options. Importantly, the HMI submits that there is unaffordability of private health insurance which is compounded by variable access to private healthcare services based on geographic locations and the availability of health facilities and specialists who are concentrated in urban areas. Furthermore, the HMI has concluded that the

[1] See Appendix A for the theoretical underpinnings of economic competition.

[2] The South African healthcare sector comprises of both the public healthcare sector and the private healthcare sector. Most of the population are served by the public health sector as a result of lacking medical insurance for the most part. The private healthcare sector mostly serves consumers who are covered by medical schemes, health insurance products and those who pay out of pocket. According to the Health Market Inquiry (2018), the public health sector does not offer a significant competitive constraint to the private healthcare sector.

South African private healthcare sector is "*neither efficient nor competitive*" (HMI, 2019, p.30). This lack of competition has direct implications regarding the efficiency of the South African private healthcare sector as microeconomic theory, in most instances, suggests that efficiency will be postively correlated with the level of competition (Chua et al., 2011).

The lack of effective competition in the South African private healthcare sector may imply an inefficient industry in terms of productive, technical and allocative efficiencies.[3] Exisiting literature suggests that markets with high levels of competition will result in firms being more productive or efficient (Chang and Gurbaxani, 2013). This is a result of the efficiency gains that occur because of competitive pressures from rival firms which force the reduction of management slack as competitive pressures from rivals force firms to adopt best efficient practices in order to compete and survive (Chang and Gurbaxani, 2013). As a matter of economics, the term efficiency relates to both technical and allocative elements. The most common reference to efficiency is technical efficiency which relates to the reduction in wastages in the production process, by means of output maximation with a given set of inputs or input minimisation with a given set of outputs (Greene, 2008). The allocative element of efficiency refers to the ability to combine both inputs and outputs in optimal proportions under prevailing prices. This study thus sought to understand the competition and technical efficiency dynamics within the South African private healthcare sector and specifically the South African private medical scheme sector.

1.2 Background to the Study

The Competition Commission of South Africa (the Commission) undertook to conduct the HMI based on the following rationale "*The Commission rationale for the HMI was that it believed that there are features of the private healthcare sector that prevent, distort or restrict competition and that the conduct of this inquiry will assist the Commission in achieving the purposes of the Competition Act 89 of 1998, as amended (the Act)*" (HMI, 2018, p.65). The HMI identified six theories of harm to pursue. These are listed as follows: (i) Market power and distortions in healthcare financing; (ii) Market power and distortions in relation to healthcare facilities; (iii) Market power and distortions in relation to healthcare practitioners; (iv) Barriers to entry, expansion and innovation; (v) Imperfect information; and (vi) Regulatory

[3] See Appendix A for the theoretical underpinnings of economic efficiency.

framework. This study investigated the first theory of harm, that being, market power and distortions in healthcare financing. This was done by assessing the competition and efficiency dynamics of South African medical scheme markets.

1.3 Problem Statement

The work of Arrow (1963), Cutler (2010), Skinner (2011) and Chandra et al. (2016) revealed that there are certain elements within healthcare markets which prevent markets forces, such as competition, to take form in the healthcare sector. In its conclusions, the HMI reveals that the South African private healthcare sector is neither competitive nor efficient. This study then aimed to assess the dynamics within South Africa's healthcare insurance market by assessing its competition and efficiency dynamics.

This is relevant as the South African private healthcare sector specifically has experienced sustained increases in prices and expenditure which are believed to be above inflation (HMI, 2018). The impact of this is that only a minority of South Africans can truly afford to access private healthcare (HMI, 2018) This potentially highlights issues regarding the competition and efficiency dynamics of South Africa's private healthcare sector as there could be elements that undermine both competition and efficiency dynamics. The HMI broadly assessed the competition dynamics within the overall South African private healthcare sector from a legal and regulatory framework. This study narrowly assesses the South African private healthcare insurance market from an academic perspective which will assist in either supporting the conclusions found in the HMI or arrive at differing views.

1.4 Research Questions

This study aimed to answer the following research questions:

i. Are South African medical schemes efficient?
ii. Can South African medical schemes be characterised to exhibit efficiencies, returns to scale and productivities?
iii. What is the market structure within South African medical scheme markets?
iv. What is the relationship between competition and efficiency within South African medical scheme markets?

1.5 Objectives of the Study

The main objective of this study was to assess the competition and efficiency dynamics within healthcare markets, and specifically, the study sought to do the following:

- Estimate the efficiency scores for South African private medical schemes;
- Examine the efficiency, returns to scale and productivity of South African private medical schemes;
- Understand the existing competition dynamics of the South African private medical scheme industry;
- Understand the relationship between competition and efficiency with the South African private medical scheme industry.

The objectives have been addressed in separate essays, which form empirical chapters of this thesis.

1.6 Significance of the Study

The study has four key contributions. First, it has estimated the efficiency frontiers of South African medical schemes. Second, the study assessed the efficiency, returns to scale and productivity of South African medical schemes. Third, the study assessed the market structure, efficiency and performance of the South African healthcare private medical scheme industry. Fourth, the study assessed the nature of competition of South African private medical scheme industry.

Overall, the study thus offers insights into the competition dynamics within the South African private medical scheme industry. Currently, there is limited literature on the competition dynamics of South African insurer healthcare markets and thus the study's contribution may prove to be substantial.

This study will benefit policymakers regarding the overall performance of the South African healthcare insurance market by determining the level of both competition and efficiencies. This will lead to policies being formulated to improve the overall private healthcare insurance market.

1.7 Organisation of the Thesis

This thesis is structured into seven chapters, with four of these being empirical papers. Chapter One is the introduction and background of the study and presents the problem statement, research questions, objectives and the significance of the study. Chapter Two provides an overview of South Africa's healthcare insurer industry. The first empirical paper is found in Chapter Three and examines whether South African medical schemes are efficient by employing both data envelopment analysis and stochastic frontier analysis approaches in order to estimate efficiency scores for the period 2011 to 2017.[4] Chapter Four comprises a comprehensive assessment of efficiency, productivity and returns to scale economies in South Africa's private medical scheme industry for the period 2011 to 2017. Chapter Five assesses the relationship between market structure, conduct and performance in the South African private medical scheme industry for the period 2011 to 2017. Further, Chapter Six assesses the competition dynamics within the South African medical scheme industry using the New Empirical Industrial Organization paradigm. Chapter Seven draws conclusions from the empirical findings and provides a discussion on policy recommendations. Furthermore, the theoretical framework which this study relied on is in Appendix A.

[4] Due to data availability, the sample period is limited between 2011 to 2017.

2 Chapter Two: Overview of South Africa's Medical Scheme Industry

2.1 Industry Overview

The primary function of medical schemes is the provision of healthcare financing in the private healthcare sector. Indeed, medical scheme members contribute monthly in the form of premiums to their respective medical schemes, which are then tasked with the responsibility of financing their members' various healthcare expenses as part of their benefit packages. Similarly to short-term insurers, medical schemes employ the principle of shared risk in order to meet their members' healthcare claims. To understand how this is achieved, consider that over a given year, the vast majority of members will tend to only make minor claims, if any, which then allows a significant reserve of funds to meet the major claims of the relatively small minority of those who make such claims.

Medical schemes in South Africa play a crucial role as it is believed that the vast majority of the population in South Africa, which receives private care, are unable to afford it without the help of an insurer. Medical schemes are non-profit organisations which are governed by a board of trustees. Given this, medical schemes do not have shareholders or pay dividends and therefore a medical scheme's income is derived from member contributions and investment returns. Indeed, in the South African context, medical schemes exist for their members whereby all funds are pooled and safeguarded for the purpose of paying claims. Further, according to the HMI, medical schemes can be considered as quasi profit-maximising firms (HMI, 2018, p. 81). This is a result of the fact that for-profit administrators offer administration services to medical schemes. In addition, the HMI concludes that there is no clear separation of commercial interests between medical schemes and their for-profit administrators (HMI, 2018). This, according to the HMI, suggests that medical schemes are indeed quasi profit-maximising firms as their growth is driven by for-profit administrators (HMI, 2018, p. 78).

The private medical scheme industry consists of two types of medical schemes, that being open and restricted medical schemes. Everyone is allowed to join open medical schemes whereas memberships in restricted medical schemes is strictly limited to a selected group of individuals

such as those of a particular industry or organisation, or members of a certain professional association union. Open and restricted medical schemes are believed to be competing in distinct separate markets (HMI, 2018, p. 81). Further, Figure 2.1 reflects the percentage of the South African population which belonged to private medical schemes for the period 2011 to 2017. The percentage of South Africa's population who are members of medical schemes has declined over the relevant period from 16.4% in 2011 to 15.6% in 2017. Figure 2.1 below reflects this downward trend. This potentially points to the socio-economic conditions of South Africa, as the majority of the population are unable to access private healthcare (HMI, 2018).

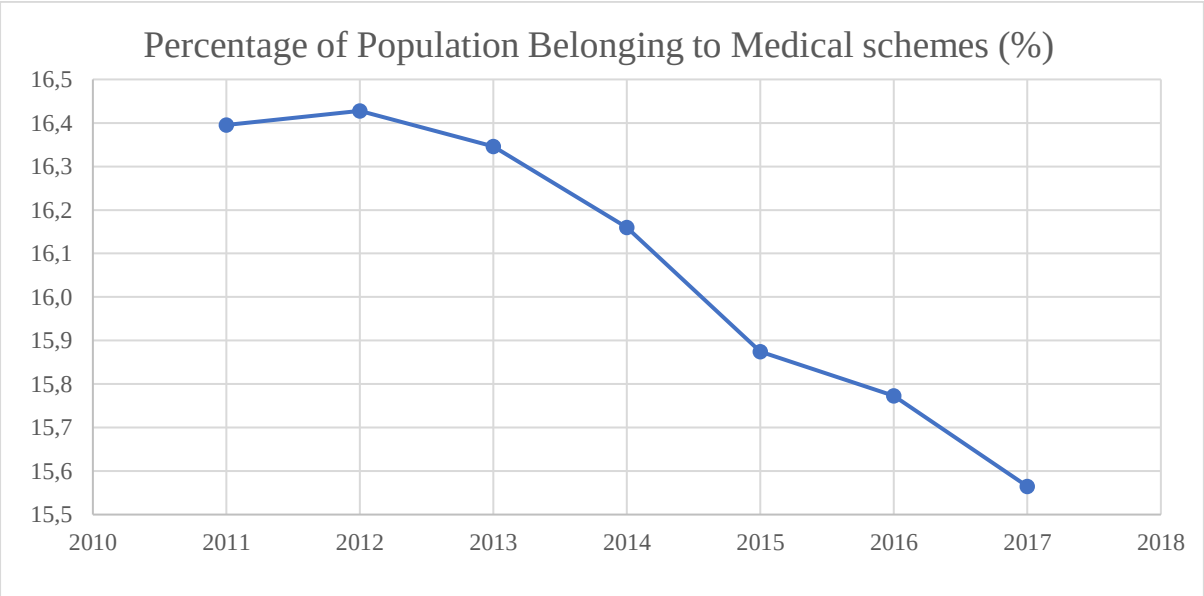

Figure 2.1: South African population belonging to a medical scheme

Source: Council of Medical Schemes and Stats SA

Moreover, Figures 2.2 and 2.3 and Table 2.1 reveal that open medical schemes have higher beneficiaries than restricted medical schemes over the relevant period. Indeed, on average, open medical schemes hold 56% of total beneficiaries whereas restricted medical schemes hold 44% of total beneficiaries. This could be explained by the fact that open medical schemes are open to everyone whereas restricted medical schemes are limited to designated groups.

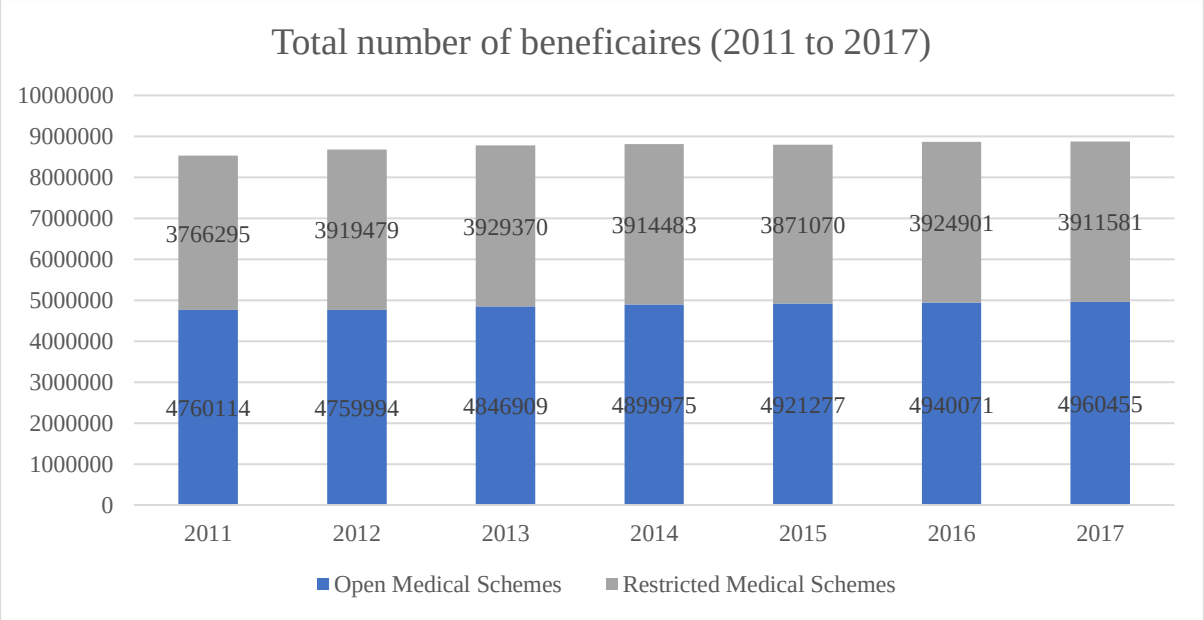

Figure 2.2: Total number of medical scheme beneficiaries

Source: Council of Medical Schemes

Table 2.1: Percentage of beneficiaries in open and restricted medical schemes

Year	Open Medical Scheme (%)	Restricted Medical Scheme (%)
2011	56	44
2012	55	45
2013	55	45
2014	56	44
2015	56	44
2016	56	44
2017	56	44
Average	56	44

Source: Council of Medical Schemes

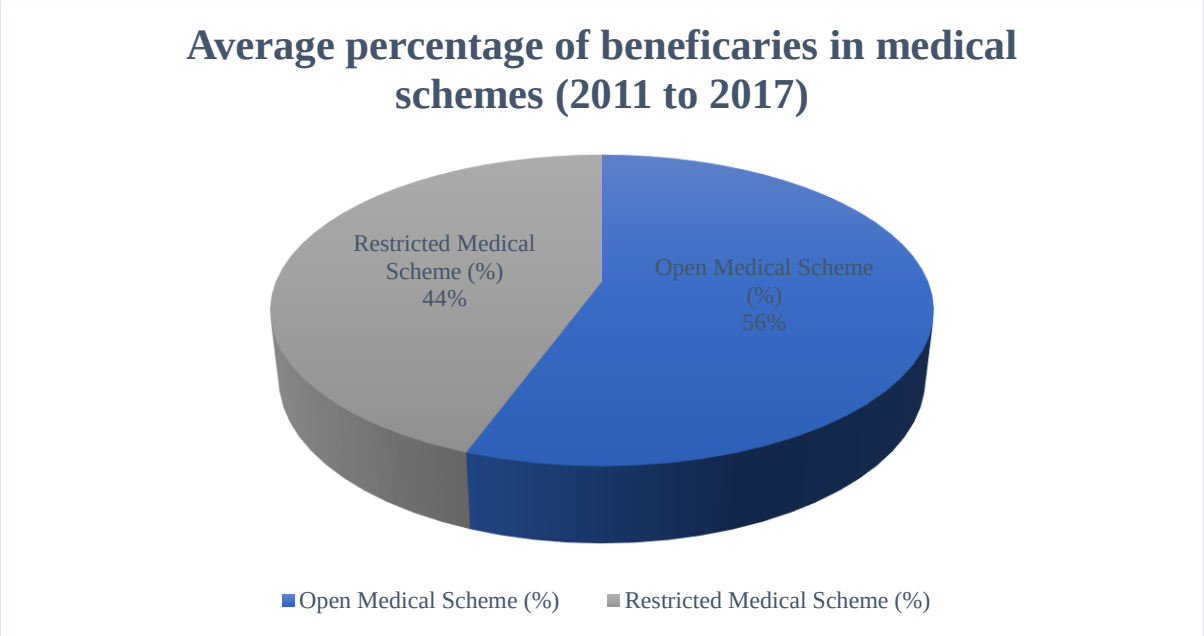

Figure 2.3: Average percentage of beneficiaries in open and restricted medical schemes

Source: Council of Medical Schemes

Further, it appears that there has been limited growth in terms of beneficiaries in regard to both open and restricted medical schemes. According to Figure 2.4 below, open medical schemes on average have had a growth rate of 0.69%.

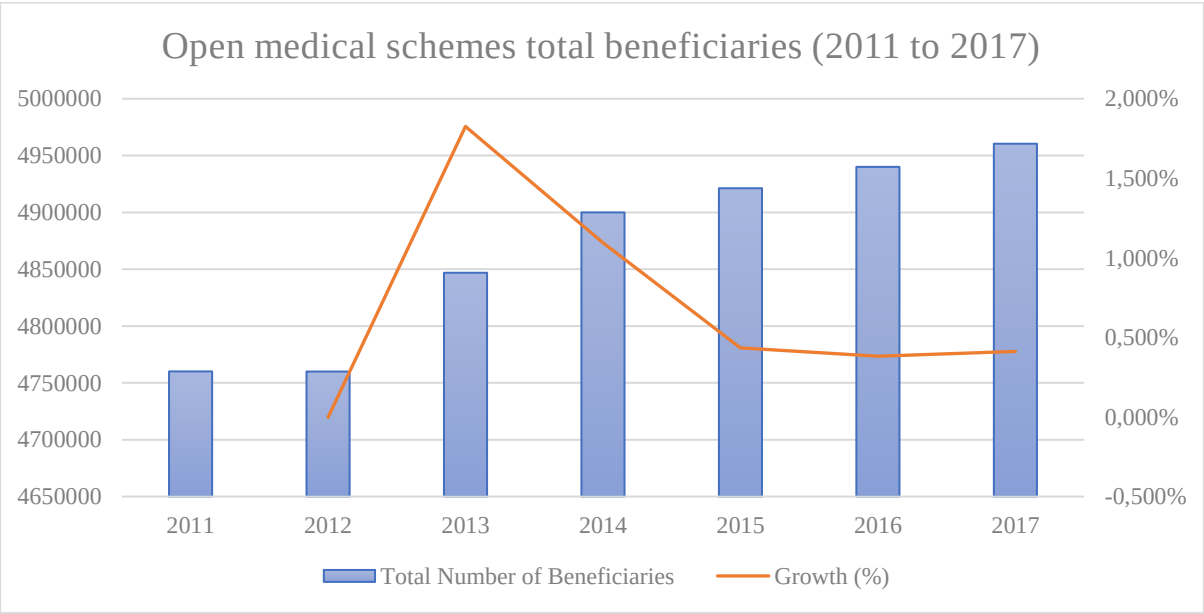

Figure 2.4 Total number of open medical scheme beneficiaries

Source: Council of Medical Schemes

Restricted medical schemes have been able to achieve similar growth rates. Figure 2.5 below reveal that restricted medical schemes had on average a growth rate of 0.65% over the relevant period.

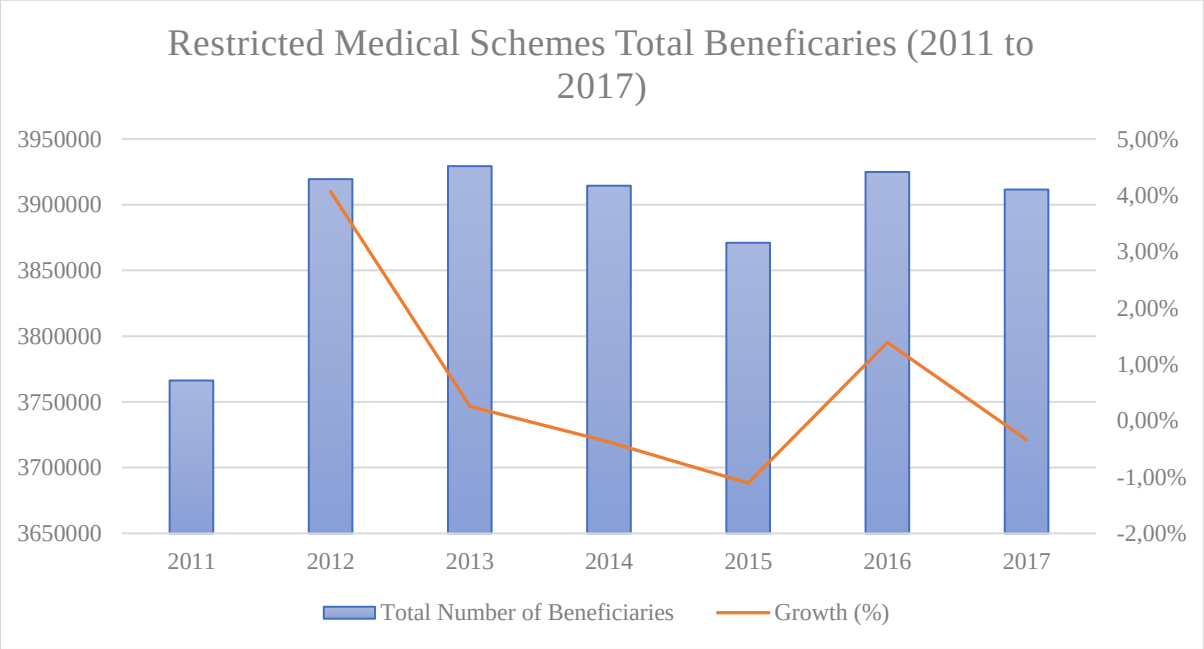

Figure 2.5: Total number of restricted medical scheme beneficiaries

Source: Council of Medical Schemes

Tables 2.2 and 2.3 below display the average monthly gross contributions paid for both open and restricted medical schemes.[5] Interestingly, the monthly contributions paid by members in restricted medical schemes are higher than the monthly contributions paid by members in open medical schemes. On average, scheme members who belong to restricted medical schemes paid monthly contributions of R1310,09 whereas those in open medical schemes paid average monthly contributions of R1292,07. More so, open medical schemes imposed higher increases in terms of average monthly contributions. On average, monthly contributions increased by 9% for open medical schemes whereas average monthly average contributions increased by 8% for restricted medical schemes over the relevant period.

[5] Note that monthly contributions depend on a number of factors, that being, the number of dependents and the medical scheme package selected. However, as a result of data availability, average monthly contributions were used for comparisons.

Table 2.2 Open medical scheme average monthly gross contribution income

Year	Average contribution income (ZAR)	Growth (%)
2011	941,19	
2012	1174,98	25%
2013	1136,65	-3%
2014	1266,02	11%
2015	1416,13	12%
2016	1526,69	8%
2017	1582,86	4%
Average	1292,07	9%

Source: Council of Medical Schemes

Table 2.3 Restricted medical scheme average monthly gross contribution income

Year	Average contribution income (ZAR)	Growth (%)
2011	1051,31	
2012	1101,64	5%
2013	1255,07	14%
2014	1228,15	-2%
2015	1368,70	11%
2016	1519,89	11%
2017	1645,88	8%
Average	1310,09	8%

Source: Council of Medical Schemes

2.2 Historical Overview

The first medical scheme in South Africa, the De Beers Consolidated Mines Ltd, is documented to have been established in 1888 (Department of Health (DoH), 2002, p.18). Twenty-one years later in 1909, seven medical schemes were in existence in South Africa (DoH, 2002). At the start of the Second World War in 1940, South Africa had 48 established medical schemes. After World War II, the number of medical schemes increased which led to the creation of the Advisory Council for Medical Fund Societies in 1950 (DoH, 2002). The primary goal of this society was to act as representatives for all affiliated medical schemes in negotiation with the then Medical Association of South Africa.

The behaviour of medical schemes at the time was regulated by the Friendly Societies Act, No. 25 of 1956 (*Friendly Societies Act [FSA]*), which required all medical schemes to register prior to operating (DoH, 2002). Further, by the time 1960 came along, the number of medical schemes had reached 169 which covered a total of 368 890 members and a total of 588 997

dependants (DoH, 2002). These medical schemes were tailored to serve the needs of the then white middle class population, specifically those located in urban areas (DoH, 2002). The year 1967 brought about the first medical schemes act referred to as the Medical Schemes Act, No. 72 of 1967 (*The 1967 Act*) (DoH, 2002). The following were the primary objectives of the 1967 Act:

- "*To invent an insurance type of scheme to distribute the costs of medical expenses over a period of years.*
- *To retain the costs of medical expenses at a low level.*
- *To co-ordinate and control the functioning of medical benefit and medical aid funds and to develop and propagate these schemes*."

The 1967 Act led to the creation of the Central Council for Medical Schemes which was tasked with the following tasks:

- "*Control, promote, encourage and co-ordinate the establishment, development and functioning of medical schemes.*
- *Investigate complaints and settle disputes in relation to the affairs of registered medical schemes.*
- *Perform such other functions as may be prescribed*."

The number of medical schemes grew to a total of 289 by 1980. These medical schemes covered 4 329 256 beneficiaries which translated to about 17.3% of the population at the time (HMI, 2018). More so, during the 1980s, it was identified that they were too many medical schemes but with inadequate spread of risk (DoH, 2002). This led to "Free-Market" reforms which took place between 1984 to 1988 and which introduced amendments to the Medical Schemes Act. Indeed, the Amendment Act, No. 59 of 1984 pursued the following key objectives:

- "*To have a health service which the ordinary person will be able to afford.*
- *To achieve optimal security of cover by medical schemes to save their members from a financial catastrophe in times of serious or lengthy illness.*
- *To create and maintain, in the interest of medical care, the best possible doctor/patient relationship.*
- *To prevent the socialisation of health services.*"

Further, 1980 to 1990 saw the decline of medical schemes to 250. This was however accompanied by an increase in the number of beneficiaries to 6 187 974 which translated to 17.1% of the then population (HMI, 2018). The current Medical Schemes Act came into effect in February 1999.

Furthermore, from 1980 onwards, the history of medical schemes can be viewed as four distinct periods. The first period, which was between 1980 to 1989 is characterized by regulation being geared to support the needs of employer and industry-based medical schemes. During this period, there were no open medical schemes competing with employer and industry-based medical schemes. In addition, medical schemes were mandated to comprehensively cover minimum benefits. Moreover, medical schemes could only differentiate their contributions based on income and the number of beneficiaries (HMI, 2018).

The second period which took place between 1989 to 1993 permitted medical schemes to differentiate their premiums on the basis of health status, age, gender, claim patterns, geography and income. This allowed the medical scheme environment to be similar to the actuarial insurance environment through removing their social protection function (HMI, 2018).

The third period which was between 1994 to 2000 removed the requirement of medical schemes needing to offer minimum benefits. This allowed the entry and growth of multi-employer and open medical schemes. Medical schemes were therefore permitted to discriminate against poor health risks through adjusting the contribution structure, the application of wide exclusions and changing the benefits provided (HMI, 2018). This led to a substantial movement of beneficiaries from restricted medical schemes to open medical schemes. During this period, open medical schemes grew in relation to restricted medical schemes whilst the total medical scheme population remained the same implying that open medical schemes gained additional market share at the expense of restricted medical schemes (HMI, 2018).

The fourth period which was from 2000 onwards removed medical scheme discrimination on the basis of health status and implemented a system of mandatory minimum benefits for medical schemes to offer (HMI, 2018).

2.3 Current Supervision and Regulation

According to section 27 of The Constitution of the Republic of South Africa (RSA), 1996 (The Constitution), the state is obliged to develop legislation in order to realise the right of access to healthcare. Indeed, The Medical Schemes Act 131 of 1998 (The Medical Schemes Act), is one such piece of legislation that aims to facilitate the access to healthcare. It achieves this by adopting a framework of non-discriminating access to medical schemes.

Further, private medical schemes are regulated by the Council for Medical Schemes (CMS) which is a statutory body established in accordance of the Medical Schemes Act. Indeed, the Medical Schemes Act sets certain restrictions in the medical schemes environment by restricting the business of medical schemes to entities which are registered to the CMS and by requiring these entities to comply with the provisions found within the Medical Schemes Act. According to section 7 of the Medical Schemes Act, the CMS is mandated to perform the following tasks:

- "*Protect the interests of beneficiaries (of medical schemes) at all times.*
- *Control and co-ordinate the functioning of medical schemes in a manner that is complementary to national health policy.*
- *Make recommendations to the Minister of Health on criteria for the measurement of the quality and outcomes of relevant health services provided for by medical schemes and such other services as the Council may from time to time determine.*
- *Investigate complaints and settle disputes in relation to the affairs of medial schemes as provided for in this Act.*
- *Collect and disseminate information about private healthcare.*
- *Make rules, not inconsistent with the provisions of this Act, for the purpose of the performance of its functions and the exercise of its powers.*
- *Advise the Minister of Health on any matter concerning medical schemes.*
- *Perform any other functions conferred on Council by the Minister of Health or by this Act.*"

More so, section 5 of the Medical Schemes Act relates the assessment of competition within the private healthcare sector and the rules of medical schemes. Specifically, section 29 (n) relates to how medical schemes should set their contributions and states:

"*The terms and conditions applicable to the admission of a person as a member and his or her dependents, which terms and conditions shall provide for the determination of contributions on the basis of income or the number of dependents or both the income and the number of dependants, and shall not provide for any other grounds, including age, sex, past or present state of health, of the applicant or one or more of the applicant's dependants, the frequency of rendering of relevant health services to an applicant or one or more of the applicant's dependants other than for the provisions as prescribed*."

2.4 Market Structure

The private medical scheme market has witnessed significant consolidation since 2000 (HMI, 2019). Table 2.4 and Figure 2.6 below show a decline in the total number of medical schemes in South Africa, from 97 (consisting of 26 open medical schemes and 71 restricted medical schemes) in 2011 to 80 (consisting of 21 open medical schemes and 59 restricted medical schemes) in 2017. This consolidation which is accompanied with the rise in average monthly contributions for both open and restricted medical schemes (as seen in table 2.5 and 2.6) has led to potential inferences of increased inefficiencies that led to higher costs.

Table 2.4 Total number of medical schemes (2011-2017)

Year	Open medical schemes	Restricted medical schemes
2011	26	71
2012	25	68
2013	24	63
2014	23	60
2015	23	60
2016	23	60
2017	21	59

Source: Council of Medical Schemes

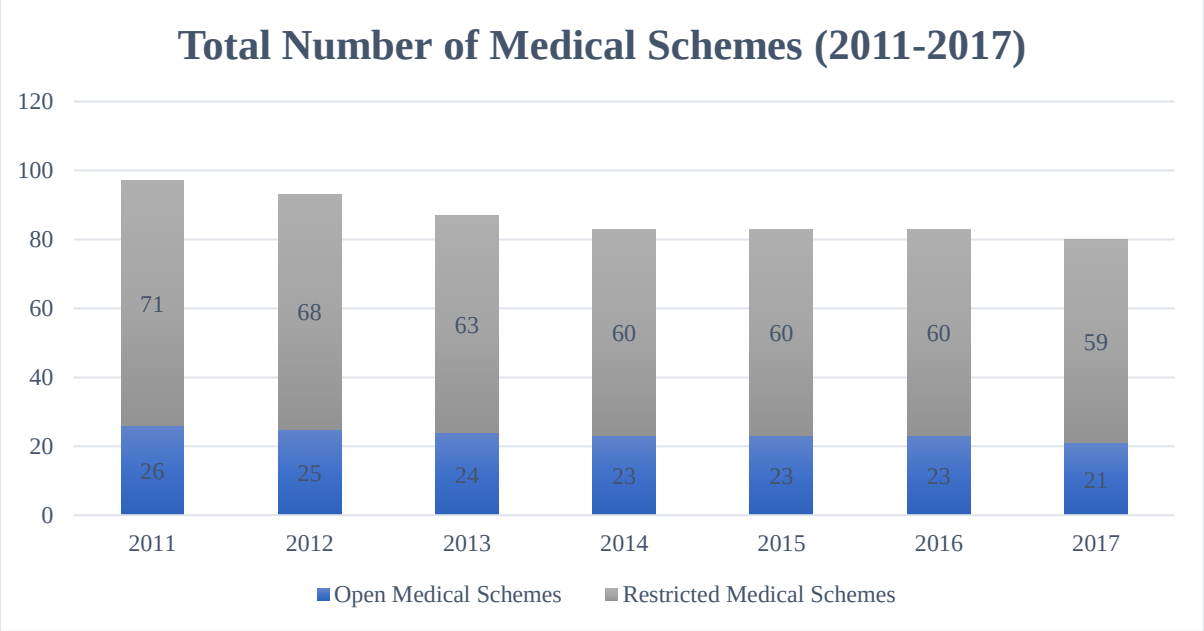

Figure 2.6 Total number of medical schemes (2011-2017)

Source: Council of Medical Schemes

According to Table 2.5 to 2.8 below, for the period 2011 to 2017, Discovery Health Medical Scheme is the largest open medical scheme in terms of member beneficiaries and total assets. Following behind is Bonitas Medical Scheme. Regarding the restricted medical scheme market, the Government Employees Medical Scheme is the largest restricted medical scheme in terms of member beneficiaries and total assets. Following behind that is the South African Police Service Medical Scheme. These market shares have remained rather consistent throughout the period.

Table 2.5 Open medical scheme market share (%) (total beneficiaries)

Medical scheme	2011	2012	2013	2014	2015	2016	2017	Average
Discovery Health Medical Scheme	49	52	53	54	55	55	56	53
Bonitas Medical Fund	13	13	13	13	13	15	15	14
Momentum Health	4	4	4	5	5	5	6	5
Medihelp	5	5	5	5	4	4	4	4
Bestmed Medical Scheme	3	3	4	4	4	4	4	4
Medshield Medical Scheme	5	4	4	3	3	3	3	4
Fedhealth Medical Scheme	3	3	3	3	3	3	3	3
Sizwe Medical Fund	3	3	3	2	3	2	2	3
Liberty Medical Scheme	3	3	2	2	2	0	0	2
Keyhealth	2	2	2	2	2	2	1	2
Other	10	9	8	7	6	6	5	7

Source: Council of Medical Schemes

Table 2.6 Open medical scheme market share (%) (total assets)

Medical scheme	2011	2012	2013	2014	2015	2016	2017	Average
Discovery Health Medical Scheme	40	42	44	47	50	52	54	47
Bonitas Medical Fund	13	13	13	12	11	12	13	13
Medshield Medical Scheme	6	6	6	6	5	5	4	5
Bestmed Medical Scheme	5	5	5	5	5	5	5	5
Medihelp	6	6	5	4	4	4	4	5
Fedhealth Medical Scheme	5	5	5	4	4	3	3	4
Momentum Health	3	4	4	4	4	4	4	4
Sizwe Medical Fund	3	3	3	3	3	3	3	3
Keyhealth	2	2	2	2	2	2	2	2
Topmed Medical Scheme	2	2	2	2	2	2	2	2
Other	14	13	11	10	9	7	6	10

Source: Council of Medical Schemes

Table 2.7 Restricted medical scheme market share (%) (total beneficiaries)

Medical scheme	2011	2012	2013	2014	2015	2016	2017	Average
Government Employees Medical Scheme (GEMS)	44	46	47	47	46	47	46	46
South African Police Service Medical Scheme (POLMED)	13	13	13	13	13	13	13	13
Bankmed	5	5	5	5	6	5	6	5
LA Health Medical Scheme	2	3	3	3	4	4	4	3
Platinum Health	2	2	2	2	3	2	2	2
SAMWUMed	2	2	2	2	2	2	2	2
Transmed Medical Fund	4	3	2	2	2	1	1	2
Sasolmed	2	2	2	2	2	2	2	2
Profmed	2	2	2	2	2	2	2	2
Motohealth Care	2	2	2	1	1	1	1	1
Other	22	21	21	20	21	20	20	21

Source: Council of Medical Schemes

Table 2.8 Restricted medical scheme market share (%) (total assets)

Medical scheme	2011	2012	2013	2014	2015	2016	2017	Average
Government Employees Medical Scheme (GEMS)	12	14	15	14	15	15	22	15
South African Police Service Medical Scheme (POLMED)	13	14	14	15	15	14	13	14
Anglo Medical Scheme	10	10	9	10	9	9	8	9
Bankmed	9	9	9	9	8	8	8	9
LA Health Medical Scheme	2	2	3	3	4	4	4	3
SAMWUMed	2	2	2	3	3	3	4	3
Nedgroup Medical Aid Scheme	5	4	4	1	1	1	1	3
Profmed	2	2	3	3	3	3	2	3
Sasolmed	3	2	2	3	3	3	3	3
Remedi Medical Aid Scheme	2	2	2	2	2	2	2	2

Other	39	37	37	38	36	36	33	37

Source: Council of Medical Schemes

Tables 2.9 and 2.10 below reflect the concentration ratios for both open and restricted schemes for the years 2011 to 2017. The concentration ratios for the largest open medical schemes range from 72% to 78% whereas the concentration ratios for the four largest restricted medical schemes range from 64% to 69%. It appears that open schemes are slightly more concentrated than restricted schemes. Moreover, the HHI reflects the number and dispersion of medical schemes in a market. A market is believed to be unconcentrated if the HHI is below 0.1, moderately concentrated if the HHI is between 0.1 and 018 and highly concentrated if the HHI is over 0.18.6 Given this, it appears that both the markets that open and restricted medical schemes operate in are highly concentrated.

Table 2.9: HHI and CR4 results for open medical schemes

Year	HHI	CR4
2011	0.2724701	0.72
2012	0.2952967	0.74
2013	0.3078535	0.75
2014	0.316833	0.75
2015	0.3264828	0.75
2016	0.3390621	0.77
2017	0.3449507	0.78

Table 2.10: HHI and CR4 results for restricted medical schemes

Year	HHI	CR4
2011	0.2193158	0.64
2012	0.2367863	0.67
2013	0.2455902	0.68
2014	0.2438871	0.68
2015	0.2360733	0.69
2016	0.2421723	0.69
2017	0.2382731	0.69

6 See US Department of Justice Guidelines.

2.5 Conclusion

This chapter provided the industry overview of the South African medical scheme industry. In addition, this chapter discussed the historical development of the South African medical scheme industry. At first glance it appears as if the open medical scheme market is dominated by Discovery Health Medical Scheme which has consistently achieved significantly high market shares in terms of total beneficiaries and total assets, respectively, over the sample period. More so, in the market for restricted medical schemes, the Government Employees Medical Scheme appears to dominate in terms of total beneficiaries over the sample period.

Further, from 2011 to 2017 there has been a decline in the number of medical schemes operating within the South African medical scheme industry. This decrease in medical scheme numbers is accompanied by a decrease in the overall South African population that belongs to a medical scheme and increases in the monthly contributions paid by members.

3 Chapter Three: Are South African Medical Schemes Efficient? A Longitudinal Analysis

3.1 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 (WHO, 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*" (HMI, 2018, p.76).

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 (HMI, 2018).

Both open and restricted medical schemes are regulated by the 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.

Medical schemes are not-for-profit entities[7], 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 (HMI, 2019). Accordingly, both the open and restricted medical scheme markets are highly concentrated. Tables 3.1 and 3.2 below reflect the historic market shares for open and restricted medical schemes for the period 2011 to 2017.

Table 3.1: 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 3.2: 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

[7] See Competition Commission Health Market Inquiry final report, para 17, page 46.

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 (HMI, 2019).

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 this chapter is structured as follows: Section 3.2 is the literature review, Section 3.3 outlines the methodology used, Section 3.4 displays the results and the subsequent discussion of those results and Section 3.5 concludes the study.

3.2 Literature Review

3.2.1 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 et al., 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.

3.2.2 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 et al. (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 et al. (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 6 000 insurers which translates to 23 807 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 et al. (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 et al. (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 et al. (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.

In addition to the above, Table 7.1, presented in Appendix I is a summary of the inputs and outputs employed by various authors when conducting the DEA approach.

3.3 Methodology and Data

3.3.1 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 et al. (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 3.1 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.

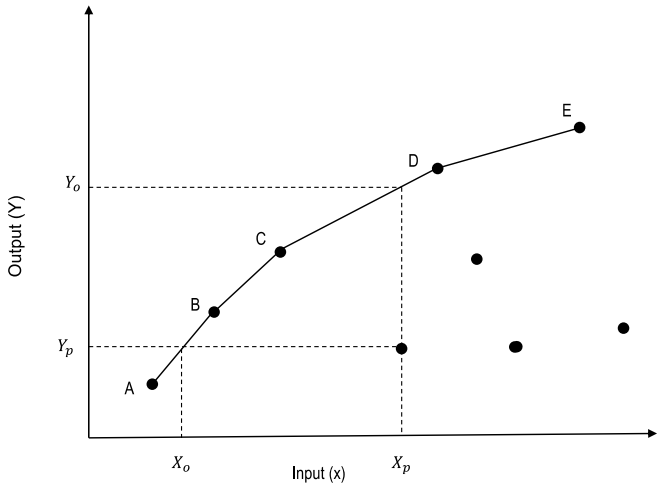

Figure 3.1: Efficiency frontier

3.3.2 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:

$$F^t(y_i^t, x_i^t) = [D^t(y_i^t, x_i^t)]^{-1} = \min [\lambda_i^t : \lambda_i^t x_i^t \epsilon L^t(y^t)] \qquad (3.1)$$

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:

$$
\begin{aligned}
& Min_{\theta,\lambda^{\lambda}} \\
& subject\ to\ -y_i + Y\lambda\ \geq 0 \\
& \qquad\qquad \theta x_i - X\lambda \geq 0 \\
& \qquad\qquad N1'\lambda = 1 \\
& \qquad\qquad \lambda \geq 0
\end{aligned}
\tag{3.2}
$$

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 problem 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).

3.3.2.1 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 3.2 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.

3.3.2.2 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.

3.3.3 Bootstrapping DEA

The main disadvantage of employing the DEA methodology is found in the fact that it does not take into account statistical noise or random error (Assaf and Matawie, 2010). This is a result of the DEA approach using linear programming which is a non-statistical approach to estimate efficiency frontiers. This implies that the inefficiency scores and the envelopment surface derived from the DEA approach are much rather calculated than statistically estimated (Assaf and Matawie, 2010).

Given this, the DEA approach alone is unable to determine the accuracy of the efficiency scores or provide statistical foundations for the estimated frontier. In order to address this limitation, this study employed the bootstrapping approach developed by Simar and Wilson (1998) and Simar and Wilson (2000). The bootstrapping approach estimates the population distribution of the DEA efficiency scores which allows hypothesis testing on the efficiency scores (Assaf and Matawie, 2010). Below is a description of the bootstrapping methodology.

In their initial work, Simar and Wilson (1998) introduced a DEA-bootstrapped methodology based on a variable return to scale (VRS) assumption. Under this approach, bootstrapping involves employing a random selection of thousands of pseudo samples from the observed set of sample data (Simar and Wilson, 1998). These pseudo estimates are then derived from each of these samples. These aforementioned pseudo estimates form an empirical distribution. This distribution is then employed as an approximation of the true underlying sampling distribution of the estimator.

For further illustration, consider a random sample depicted as $X = (X_1, X_2, \dots, X_n)$ from a population with the following unknown distribution function F. The primary goal would be the estimation of the sampling distribution of a distribution function of some pre-specified random variable in the form $R(X, F)$ by employing a real dataset x, whereby $x = (x_1, x_2, \dots, x_n)$ symbolises the observed realisation of $X = (X_1, X_2, \dots, X_n)$.

Given this, the first step of the bootstrapping procedure is the construction of a sample probability distribution in the form of $\hat{F}$, by employing $1/n$ at each point in the observed sample $x_1, x_2, \dots x_n$. After this initial step, a random sample is drawn with a replacement from $\hat{F}$ where $\hat{F}$ is fixed at its observed value. This leads to the following sample $X^* = (X_1^*, X_2^*, \dots, X_n^*)$ and is defined as the bootstrap sample $X_i^* = x_i^*, X_i^* \sim_{ind} \hat{F}, i = 1,2, \dots, n$. This implies that the distribution of the random sample is approximated by the bootstrap distribution of $R^* = R(X^*, \hat{F})$. To apply the bootstrapping procedure to nonparametric analysis, Simar and Wilson (1998) employed the algorithm outlined below.

Simar and Wilson (1998) began by defining a production set as follows:

$$\psi = \{(x, y) \in R_+^{p+q} | x \; can \; produce \; y\} \tag{3.3}$$

Which details the amount of p inputs x that can produce q outputs y. This suggests that for a given level of output y, the level of inputs x that can make it possible can be defined by the following:

$$X(y) = \{x \in R_+^p | (x, y) \in \psi\} \tag{3.4}$$

Where the efficient production limit can be derived as a subset of $X(y)$ where:

$$\partial X(y) = \{x | x \in X(y), \theta x \notin X(y), \forall \theta \in (0,1)\} \tag{3.5}$$

Which suggests that it may not be plausible to achieve more output with a given level of input. This is given the fact that a DEA input-orientated efficiency measure can be derived as $\theta_i = \min \{\theta | \theta x_i \in X(y_i)\}$. Further, $\theta_i = 1$ will mean that the unit (x_i, y_i) is fully efficient. It is also believed that the following sets ψ,$X(y)$ and $\partial X(y)$ are unknown, suggesting that for any given unit, θ_i will be also unknown.

This implies that it is assumed that some data generating process (DGP), P, will generate a random sample $X = \{(x_i, y_i) | i = 1, \dots, n\}$ of n homogenous firms. $\hat{\theta}_i$ can thus be derived as the following:

$$\hat{\theta}_i = \min \left\{ \theta | y_i \leq \sum_{i=1}^{n} \lambda_i y_i, \theta_{xi} \geq \sum_{i=1}^{n} \lambda_i x_i, \sum_{i=1}^{n} \lambda_i = 1 \right\} \tag{3.6}$$

These approximate efficiency scores can then be employed in the bootstrapping procedure in order to achieve pseudo-samples of the efficient input vectors as shown below:

$$\hat{x}^{\partial}(x_i | y_i) = \hat{\theta}_i x_i \tag{3.7}$$

Where $\hat{x}^{\partial}(x_i | y_i)$ symbolises the level of inputs that a firm should seek to achieve in order to be on the DEA efficiency frontier. In order to do so, a random sample in the form of $\theta_i^*, i = 1, \dots, n$ with a replacement from $(\hat{\theta}_1, \dots, \hat{\theta}_n)$ and $i = 1, \dots, n$. The bootstrap inputs can then be derived as follows:

$$x_i^* = \frac{\hat{\theta}_i}{\theta_i^*} x_i \tag{3.8}$$

The above bootstrapped inputs are then employed in the DEA methodology in order to achieve bootstrap estimated of the efficiency scores, $\hat{\theta}_i^*$. This procedure is repeated B times in order to

arrive at the sampling distribution for θ_i, which will be further employed to estimate the bias and to conduct inference on the DEA efficiency scores.

Important to note is the fact that the nature of the DEA efficiency scores will lead to certain complications in the bootstrapping process. This is a result of the empirical distribution $\hat{F}$ of $\hat{\theta}$ which provides inconsistent estimates of the true density function F. Given that the efficiency scores are limited to 0 and 1, the empirical distribution will be discontinuous on this interval and will therefore lead to inconsistences in the bootstrap measurements.

To address this issue, Simar and Wilson (1998) advocate for the use of a smoothed bootstrapping procedure by employing a Gaussian kernel density estimator in order to obtain $\hat{F}$ as F is seen to be bound at 1. This leads to the following algorithm, as discussed in Simar and Wilson (1998, 2000).

Step One – DEA efficiency scores are calculated by employing VRS DEA.
Step Two – DEA efficiency scores are calculated by employing constant returns to scale (CRS) and non-increasing return to scale (NIRS) in order to show the nature of return to scale (RTS) for the differing operations. RTS is calculated through dividing the bootstrapped results from the CRS assumption by the bootstrapped results from NIRS assumption as advocated by the work of Lothgren and Tambour (1999).
Step Three – The smoothed bootstrapping procedure is then employed in order to generate $\theta_i^*, i = 1, \dots, n$ with replacement from $(\hat{\theta}_1, \dots, \hat{\theta}_n)$, which yields $(\theta_{1b}^*, \theta_{2b}^*, \dots, \theta_{nb}^*)$, where b is the b-th iteration of the bootstrap.

Step Four – The bootstrap inputs are calculated which are given by $x_{ib}^* = (\hat{\theta}_i / \theta_{ib}^*) x_i$.

Step Five – The bootstrapped inputs are employed in order to obtain the DEA-bootstrap estimates of the efficiency scores $\hat{\theta}_{ib}^*$.
Step Six – Steps one to five are repeated B times in order to generate a set of estimates in the form $\{\hat{\theta}_{ib}^*, b = 1, \dots, B\}$.
Step Seven – The mean of the bootstrap estimator is then employed as an approximation in the DEA estimator which is not being bias free. The bootstrap estimate of the DEA estimator bias can be derived as follows:

$$\hat{bias}_i = \frac{1}{B}\sum_{b=1}^{B}\hat{\theta}_{ib}^{*} - \hat{\theta}_{in} \tag{3.9}$$

Where the right-hand side term symbolises the mean of the bootstrap efficiency score and the second represents the original DEA estimate of the efficiency score. Moreover, confidence intervals are approximated by employing the empirical distribution of θ_{ib}^{*}.

3.3.4 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:

$$y_{it} = x_{it}'\beta + v_{it} - u_{it} \tag{3.10}$$

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:

$$u_{it} = z_{it}\delta + w_{it} \tag{3.11}$$

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.

Moreover, the technical efficiency of production for the '*i-th'* medical scheme at '*t-th'* observation can be defined by the following equation:

$$TE_{it} = \exp(-U_{it}) = \exp\,(z_{it}\delta - W_{it}) \tag{3.12}$$

3.3.5 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, Total Equity and Total Liabilities.

In regards to the output variable, this study followed the suggestions of the existing literature and used both Net Contribution Income, which is the net premiums paid by members and Net Relevant Healthcare Expenses which is medical schemes' net claims incurred. According to Eling and Luhnen (2010), there is inconclusive evidence regarding the best proxy for output variables. Given this, the DEA efficiency scores were estimated using both Net Contribution Income and Net Relevant Healthcare Expenses as the output variables. Similarly, the SFA efficiency scores were estimated using Net Contribution Income which is identified as Model One and Net Relevant Healthcare Expenses which is identified as Model Two.

3.3.6 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. Moreover, both the DEA and SFA efficiency scores were estimated using pooled data which allowed the comparison between years and medical schemes.

3.4 Results and Discussion

3.4.1 Efficiency scores

Tables 3.5 and 3.6 reflect the disaggregated medical scheme efficiency scores for both open medical and restricted medical schemes for the period 2011 to 2017. Tables 3.3 and 3.4 below reflect the industry aggregated DEA efficiency scores for both open and restricted medical schemes for the period 2011 to 2017. As reflected in Tables 3.3 and 3.4 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 79.8% whereas restricted medical schemes achieved a lower average technical efficiency score of 52.4%. The bias corrected technical efficiency scores reveal lower scores of 75.3% for open medical schemes and 47.5% for restricted medical schemes.

The scale efficiency scores show a similar trend whereby open medical schemes were able to achieve higher scale efficiencies than restricted medical schemes. Open medical schemes achieved on average scale efficiencies of 94.3%, whereas restricted medical schemes achieved a slightly lower average score of 87.5%. Furthermore, open medical schemes on average achieved higher pure technical efficiency scores obtaining an average score of 80.3%, whereas restricted medical schemes achieved an average score of 55% over the sample period.

Table 3.3: Aggregated DEA efficiency results for open medical schemes

Year	Technical efficiency	Bias corrected technical efficiency	Technical efficiency lower bound	Technical efficiency upper bound	Scale efficiency	Pure technical efficiency
2011	78,2%	74,0%	70,2%	77,1%	93,5%	79,8%
2012	73,9%	69,5%	65,9%	73,0%	92,3%	76,1%
2013	74,3%	70,9%	67,4%	73,5%	94,4%	75,6%
2014	76,4%	71,3%	67,8%	75,2%	93,7%	76,8%
2015	86,0%	80,8%	76,6%	84,7%	95,7%	84,7%
2016	85,4%	80,4%	76,8%	84,1%	95,1%	84,9%
2017	84,6%	80,1%	76,7%	83,6%	95,2%	84,3%
Average	79,8%	75,3%	71,6%	78,7%	94,3%	80,3%

Table 3.4: Aggregated DEA efficiency results for restricted medical schemes

Year	Technical efficiency	Bias corrected technical efficiency	Technical efficiency lower bound	Technical efficiency upper bound	Scale efficiency	Pure technical efficiency
2011	48,4%	44,2%	40,9%	47,5%	87,5%	51,5%
2012	47,4%	43,0%	39,8%	46,4%	87,3%	50,5%
2013	49,4%	45,1%	42,2%	48,4%	88,1%	51,9%
2014	51,4%	46,5%	43,5%	50,3%	88,2%	53,4%
2015	57,0%	51,5%	47,8%	55,9%	87,6%	59,4%
2016	57,2%	51,7%	47,8%	56,1%	87,3%	59,5%
2017	55,6%	50,3%	46,5%	54,6%	86,5%	58,7%
Average	52,4%	47,5%	44,1%	51,3%	87,5%	55,0%

In addition to the above, Tables 7.2 and 7.3, presented in Appendix I, reveal the existence of best practice medical schemes. In regard to open medical schemes, the following medical schemes can be considered best practice firms if we consider the DEA technical efficiency scores: (i) Bonitas in 2017; (ii) Hosmed in 2015 and 2016; (iii) Keyhealth in 2012, 2015, and 2016; (iv) Liberty Medical Scheme in 2015; (v) Makoti Medical Scheme in 2011; (vi) Medihelp in 2016 and 2017; (vii) Medimed in 2016 and 2017; (viii) The National Independent Medical Aid Society (NIMSA) in 2011; (ix) Resolution Health Medical Scheme in 2012, 2013 and 2015; and (x) Thebemed in 2011, 2012 and 2017. None of the open medical schemes can be considered best practice if we consider the bias corrected DEA efficiency scores.

In regard to restricted medical schemes, the following can be considered best practice firms: (i) the Government Employees Medical Scheme (GEMS) in 2014, 2015, 2016 and 2017; (ii) Impala Medical plan in 2014 and 2017; (iii) Lonmin Medical Scheme in 2016 and 2017; and (vi) Transmed Medical Fund in 2015 and 2016. Similar to open medical schemes, none of the restricted medical schemes can be considered best practice if we consider the bias corrected DEA efficiency scores.

3.4.2 Stochastic frontier production function estimates

Furthermore, Tables 3.5 and 3.6 below present the industry aggregated SFA efficiency scores for both open and restricted medical schemes for the period 2011 to 2017. 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 Model One SFA technical efficiencies scores achieved were 92.3% and 83.7% for open and restricted schemes respectively. Model Two SFA technical efficiency scores appear to be lower for both open and restricted medical schemes. Open medical schemes achieved an average technical efficiency score of 89.2% whereas restricted medical schemes achieved an average technical efficiency score of 79.2% Similar to the DEA average technical efficiency scores, open medical schemes were able to reach higher scores than those of restricted medical schemes over the sample period.

Table 3.5: Aggregated SFA efficiency results for open medical schemes

Year	Model One SFA technical efficiencies	Model Two SFA technical efficiencies
2011	93,5%	90,8%
2012	92,3%	88,8%
2013	91,0%	87,3%
2014	90,6%	87,0%
2015	93,1%	90,7%
2016	93,3%	90,7%
2017	92,6%	89,2%
Average	92,3%	89,2%

Table 3.6: Aggregated SFA efficiency results for restricted medical schemes

Year	Model One SFA technical efficiencies	Model Two SFA technical efficiencies
2011	84,9%	80,7%
2012	83,9%	79,4%
2013	82,8%	77,7%
2014	81,8%	76,6%
2015	84,8%	80,9%
2016	84,1%	80,2%
2017	83,3%	78,8%
Average	83,7%	79,2%

In addition, Tables 3.7 and 3.8 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 3.5 reveals the Battese and Coelli (1995) model results for Model One whereas Table 3.6 shows the results for Model Two. In Table 3.5, 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 non-relevant healthcare expenditure appears to be the most important factor of production for Model One. Similar results are found in Table 3.6. The output elasticities of all the inputs appear to be positive and statistically significant at a 1% level. More so, net non-relevant healthcare expenditure appears to be the most important factor of production for Model Two.

Table 3.7: Open medical scheme Stochastic frontier production function estimates Model One

Variable	Coefficient	Standard error
Production function		
Net contributions		
Net non-relevant healthcare expenditure	0.826***	(0.0254)
Total equity	0.0753***	(0.0186)
Total liabilities	0.124***	(0.0270)
Year	0.0298***	(0.00627)
Constant	-58.55***	(12.61)
Observations	162	
Prob > chi2	0.0000	
σ_u	0.985	(11.73)
σ_v	-3.998***	(0.197)
Wald chi2(4)	865.86	

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

Table 3.8: Open medical scheme stochastic frontier production function estimates Model Two

Variable	Coefficient	Standard error
Production function		
Net relevant healthcare expenditure		
Net non-relevant healthcare expenditure	0.788***	(0.0279)
Total equity	0.103***	(0.0202)
Total liabilities	0.136***	(0.0287)
Year	0.0378***	(0.00701)
Constant	-74.86***	(14.10)
Observations	162	
Prob > chi2	0.0000	
σ_u	0.575	(4.413)
σ_v	-3.982***	(0.265)
Wald chi2(4)	12657.66	

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

Furthermore, Tables 3.7 and 3.8 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 3.7 reveals the Battese and Coelli (1995) model for Model One whereas Table 3.8 shows the Battese and Coelli (1995) model for Model

Two. Similar to open medical schemes, Table 3.9 below reveals that the output elasticities of all the inputs appear to be positive and statistically significant at a 1% level where net non-relevant healthcare expenditure appears to be the most important factor of production. The same conclusions are drawn from Table 3.10 below which represents Model Two.

Table 3.9: Restricted medical scheme stochastic frontier production function estimates Model One

Variable	Coefficient	Standard error
Production function		
Net Contributions		
Net non-relevant healthcare expenditure	0.756***	(0.0287)
Total equity	0.190***	(0.0292)
Total liabilities	0.0945***	(0.0237)
Year	0.0440***	(0.00844)
Constant	-87.17***	(16.94)
Observations	439	
Prob > chi2	0.0000	
σ_u	1.218	(2.336)
σ_v	-2.423***	(0.122)
Wald chi2(4)	6222.05	

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

Table 3.10: Restricted medical scheme stochastic frontier production function estimates Model Two

Variable	Coefficient	Standard error
Production function		
Net relevant healthcare expenditure		
Net non-relevant healthcare expenditure	0.716***	(0.0312)
Total equity	0.203***	(0.0304)
Total liabilities	0.103***	(0.0248)
Year	0.0535***	(0.00909)
Constant	-106.0***	(18.25)
Observations	439	
Prob > chi2	0.0000	
σ_u	1.292*	(0.743)
σ_v	-2.415***	(0.123)
Wald chi2(4)	6222.05	

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

3.5 Conclusion

This study 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 non-relevant healthcare expenditure, total equity and total liabilities 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 Model One and Model Two of the SFA production function. Furthermore, the empirical results show that input proxy, net non-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.

4 Chapter Four: Efficiency, Productivity and Returns to Scale Economies in South Africa's Healthcare Insurance Market

4.1 Introduction

According to economic theory, a relationship exists between market concentration and the overall level of efficiency within a market (Hicks, 1935). One school of thought postulates that monopolies definitely prefer a quiet life free from competition and will thus limit their initiatives for improving competition. This school of thought suggests that firms with market power, operating in highly concentrated markets, will limit competition and will operate under a reduced efficiency level (Lelissa and Kuhil, 2018). An alternative to this view is that market concentration is a result of competition from firms that enjoy low cost structures that increase profits by reducing their prices (Smirlock, 1985). This implies that the better performance achieved from firms which have market power is a result from the efficiencies they enjoy (Demsetz, 1973).

These two theories have important consequences for South Africa's medical scheme industry which, according to the Health Market Inquiry (HMI), resembles an uncompetitive market structure. 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 (WHO, 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. This provides an incentive for medical schemes and members to be efficient.

Given this, there have been attempts across countries to find a balance between affordability and efficiency goals. According to the Competition Commission's (the Commission) 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" (HMI, 2018, p.76).

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 are open only to the members of the association. According to the HMI, open and restricted medical schemes compete in separate markets (HMI, 2018). Both the open and restricted medical scheme markets are highly concentrated. Tables 4.1 and 4.2 reflect the historic market shares for open and restricted medical schemes for the period 2011 to 2017.

Table 4.1: Open scheme market share[8]

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 4.2: Restricted scheme market share[9]

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 medical schemes should

[8] Market shares are based on the number of medical scheme beneficiaries.
[9] Market shares are based on the number of medical scheme beneficiaries.

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 (HMI, 2019).

Given the above, the primary goal of this study was to assess efficiency, productivity and returns to scale economies of both open and restricted medical schemes. As a matter of economics, efficiency refers to both technical and allocative elements. The technical aspect relates to the ability not to waste, that being either producing as much output as the available technology and inputs allow or by utilising as few inputs as required by available technology and output production. The allocative aspect of efficiency relates to the ability to combine both inputs and outputs in optimal proportions under prevailing prices. Given this definition of economic efficiency, economic productivity can be understood as the measurement of how efficiently inputs are employed in the process of producing a given level of output. Moreover, returns to scale relates to the rate in which output changes as a result of all inputs being adjusted by the same factor.

This study has three different stages. First, efficiency and returns to scale economies were estimated using the data envelope analysis technique. In addition to this, the Malmquist index was estimated in order to examine the productivity changes over the relevant period (2011 to 2017). Second, the study employed a truncated bootstrapped regression procedure advocated by Simar and Wilson (2007) to identify the determinants of efficiency. A logistic model was then utilised to examine the factors that affect the probability of operating at optimal capacity of constant returns to scale. Third, the study assessed the rate of efficiency convergence in the markets for open and restricted medical schemes using the growth concepts advocated by Barro and Sala-i-Martin (1991). The empirical results reveal that open medical schemes tend to be more efficient than restricted medical schemes. More so, the empirical evidence reveals that there is room for improvement of efficiencies for both open and restricted medical schemes.

The rest of this chapter is structured as follows: Section 4.2 is the literature review, Section 4.3 outlines the methodology used, Section 4.4 displays the results and the subsequent discussion of those results and Section 4.5 concludes the study.

4.2 Literature Review

4.2.1 Theoretical review

According to Cummins and Xie (2013), the primary objective of efficiency analysis is attempting to separate firms that perform well, i.e. benchmark firms, from those that perform poorly. To do so the estimation of best practice efficient frontiers which are derived from benchmark firms are estimated in a particular industry. These best practice efficient frontiers are than 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) (Coelli, 1995; Watkins et al., 2014). The most common adopted of these two approaches is the DEA approach as it has advantages over the SFA approach.

The SFA approach is based on econometric techniques that require the specification of a functional form for the production technology and then employs statistical procedures to determine the parameters for the function (Coelli, 1995). More so, the SFA approach incorporates an error term which has two components, namely a symmetric component which accommodates statistical noise usually associated with data measurement errors (Coelli, 1995). Secondly, the error term includes a nonnegative component that is used to estimate inefficiency in production (Coelli, 1995).

On the other hand, the DEA approach is a non-parametric methodology which utilises linear programming techniques to derive efficient frontiers which envelop all input-output combinations of decision-making units within a particular sample (Luhnen, 2009). Therefore, it could be understood that the input-output combinations of efficient firms are found on the efficiency frontier, whereas the input-output combinations of less efficient firms are found below the efficient frontier (Watkins et al., 2014).

Given its nonparametric nature, the DEA approach does not require assumptions to be made regarding the functional form or distribution type of the data and therefore is less sensitive to misspecification when compared to the SFA approach (Coelli, 1995). Moreover, the DEA approach can incorporate multiple input and output combinations in its analysis which the SFA approach cannot do (Barros et al., 2005).

For purposes of this study, the DEA approach is preferred over the SFA approach as a result of its more simplistic nature. More so, according to Cummins and Weiss (2000), the efficiency scores obtained from the DEA approach are from individual firm observations rather than the central tendency averages obtained from the SFA approach which tend to be vulnerable to specification errors.

4.2.2 Empirical review

There has been extensive research on the efficiency, productivity and returns to scale on many insurance markets for both developed and emerging markets (Fukuyama, 1997; Cummins, 1999; Fukuyama and Weber, 2001; Meimand et al., 2002; Coelli et al., 2005; Barros et al., 2005; Jeng et al., 2007; Cummins and Xie, 2008; Luhnen, 2009; Cummins and Xie, 2013; Biener et al., 2016; Cummins and Xie, 2016; Eling and Schaper, 2017). One such study is the work of Cummins and Xie (2013) which assessed the efficiency, productivity and existing scale economies in the American property-liability insurance industry. Cummins and Xie (2013) estimated efficiency, productivity and scale economies for American property-liability insurers for the period 1993–2009 using DEA. Cummins and Xie (2013) found that a majority of firms below industry median size are operating with increasing returns to scale. More so, they found that the majority of firms above industry median size are operating with decreasing returns to scale. The researchers also found that a significant number of firms, below and above industry median size, are operating at constant returns to scale.

Further, Cummins and Xie (2013) found that the property-liability industry attained significant gains in total factor productivity and the existence of an upward trend in scale and allocative efficiency. In addition, the researchers found that more diversified firms and insurance groups were likely to achieve greater efficiency and productive gains than less diversified firms. Furthermore, it was found that higher technology investment was positively related to efficiency and productivity improvements.

A similar study conducted by Luhnen (2009) assessed efficiencies and productivity in the German property-liability insurance market. The objective of the work of Luhnen (2009) was to evaluate the efficiency and productivity in the Germany property-liability insurance industry for the period 1995 to 2006. Using a sample of 295 companies, the study employed DEA in order to estimate efficiency scores. The study found potential for the German property-liability

insurance industry to improve by around 20% in regard to technical efficiency. In addition, the study found the potential to improve by around 50% in terms of cost efficiency. Furthermore, the findings revealed moderate total factor productivity growth and low efficiency growth during the time period.

Regarding the emerging markets, the work of Alhassan and Biekpe (2015) assessed the efficiency, productivity and returns to scale economies of the non-life insurance market in South Africa for the period 2007 to 2012. Employing the DEA technique, the researchers estimated efficiency and returns to scale scores for non-life insurance firms in South Africa. In addition, the researchers assessed productivity growth through the estimation of a Malmquist index for non-life insurance firms. Alhassan and Biekpe (2015) found that non-life insurers in South Africa are operating with around 50% inefficiencies, whereas around 20% of non-life insurers in South Africa operate at an optimal scale. Furthermore, the researchers found productivity improvements as a result of technical changes.

Overall, there are limited efficiency studies that focus on the South African context and more specifically South African healthcare insurer markets. The above review highlights the lack of efficiency studies both in terms of South African insurer markets as well as South African healthcare insurer markets. As a result, this study has aimed to contribute to the literature which will aid South African medical schemes by offering a point of reference in terms of effective resource use.

4.3 Methodology

This section of the chapter details the methodology used in this study. Section 4.3.1 outlines the procedure used to estimate efficiency scores. Section 4.3.2 outlines the methodology used to estimate productivity changes. Section 4.3.3 details the input and output variables used. Section 4.3.4 is the variable description. Section 4.3.5 details the hypotheses. Section 4.3.6 outlines the model estimation. Section 4.3.7 details the methodology used in modelling the determinants of returns to scale. Section 4.3.8 outlines the procedure used to estimate the efficiency convergence.

4.3.1 Estimating efficiency scores

In estimating efficiency scores, this study used the procedure advocated by Farrell (1957) and Charnes et al. (1978). This technique, referred to as DEA utilises a linear programming technique to estimate efficiencies scores for each unit relative to the best practice firms on the frontier. The DEA approach can be employed as either an input-oriented model or an output-oriented model. For an input-oriented model, the efficiency measure is referred to as the maximum radial reduction of all inputs which is feasible given the available technology and output. In regard to the output-oriented model, the efficiency measure is referred to as the maximum radial expansion in outputs which is feasible given the available technology and inputs (Fried et al., 2008). Importantly, assuming constant returns to scale, the estimated efficiency scores will have the same values whether an input or output-oriented model is employed (Hugeunin, 2012). Given this, the study employed an output-oriented DEA model under assumptions of constant returns to scale.

Moreover, this study considered "n" medical schemes with "m" different outputs "y" produced from "k" different inputs "x". Staying consistent with the work of Charnes et al. (1978), the medical scheme specific output-oriented technical efficiency assuming constant returns to scale was modelled into linear programming which was solved "n" times for each firm in the sample, as shown below:

$$\hat{\theta}_i = \max\left\{\theta_i > 0 | \hat{\theta}_i y_i \leq \sum_{i=1}^{n} y_i\lambda;\ x_i \geq \sum_{i=1}^{n} x_i\lambda;\ \lambda \geq 0\right\},\quad i = 1, \dots, n \tag{4.1}$$

Where y_i and x_i symbolise vectors of output and inputs respectively, λ represents a non-negative vector of constants which specifies the optimal weights of inputs and outputs. $\hat{\theta}_i$ illustrates the efficiency score for the ith firm. Technically efficient (TE) medical schemes are believed to have $\hat{\theta}_i = 1$ while those with efficiency scores $\hat{\theta}_i < 1$ operate below the efficient frontier and are thus deemed inefficient. Further, to estimate scale efficiency (SE), pure technical efficiency (PTE) under variable returns to scale was estimated by imposing the following constraint: $\sum_{i=1}^{N} \lambda_i = 1$.

This constraint aids in ensuring that firms of similar size are compared to each other to generate efficiency scores greater than or equal to the TE scores. Further, the differences between TE

and PTE reflect scale inefficiency. These scale efficiency scores were estimated by the following:

$$SE(x,y) = \frac{TE(x,y)}{PTE(x,y)} \tag{4.2}$$

Furthermore, for non-increasing returns to scale (NIRS), the constraint for PTE was adjusted to $\sum_{i=1}^{N} \lambda_i \leq 1$. Based on TE, PTE and NIRS, three returns to scale (RTS) categories for each medical scheme were identified. Given this, this study employed the same procedure used in Aly et al. (1990) and Cummins and Xie (2013), such that this study reflects to scale economies of medical schemes as follows:

If SE < 1 and PTE ≠ NIRS, a medical scheme will be deemed to be operating with increasing returns to scale (IRS). However, if SE < 1 and PTE = NIRS, a medical scheme will be deemed to be operating with decreasing returns to scale (DRS). Accordingly, IRS symbolises inefficiencies from underutilisation of resources whereas DRS symbolises inefficiencies which result from overutilisation of a medical schemes' resources. Furthermore, medical schemes that are seen to have SE = 1 are believed to be operating with constant returns to scale (CRS) as this represents the optimum scale of production of a medical scheme.

4.3.2 Productivity changes

In estimating productivity change, this study employed a methodology similar to the works of Malhberg and Url (2003), Luhnen (2009) and Cummins and Xie (2013). These studies advocated the use of the Malmquist productivity index (MPI). The MPI is used to estimate the changes in output arising out of input changes over different time periods in order to identify the sources of productivity changes.

Fare et al. (1994) indicated that the MPI between period t-1, the base technology period, and period t+1, the referenced technology period can be derived by the following:

$$MPI(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{d^t(x^{t+1}, y^{t+1})}{d^t(x^t, y^t)} \tag{4.3}$$

Further, under the assumptions of constant returns to scale output-oriented total productivity changes can be derived as follows:

$$MPI(x^{t+1}, y^{t+1}, x^t, y^t) = \left[\frac{d^t(x^{t+1}, y^{t+1})}{d^t(x^t, y^t)} \times \frac{d^t(x^{t+1}, y^{t+1})}{d^{t+1}(x^t, y^t)}\right]^{1/2} \quad (4.4)$$

Where x^t and y^t represent the input and output vectors respectively, $d^t(x^t, y^t)$ represents the distance between t and t+1. Accordingly, if the value of MPI is greater than 1, TFP >1, then it is believed that a positive total factor productivity change occurred between periods t and t+1. Whereas if MPI < 1, then it is believed that there was a decline in productivity between the periods.

In addition, the MPI can be decomposed into productivity growth arising from efficiency changes (EFFCH) and (TECHCH) as represented below:

$$MPI(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{d^t(x^{t+1}, y^{t+1})}{d^t(x^t, y^t)}\left[\frac{d^t(x^{t+1}, y^{t+1})}{d^t(x^t, y^t)} \times \frac{d^t(x^{t+1}, y^{t+1})}{d^{t+1}(x^t, y^t)}\right]^{1/2} \quad (4.5)$$

Where it is understood that the ratio in the squared brackets above measures shifts in frontier technology (TECHCH). The frontier shifts arise from innovation in production techniques and new product developments. The ratio outside the squared brackets is understood to represent (EFFCH) which measures changes in efficiency between the base period t and the reference period t+1, which is termed the catch-up effect.

4.3.3 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 are labour and capital inputs. Due to data availability, these inputs are: (i) Non-Relevant Healthcare Expenses which consist of broker service fees, administration fees and other operating expenses which are incurred when operating a medical scheme; (ii) Relevant Healthcare Expenses which comprise the healthcare expenses incurred by medical schemes; and (iii) Medical Scheme Year-end reserve position. These input variables are proxied as labour and capital inputs as recommended by existing literature as the functions of medical schemes are of risk pooling and bearing as well as the provision of intermediation services (Eling and Luhnen, 2010).

Concerning the output variables, this study followed the suggestions of the existing literature and used both Net Contribution Income, which is the net premiums paid by members and Net

Relevant Healthcare Expenses which is medical schemes' net claims incurred. According to Eling and Luhnen (2010), there is inconclusive evidence regarding the best proxy for output variables. Given this, the DEA efficiency scores were estimated using both Net Contribution Income and Net Relevant Healthcare Expenses as the output variables.

4.3.4 Variable description

The empirical model used by the study is derived from the work of Worthington and Hurley (2002), Luhnen (2009) and Huang and Eling (2013) and is shown below:

$$\hat{\theta}_{i,t} = \beta_0 + \beta_1 size_{i,t} + \beta_2 size^2{}_{i,t} + \beta_3 div_{i,t} + \beta_4 age_{i,t} + + \beta_5 lev_{i,t} + \varepsilon_{i,t} \quad (4.6)$$

Where θ represents the efficiency scores TE and PTE from the DEA, $size$ is the natural logarithm of total assets, $size^2$, is the square of $size$, div represents $1 - HHI$ which represents product line diversification, age is the natural logarithm of the number of years since a medical scheme was first registered. lev is the ratio of total liabilities to total assets. Furthermore, $\varepsilon_{i,t}$ represents the one-way error terms is made of μ_i which is the unobservable firm-specific effects and $\nu_{i,t}$ is the time-varying error term.

Furthermore, 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.

4.3.5 Hypotheses

This section details the hypotheses and justifies the variables used in the study. Similar to the work of Coelli et al. (1999), this study attempted to assess the effect of insurer-specific variables on estimated efficiency scores. In addition, this study considered the relationship between insurer size and efficiency. Similar to the work of Malhberg and Url (2003) and Luhnen (2009), it is expected that large medical schemes will exhibit economies of scale and scope in the form of lower per unit cost of production derived from large scale production, suggesting that they will be closer to the efficient frontier. However, larger firms may be unable to monitor and control activities of large-scale operation, resulting in diseconomies of scale and therefore a negative relationship may be seen.

Further, it is believed that in the long-run, firms could potentially be able to adjust their scale of operating. Issues in managing large scale operations could lead to a non-linear relationship between size and efficiency. In addition, small firms may be required to reach a size threshold to become more efficient, while large firms could become inefficient after a certain size threshold.

There has been empirical evidence in the literature to suggest that there is a curve-linear relationship between size and efficiency in other insurance markets (Worthington and Hurley 2002; Eling and Luhnen 2010). Given this, this study assessed the non-linearity of the size-efficiency relationship by including a quadratic term for size.

More so, according to the conglomeration hypothesis, diversified business operations are accompanied with the benefits of economies of scope from complementarities in production and cost sharing. Diversified medical schemes will thus be seen as more efficient. In addition, according to the strategic focus hypothesis, an inefficient internal capital market will lead to the cross-subsidisation of inefficient ones. Inefficiencies of diversified firms will be compromised with issues of monitoring and control in a large diversified organisation.

Further, this study assessed the relationship between a medical scheme's age and its efficiency. It is assumed that older firms will become more efficient from learning-by-doing (Arrow, 1962). However, some argue that aging firms tend to use outdated technology and are likely to be more inefficient. Further, older medical schemes may also be believed to have passed the test of confidence by policyholders to have the ability to provide cover for their client base.

Furthermore, according to the work of Jensen (1986), leverage will place a financial cost on firms and will increase the probability of financial distress. Therefore, leverage will place pressure on management to generate high cash flows in order to meet interest obligations. Given this, the management of highly levered firms can also become efficient. It is believed that a conflict exists between debt holders and shareholders, suggesting higher leverage results in a negative leverage-performance relationship (Jensen and Meckling, 1976).

Moreover, economic theory suggests that the level of competition within markets has direct implications on the level of market efficiency. For the most part, economic theory postulates that market efficiency will be positively correlated with the level of existing competition.

Accordingly, markets with high levels of competition will result in firms being more productive and efficient as result of the competitive pressures brought about by competing firms which force firms to adopt best efficient practices in order to be able to compete and survive (Chang and Gurbaxani, 2013). Given the HMI's finding that the South African medical scheme industry resembles an uncompetitive market structure, it can be predicted that South African medical scheme markets will be found to be inefficient.

4.3.6 Model estimation

In estimating the empirical model, this study followed the work of Simar and Wilson (2007) by applying a truncated bootstrapping regression. This methodology involves a seven-step procedure in which the bias corrected efficiency scores in the first stage DEA estimation are employed as the dependent variable in a truncated bootstrapped regression analysis.

4.3.7 Modelling determinants of return to scale

According to Cummins and Xie (2013), scale efficiency can be categorised as constant returns to scale (CRS), increasing returns to scale (IRS) or decreasing returns to scale (DRS). More so, every firm prefers CRS as both IRS and DRS are undesirable and reflect scale inefficiencies (Cummins and Xie, 2013). Given this, it is believed that the long-term goal of firms is focused on being able to operate at the minimum efficient scale of production at CRS. Thus, this study examined the factors that increase the likelihood of a medical scheme to operate at their optimum capacity or not. Therefore, the study used a logistic regression technique to determine the probability of a medical scheme to either operate with CRS or not. This model is expressed below as:

$$P_{i,t}\left(Y = 1 \middle| X_{i,t}\right) = \frac{\exp\left(\alpha + \beta X_{i,t}\right)}{1 + \exp\left(\alpha + \beta X_{i,t}\right)} \tag{4.7}$$

Where $P(Y = 1|X)$ represents the probability of a medical scheme operating with CRS, X symbolises the explanatory factors that explain the probability of a medical scheme to operate with a return to scale category. β represents the coefficient of X and α represents the intercept equation 4.7 above which can be expanded to derive the following equation:

$$RTS_{i,t} = \ln\left(\frac{P_{i,t}}{1 - P_{i,t}}\right) = \alpha + \beta X_{i,t} + \varepsilon_{i,t} \ldots\ldots \quad (4.8)$$

Where RTS represents the dummy variable coded as 1 if a medical scheme operates under CRS and 0 otherwise. Further, the marginal effects of the independent variables on the returns to scale categories are estimated in order to allow for meaningful interpretations of the coefficients.

Furthermore, the marginal effect of the mean level coefficient β_k can be estimated by the following equation:

$$\frac{\partial P_{k,i}}{\partial X_{j,i}} = P_{k,i}(\beta_{kj} - \sum_{k=0}^{K} P_{ki}\beta_j) \ for\ k = 1 \quad (4.9)$$

Where β_j symbolises the coefficient of the independent variable xj for returns to scale category k. The marginal effect of X on the RTS is interpreted as the probability of a medical scheme operating in a return to scale category that arises from mean changes in the independent variable. This model was estimated using the maximum likelihood estimation.

4.3.8 Estimating efficiency convergence

Barro and Sala-i-Martin (1991) offer a methodology which assesses the rate of efficiency convergence which this study used. In this context, convergence is seen as the tendency of medical schemes achieving an equal level of efficiency over time. There are two commonly used convergence concepts in the literature, β-convergence and α-convergence.

β-convergence is the ability of inefficient decision-making units (DMU) to catch-up with more efficient ones and thus becomes more efficient overtime. If it is found that DMUs are able to improve their efficiency levels more rapidly than efficient ones, β-convergence is believed to have transpired. β-convergence is assessed by estimating regressions of initial levels of efficiency on the growth rate in efficiency scores. To this regard, Casu and Giarandone (2010) propose the following equation:

$$\Delta y_{i,t} = \alpha + \delta \Delta y_{i,t-1} + \beta ln y_{i,t-1} + \varepsilon_{i,t} \quad (4.10)$$

Where $y_{i,t}$ represents the bias corrected efficiency score for medical scheme i at time t, $y_{i,t-1}$ is the bias corrected efficiency score for medical scheme i at time $t-1$. $\Delta y_{i,t} = ln y_{i,t} -$

$lny_{i,t-1,}$ β represents the coefficient that measures the rate of efficiency convergence. α represents the constant term and finally δ is the coefficient of the lagged dependent variable.

A negative value for β indicates convergence of technically inefficient medical schemes while a higher absolute β suggests a faster rate of efficiency convergence. According to Sala-i-Martin (1996), evidence of β-convergence is a necessary but not sufficient for α-convergence which is the reduction in the dispersion of efficiency over the period. The model for α-convergence is derived as:

$$\Delta E_{i,t} = \alpha + \varphi \Delta E_{i,t-1} + \sigma E_{i,t-1} + \varepsilon_{i,t} \quad (4.11)$$

Where $E_{i,t} = \ln(y_{i,t}) - \ln(\bar{y}_t)$; $E_{i,t-1} = \ln(y_{i,t-1}) - \ln(\bar{y}_{t-1})$; $y_{i,t}$ and $\Delta E_{i,t} = E_{i,t} - E_{i,t-1}$.

More so, $y_{i,t-1}$, as indicated above, represents the bias corrected efficient score for medical scheme i at time $t-1$, $\bar{y}_t$ represents the mean efficiency score for the industry in period t. $\bar{y}_{t-1}$ represents the mean efficiency score for the industry in period $t-1$. $E_{i,t}$ represents the time-varying error term. α represents the constant term and φ represents the coefficient of the dynamic term. σ captures the rate of convergence from $y_{i,t}$ to $\bar{y}_t$. Furthermore, equations 4.10 and 4.11 above were estimated using Ordinary Least Squares (OLS), fixed effects, and the system generalised method of moments of Arellano and Bover (1995) with forward orthogonal deviations.

4.4 Empirical Results

Tables 4.3 and 4.4 below display the efficiency results for both open and restricted medical schemes respectively. As reflected below, it appears that for the period 2011 to 2017, open medical schemes on average were able to achieve higher efficiency scores when compared to restricted medical schemes. The empirical results indicate that open medical schemes on average achieved efficiency scores of 92%, 98% and 94% for technical, scale and pure technical efficiency, respectively. Whereas for restricted medical schemes, the empirical results suggest that on average they achieved efficiency scores of 85%, 98% and 87% for technical, scale and pure technical efficiency, respectively.

Table 4.3: Efficiency results for open medical schemes

Year	Technical efficiency	Scale efficiency	Pure technical efficiency
2011	0.93190689	0.97598407	0.95532698
2012	0.92027633	0.97297726	0.94649522
2013	0.90953762	0.97681814	0.93145766
2014	0.90752973	0.97729105	0.92859434
2015	0.92143482	0.9821534	0.93850296
2016	0.91864272	0.9831096	0.93491234
2017	0.92356983	0.98523682	0.93760313
Average	0.91898542	0.979081477	0.938984661

Table 4.4: Efficiency results for restricted medical schemes

Year	Technical efficiency	Scale efficiency	Pure technical efficiency
2011	0.8500416	0.97677231	0.87047843
2012	0.84865734	0.9764483	0.86908677
2013	0.85117622	0.97928416	0.86922833
2014	0.84207369	0.97935849	0.85998856
2015	0.85243174	0.97975564	0.87018395
2016	0.84518145	0.97926336	0.86344498
2017	0.85309092	0.9781872	0.87267331
Average	0.848950423	0.978438494	0.86786919

Furthermore, for both open and restricted medical schemes, the empirical results reveal lower pure technical efficiency scores than scale efficiency scores. This reveals that technical inefficiency is a result of pure technical inefficiency. As previously indicated, pure technical efficiency is the ability of firms to fully use state-of-the-art technology in attempts to operate on the efficient frontier. Given this, both open and restricted medical schemes could improve their efficiency scores by adopting technology enhancing systems for premium pricing.

4.4.1 Productivity analysis

Tables 4.5 and 4.6 below reflect the productivity analysis results for both open and restricted medical schemes respectively. These tables display the Malmquist total factor productivity change (MPI), the efficiency changes (EFFCH) and the technology changes (TECHCH) for both open and restricted medical schemes. For open medical schemes, the results reveal that on average, for the period 2011 to 2017, there was a decline of 0.13%, 0.10% and 0.02% in MPI, EFFCH and TECHCH respectively. The results also reveal, on average, a productivity

decline in open medical schemes, suggesting that for any given level of input over the period 2011 to 2017, open medical schemes did not maximise their output.

Table 4.5: Productivity results for open medical schemes

Year	MPI	MPI change (%)	EFFCH	EFFCH change (%)	TECHCH	TECHCH change (%)
2011/2012	0,99921562		1,0149934		0,98623388	
2012/2013	1,0164903	1,73	1,0095288	-0,54	1,0075942	2,17
2013/2014	1,0040929	-1,22	0,99694709	-1,25	1,0087689	0,12
2014/2015	0,98828215	-1,57	0,96926424	-2,78	1,0203472	1,15
2015/2016	1,0014171	1,33	1,0040008	3,58	0,99827973	-2,16
2016/2017	0,99226695	-0,91	1,008558	0,45	0,98445104	-1,39
2011/2017	1,00029417	-0,13	1,000548722	-0,10	1,000945825	-0,02

Table 4.6: Productivity results for restricted medical schemes

Year	MPI	MPI change (%)	EFFCH	EFFCH change (%)	TECHCH	TECHCH change (%)
2011/2012	1,011128		0,99496677		1,0195418	
2012/2013	1,0122247	0,11	0,9790116	-1,60	1,0355906	1,57
2013/2014	0,99228808	-1,97	1,0447008	6,71	0,9523896	-8,03
2014/2015	0,99975282	0,75	0,98443321	-5,77	1,0170617	6,79
2015/2016	0,99451887	-0,52	1,0258474	4,21	0,9711126	-4,52
2016/2017	1,0029698	0,85	0,99753261	-2,76	1,0070088	3,70
2011/2017	1,002147045	-0,16	1,004415398	0,16	1,00045085	-0,10

Regarding restricted medical schemes, the results reveal that on average, for the period 2011 to 2017, a decline of MPI and TECHCH reflected by 0.16% and 0.10% respectively. However, EFFCH experienced slight growth of 0.16%. Similarly, compared to open medical schemes, restricted medical schemes experienced a productivity decline. This decline in productivity is a result of a decline in TECHCH, suggesting that the productivity decline for restricted medical schemes is a result of frontier shifts.

4.4.2 Determination of efficiency

Table 4.7 below reflects the bootstrapped truncated regression results for both open and restricted medical schemes. The Wald $\chi^2(Prob > \chi^2 \; of \; less \; than \; 0.05)$ is a reflection of the fit for the regression models. For open medical schemes, the linear coefficient for size is negative for both pure technical efficiency and technical efficiency. This suggests that there

may be issues regarding monitoring and control, as open medical schemes grow larger. However, it should be noted that the size coefficient is only significant for pure technical efficiency.

In regard to restricted medical schemes, the linear coefficient for size is negative and statistically insignificant for pure technical efficiency and positive and statistically significant (at 1%) for technical efficiency. In contrast to open medical schemes, it appears that restricted medical schemes do not encounter issues of monitoring and control as they grow larger.

Regarding the squared coefficient for size, open medical schemes appear to be able to adjust to their increased scale of operations and maximise the use of their investments in systems. This is reflected in the positive squared size coefficient found for both pure technical efficiency and technical efficiency although it appears that the coefficient is only significant for pure technical efficiency. In terms of restricted medical schemes, the squared size coefficient is positive for pure technical efficiency and negative for technical efficiency. Further, the squared size coefficients for restricted medical schemes is statistically insignificant for both pure technical efficiency and technical efficiency.

The coefficients for product line diversification are statistically insignificant for both open and restricted medical schemes. In respect of open medical schemes, the coefficient for product line diversification is positive for pure technical efficiency and negative for technical efficiency. For restricted medical schemes, the coefficient for product line diversification is positive for both pure technical efficiency and technical efficiency.

The age coefficient is negative and statistically significant for both open and restricted medical schemes in terms of pure technical and technical efficiency. This appears to be inconsistent with the positive age efficiency theory postulated by Arrow (1962) and Jovanovic (1982). The results seem to support the hypothesis postulated by Barron et al. (1994) which indicates that older firms tend to be characterised by accumulated bureaucratic processes. Given this, they are unable to utilise the best available technology to be productive and efficient.

Furthermore, it appears that the leverage coefficient for open medical schemes is negative for both pure technical efficiency and technical efficiency. However, the leverage coefficient is only statistically significant for technical efficiency. This suggests that high leverage will lead

to declines in overall efficiency among open medical schemes. The opposite can be said about restricted medical schemes as the leverage coefficient is significant and positive for both pure technical and technical efficiency.

Table 4.7: Medical scheme bootstrapped truncated regression results

	Open Medical Schemes				Restricted Medical Schemes			
	PTE		**TE**		**PTE**		**TE**	
	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z
Constant	8.561***	3.58	1.853**	2.33	0.930	0.83	-0.619	-0.69
	(2.390)		(0.795)		(1.123)		(0.896)	
size	-0.792***	-3.26	-0.0908	-1.16	-0.0321	-0.31	0.146*	1.79
	(0.243)		(0.0781)		(0.105)		(0.0815)	
$\boldsymbol{size^2}$	0.0205***	3.35	0.00253	1.31	0.00120	0.44	-0.00346	-1.62
	(0.00613)		(0.00193)		(0.00273)		(0.00213)	
div	0.181	0.58	-0.0196	-0.09	0.219	0.34	0.00581	0.01
	(0.313)		(0.217)		(0.653)		(0.560)	
age	-0.00399***	-3.73	-0.00302***	-4.32	-0.00178***	-4.23	-0.00191***	-5.22
	(0.00107)		(0.000700)		(0.000421)		(0.000366)	
Lev	-0.00141	-1.06	-0.00213**	-2.24	0.000863*	1.90	0.000691*	1.74
	(0.00133)		(0.000953)		(0.000455)		(0.000396)	
$\boldsymbol{Wald\ \chi^2(5)}$	29.61		33.44		23.19		39.14	
$\boldsymbol{Prob > \chi^2}$	0.0000		0.0000		0.0003		0.0000	
Variance	0.0612***		0.0528***		0.0896***			
Observations	128		147		391		405	

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

4.4.3 Determinants of returns to scale

Table 4.8 below displays the maximum likelihood estimation results for the determinants of returns to scale for both open and restricted medical schemes. Regarding the size coefficient, it appears that size is positively related to the probability of operating with constant returns to scale in terms of open medical schemes. The opposite occurrence is found in relation to restricted medicals schemes as size is inversely related to the probability of operating with constant returns to scale. However, the size coefficient is not statistically significant for both open and restricted medical schemes.

Further, regarding the quadratic size term, it appears that it is inversely related to the probability of operating with constant returns to scale for open medical schemes and positively related to the probability of operating with constant returns to scale for restricted medical schemes.

Similarly, to the size coefficient, the quadratic size term is not statistically significant for both open and restricted medical schemes.

In regard to product line diversification, it appears that there is a negative relationship in open medical schemes and a positive relationship in restricted medical schemes. However, the coefficients for product line diversification do not appear to be statistically significant for both open and restricted medical schemes. In terms of the age coefficient, it appears that medical scheme age is inversely related to the probability of operating with constant returns to scale for both open and restricted medical schemes. However, the age coefficient is only statistically significant for restricted medical schemes.

Furthermore, it appears that for the leverage term of open medical schemes there is an inverse probability of operating with constant returns to scale; however, the leverage coefficient for open medical schemes is statistically insignificant. In restricted medical schemes, there appears to be a positive and statistically significant related probability of operating with constant returns to scale and having a high leverage ratio. This suggests that highly levered restricted medical schemes have a high probability of operating with constant returns to scale.

Table 4.8: Medical scheme determinants of returns to scale

	Open medical schemes		Restricted medical schemes	
	dy/dx	z	dy/dx	z
size	0.1065231	0.33	-0.0939326	-1.31
	(0.32398)		0.07157	
$size^2$	-0.0029704	-0.37	0.0025241	1.38
	(0.00812)		(0.00183)	
DIV	-0.4808072	-0.55	0.7136755	1.38
	(0.87536)		(0.51708)	
Age	-0.0017371	-0.82	-0.0011595***	-2.95
	(0.00211)		(0.00039)	
Lev	-0.0080922	-1.20	0.0006755***	2.72
	(0.00673)		(0.00025)	
$LR\chi^2(5)$	4.69		22.90	
$Prob > \chi^2$	0.4542		0.0004	
Pseudo R-squared	0.0470		0.1866	
Log likelihood	-47.628812		-49.898147	
Observations	162		419	

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

4.4.4 Efficiency converging

Tables 4.9 and 4.10 below show the efficiency convergence results for both open and restricted medical schemes respectively. For open medical schemes the result reveals that for all models, for the test of unconditional β-Convergence, for both pure technical and technical efficiency, β is negative and statistically significant at 1%. This suggests the existence of unconditional β-Convergence in the open medical scheme market, implying that inefficient open medical schemes have been able to catch-up with best-practice medical schemes over the period assessed.

The same is true with regard to restricted medial schemes, as for all models, for the test of unconditional β-Convergence, for both pure technical and technical efficiency β is negative and statistically significant at 1%. Likewise, unconditional β-Convergence exists in the restricted medical scheme market, implying that inefficient restricted medical schemes have also been able to catch-up with best-practice medical schemes over the period assessed.

In regard to σ -convergence in open medical schemes, in the test for σ-convergence, σ appears to be positive and statistically significant for both pure technical and technical efficiency for all models. This suggests that there is no evidence of σ-convergence in the open medical schemes market as there is no reduction in the variability of efficiency and conversion towards a common level. The same is true for restricted medical schemes as σ appears to be positive and statistically significant for both pure technical and technically efficiency for all models.

Table 4.9: Open medical scheme efficiency convergence

	OLS				**Fixed effects**				**GMM**			
	PTE		TE		PTE		TE		PTE		TE	
	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z
Unconditional β-Convergence												
Constant	-0.0282***		-0.0199***		-0.0740***		-0.0546***		-0.114***		-0.0891***	
	(0.00675)		(0.00540)		(0.00693)		(0.00526)		(0.00938)		(0.00701)	
$\boldsymbol{\delta(\Delta ln y_{i,t-1})}$	-0.0206		0.0228		0.129*		0.134**		0.234***		0.234***	
	(0.0804)		(0.0807)		(0.0662)		(0.0649)		(0.0602)		(0.0586)	
$\boldsymbol{\beta(ln y_{i,t-1})}$	-0.323***		-0.302***		-0.858***		-0.847***		-1.297***		-1.338***	
	(0.0659)		(0.0630)		(0.0739)		(0.0705)		(0.104)		(0.103)	
$\boldsymbol{m1\ p-value}$									0.0318		0.0337	
$\boldsymbol{m2\ p-value}$									0.5034		0.6846	
$\boldsymbol{R^2}$	0.162		0.144		0.536		0.544					
	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z
σ-convergence												
Constant	0.00894**		-0.00825**		0.0184***		-0.0164***		0.0240***		-0.0196***	

	(0.00374)		(0.00364)		(0.00407)		(0.00394)		(0.00290)		(0.00241)	
$\varphi(\Delta E_{i,t-1})$	-0.318***		-0.276***		-0.399***		-0.361***		-0.244***		-0.251***	
	(0.0709)		(0.0734)		(0.0698)		(0.0735)		(0.0456)		(0.0447)	
$\sigma(E_{i,t-1})$	0.407***		0.371***		0.809***		0.775***		0.986***		0.945***	
	(0.0578)		(0.0568)		(0.0997)		(0.104)		(0.0791)		(0.0821)	
$m1\ p-value$									0.1697		0.2020	
$m2\ p-value$									0.0727		0.0771	
R^2	0.266		0.228		0.375		0.329					

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

Table 4.10: Restricted medical scheme efficiency convergence

	OLS				Fixed effects				GMM			
	PTE		TE		PTE		TE		PTE		TE	
	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z
Unconditional β-Convergence												
Constant	-0.0484***		-0.0417***		-0.159***		-0.142***		-0.246***		-0.220***	
	(0.00716)		(0.00646)		(0.00692)		(0.00618)		(0.0108)		(0.00989)	
$\delta(\Delta lny_{i,t-1})$	0.00654		-0.0178		0.0837***		0.0809**		0.155***		0.177***	
	(0.0481)		(0.0481)		(0.0323)		(0.0324)		(0.0310)		(0.0315)	
$\beta(lny_{i,t-1})$	-0.286***		-0.284***		-0.937***		-0.964***		-1.482***		-1.528***	
	(0.0363)		(0.0366)		(0.0386)		(0.0392)		(0.0645)		(0.0677)	
$m1\ p-value$									0.4827		0.2918	
$m2\ p-value$									0.4546		0.6316	
R^2	0.142		0.145		0.651		0.659					
	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z	Coefficient	z
σ-convergence												
Constant	0.00971***		-0.00556		0.0248***		-0.0154***		0.0257***		-0.0222***	
	(0.00361)		(0.00345)		(0.00362)		(0.00318)		(0.00196)		(0.00175)	
$\varphi(\Delta E_{i,t-1})$	-0.262***		-0.279***		-0.356***		-0.364***		-0.289***		-0.290***	
	(0.0445)		(0.0440)		(0.0401)		(0.0394)		(0.0216)		(0.0208)	
$\sigma(E_{i,t-1})$	0.341***		0.346***		0.883***		0.936***		1.092***		1.107***	
	(0.0336)		(0.0335)		(0.0714)		(0.0707)		(0.0497)		(0.0480)	
$m1\ p-value$									0.6250		0.6707	
$m2\ p-value$									0.0030		0.0018	
R^2	0.207		0.218		0.353		0.385					

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

4.5 Conclusion and Policy Implications

This study assessed the efficiency, productivity and returns to scale of both open and restricted medical schemes in South Africa for the period 2011 to 2017. The empirical results revealed that open medical schemes tend to be more efficient than restricted medical schemes. Open medical schemes achieved, on average, efficiency scores of 92%, 98% and 94% for technical, scale and pure technical efficiency, respectively, whereas restricted medical schemes on average achieved efficiency scores of 85%, 98% and 87% for technical, scale and pure technical efficiency, respectively.

A plausible explanation for the differences in efficiencies for open and restricted medical schemes is the fact that open medical schemes are open to more members of the public whereas

restricted medical schemes are only restricted to specific groups such as a particular employer, industry or union. This implies that, for the most part, open medical schemes are able to compete with one another in attempts to attract new members or gain existing members from other competing open medical schemes. In order to compete, economic theory indicates that open medical schemes will compete for membership by reducing their cost base, charging lower premiums and by offering overall better products and/or services to consumers as a result of the competitive pressures exerted by rivals.

In contrast, in the restricted medical scheme market, the incentive to compete will tend to be lower as a result of membership being restricted to specific groups. This implies that there is limited competition amongst restricted medical schemes as scheme membership is restricted to specific consumer groups. Given this, each restricted medical scheme could be seen to hold a hypothetical monopoly of that particular designated employer or union. This, according to economic theory, would have direct implications on economic efficiencies as theory postulates that monopolies prefer a quiet life free from competition and thus will limit their initiatives for improving competition and will tend to operate under a reduced efficiency level.

Regarding the efficiency determinants, the empirical results revealed that restricted medical schemes do not encounter issues of monitoring and control as they grow larger which was in contrast to open medical schemes. Further, it appears that the empirical results regarding the age of the medical scheme is inconsistent with the positive age efficiency theory postulated by Arrow (1962) and Jovanovic (1982). The results seem to support the hypothesis postulated by Barron et al. (1994) which indicates that older firms tend to be characterised by accumulated bureaucratic processes.

More so, concerning the effect of leverage on efficiency, the empirical results revealed that high leverage rates will lead to declines in overall efficiency in open medical schemes. The opposite can be said about restricted medical schemes as the leverage coefficient is significant and positive for both pure technical and technical efficiency.

With regard to the determinants of scale efficiency, the results revealed that medical scheme age appears to be inversely related to the probability of a medical scheme operating with constant returns to scale for both open and restricted medical schemes. However, the age coefficient was only statistically significant for restricted medical schemes. Further, the results

suggest that in terms of the leverage rate for restricted medical schemes, there appears to be a positive and statistically significant related probability of having a high leverage rate and operating with constant returns to scale. This suggests that highly levered restricted medical schemes have a high probability of operating with constant returns to scale.

Furthermore, regarding efficiency divergence, the empirical results revealed unconditional β-Convergence in both open and restricted medical schemes, implying both inefficient open and restricted medical schemes have been able to catch-up with best-practice medical schemes over the period assessed. However, the empirical results did not reveal evidence of σ-convergence in both the open and restricted medical scheme markets, implying that there is no reduction in the variability of efficiency and conversion towards a common level.

Overall, the empirical study reveals that there is room for improvement in efficiencies for both open and restricted medical schemes. The empirical results seem to suggest that concentrated markets operate under a reduced efficiency level. The empirical results appear to contradict the view that market concentration is a result of competition from firms that enjoy low cost structures that increase profits by reducing their prices, implying that the better performance achieved from firms which have market power is a result of the efficiencies they enjoy.

Given this, policy should be formulated in a way that spurs competition in the markets for open and restricted medical schemes in order to improve efficiencies. One way to do this would be the introduction of for-profit medical schemes which would aim to maximise profits through the reduction of costs and the introduction of innovative efficient practices. This will also ensure that the markets for open and restricted medical schemes are more competitive as medical schemes will compete to attract members through reducing their cost base and offering competitive premiums or through offering better overall products and/or services to the benefit of consumers.

Caution should be taken when interpreting the results and drawing on the study's conclusions. Due to data availability, the sample period is limited between 2011 to 2017. However, inferences can still be made given the available results. An important finding made by this study is that open medical schemes tend to be more efficient than restricted medical schemes. As discussed above, the incentive to compete is higher for open medical schemes than it is for restricted medical schemes. Drawing inferences from this finding, it could be suggested that

efficiencies could be improved by further increasing the incentives to compete in both open and restricted medical scheme markets.

A limitation of this study is found in the lack of the direct assessment of market concentration and market efficiency. This offers an opportunity for researchers to test the direct relationship between market competition and efficiency in South African healthcare insurer markets.

5 Chapter Five: Market structure, efficiency and performance: Empirical evidence from South Africa's Medical Scheme Markets.

5.1 Introduction

After the Introduction of the Medical Schemes Act No. 131 of 1998 (Medical Scheme Act) in 2000, there has been considerable consolidation in South Africa's healthcare insurer market. The South African Competition Commission (SACC) conducted a market inquiry into South Africa's Healthcare Industry and found that in terms of South Africa's healthcare insurer market, they were, "*consistently high market shares for some players and high concentration levels for both open and restricted medical schemes, the HMI is concerned with whether there are barriers to entry and expansion. Barriers to entry, by creation and reinforcing the market power of large firms, tend to lead to high prices, lower levels of quality and a less competitive market*" (HMI, 2018, p.83).

Indeed, South Africa's Health Market Inquiry (HMI) revealed concerns regarding the structure and potential performance of South Africa's healthcare insurer market as the SACC found that both markets for open and restricted medical schemes appeared to be concentrated and thus raised concerns around the level of competition within these market structures. These concerns are valid as economic theory suggests that competition in highly concentrated markets tends to be less vigorous. However, others argue that a smaller number of firms will lead to the achievement of economies of scale and scope which leads to better efficiencies and better performance.

More so, there appears to be a debate on whether competition truly improves efficiency and performance. To this score, there are four hypotheses which aim at explaining the structure-performance relationship. The aim of this study was to assess whether any of those hypotheses are supported by empirical evidence in terms of South Africa's healthcare insurer market. This will further assist in informing policy and reforms as the HMI submitted that "*Healthcare markets everywhere suffer from failures on both the demand and supply side. These failures*

can drive up healthcare costs beyond what would prevail in a well-functioning and competitive market and can limit access. As a consequence, healthcare markets are universally (structurally) regulated in one form or another. Market failures persist where regulation is incomplete or compliance with regulation is inadequately enforced." (HMI, 2018, p.87).

Effective reforms and policy however would depend on a comprehensive understanding of firm behaviour and the market and/or the industry in which those firms operate. Therefore, before the formulation and implementation of new reforms and regulations in South Africa's healthcare insurer market, it is critical to first understand the current structure and performance of South Africa's healthcare insurer market.

5.1.1 Industry overview

South African medical schemes are governed by the Medical Schemes Act and regulated by the Council of Medical Schemes (CMS), which is a statutory body mandated in terms of the Medical Scheme Act. Medical schemes play a crucial role in South Africa, in terms of providing healthcare financing for private healthcare.

Accordingly, scheme members pay monthly contributions to their chosen medical schemes which have the function of financing beneficiary expenses. Two types of medical schemes are prominent in South Africa. First, there are open medical schemes which are legally obligated to accept anyone who wishes to join. Second, there are restricted medical schemes which are only open to members of a particular employer, union or industry.

According to the HMI (2019), South African medical schemes cover approximately 8.88 million lives which translates to 15.9% of South Africa's total population. This figure has remained rather consistent over the past two decades as in 1997, 16.9% of South Africa's total population belonged to a medical scheme (HMI, 2019, p.79). Table 5.1 below reflects the percentage of South Africans who belonged to medical schemes for the years 2011 to 2017.

Table 5.1: South Africans belonging to a medical scheme

Year	2011	2012	2013	2014	2015	2016	2017
Percentage	16.4%	16.4%	16.3%	16.2%	15.9%	15.8%	15.6%

Source: Own Calculations

Importantly, the South African medical scheme industry has seen significant consolidation. In 2000, they were 163 medical schemes which consisted of 47 open, 97 restricted and 19 exempted medical schemes. In 2017 there were 81 medical schemes which comprised 21 open and 60 restricted medical schemes (HMI, 2019). Further, the industry has been limited in terms of new entrants. Tables 5.2 and 5.3 below show historic market shares for open and restricted medical schemes in South Africa for the period 2011 to 2017.

Table 5.2: 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 5.3: 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 shown above, it appears that the Discovery medical scheme has consistently been the largest open medical scheme, attaining a market share of between 49% and 56% for the period 2011 to 2017. Similarly, GEMS appears to be the largest restricted medical scheme attaining 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 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 (HMI, 2019).

Indeed, in a competitive market structure, more variance should be evident in market shares which would provide evidence that medical schemes are competing effectively and hence would gain and lose market share. However, the above market share estimates reveal

consistently high market shares for both Discovery Health and GEMS which could point to a lack of effective competition in both open and restricted medical scheme markets.

Given the above, this study assessed the relationship between the market structure, efficiency, and performance of South Africa's healthcare insurer market. This chapter is structured as follows: Section 5.2 discusses the literature which outlines the four hypotheses regarding market structure, conduct and performance. Section 5.3 outlines the estimation methodology and the conditions needed to test each hypothesis and also identifies the data used. Section 5.4 presents the empirical results and discussion of those results. Section 5.5 concludes the chapter.

5.2 Literature Review

5.2.1 Theoretical review

This section outlines the four hypotheses which relate to market structure, conduct and performance. Section 5.2.1.1 relates to the structure-conduct-performance hypothesis; Section 5.2.1.2 relates to the efficient structure hypothesis. Section 5.2.1.3 outlines the relative market power paradigm, whereas Section 5.2.1.3 outlines the quiet life hypothesis.

5.2.1.1 The structure-conduct-performance hypothesis

The structure, conduct and performance (SCP) hypothesis originates from the work of Mason (1939) and Bain (1951). According to Mason (1939), the extent of the relative size of a selling unit will be determined by the structure of a particular market. The market structure in which a firm operates will influence its policies and practices. Given this hypothesis, Mason (1939) indicated that a firm of a given size, relative to the market in which it operates will follow different price and production strategies given different market conditions. More so, Bain (1951) postulated that firms operating in highly concentrated markets will be able to earn higher profit rates than firms operating in less concentrated markets.

Indeed, Bain (1951) suggested that "*a single firm monopolist or a group of oligopolists operating with effective express or tactic collusion should approach a conventional maximization solution and realize in long-run equilibrium the maximum excess profit aggregate which is permitted by the relation of the industry demand curve to the costs of production and selling and by the conditions of selling and by conditions of entry*". Further, firms operating in more competitive markets or oligopolists operating without coordination

will not be able to maximise the excess profit aggregates and will tend to sell their goods and/ or services at a lower price and thus earn lower profits.

One can determine that the central hypothesis of the work of Mason (1939) and Bain (1951) is that the structural characteristics of a particular market will determine the behaviour of firms operating in that market which affects overall market performance. Therefore, it is safe to conclude that the SCP hypothesis assumes a one-way relationship between structure, conduct and performance (Church & Ware, 2000).

A number of studies support this notation, with Smith and Trigeorgis (2004) indicating that conditions of supply and demand in a particular industry will determine its structure. Further, the competitive conditions of a particular market structure will dictate the behaviour of firms operating within that market structure which will in turn dictate the performance of that market. Sathye (2005) also added that the degree of market concentration will influence overall output as a highly concentrated market structure will produce more effective collusive outcomes.

Carlton and Perloff (2000) also postulated that market structures characterised by many firms supplying similar products and/or services, which are relatively equal in size, can be defined as competitive markets that generate greater market performance.

This implies that there is a direct relationship between the degree of market concentration and the level of competition among firms. The SCP hypothesis postulates that market concentration and the degree of competition are inversely related as concentration encourages collusion (Edwards et al., 2006). Therefore, firms which operate in highly concentrated markets will tend to have a higher return than those that operate in less concentrated markets.

Tucker (2010) indicated that conceptually, a market structure is a classification system used to characterise key traits of markets which include the number of firms, the similarity of goods sold and the ease at which firms can enter and exit the market. Shepherd (1986a) stated that market structures range from monopolies to perfectively competitive markets. Therefore, for purposes of the SCP hypothesis, market structure includes a set of variables which are seen to be stable over time and affect the conduct of sellers and/or buyers.

Market conduct can be understood as a set of strategies used by sellers to attract buyers to their business (Moore, 1973). This includes various price competition methods and non-price inducements. More so, Purcell (1973) indicated that market conduct refers to the actions of firms and their behaviour given a market structure. Therefore, various strategic pricing policies, non-price competition policies are activities of market conduct.

Market conduct within the SCP paradigm can then be understood as how firms set their prices, whether independently or in a collusion with other firms in the market and how firms take decisions about their advertising and research budgeting (Ferguson & Ferguson, 1994).

Market performance can be understood as the economic results that flow from the system in terms of pricing efficiency and the flexibility of adapting to changing situations (Bain, 1968). Market performance is the economic result of market structure and conduct. According to Narver and Savitt (1971), market performance is the net result of conduct and can be measured in terms of net profits, rate of return on owners' equity, and the efficiency with which plant equipment and other resources were used.

Furthermore, Neuberger (1997) suggested that market performance can be measured through comparing the results of firms within the industry in terms of price, quantity, product quality, resource allocation and production efficiency.

5.2.1.2 Efficient structure hypothesis

An alternative to the SCP hypothesis is the efficient structure (ES) hypothesis which postulates that market concentration arises from competition from firms that enjoy low cost structures that increase profits by reducing their prices (Smirlock, 1985). Demsetz (1973) suggested that better performance from firms arises from the efficiencies that they enjoy. This hypothesis in in stark contrast to the SCP hypothesis which assumes a positive relationship between market concentration and performance.

The ES hypothesis postulates that the huge gains in market share enjoyed in some firms are a result of superior efficiencies (Lelissa, 2018). Indeed, this suggests that highly concentrated markets are a result of superior practices and policies from more efficient firms. More so, the work of Molyneux and Forbes (1995) indicates that higher profits are not a result of collusion

among firms but are credited to superior management or production technologies that have lower costs.

Further, Sathye (2005) suggested that more efficient firms will tend to win more competition and grow to become large, obtain greater market share and thus earn higher profits. As a result of this phenomenon, efficiencies enjoyed by firms lead to highly concentrated markets.

According to Berger and Hannan (1993), testing the ES hypothesis requires testing two efficiency elements. First, one can test X-efficiency where firms are seen to have lower costs, higher profits and thus larger market share as a result of having greater ability in limiting their costs to produce any given outputs. Second, one can test scale efficiency which sees more scale efficient producing at or close to their minimum average cost point (Berger & Hannan, 1993).

5.2.1.3 Relative market power hypothesis

Shepherd (1986b) postulated that only those firms with large market shares and differentiated products and/or services will have the ability to exercise market power in regard to pricing and, hence earning supernormal profits. Maudas and Guevara (2007) further indicated that market shares tend to capture the influence of factors which are unrelated to efficiency such as market power and/or product differentiation and hence under the relative market power hypothesis, individual market share can be considered as a proxy for assessing market power.

5.2.1.4 Quiet life hypothesis

According to Hicks (1935), a relationship exists between market concentration and the level of overall efficiency in a market. This hypothesis is referred to as the quiet life (QL) hypothesis which postulates that monopolies prefer a quiet life free from competition and hence limit their initiatives for improving efficiencies (Lelissa, 2018). The QL hypothesis suggests that firms with market power operating in highly concentrated markets will limit competition and will tend to operate under a reduced efficiency level.

5.2.2 Empirical review

The empirical literature on the market power hypothesis spans over a number of industries, with one particular study that focused on the banking sector being the work of Evanoff and

Fortier (1988). In this particular study, the researchers used data of more than 6300 American banks in 30 States to assess the effect of regulation on bank performance by dividing the market into those with high entry barriers and those with low entry barriers. The researchers found that in markets that have high entry barriers, market share will have a strong impact on profitability. Yet, in markets with low entry barriers, market growth has a negative effect on profitability.

Choi and Weiss (2005) studied the relationship between market structure and performance in the insurance industry in the United States of America over the period of 1992–1998. Utilising data from company group level, the researchers formulated a structure-conduct-performance, relative market power and efficient structure framework. The researchers found evidence supporting the efficient structure hypothesis.

Relevant to this study is the work of Dranove et al. (2003). The researchers employed a methodology inspired by the work of Bresnahan and Reiss (1991) and Mazzeo (2002) to investigate competition amongst Health Maintenance Organizations (HMO). Using data for the year 1997, on the number of HMOs in local markets in which they distinguish between HMOs that are national and those that are regional. Estimating threshold ratios for all HMOs, the researchers found that the profits for local HMOs were unaffected by the number of national HMOs, and vice versa. The results indicate that there is substantial competition in American HMO markets but also substantial product differentiation.

5.3 Methodology and Data

This section details the methodology used in this study. Section 5.3.1 outlines the procedure to estimate efficiency scores. Section 5.3.2 details the input and output variables used. Section 5.3.3 outlines the concentration measure employed. Section 5.3.4 outlines the empirical model used. Section 5.3.5 describes the data used.

5.3.1 Data envelopment analysis

In order to estimate technical and scale efficiency, this study used a technique referred to as data envelopment analysis (DEA). This technique was introduced by Charnes et al. (1978) based on the work of Farrell (1957). 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. Next is a brief discussion on technical efficiency, scale efficiency and pure technical efficiency.

5.3.1.1 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:

$$F^t(y_i^t, x_i^t) = [D^t(y_i^t, x_i^t)]^{-1} = \min [\lambda_i^t : \lambda_i^t x_i^t \epsilon L^t(y^t)] \quad (5.1)$$

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 on 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:

$$\begin{aligned} & Min_{\theta,\lambda^{\lambda}} \\ & subject\ to\ \ -y_i + Y\lambda\ \geq 0 \\ & \qquad\qquad \theta x_i - X\lambda \geq 0 \\ & \qquad\qquad N1'\lambda = 1 \\ & \qquad\qquad \lambda \geq 0 \end{aligned} \quad (5.2)$$

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 of 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).

5.3.1.2 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 5.2 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.

5.3.1.3 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.

5.3.2 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 are labour and capital inputs. Due to data availability, these inputs are Non-Relevant Healthcare Expenses, Total Equity and Total Liabilities.

Concerning the output variables, this study followed the suggestions of the existing literature and used both Net Contribution Income, which is the net premiums paid by members and Net Relevant Healthcare Expenses which are medical schemes' net claims incurred. According to Eling and Luhnen (2010), there is inconclusive evidence regarding the best proxy for output variables. Given this, the DEA efficiency scores were estimated using both Net Contribution Income and Net Relevant Healthcare Expenses as the output variables.

5.3.3 Herfindahl Hirschman index

Existing literature identifies several metric measures to measure the market structure of a particular industry (Alhassan & Addison, 2013). For the purpose of this research study, the Herfindahl Hirschman index (HHI) and concentration ratios (4-firm CR) were used to measure the structure of South African healthcare insurance market.

The HHI is calculated as the sum of squares of the market share of firms within an industry as shown below:

$$\boldsymbol{HHI_t = \sum_{i=1}^{n} ms_i^2} \tag{5.3}$$

Where ms_i^2 is the market share of medical scheme i.

Concentration ratios measure the degree to which the few dominant firms within a particular industry account for the greater portion of economic activities of that particular industry (Alhassan & Addison, 2013). This study used 4-firm (CR4) concentration ratios.

5.3.4 Econometric model

Given the above discussed hypotheses, this study estimates the following model:

$$\pi_{it} = \beta_0 + \beta_1 CONC_t + \beta_2 MS_{it} + \beta_3 XEFF_{it} + \beta_4 SEFF_{it} + \sum \beta_j Z_{it} \tag{5.4}$$

Where π_{it} represents the performance of medical scheme "i" in period "t", $CONC_t$ reflects market concentration in period "t", MS_{it} represents the market share of medical scheme "i" in period "t", $XEFF_{it}$ represents the pure technical efficiency of medical scheme "i" in period "t", $SEFF_{it}$ reflects the scale efficiency of medical scheme "i" in period "t", whereas Z_{it} is a vector of control variables for medical scheme "i" in period "t".

In addition to the above equation, for purposes of testing the hypotheses found in table 5.4 below, the researcher further introduced the following equations[10]:

$$CONC_t = a_1 + a_2 XEFF_{it} + a_3 SEFF_{it} \tag{5.5}$$

$$MS_{it} = b_1 + b_2 XEFF_{it} + b_3 SEFF_{it} \tag{5.6}$$

$$XEFF_{it} = c_1 + c_2 CONC_t + c_3 MS_{it} + \sum c_j Z_{it} \tag{5.7}$$

$$SEFF_{it} = d_1 + d_2 CONC_t + d_3 MS_{it} + \sum d_j Z_{it} \tag{5.8}$$

[10] The author notes that the bi-directional relationship between efficiency and market structure variables may result to potential endogeneity. The author however has not corrected for endogeneity thus caution should be taken when interpreting the results for equations 5.5 to 5.8.

Equations 5.5 to 5.8 test the bi-directional relationship between efficiency and market structure variables. Importantly, if the SCP hypothesis holds, market concentration should have a positive impact on medical scheme performance. Moreover, scale efficiency and technical efficiency should also be seen to have no significant impact on concentration (Ye et al., 2012). More so, if the RMP hypothesis holds, market share should have a positive impact on medical scheme performance. Likewise scale efficiency and technical efficiency should have no significant impact on market share (Ye et al., 2012). Further, if the RES hypothesis holds, technical efficiency should a positive impact on medical scheme performance. More so, technical efficiency should have a significant impact on both on market concentration and market share (Ye et al., 2012). Lastly, if the SES hypothesis holds, scale efficiency should have a positive impact on medical scheme performance. Furthermore, scale efficiency should have a significant impact on both market concentration and market share (Ye et al., 2012). The above discussed equations assisted in testing the hypotheses tabulated below:

Table 5.4: Summary of hypotheses

Hypothesis	Conditions
SCP	$\beta_1 > 0, and\ a_2, a_3\ both\ equal\ to\ zero$
RMP	$\beta_2 > 0, and\ b_2, b_3\ both\ equal\ to\ zero$
RES	$\beta_3 > 0, and\ a_2 > 0\ and\ b_2 > 0$
SES	$\beta_4 > 0, and\ a_3 > 0\ and\ b_3 > 0$
Quiet Life	$All\ c_2, c_3, d_2 and\ d_3\ are\ negative\ and\ significant$

5.3.5 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. Below is a tabulated summary of the variables that were used.

Table 5.5: Variable description

Variable	Description
ROA	Return on assets = Net income/total assets
XEFF	Pure technical efficiency
SEFF	Scale efficiency
TEFF	Technical efficiency
MS	i th medical scheme market share
CR4	concentration ratios

HHI	calculated as the sum of squares of the market share of medical schemes
Net Contribution Income	Net Contribution Income (ZAR)
Non-Relevant Healthcare Expenses	Non-Relevant Healthcare Expenses (ZAR)
Relevant Healthcare Expenses	Relevant Healthcare Expenses (ZAR)
Total Equity	Medical Scheme Total Equity (ZAR)
Total Liabilities	Medical Scheme Total Liabilities (ZAR)
Control variables	
Size	Natural logarithm of total assets
Scheme Beneficiaries	Natural logarithm of the number of beneficiaries
Leverage	Liabilities to assets ratio
GDP	GDP growth rate
Inflation	Inflation rate

5.4 Empirical Results

This section displays and discusses the empirical results. Tables 5.6 and 5.7 present descriptive statistics for both open and restricted medical scheme regression model variables. There are 162 observations for open schemes and 439 observations for restricted schemes. The return on assets for open medical schemes has a mean of 1.96 whereas a mean of 1.3 for restricted schemes. Further, the concentration ratios for the four largest open medical schemes were 53%, whereas the concentration ratios for the four largest restricted medical schemes were 51%. In regard to efficiencies, open schemes had an average pure technical efficiency score of 0.93, an average scale efficiency score of 0.98 and a technical efficiency score of 0.92. Restricted schemes achieved on average a pure technical efficiency score of 0.87, a scale efficiency score of 0.98 and a technical efficiency score of 0.85. In general, South African medical schemes appear to be rather efficient. In regard to the macroeconomic variables used as control variables, GDP growth and the inflation rate were on average 6.4% and 5.6% respectively.

Table 5.6: Descriptive statistics open medical schemes

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
ROA	162	1,96	1,20	0,45	6,03
Technical efficiency	162	0,75	0,05	0,76	1,00
Scale efficiency	162	0,94	0,03	0,82	1,00
Pure technical efficiency	162	0,80	0,06	0,76	1,00
Market share (%)	162	0,04	0,11	0,00	0,56
HHI	162	0,31	0,02	0,27	0,34
CR4	162	0,53	0,01	0,51	0,54
Net Contribution Income	162	3110000000,00	7600000000,00	35500000,00	48700000000,00
Relevant Healthcare Expenses	162	2680000000,00	6440000000,00	32300000,00	41800000000,00
Non-Relevant Healthcare Expenses	162	422000000,00	1080000000,00	5156274,00	5990000000,00

Total equity	162	1100000000,00	2430000000,00	15400000,00	16700000000,00
Total liabilities	162	440000000,00	1170000000,00	1238931,00	8960000000,00
Leverage	162	5,81	5,37	1,60	41,20
GDP growth (%)	162	0,06	0,06	0,01	0,17
Inflation rate (%)	162	0,06	0,01	0,05	0,07
Size	162	1540000000,00	3600000000,00	23600000,00	25700000000,00
Scheme beneficiaries	162	210424,70	529855,70	2514,00	2777946,00

Table 5.7: Descriptive statistics restricted medical schemes

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
ROA	439	1,30	0,91	0,13	6,17
Technical efficiency	439	0,47	0,08	0,49	1,00
Scale efficiency	439	0,87	0,03	0,78	1,00
Pure technical efficiency	439	0,55	0,08	0,51	1,00
Market share (%)	439	0,02	0,06	0,00	0,47
HHI	439	0,24	0,01	0,22	0,25
CR4	439	0,51	0,01	0,50	0,52
Net Contribution Income	439	890000000,00	3400000000,00	5127313,00	34700000000,00
Relevant Healthcare Expenses	439	821000000,00	3140000000,00	4316009,00	29800000000,00
Non-Relevant Healthcare Expenses	439	65000000,00	212000000,00	763437,00	1980000000,00
Total equity	439	378000000,00	685000000,00	6607451,00	5450000000,00
Total liabilities	439	103000000,00	293000000,00	759154,00	3080000000,00
Leverage	439	10,37	13,30	0,00	120,30
GDP growth (%)	439	0,06	0,06	0,01	0,17
Inflation rate (%)	439	0,06	0,01	0,05	0,07
Size	439	481000000,00	909000000,00	7386833,00	8520000000,00
Scheme beneficiaries	439	62043,69	231639,10	703,00	1853252,00

Tables 5.8 and 5.9 below reflect the concentration ratios for both open and restricted schemes for the years 2011 to 2017. The concentration ratios for the largest open medical schemes range from 72% to 78% whereas the concentration ratios for the four largest restricted medical schemes range from 64% to 69%. It appears that open schemes are slightly more concentrated than restricted schemes. Moreover, the HHI reflects the number and dispersion of medical schemes in a market. A market is believed to be unconcentrated if the HHI is below 0.1, moderately concentrated if the HHI is between 0.1 and 018 and highly concentrated if the HHI is over 0.18.11 Given this, it appears that both the markets that open and restricted medical schemes operate in are highly concentrated.

11 See US Department of Justice Guidelines.

Table 5.8: HHI and CR4 results for open medical schemes

Year	HHI	CR4
2011	0.2724701	0.72
2012	0.2952967	0.74
2013	0.3078535	0.75
2014	0.316833	0.75
2015	0.3264828	0.75
2016	0.3390621	0.77
2017	0.3449507	0.78

Table 5.9: HHI and CR4 results for restricted medical schemes

Year	HHI	CR4
2011	0.2193158	0.64
2012	0.2367863	0.67
2013	0.2455902	0.68
2014	0.2438871	0.68
2015	0.2360733	0.69
2016	0.2421723	0.69
2017	0.2382731	0.69

Tables 5.10 and 5.11 reflect the efficiency scores for both open medical schemes and restricted medical schemes. The results below indicate that both open medical schemes and restricted medical schemes were able to achieve modest efficiency scores for the period 2011 to 2017.

Table 5.10: Efficiency results for open medical schemes

Year	Technical efficiency	Scale efficiency	Pure technical efficiency
2011	0,7401159	0,9345331	0,7978486
2012	0,6948643	0,9230645	0,7613633
2013	0,7087170	0,9435741	0,7563530
2014	0,7134026	0,9369183	0,7680489
2015	0,8080181	0,9574564	0,8467655
2016	0,8044496	0,9507906	0,8486110
2017	0,8013963	0,9524588	0,8425388
Average	0,7529948	0,9426851	0,8030756

Table 5.11: Efficiency results for restricted medical schemes

Year	Technical efficiency	Scale efficiency	Pure technical efficiency
2011	0,4418620	0,8746360	0,5146932
2012	0,4296229	0,8728582	0,5045590
2013	0,4514092	0,8814088	0,5188763
2014	0,4654963	0,8819194	0,5336425
2015	0,5150519	0,8755065	0,5939701
2016	0,5169900	0,8731514	0,5945291
2017	0,5029315	0,8646352	0,5873646
Average	0,4747663	0,8748736	0,5496621

Table 5.12 below displays the results for equation 5.4 for both open and restricted medical schemes. For open medical schemes the results appear to be positive and statistically insignificant. In contrast, the results appear to be negative and statistically significant (at 1%) for restricted medical schemes. This suggests that high levels of market concentration are not associated with greater profitability for restricted medical schemes. Given this, the SCP hypothesis can be rejected for both open and restricted medical schemes.

Further, the coefficients for market shares are positive and statistically significant (at 5%) only for the restricted medical scheme random effects model and statistically insignificant for open medical schemes. This implies that, for restricted medical schemes, an increase in market shares will lead to an increase in profitability. Moreover, the scale efficiency coefficients are positive and statistically significant for both open and restricted medicals. In regard to the pure technical efficiency, the coefficients are positive and statistically significant for both open and restricted medical schemes.

The size coefficients appear to be negative and significant for both open and restricted medical schemes, implying a decline in total asset size will lead to a decline in profitability. Similarly, the leverage coefficients are both negative; suggesting a decline in the leverage ratio for both open and restricted medical schemes will lead to a decline in profitability. Importantly, the results reveal that an increase in medical scheme members will lead to high profitability as shown by the scheme beneficiary coefficient being both positive and statistically significant for both open and restricted medical schemes.

Table 5.12: Results for equation 5.4

	Open medical schemes		Restricted medical schemes	
VARIABLES	**Random effects**	**Fixed effects**	**Random effects**	**Fixed effects**
	ROA		**ROA**	
CR4	0.642	0.389	-2.886***	-3.585***
	(1.892)	(1.564)	(0.808)	(0.807)
Market share	0.0170	0.0463	0.0586***	0.0766
	(0.0107)	(0.0321)	(0.00912)	(0.0469)
Pure technical efficiency	0.971***	0.921***	1.202***	1.047***
	(0.255)	(0.323)	(0.114)	(0.125)
Scale efficiency	2.547***	2.369**	1.217***	0.980***
	(0.447)	(0.904)	(0.171)	(0.192)
Leverage ratio	-0.0325***	-0.0273**	-0.0159***	-0.0136***
	(0.00769)	(0.0103)	(0.00205)	(0.00250)
Size	-1.359***	-1.405***	-0.750***	-0.868***
	(0.0781)	(0.256)	(0.0378)	(0.0462)
Scheme beneficiaries	1.183***	1.039***	0.693***	0.636***
	(0.0785)	(0.173)	(0.0460)	(0.0764)
GDP growth rate	-0.379	-0.447	-0.913***	-1.186***
	(0.355)	(0.345)	(0.156)	(0.161)
Inflation rate	1.574	1.355	3.445**	3.840***
	(2.820)	(0.808)	(1.387)	(1.354)
Constant	12.76***	15.47***	8.616***	12.02***
	(1.733)	(5.230)	(0.762)	(1.094)
Observations	162	162	439	439
Number of medical schemes	26	26	74	74
R-squared	0.8818	0.74	0.8148	0.605
$Prob > \chi^2$	0.0000	0.0000	0.0000	0.0000
$Wald\ \chi^2(9)$	524.06		853.85	

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

Table 5.13 below displays the results for equation 5.5. The coefficients for both pure technical and scale efficiency for open schemes do not appear to be statistically significant. This implies that efficiencies are not leading to concentration in open medical scheme markets. However, the opposite is true for restricted medical schemes whereby the coefficients are negative and statistically significant. Given this, the efficiency hypothesis can only be rejected for open medical schemes. Further, it appears that the high concentration ratios found in the market for open medical schemes are not a result of the ES hypothesis but more likely support the RMP hypothesis.

Table 5.13: Results for equation 5.5

	Open medical schemes		Restricted medical schemes	
VARIABLES	**Random effects**	**Fixed effects**	**Random effects**	**Fixed effects**
	CR4		**CR4**	
Pure technical efficiency	-0.00713	-0.0191	-0.00652**	-0.0327***
	(0.00615)	(0.0117)	(0.00308)	(0.00744)
Scale efficiency	-0.00384	0.00147	-0.000107	0.00368
	(0.00867)	(0.0186)	(0.00470)	(0.0144)
Constant	0.538***	0.543***	0.514***	0.525***
	(0.0109)	(0.0200)	(0.00488)	(0.0141)
Observations	162	162	439	439
Number of medical schemes	26	26	74	74
R-squared	0.0084	0.0195	0.0109	0.055
$Prob > \chi^2$	0.5098	0.2672	0.0903	0.0000
$Wald\ \chi^2(2)$	1.35		4.81	

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

Table 5.14 below shows the results for equation 5.6. The coefficients for pure technical efficiency appear to statistically insignificant for both open and restricted medical schemes. Moreover, the coefficients for scale efficiency appear to be significant but positive for open medical schemes. This suggests that scale efficiency is leading to higher market shares for open medical schemes which provides further evidence to reject the ES hypothesis.

Table 5.14: Results for equation 5.6

	Open medical schemes		Restricted medical schemes	
VARIABLES	**Random effects**	**Fixed effects**	**Random effects**	**Fixed effects**
	Market share		**Market share**	
Pure technical efficiency	0.471	0.411	-0.00799	-0.0183
	(0.673)	(0.648)	(0.124)	(0.123)
Scale efficiency	3.122***	3.306***	-0.124	-0.137
	(1.064)	(1.024)	(0.238)	(0.237)
Constant	0.598	0.878	1.502**	1.724***
	(2.098)	(1.101)	(0.667)	(0.233)
Observations	162	162	439	439
Number of medical schemes	26	26	74	74
R-squared	0.2270	0.074	0.007	0.001
$Prob > \chi^2$	0.0109	0.0056	0.8714	0.8473
$Wald\ \chi^2(2)$	9.05			

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

Table 5.15 reflects results for equation 5.7. The concentration ratio coefficients appear to be negative for both open and restricted medical schemes. However, the concentration ratio coefficients are statistically significant for both open (the random effects model) and restricted medical schemes.

Table 5.15: Results for equation 5.7

	Open medical schemes		Restricted medical schemes	
VARIABLES	**Random effects**	**Fixed effects**	**Random effects**	**Fixed effects**
	Pure technical efficiency		**Pure technical efficiency**	
CR4	-1.059*	-1.009	-1.651***	-1.644***
	(0.619)	(0.623)	(0.358)	(0.359)
Market share	0.00402**	0.00599	0.00783**	-0.000702
	(0.00193)	(0.0110)	(0.00340)	(0.0224)
Constant	1.342***	1.309***	1.382***	1.387***
	(0.328)	(0.334)	(0.184)	(0.187)
Observations	162	162	439	439
Number of medical schemes	26	26	74	74
R-squared	0.1140	0.022	0.0790	0.055
$Prob > \chi^2$	0.0267	0.2310	0.0000	0.0000
$Wald\ \chi^2(2)$	7.25		26.54	

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

Table 5.16 below shows the results for equation 5.8. The concentration ratio coefficients for both open and restricted medical schemes are both positive and statistically insignificant. More so, in regard to open medical schemes, the market share coefficients are negative and statistically significant for the random effects model and positive and statistically insignificant for the fixed effects model. For the restricted medical schemes, the results appear to be statistically insignificant. Similar to the results above, the results below support the quiet life hypothesis.

Table 5.16: Results for equation 5.8

	Open medical schemes		Restricted medical schemes	
VARIABLES	**Random effects**	**Fixed effects**	**Random effects**	**Fixed effects**
	Scale efficiency		**Scale efficiency**	
CR4	0.0146	0.0667	0.237	0.239
	(0.398)	(0.384)	(0.190)	(0.191)
Market share	-0.00372***	0.0217***	0.00139	-0.00659
	(0.00127)	(0.00675)	(0.00247)	(0.0119)
Constant	0.953***	0.813***	0.747***	0.763***
	(0.211)	(0.206)	(0.0981)	(0.0992)
Observations	162	162	439	439
Number of medical schemes	26	26	74	74
R-squared	0.2712	0.072	0.0062	0.005
$Prob > \chi^2$	0.0137	0.0068	0.3930	0.3917
$Wald\ \chi^2(2)$	8.57		1.87	

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

5.4.1 Robust analysis

5.4.1.1 The Hausman test

In considering the most appropriate efficient estimators, the Hausman (1978) specification test was utilised. The results of this test are shown below in Tables 5.17 and 5.18. As reflected below, the Hausman test favoured the random effects model for open medical schemes and the fixed effects model for restricted medical schemes. 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 5.17: Hausman test results for open medical schemes

	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	Fixed effects	**Random effects**	**Difference**	**S.E.**
CR4	0.3885029	0.6424109	-0.253908	
Market share	0.0463293	0.0170211	0.0293082	0.03514
Pure technical efficiency	0.9206723	0.9714952	-0.0508229	0.070853
Scale efficiency	2.368905	2.547401	-0.1784958	0.241625
Leverage ratio	-0.0273309	-0.0324631	0.0051323	0.003893
Size	-1.405216	-1.359248	-0.0459681	0.091573
Scheme beneficiaries	1.03854	1.183499	-0.1449592	0.059234
GDP growth rate	-0.4473309	-0.37894	-0.068391	0.112253
Inflation rate	1.354602	- 1.574082	-0.2194799	

Prob>chi2 = 0.4865

Table 5.18: Hausman test results for restricted medical schemes

	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	Fixed effects	**Random effects**	**Difference**	**S.E.**
CR4	-3.585121	-2.885706	-0.6994149	
Market share	0.0765616	0.0585621	0.0179995	0.045961
Pure technical efficiency	1.04661	1.202133	-0.1555237	0.050821
Scale efficiency	0.9802845	1.217359	-0.237075	0.086741
Leverage ratio	-0.0135749	-0.0159216	0.0023466	0.001418
Size	-0.867837	-0.7499349	-0.1179022	0.026526
Scheme beneficiaries	0.6359755	0.6930234	-0.0570479	0.06097
GDP growth rate	-1.186332	-0.9126453	-0.2736863	0.038696
Inflation rate	3.839961	3.444918	0.3950426	

Prob>chi2 = 0.0000

5.5 Conclusion

This study assessed the relationship between market structure, efficiency and medical scheme performance in South Africa for the period 2011 and 2017. Through empirically assessing the SCP and ES hypotheses on South African medical schemes, this study offers an understanding on medical scheme behaviour in both the markets for open and restricted medical schemes with could assist in informing regulatory and competition policies. The empirical evidence reveals that both the SCP and ES hypotheses can be rejected in relation to South African medical schemes. The empirical evidence reveals support for differing hypotheses for open and restricted medical schemes. Moreover, the empirical evidence suggests that the market for restricted medical schemes is highly concentrated and operating under a reduced efficiency level which produces less than desirable outcomes. Given this, policy should be formulated to deconcentrate this market and improve efficiency outcomes.

In regard to open medical schemes, the empirical results reveal strong support for the RMP hypothesis which suggests that medical schemes with more differentiated product and/or service offerings will achieve higher market share, be in a position to exercise market power and thus able to set higher prices and earn higher profits. Given this, policymakers should focus on policies which would encourage competition and aim at deconcentrating the market for open medical schemes as it too appears to be highly concentrated, with market power at the hands of a few medical schemes. This will prevent prices at higher than competitive levels, low levels of quality product and/or service offerings and a less competitive market structure.

6 Chapter Six: Competition and Efficiency in South African Private Medical Scheme Markets

6.1 Introduction

One of the findings of the Competition Commission's Health Market Inquiry (HMI) is that South African medical schemes are operating in uncompetitive market structures. In arriving at this conclusion, the HMI relies on the limited change in market shares over time. Indeed, the HMI finds that consistently high market shares for some medical schemes and high levels of concentration exist for both open and restricted medical schemes (HMI, 2018). This uncompetitive market structure has the potential to lead to undesirable outcomes for consumers.

The South African private medical scheme industry consists of two types of medical schemes. Open medical schemes, where anyone is allowed to join and restricted medical schemes where inclusion is restricted to a select group of individuals of a particular industry or organisation or members of a certain professional association union. According to the HMI (2018), open and restricted medical schemes compete in distinct separate markets. Moreover, the HMI (2018) have found that both open and restricted medical schemes are dominated by single large medical schemes. In the open medical scheme market, Discovery Medical Scheme has consistently been the most dominant scheme in terms of market shares. Similarly, Government Employees Medical Scheme (GEMS) has been the most dominant scheme in the restricted medical scheme market.

According to Hicks (1935), market power leads to fewer managerial efforts to manage efficiencies. This hypothesis is referred to as the Quiet Life hypothesis and postulates that firms that possess market power and operate in highly concentrated markets will tend to limit competition and operate under a reduced efficiency level (Hicks, 1935). Alternatively, Demsetz (1973) postulates a positive relationship between market concentration and efficiency. This hypothesis is referred to as the efficient structure hypothesis and postulates that market concentration is a result of competition from firms with low-cost structures that are able to increase profits by reducing their prices (Smirlock, 1985).

Interestingly, there have been new methods of assessing competition which move away from relying on traditional approaches such as market share and market concentration. These methods, referred to as the New Empirical Industrial Organization Paradigm rely on non-structural approaches of assessing competition. These new measures of assessing competition have arisen from the fact that criticisms and doubts exist on the reliability of the traditional structural measures of competition. More so, as a response to the shortcomings of the more traditional structural approach, non-structural measures of competition have been recently introduced.

These tools aim to directly assess the direct conduct of firms. The first generation of these tools is based on economic oligopoly theory and a static model of competition, whereas recently developed non-structural measures of competition rely on capturing the competitive dynamic of a particular market. Existing literature identifies two concepts of competition, competition as a static state and competition as a process of rivalry. Accordingly, earlier theory on competition suggested that the result of perfect competition is a static state whereby firms are not able to charge over the competitive prices and therefore earn abnormal profits. In this state, perfect competition is a situation whereby prices equal the cost of production. Moreover, a few assumptions are required in order to achieve perfect competition, these are, (i) Free entry and exit within a market; (ii) A good number of competitors within a market; and (iii) Competitors which have common knowledge about market opportunities.

This static view on competition was however challenged by the Austrian school of thought which believed that competition is not static but rather a dynamic process. In this regard, competition is seen to be a complex process of rivalry among firms, as competitors are continuously engaged in dynamic competitive processes of creating and developing new products and processes for the purpose of coping with competition. This competitive process acts as a selection mechanism whereby less efficient firms are removed and replaced by more efficient firms. Given this view on competition, a competitive market would be one where competitors are effective in giving the incumbent an incentive to lower prices, improve quality and be more efficient in order to still maintain its advantages.

Moreover, the lack of effective competition has direct implications on the level of efficiencies. For the most part, microeconomic theory suggests that efficiencies will be positively correlated

with the level of competition. A lack of effective competition may imply an inefficient industry in terms of productive, technical and allocative efficiencies. Indeed, existing literature suggests that markets with high levels of competition will lead to firms being more productive and efficient (Chang and Gurbaxani, 2013). This efficiency gain is a result of the competitive pressures from rival firms that force firms to adopt best efficient practices in order to compete and survive (Chang and Gurbaxani, 2013).

The purpose of this chapter is therefore to present the assessment of competition and efficiencies in South Africa's private medical scheme markets using New Empirical Industrial Organization tools. The rest of this chapter is structured as follows: Section 6.2 discusses the literature which outlines the hypotheses regarding market structure and performance. Section 6.3 outlines the estimation methodology and the conditions needed to test each hypothesis as well as identifying the data used. Section 6.4 presents the empirical results and the discussion of those results. Section 6.5 concludes the chapter.

6.2 Literature Review

6.2.1 Structural approaches

Traditionally, economists and researchers have opted to utilise structural approaches in attempts to assess competition. The use of the structure-conduct-performance (SCP) paradigm and concentration measures were the tools used earlier on. Indeed, the SCP paradigm, which was developed by Mason (1939) and Bain (1965), attempted to assess the conduct and performance of firms in regard to the structural characteristics of the markets in which they operate. The structural characteristics of a market can be understood as the number of firms within that market in addition to their absolute and relative size. Further, the extent of product differentiation and the extent of the entry and exit conditions can be used to determine the structure of a particular market.

Firm conduct can be understood as the pricing strategies, collusion and other forms of strategic decisions undertaken by firms in a particular market. Accordingly, the conduct of firms is influenced by the market structure which has an influence on market performance. The SCP paradigm postulates that the more concentrated a particular market is, the easier it is for firms within that market to operate in an uncompetitive manner (Bain, 1965).

Advocates of the SCP paradigm suggest that the competitive features of a particular market can be inferred from its structural characteristics. Empirical work to determine market structure has relied on estimating the number of firms in a market as well as their relative size in order to determine market concentration. Given this, economists and researchers commonly use three measures of concentration, namely (i) The total number of firms with a particular market; (ii) Concentration ratios; and (iii) The Herfindahl-Hirschman index (HHI).

In determining market concentration, the easiest method would be to count the number of firms within a particular market. The issue with this approach, however, is it would fail to consider the distribution of firms within a market. It is common to find that the level of concentration between two markets with the same number of firms would be different if one industry is dominated by one firm, while another market has firms with the same size (Léon, 2015).

As a result of this, economists and researchers have developed concentration ratios which are based on market shares of the top firms. Concentration ratios measure the concentration of a particular market by employing the following equation:

$$CR_k = \sum_{i=1}^{k} s_{i,} \quad with\ s_1 \geq \cdots \geq s_k \geq s_N, \forall N \geq K$$

Where $s_{i,}$ illustrates the market share of firm i, where firms are ranked from largest to smallest in order of market share. Further, N represents the total number of firms. Concentration ratios approach zero for an infinite number of equally sized firms and will equal one if the firms in the estimation make up the entire market.

The most commonly used concentration measure is the Herfindahl-Hirschman index. The HHI requires more data than the concentration ratios as it needs data on the entire firm size distribution of a particular market. The following equation is used to calculate the HHI:

$$HHI = \sum_{i=1}^{N} s_i^2, \ \forall i = 1, \dots, N$$

Where N represents the total number of firms within a particular market. Accordingly, the HHI ranges between $\frac{1}{N}$ and 1.

Concentration measures are popular as they require minimum data in order to be calculated. This is helpful in developing countries where data is hard to come by. Moreover, the SCP paradigm has been heavily criticised. There is existing literature which questions the theoretical underpinnings of the SCP paradigm and its associated concentration measures. According to the SCP paradigm, an increase in concentration is seen as an increase in collusive opportunities amongst firms and therefore would lead to higher prices. However, alternative theories go against the SCP paradigm in regard to the linkage between structure and conduct. Indeed, in a market characterised as a duopoly, price competition can still be effective as the Bertrand equilibrium is a possible outcome (Léon 2015).

Further, according to Baumol et al. (1982), a concentrated market can still behave competitively provided that barriers of entry and exit are low. The potential of new entrants can exert competitive pressure on existing market participants. More so, Bernheim and Whinston (1990) postulate that collusive strategies can be sustained in the presence of many firms through multimarket contacts which increase the incentive for collusion by altering the relative costs and benefits of cooperating.

In addition to the above, other studies have showed that not only is the linkage between structure and conduct in question, but also question the direction of the causality. Demsetz's (1973) Efficient Structure (ES) hypothesis postulates that the structure of a particular market reflects efficiency rather than competition. This school of thought suggests that firms that are able to achieve higher efficiencies are able to obtain higher market share which leads to higher market concentration. Given this, it can be understood that concentration indices are not in fact exogenous but potentially reflect differences in terms of efficiencies.

6.2.2 New Empirical Industrial Organization (Non-structural approaches)

The shortcomings of the structural approach have led to the development of new non-structural empirical tools that are used to assess competition. These new tools are referred to as the New Empirical Industrial Organization (NEIO) and include a variety of new methodologies which directly assess competition (Léon, 2015). The primary function of these NEIO methodologies is measuring competition through quantifying the competitive behaviour of firms, rather than measuring the level of competition by assessing the level of competition. The most commonly employed NEIO methodology is the Panzar and Rosse (1987) model which is briefly explained

in Section 6.2.2.1 below. This approach directly quantifies the competitive behaviour of firms and determines whether the witnessed behaviour is consistent with conditions of monopoly, monopolistic competition or perfect competition.

6.2.2.1 Panzar-Rosse model

The Panzar-Rosse model developed by Rosse and Panzar (1977), Panzar and Rosse (1982), and Panzar and Rosse (1987) is an indicator which captures the transmission of input prices on firms' revenues. A weak transmission indicates the exercise of market power in pricing whereas higher transmission suggests higher competition. In a monopolist market, marginal costs will equal marginal revenue at the equilibrium. Should input prices increase, this should be followed by corresponding marginal cost increases. In order to maintain the equilibrium between marginal cost and marginal revenue, it is assumed that the monopolist will increase marginal revenue by reducing quantity.

Rosse and Panzar (1977) indicate that total revenue will be reduced in the situation where the price elasticity of demand is greater than one. Indeed, an increase in marginal costs will reduce quantity but in turn increase output price. Should demand elasticity be greater than one, the gain as a result to price increases will not compensate for the loss due to the reduction in quantity. However, in a competitive setting, an increase in input prices will lead to an increase in total revenue as cost functions are assumed to be homogenous to a degree of one in the input prices. Thus, an increase in input prices will generate an equal percentage increase in costs.

According to Rosse and Panzar (1977), a firm's revenue will change by the same percentage as its total cost, and the same percentage as its input prices ensuring the zero-profit condition. It is understood that an increase of one percent in input prices leads to an increase of one percent of total revenue in competitive markets. Given this, it is possible to determine the competitive conditions of a market by estimating the sum of revenue elasticities with respect to all input prices. The sum of elasticities, referred to as the H-statistic can range from $-\infty \; to \; +1$. Indeed, the higher transmission of cost changes into revenue changes, the more competitive the market is.

6.3 Empirical Review

A vast number of studies employ the Panzar-Rosse model in order to assess competition. The majority of these studies are in the banking industry. One of the first studies to employ the Panzar-Rosse model in assessing competition was the work of Nathan and Neave (1989). The authors employed the Panzar-Rosse model in order to assess competition in Canada's financial system. Using cross-sectional data from 1982 to 1984, the authors found evidence which suggested that Canada's financial system did not resemble conditions of monopoly power over the sample period.

Molyneus et al. (1994) used the the Panzar-Rosse model in order to test the competitive conditions of European Commission banking markets for the years 1986 to 1989. The authors found evidence suggesting that for banks operating in the countries France, Germany, Spain and the United Kingdom, revenues earned indicated conditions of monopolistic competition. In addition, the authors found that banks operating in Italy were operating under conditions of monopoly power. Further, the authors found that under the sample period, no change in market conditions were found.

Similarly, the work of Bikker and Groenveld (1998) utilised the Panzar-Rosse model to assess the competitive conditions of the European Union (EU) banking industry for the years 1989 to 1996. The authors found evidence that suggested that banks operating in the EU banking industry during the sample period did not exhibit monopoly behaviour but instead revealed conditions of monopolistic competition.

Bandt and Davis (2000) employed the Panzar-Rosse model in order to assess the competitive conditions of the European banking industry as well to assess the effect of the Economic and Monetary Union (EMU) on the market conditions. Using a panel analysis for the years 1992 to 1996, the authors found evidence indicating that banks operating in France and Germany exhibited conditions of monopolistic competition for large banks and conditions of monopoly for small banks. In Italy, the authors found evidence of monopolistic competition for both large and small banks.

Bikker and Haaf (2002) employed the Panzar-Rosse model in order to test the competitive conditions and the market structure of the European banking industry for the years 1988 to

1998. The authors found evidence indicating that banks in the European banking industry, for the most part, operated in monopolistic competitive conditions whereas some were found to be operating under conditions of perfect competition over the sample period.

Claessens and Laevern (2004) employed the Panzar-Rosse model in order to assess the competitive conditions of the banking systems of 50 countries spread across the world for the period 1994 to 2001. Using bank-level data obtained from the database '*BANKSCOPE*', the authors found evidence indicating that greater foreign bank presence and lesser activity restrictions resulted in more competitive banking systems. Further, the authors found that entry restrictions on commercial banks resulted in reduced competition.

In regards to insurance markets, Coccorese (2010) used the Panzar-Rosse model to empirically test the competitive conditions of the Italian car insurance market for the years 1998 to 2003. Using the net claims and net commission expenses as proxies for input prices and premium revenue and investment income as proxies for revenues, the author found that car insurance firms, for the most part, operated under conditions of monopoly under the sample period.

Another study that employed the Panzar-Rosse model in insurance markets was the work of Jeng (2015). In this instance, the author used the Panzar-Rosse model in order to assess the competitive conditions of the Chinese life and property-liability insurance industry for the period 2001 to 2009. Using the labour price, the fixed capital price and the capital price as proxies for input prices and the ratio of revenue to total assets as well as the ratio of premiums to total assets as proxies for the dependent variables, the author found evidence indicating that for the period 2001 to 2002, the Chinese life insurance market was operating under conditions of monopoly whereas from the year 2003 to 2009, the Chinese life insurance market was operating under conditions of monopolistic competition. In addition, the author found evidence indicating that the property-liability insurance market was operating under conditions of monopoly for the entire sample period.

In the African context, Alhassan and Biekpe (2015) employed the Panzar-Rosse model in order to assess the competitive conditions of South African non-life insurance firms for the years 2007 to 2012. Using the price of labour, debt and equity capital as input prices and two separate dependent variables, namely premiums and total revenues, the authors found that South African

non-life insurance firms were operating under conditions of monopolistic competition during the sample period.

6.4 Methodology

6.4.1 Measuring efficiencies

The subsections below briefly discuss the methodologies used to measure efficiencies. Economic efficiency entails a comparison of actual performance against optimal performance located on the relevant efficiency frontier. The actual true frontier is unmeasurable and therefore an empirical approximation is used. This empirical approximation is termed as the 'best-practice frontier'. Below are two of the most used approaches in estimating the 'best-practice' frontiers, namely the DEA approach and the SFA approach.

6.4.1.1 Data envelopment analysis

The DEA approach seeks to estimate the relative performance of firms by comparing the multiple inputs and outputs employed and produced by firms in order to estimate relevant efficiency scores. These efficiency scores are estimated by the ratio of the weighted sum of outputs to the weighted sum of inputs. The DEA approach seeks to assess a set of firms, referred to as decision-making units (DMUs), for purposes of identifying efficient DMUs from inefficient DMUs. To do so, the DEA approach uses a range of inputs and outputs through linear programming in order to establish a frontier of efficient DMUs and envelops inefficient DMUs (Dyson & Shale, 2010).

The DEA approach is based on the Farrell Efficiency measure which was developed by Farrell (1957) and that can be seen as the inverse of the Shephard (1953) distance function. Therefore, the efficiency frontier can be illustrated as:

$$F^t(y_i^t, x_i^t) = [D^t(y_i^t, x_i^t)]^{-1} = \min [\lambda_i^t : \lambda_i^t x_i^t \epsilon L^t(y^t)] \qquad (6.1)$$

Where $D^t(y_i^t, x_i^t)$, the distance function, illustrates 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. Further, it is understood that the efficiency measure will take up a value of 1 for efficient firms which will be on the efficiency frontier, and between 0 and 1 for less efficient firms off the frontier.

For further illustration, 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 $(M \times N)$.

Considering 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:

$$\begin{aligned} & Min_{\theta,\lambda^{\lambda}} \\ & subject\ to\ \ -y_i + Y\lambda\ \geq 0 \\ & \qquad\qquad \theta x_i - X\lambda \geq 0 \\ & \qquad\qquad N1'\lambda = 1 \\ & \qquad\qquad \lambda \geq 0 \end{aligned} \tag{6.2}$$

Where $N1$ illustrates $(N \times 1)$ vector of ones and λ can be understood as $(N \times 1)$ vector of constants. Furthermore, it is suggested that the linear programming problem 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).

6.4.1.2 Bootstrapping data envelopment analysis

The main drawback of employing the DEA approach is found in the fact that it does not account for statistical noise or random error (Assaf and Matawie, 2010). This is due to the fact that the DEA approach employs linear programming which is a non-statistical approach to estimate efficiency frontiers. Given this, it is understood that the inefficiency scores and the envelopment surface obtained from the DEA approach are calculated and not statistically estimated (Assaf and Matawie, 2010).

Therefore, the DEA approach alone is unable to determine the accuracy of the efficiency scores or provide statistical foundations for the estimated frontier. To address this limitation, this study employed the bootstrapping approach developed by Simar and Wilson (1998) and Simar and Wilson (2000). The bootstrapping approach estimates the population distribution of the DEA efficiency scores which allows hypothesis testing on the efficiency scores (Assaf and Matawie, 2010). Below is a brief description of the bootstrapping methodology.

Simar and Wilson (1998) developed a DEA-bootstrapped methodology based on a variable return to scale (VRS) assumption. Under this approach, bootstrapping involves employing a random selection of thousands of pseudo samples from the observed set of sample data (Simar and Wilson, 1998). These pseudo estimates are then derived from each of these samples. These aforementioned pseudo estimates form an empirical distribution which is used as approximation of the true underlying sampling distribution of the estimator.

For clear illustration, consider a random sample depicted as $X = (X_1, X_2, \dots, X_n)$ from a population with the unknown distribution function F. The primary objective would be the estimation of the sampling distribution of a distribution function of some pre-specified random variable in the form $R(X, F)$ by employing a real dataset x, whereby $x = (x_1, x_2, \dots, x_n)$ and symbolises the observed realisation of $X = (X_1, X_2, \dots, X_n)$.

Therefore, the first step of the bootstrapping procedure is the construction of a sample probability distribution in the form of $\hat{F}$, by employing $1/n$ at each point in the observed sample $x_1, x_2, \dots x_n$. After the first step, a random sample is drawn with a replacement from $\hat{F}$ where $\hat{F}$ is fixed at its observed value. This results in the following sample $X^* = (X_1^*, X_2^*, \dots, X_n^*)$ and is defined as the bootstrap sample $X_i^* = x_i^*, X_i^* \sim_{ind} \hat{F}, i = 1,2, \dots, n$. This suggests that the distribution of the random sample is approximated by the bootstrap distribution of $R^* = R(X^*, \hat{F})$. To apply the bootstrapping procedure to nonparametric analysis, Simar and Wilson (1998) employed the algorithm outlined below.

Simar and Wilson (1998) began by defining a production set as follows:

$$\psi = \{(x, y) \in R_+^{p+q} | x \; can \; produce \; y\} \tag{6.3}$$

Which outlines the amount of p inputs x that can produce q outputs y. This implies that for a given level of output y, the level of inputs x that can make it possible can be defined by the following:

$$X(y) = \{x \in R_+^p | (x, y) \in \psi\} \tag{6.4}$$

Where the efficient production limit can be derived as a subset of $X(y)$ where:

$$\partial X(y) = \{x | x \in X(y), \theta x \notin X(y), \forall \theta \in (0,1)\} \tag{6.5}$$

Which implies that it may not be plausible to achieve more output with a given level of input. Given the fact that DEA input-orientated efficiency measure can be derived as $\theta_i = \min\{\theta|\theta x_i \in X(y_i)\}$, $\theta_i = 1$ will mean that the unit (x_i, y_i) is fully efficient. It is also believed that the following sets ψ, $X(y)$ and $\partial X(y)$, are unknown suggesting that for any given unit, θ_i will be also unknown.

This suggests that if it is assumed that some data generating process (DGP), P, will generate a random sample $X = \{(x_i, y_i)|i = 1, \dots, n\}$ of n homogenous firms. $\hat{\theta}_i$ can thus be derived as the following:

$$\hat{\theta}_i = \min\left\{\theta|y_i \leq \sum_{i=1}^{n} \lambda_i y_i, \theta_{xi} \geq \sum_{i=1}^{n} \lambda_i x_i, \sum_{i=1}^{n} \lambda_i = 1\right\} \tag{6.6}$$

These approximate efficiency scores can then be employed in the bootstrapping procedure in order to achieve pseudo-samples of the efficient input vectors as shown below:

$$\hat{x}^{\partial}(x_i|y_i) = \hat{\theta}_i x_i \tag{6.7}$$

Where $\hat{x}^{\partial}(x_i|y_i)$ illustrates the level of inputs that a firm should seek to achieve in order to be on the DEA efficiency frontier. In order to do so, a random sample in the form of $\theta_i^*, i = 1, \dots, n$ with a replacement from $(\hat{\theta}_1, \dots, \hat{\theta}_n)$ and $i = 1, \dots, n$. The bootstrap inputs can then be derived as follows:

$$x_i^* = \frac{\hat{\theta}_i}{\theta_i^*} x_i \tag{6.8}$$

The bootstrapped inputs are then used in the DEA methodology in order to achieve bootstrap estimated of the efficiency scores, $\hat{\theta}_i^*$. This procedure is repeated B times in order to arrive at the sampling distribution for θ_i, which will be further employed to estimate the bias and to conduct inference on the DEA efficiency scores.

Important to consider is the fact that the nature of the DEA efficiency scores will lead to certain complications on the bootstrapping process. This is a result of the empirical distribution $\hat{F}$ of $\hat{\theta}$ which provides inconsistent estimates of the true density function F. Given that the efficiency scores are limited to 0 and 1, the empirical distribution will be discontinuous on this interval and will therefore lead to inconsistences in the bootstrap measurements.

To address this issue, Simar and Wilson (1998) advocate for the use of a smoothed bootstrapping procedure by employing a Gaussian kernel density estimator in order to obtain $\hat{F}$ as F is seen to be bound at 1. This leads to the following algorithm as discussed in Simar and Wilson (1998, 2000).

Step One – DEA efficiency scores are calculated by employing VRS DEA.

Step Two – DEA efficiency scores are calculated by employing constant returns to scale (CRS) and non-increasing return to scale (NIRS) in order to show the nature of return to scale (RTS) for the differing operations. RTS is calculated through dividing the bootstrapped results from the CRS assumption by the bootstrapped results from NIRS assumption as advocated by the work of Lothgren and Tambour (1999).

Step Three – The smoothed bootstrapping procedure is then employed in order to generate $\theta_i^*, i = 1, \dots, n$ with replacement from $(\hat{\theta}_1, \dots, \hat{\theta}_n)$, which yields $(\theta_{1b}^*, \theta_{2b}^*, \dots, \theta_{nb}^*)$, where b is the b-th iteration of the bootstrap.

Step Four – The bootstrap inputs are calculated which are given by $x_{ib}^* = (\hat{\theta}_i / \theta_{ib}^*) x_i$.

Step Five – The bootstrapped inputs are employed in order to obtain the DEA-bootstrap estimates of the efficiency scores $\hat{\theta}_{ib}^*$.

Step Six – Steps one to five are repeated B times in order to generate a set of estimates in the form $\{\hat{\theta}_{ib}^*, b = 1, \dots, B\}$.

Step Seven – The mean of the bootstrap estimator is then employed as an approximation in the DEA estimator which is not being bias free. The bootstrap estimate of the DEA estimator bias can be derived as follows:

$$\hat{bias}_i = \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_{ib}^* - \hat{\theta}_{in} \tag{6.9}$$

Where the right-hand side term illustrates the mean of the bootstrap efficiency score and the second represents the original DEA estimate of the efficiency score. More so, confidence intervals are approximated by employing the empirical distribution of θ_{ib}^*.

6.4.1.3 Stochastic frontier analysis

In addition to DEA approach discussed above, this study also used a stochastic production frontier model similar to that of Battese and Coelli (1995) and Ogloblin (2011) to estimate technical efficiency. This model was illustrated as follows:

$$y_{it} = x'_{it}\beta + v_{it} - u_{it} \quad (6.10)$$

Where y_{it} illustrates 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.

Furthermore, the production inefficiency for medical scheme i at time t, can be derived by the following equation:

$$u_{it} = z_{it}\delta + w_{it} \quad (6.11)$$

Where w_{it} illustrates the random variable which is 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.

Moreover, the technical efficiency of production for the '*i-th'* medical scheme at '*t-th'* observation can be illustrated by the following equation:

$$TE_{it} = \exp(-U_{it}) = \exp(z_{it}\delta - W_{it}) \quad (6.12)$$

6.4.1.4 Input and output variables

As a result of the services offered 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 were Non-Relevant Healthcare Expenses, Total Equity and Total Liabilities.

In regards to the output variable, this study followed the suggestions of the existing literature and used both Net Contribution Income, which is the net premiums paid by members and Net

Relevant Healthcare Expenses which are medical schemes' net claims incurred. According to Eling and Luhnen (2010), there is inconclusive evidence regarding the best proxy for output variables. Given this, the DEA efficiency scores were estimated using both Net Contribution Income and Net Relevant Healthcare Expenses as the output variables. Similarly, the SFA efficiency scores were estimated using Net Contribution Income which is identified as Model One and Net Relevant Healthcare Expenses which is identified as Model Two.

6.4.2 Measuring competition: Panzar-Rosse H-statistics

In order to measure competition, this study employed the Panzar and Rosse (1987) H-statistic which assesses the pricing behaviour of South African private medical schemes. The Panzar and Rosse model is a reduced-form revenue equation which assesses the elasticity of firm revenues to changes in input prices. The H-statistic is considered as the sum of elasticities of revenue with respect to input prices (Nathan and Neave, 1989).

The standard Panzar-Rosse regression model used to estimate the H-statistic is commonly referred to as a reduced-form revenue equation which can be illustrated by the following:

$$logTR_{it} = \alpha_0 + \sum_{i=1}^{n} \beta_i \, logw_{it} + \sum_{i=1}^{n} \gamma_i log\, z_{it} + \varepsilon \tag{6.13}$$

Where TR_{it} represents a firm's revenue at time 't', w_{it} represents a vector of a firm's input prices at time 't', z_{it} illustrates a vector of control variables that affect a firm's revenue and ε illustrates the error term. Given this, in order to assess competition within the private medical scheme industry, the following revenue reduced form equation is estimated:

$$lnTR_{it} = \alpha + \beta_{1lnP1_{it}} + \beta_{2lnP2_{it}} + \beta_{3lnP3_{it}} + \beta_{4lnBE_{it}} + \beta_{5lnLEV_{it}} + \varepsilon_{it} \tag{6.14}$$

Where $lnTR$, the dependent variable, represents medical scheme revenue which is proxied by net premiums. The input prices $lnP1$, $lnP2$ and $lnP3$, are the natural logs of the input price of labour,[12] the input price of capital[13] and the input price of debt[14] respectively. More so, the

[12] This is proxied by non-healthcare expenses which includes staff and administration costs.
[13] This is proxied by medical scheme total equity.
[14] This is proxied by medical scheme total liabilities.

number of medical scheme beneficiaries ($lnBE$) and the leverage ratio ($lnLEV$) are used as control variables.

A number of studies in the literature include total assets as one of the control variables. However, Bikker et al. (2009) suggested that this inclusion will lead to a positive H-statistic even in cases where the market in question is operating under conditions of monopoly. According to Bikker et al. (2009), the inclusion of total assets as a control variable contradicts the principles of the Panzar-Rosse model as this inclusion implies that output is held constant, which suggests that the model will fail to allow for output adjustments by the monopolist given the responses to the increase in input prices. Moreover, the exclusion of total assets is supported by the work of Goddard and Wilson (2009) which conducted a Monte Carlo simulation exercise which revealed that the inclusion of total assets as a control variable results in the upward shift of the H-statistic. Given this, total assets as control variable is not included in the model.

Further, the summation of β_1 to β_3 ($\beta_1 + \beta_2 + \beta_3 = H$) is the estimated H-statistic. An estimated H-statistic which is less than or equal to zero ($H \leq 0$) will suggest a monopolistic market. In competitive markets the estimated H-statistic will be greater or equal to one ($H = 1$), implying that changes in production costs are proportional to changes in input prices. Further, a monopolistic competitive market will be captured by an H-statistic value which lies between zero to 1 ($0 < H < 1$).

Furthermore, for the H-statistic to be considered valid it should be tested on the long-run equilibrium (Nathan and Neave 1989). In order to do so, this study followed the work of Khan et al. (2013) and Molyneux et al. (1994) and used the equilibrium test by estimating the Panzar and Rosse H-statistic by replacing the dependent variable total revenue with the natural log of return on assets as shown below:

$$lnROA_{it} = \alpha + \beta_{1lnP1_{it}} + \beta_{2lnP2_{it}} + \beta_{3lnP3_{it}} + \beta_{4lnBE_{it}} + \beta_{5lnLEV_{it}} + \varepsilon_{it} \quad (6.15)$$

The above equation is introduced in order to test the conclusions of the Panzar-Rosse model under assumptions of long-run equilibrium. According to Nathan and Neave (1989), in the long-run, input prices are assumed not to be correlated with the rate of returns. Given this, the long-run condition is tested by replacing the dependent variable with return on assets. Should input prices be equal to zero, i.e. $E = \beta_1 + \beta_2 + \beta_3 = 0$, it is believed that an industry is in

long-run equilibrium. Conversely, should $E \neq 0$, the industry is believed to be in long-run disequilibrium.

In addition to the above, this study attempted to assess the relationship between competition and efficiency. To do so, the efficiency frontier was estimated using data envelopment analysis which is a non-parametric technique. This allowed for the estimation of efficiency scores which were incorporated to equation 6.14 and 6.15 above to yield the following equation:

$$lnTREV_{it} = \alpha + \beta_{1lnP1_{it}} + \beta_{2lnP2_{it}} + \beta_{3lnP3_{it}} + \beta_{4lnBE_{it}} + \beta_{5lnLEV_{it}} + \beta_{6EFF_{it}} + \varepsilon_{it} \quad (6.16)$$

Furthermore, the equilibrium test had to be recalculated by replacing the dependent variable total revenue with the natural log of the return on assets as shown below:

$$lnROA_{it} = \alpha + \beta_{1lnP1_{it}} + \beta_{2lnP2_{it}} + \beta_{3lnP3_{it}} + \beta_{4lnBE_{it}} + \beta_{5lnLEV_{it}} + \beta_{6EFF_{it}} + \varepsilon_{it} \quad (6.17)$$

Importantly, the work of Goddard and Wilson (2009) reveals that the statistic panel revenue equations illustrated above from equation 6.14 to 6.17 tend to be mis-specified. Given that the dependent variable often depends on its previous values, static panel revenue models will be affected by autocorrelation that arises from the disturbance term. This will then cause the H-statistic to be biased towards zero. To remedy this issue, Goddard and Wilson (2009) advocated that the Panzar-Rosse model be estimated using General Method of Moments (GMM) in a dynamic formulation whereby a lagged dependent variable is included among the explanatory variables. Given this, the above revenue reduced form equations were modelled in a dynamic panel framework which incorporated a lagged term for the dependent variables as illustrated below:

$$lnTR_{it} = \alpha + \beta_1 lnTR_{it-1} + \beta_{2lnP1_{it}} + \beta_{3lnP2_{it}} + \beta_{4lnP3_{it}} + \beta_{5lnBE_{it}} + \beta_{6lnLEV_{it}} + \varepsilon_{it} \quad (6.18)$$

$$lnROA_{it} = \alpha + \beta_1 lnROA_{it-1} + \beta_{2lnP1_{it}} + \beta_{3lnP2_{it}} + \beta_{4lnP3_{it}} + \beta_{5lnBE_{it}} + \beta_{6lnLEV_{it}} + \varepsilon_{it} \quad (6.19)$$

$$lnTR_{it} = \alpha + \beta_1 lnTR_{it-1} + \beta_{2lnP1_{it}} + \beta_{3lnP2_{it}} + \beta_{4lnP3_{it}} + \beta_{5lnBE_{it}} + \beta_{6lnLEV_{it}} + \beta_{7EFF_{it}} + \varepsilon_{it} \quad (6.20)$$

$$lnROA_{it} = \alpha + \beta_1 lnROA_{it-1} + \beta_{2lnP1_{it}} + \beta_{3lnP2_{it}} + \beta_{4lnP3_{it}} + \beta_{5lnBE_{it}} + \beta_{6lnLEV_{it}} + \beta_{7EFF_{it}} + \varepsilon_{it} \quad (6.21)$$

Where TR_{it-1} and ROA_{it-1} represent the lags of private medical scheme revenue and return of assets respectively. Furthermore, the H-statistic for the dynamic model is estimated as follows:

$$H = (\sum_{i=2}^{4} \beta_i)/(1 - \beta_1) \quad (6.22)$$

Furthermore, the table below illustrates a summary of the H-statistic and equilibrium conditions.

Table 6.1: H-statistic and equilibrium condition interpretation

Competitive conditions	
H-statistic ≤ 0	Monopoly
H-statistic = 1	Perfect competition
0 < H-statistic < 1	Monopolistic competition
Equilibrium conditions	
$\boldsymbol{E^{ROA}}$ **= 0**	Equilibrium
$\boldsymbol{E^{ROA}}$ **< 0**	Disequilibrium

Source: Panzar and Rosse (1987) and Nathan and Neave (1989)

6.4.3 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 private medical schemes. This data was subject to the econometric analysis discussed above.

6.5 Empirical Results

6.5.1 Descriptive statistics

Tables 6.2 and 6.3 display the descriptive statistics on the sample data for the period 2011 to 2017. A total of 162 observations were used for open medical schemes whereas a total of 439 observations were used for restricted medical schemes.

Table 6.2: Descriptive statistics for open medical schemes

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
ROA	162	1,96	1,20	0,45	6,03
Technical efficiency	162	0,75	0,05	0,76	1,00
Scale efficiency	162	0,94	0,03	0,82	1,00
Pure technical efficiency	162	0,80	0,06	0,76	1,00
Market share (%)	162	0,04	0,11	0,00	0,56
HHI	162	0,31	0,02	0,27	0,34
CR4	162	0,53	0,01	0,51	0,54
Net Contribution Income	162	3110000000,00	7600000000,00	35500000,00	48700000000,00
Relevant Healthcare Expenses	162	2680000000,00	6440000000,00	32300000,00	41800000000,00
Non-Relevant Healthcare Expenses	162	422000000,00	1080000000,00	5156274,00	5990000000,00
Total equity	162	1100000000,00	2430000000,00	15400000,00	16700000000,00
Total liabilities	162	440000000,00	1170000000,00	1238931,00	8960000000,00
Leverage	162	5,81	5,37	1,60	41,20
Size	162	1540000000,00	3600000000,00	23600000,00	25700000000,00
Scheme beneficiaries	162	210424,70	529855,70	2514,00	2777946,00

Table 6.3: Descriptive statistics restricted medical schemes

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
ROA	439	1,30	0,91	0,13	6,17
Technical efficiency	439	0,47	0,08	0,49	1,00
Scale efficiency	439	0,87	0,03	0,78	1,00
Pure technical efficiency	439	0,55	0,08	0,51	1,00
Market share (%)	439	0,02	0,06	0,00	0,47
HHI	439	0,24	0,01	0,22	0,25
CR4	439	0,51	0,01	0,50	0,52
Net Contribution Income	439	890000000,00	3400000000,00	5127313,00	34700000000,00
Relevant Healthcare Expenses	439	821000000,00	3140000000,00	4316009,00	29800000000,00
Non-Relevant Healthcare Expenses	439	65000000,00	212000000,00	763437,00	1980000000,00
Total equity	439	378000000,00	685000000,00	6607451,00	5450000000,00
Total liabilities	439	103000000,00	293000000,00	759154,00	3080000000,00
Leverage	439	10,37	13,30	0,00	120,30
Size	439	481000000,00	909000000,00	7386833,00	8520000000,00
Scheme beneficiaries	439	62043,69	231639,10	703,00	1853252,00

6.5.2 Regression results

In estimating the results, this study employed four different estimation techniques, namely (i) Pooled OLS; (ii) Random Effects; (iii) Fixed Effects; and (iv) GMM. The results of these estimations are shown in Tables 6.4 to 6.7.

Accordingly, Table 6.4 below reflects the Pooled OLS estimated H-statistic for both open and restricted medical schemes. In regard to open medical schemes, it appears that they are operating in a monopolistic competitive market environment as the estimated H-statistic is equal to 0.79. Restricted medical schemes also seem to be operating in a market characterised by monopolistic competition as reflected by an H-statistic of 0.8. In addition, Table 6.4 shows the Pooled OLS equilibrium test for both open and restricted medical schemes. Accordingly, the results reveal that both open and restricted medical schemes are in long-run disequilibrium as reflected by E-statistics of -0.18 and -0.11 respectively.

Similar results are found when the H-statistic is estimated using random effects. Table 6.5 shows an estimated H-statistic of 0.5 for open medical schemes implying monopolistic competition and 0.3 for restricted medical schemes, suggesting monopolistic competition. Further, according to the equilibrium test, both open and restricted medical schemes are in long-run disequilibrium as reflected by E-statistics of -0.3 and -0.4 respectively.

Similarly, Table 6.6 reveals that estimating the H-statistic using fixed effects leads to conclusions similar to for open medical schemes, the estimated H-statistic is equal to 0.2 suggesting monopolistic competition. More so, in regard to restricted medical schemes, the estimated H-statistic is equal to 0.3 implying monopolistic competition. In addition, the equilibrium test shows that both open and restricted medical schemes are in long-run disequilibrium as reflected by E-statistics of -0.5 and -0.4.

Furthermore, Table 6.7 reveals the estimated H-statistic for both open and restricted medical schemes using GMM. In regard to open medical schemes, the estimated H-statistic is equal to 0.3 suggesting a monopolistic competition. Similarly, in regard to restricted medical schemes, the estimated H-statistic is equal to 0.2 also suggesting monopolistic competition. In addition, the equilibrium test reveals that both open and restricted medical schemes are in long-run disequilibrium as reflected by E-statistics of -0.5 and -0.4 respectively.

Table 6.4: Medical scheme H-statistics pooled OLS

	Open schemes		Restricted schemes	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
Price of labour	0.638***	0.349***	0.539***	0.236***
	(0.0426)	(0.0256)	(0.0488)	(0.0242)
Price of capital	0.198	-0.0505	0.606***	0.0977
	(0.154)	(0.0925)	(0.151)	(0.0750)
Price of debt	-0.0495	-0.483***	-0.312**	-0.447***
	(0.161)	(0.0967)	(0.150)	(0.0742)
Beneficiaries	1.032***	0.00843*	1.060***	0.0521***
	(0.00840)	(0.00504)	(0.0144)	(0.00711)
Leverage	-0.194	-0.513***	-0.542***	-0.508***
	(0.198)	(0.119)	(0.181)	(0.0895)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	3.431***	3.215***	3.038***	2.100***
	(0.380)	(0.228)	(0.393)	(0.195)
H-Statistics	0.786377***	-0.1842556***	0.8338431***	-0.1132816***
	(0.0412778)	(0.0247811)	(0.040772)	(0.0201957)
Observations	162	162	434	434
$Prob >$ F	0.0000	0.0000	0.0000	0.0000
R-squared	0.993	0.953	0.949	0.721

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

Table 6.5: Medical scheme H-statistics random effects

	Open Schemes		Restricted Schemes	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
Price of labour	0.300***	0.162***	0.148***	0.0972***
	(0.0518)	(0.0302)	(0.0220)	(0.0140)
Price of capital	-0.105	-0.270***	0.206***	0.0328
	(0.111)	(0.0645)	(0.0375)	(0.0239)
Price of debt	0.275**	-0.230***	-0.0423	-0.502***
	(0.122)	(0.0708)	(0.0303)	(0.0194)
Beneficiaries	1.013***	-0.000439	0.930***	-0.0494***
	(0.0197)	(0.0116)	(0.0175)	(0.0106)
Leverage	0.238	-0.202**	-0.0986**	-0.516***
	(0.150)	(0.0868)	(0.0420)	(0.0269)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	5.821***	4.311***	7.937***	5.127***
	(0.562)	(0.330)	(0.314)	(0.193)
H-Statistics	0.4693968***	-0.3383768***	0.3116478***	-0.3717735***

	(0.0513351)	(0.0299588)	(0.0252287)	(0.0158906)
Observations	162	162	434	434
$Prob > \chi^2$	0.0000	0.0000	0.0000	0.0000
R-squared	0.9884	0.9280	0.9120	0.5390

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

Table 6.6: Medical scheme H-statistics fixed effects

	Open schemes		**Restricted schemes**	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
Price of labour	0.102*	0.0615*	0.129***	0.0833***
	(0.0562)	(0.0339)	(0.0213)	(0.0133)
Price of capital	-0.0187	-0.240***	0.170***	-0.00204
	(0.104)	(0.0629)	(0.0364)	(0.0228)
Price of debt	0.105	-0.289***	-0.0350	-0.497***
	(0.123)	(0.0744)	(0.0290)	(0.0182)
Beneficiaries	0.867***	-0.0644***	0.888***	-0.0956***
	(0.0397)	(0.0240)	(0.0191)	(0.0120)
Leverage	0.102	-0.244***	-0.0755*	-0.498***
	(0.146)	(0.0881)	(0.0404)	(0.0253)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	9.675***	6.026***	8.726***	5.942***
	(0.946)	(0.570)	(0.327)	(0.205)
H-Statistics	0.1876515***	-0.4678577***	0.2634602***	-0.4159323***
	(0.0676786)	0.0408084	(0.0250745)	(0.015708)
Observations	162	162	434	434
$Prob > \chi^2$	0.0000	0.0000	0.0000	0.0000
R-squared	0.939	0.924	0.958	0.894

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

Table 6.7: Medical scheme H-statistics GMM

	Open schemes		**Restricted schemes**	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
L.ln_TREV / L.ln_ROA	0.0786**	0.0840**	0.138**	0.0421
	(0.0340)	(0.0356)	(0.0671)	(0.0346)
Price of labour	0.0686	0.0500	0.110***	0.0918***
	(0.0596)	(0.0421)	(0.0349)	(0.0220)
Price of capital	0.118	-0.0133	0.105**	-0.0579*
	(0.175)	(0.111)	(0.0491)	(0.0337)

Price of debt	-0.157	-0.583***	-0.00927	-0.480***
	(0.208)	(0.130)	(0.00735)	(0.0134)
Beneficiaries	0.763***	-0.120***	0.783***	-0.128***
	(0.0645)	(0.0310)	(0.0871)	(0.0361)
Leverage	-0.105	-0.551***	-0.000688***	-0.451***
	(0.237)	(0.146)	(0.000207)	(0.0235)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	10.57***	7.350***	7.483***	6.480***
	(1.601)	(0.781)	(0.763)	(0.553)
H-Statistics	0.292998	-0.5460127***	0.2057335***	-0.4464143***
	(0.0949963)	(0.0559778)	(0.0555816)	(0.033776)
Observations	111	111	288	288
$Prob > \chi^2$	0.0000	0.0000	0.0000	0.0000
$Wald\ \chi^2(11)$	8058.42	6172.36	2685.11	13886.66
$\boldsymbol{m1\ p-value}$	0.2552	0.2635	0.1090	0.2970
$\boldsymbol{m2\ p-value}$	0.2025	0.2706	0.2983	0.2581

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

Further, the results found in Tables 6.8 to 6.11 below incorporate DEA technical efficiency scores as an independent variable in the analysis. Similar to the results found in Tables 6.3 to 6.5, these results were estimated using: (i) Pooled OLS; (ii) Random effects; (iii) Fixed effects and (iv) GMM

Table 6.8 shows that, by including efficiencies into the analysis, the Pooled OLS estimated H-statistic for open and restricted medical schemes is equal to 1 implying perfect competition. In addition, the equilibrium test reveals that open medical schemes are in long-run disequilibrium as reflected by an E-statistic score of -0.03. In contrast, restricted medical schemes are in long-run equilibrium as reflected by an E-statistic score of 0.

Contrasting results are found when the H-statistic is estimated using random effects. Table 6.9 below indicates an H-statistic value of 0.9 and 0.6 for both open and restricted medical schemes, suggesting monopolistic competition both open and restricted medical schemes. In addition, the equilibrium test reveals that both open and restricted medical schemes are in long-run disequilibrium as reflected by E-statistic scores of -0.08 and -0.15 respectively.

More so, Table 6.10 which shows the estimated H-statistic for both open and restricted medical schemes using fixed effects reflects similar results. In regard to open medical schemes, the estimated H-statistic is equal to 0.5 suggesting monopolistic competition. Similarly, in regard to restricted medical schemes, the estimated H-statistic is equal to 0.4 also implying monopolistic competition. More so, the equilibrium test shows that both open and restricted medical schemes are in long-run disequilibrium as reflected by E-statistic scores of -0.3 for both open and restricted medical schemes.

Furthermore, Table 6.11 reveals the estimated H-statistic for both open and restricted medical schemes using GMM. In regard to open medical schemes, the estimated H-statistic is equal to 0.2 suggesting monopolistic competition. Similarly, in regard to restricted medical schemes, the estimated H-statistic is equal to 0.3 also suggesting monopolistic competition. In addition, the equilibrium test reveals that both open and restricted medical are in long-run disequilibrium as reflected by E-statistic scores of -0.4 for both open and restricted medical schemes.

Table 6.8: Medical scheme H-statistics pooled OLS with DEA technical efficiencies

	Open schemes		**Restricted schemes**	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
Price of labour	0.776***	0.434***	0.616***	0.276***
	(0.0232)	(0.0129)	(0.0248)	(0.0107)
Price of capital	0.226***	-0.0330	1.058***	0.331***
	(0.0801)	(0.0446)	(0.0777)	(0.0334)
Price of debt	0.0346	-0.431***	-0.619***	-0.606***
	(0.0838)	(0.0467)	(0.0764)	(0.0328)
Beneficiaries	1.027***	0.00496**	1.022***	0.0323***
	(0.00437)	(0.00244)	(0.00735)	(0.00316)
Leverage	-0.113	-0.462***	-1.073***	-0.781***
	(0.103)	(0.0574)	(0.0927)	(0.0398)
DEA technical efficiency	1.240***	0.763***	2.080***	1.073***
	(0.0615)	(0.0343)	(0.0594)	(0.0255)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	0.421*	1.362***	0.965***	1.031***
	(0.248)	(0.138)	(0.208)	(0.0893)
H-Statistics	1***	-0.030094**	1***	0.0008958
	(0.0247926)	(0.0138076)	(0.0215854)	(0.0092812)
Observations	162	162	434	434

$Prob >$ F	0.0000	0.0000	0.0000	0.0000
R-squared	0.998	0.989	0.985	0.946

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

Table 6.9: Medical scheme H-statistics random effects with DEA technical efficiencies

	Open schemes		Restricted schemes	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
Price of labour	0.657***	0.383***	0.278***	0.190***
	(0.0350)	(0.0190)	(0.0234)	(0.0143)
Price of capital	0.114	-0.104**	0.485***	0.236***
	(0.0900)	(0.0522)	(0.0415)	(0.0254)
Price of debt	0.134	-0.364***	-0.162***	-0.581***
	(0.0947)	(0.0547)	(0.0330)	(0.0211)
Beneficiaries	1.029***	0.00597	1.013***	0.0193***
	(0.00823)	(0.00422)	(0.0144)	(0.00721)
Leverage	0.000586	-0.390***	-0.391***	-0.715***
	(0.117)	(0.0679)	(0.0474)	(0.0295)
DEA technical efficiency	0.952***	0.590***	0.646***	0.479***
	(0.0720)	(0.0415)	(0.0473)	(0.0287)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	1.605***	1.888***	4.734***	2.638***
	(0.374)	(0.204)	(0.312)	(0.166)
H-Statistics	0.904486***	-0.0848336***	0.6018353***	-0.1545628***
	(0.0376482)	(0.0205037)	(0.0283192)	(0.0159271)
Observations	162	162	434	434
$Prob > \chi^2$	0.0000	0.0000	0.0000	0.0000
R-squared	0.9976	0.9869	0.9557	0.8584

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

Table 6.10: Medical scheme H-statistics fixed effects with DEA technical efficiencies

	Open schemes		Restricted schemes	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
Price of labour	0.345***	0.206***	0.192***	0.123***
	(0.0585)	(0.0355)	(0.0203)	(0.0127)
Price of capital	0.0702	-0.188***	0.327***	0.0974***
	(0.0890)	(0.0540)	(0.0368)	(0.0230)
Price of debt	0.114	-0.284***	-0.104***	-0.541***
	(0.104)	(0.0633)	(0.0271)	(0.0169)
Beneficiaries	0.946***	-0.0175	0.934***	-0.0666***

	(0.0354)	(0.0215)	(0.0179)	(0.0112)
Leverage	0.0477	-0.276***	-0.244***	-0.605***
	(0.124)	(0.0751)	(0.0406)	(0.0254)
DEA technical efficiency	0.573***	0.340***	0.388***	0.246***
	(0.0804)	(0.0488)	(0.0420)	(0.0263)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	5.691***	3.663***	7.013***	4.857***
	(0.975)	(0.592)	(0.347)	(0.217)
H-Statistics	0.528839***	-0.2655359***	0.414646***	-0.3201867***
	(0.0745548)	(0.0452566)	(0.0278278)	(0.0173858)
Observations	162	162	434	434
$Prob >$ F	0.0000	0.0000	0.0000	0.0000
R-squared	0.957	0.954	0.966	0.915

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

Table 6.11: Medical scheme H-statistics GMM with DEA technical efficiencies

	Open schemes		Restricted schemes	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
L.ln_TREV / L.ln_ROA	0.0578**	0.0563**	0.120*	0.0519
	(0.0255)	(0.0275)	(0.0694)	(0.0321)
Price of labour	0.191***	0.126***	0.138***	0.110***
	(0.0550)	(0.0442)	(0.0361)	(0.0212)
Price of capital	0.114	-0.0473	0.145**	-0.00336
	(0.122)	(0.0795)	(0.0586)	(0.0425)
Price of debt	-0.0792	-0.503***	0.00100	-0.500***
	(0.148)	(0.0919)	(0.0391)	(0.0215)
Beneficiaries	0.827***	-0.0858***	0.816***	-0.109***
	(0.0619)	(0.0264)	(0.0842)	(0.0337)
Leverage	-0.0654	-0.491***	-0.0320	-0.507***
	(0.164)	(0.109)	(0.0636)	(0.0388)
DEA technical efficiencies	0.301***	0.203***	0.157**	0.128**
	(0.0985)	(0.0783)	(0.0638)	(0.0506)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	8.487***	5.844***	6.658***	5.832***
	(1.444)	(0.689)	(0.739)	(0.523)
H-Statistics	0.2252913**	-0.4240072***	0.2840121***	-0.3929447***
	(0.097516)	(0.0513567)	0.0610879	(0.0329446)
Observations	111	111	288	288
$Prob > \chi^2$	0.0000	0.0000	0.0000	0.0000
$Wald\ \chi^2(7)$	6941.23	3778.05	2907.09	8687.06
$\boldsymbol{m1\ p-value}$	0.1691	0.1662	0.0936	0.0850
$\boldsymbol{m2\ p-value}$	0.1821	0.1291	0.4474	0.5347

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

Furthermore, the results found in Tables 6.12 to 6.19 below incorporate SFA technical efficiency scores as an independent variable in the analysis. Similar to the results found in Tables 6.3 to 6.11, these results were estimated using: (i) Pooled OLS; (ii) Random effects; (iii) Fixed effects and (iv) GMM.

Tables 6.12 and 6.13 reveal that, by including the SFA technical efficiency scores into the analysis, the Pooled OLS estimated H-statistics for Model One are equal to 1 for open medical schemes, implying conditions of perfect competition and 0.8 for restricted medical schemes,

implying conditions of monopolistic competition. In regard to Model Two, the H-statistic estimates are 0.9 and 0.7 for both open and restricted medical schemes respectively, implying monopolistic competition. Moreover, the equilibrium test reveals that for both Model One and Model Two, open and restricted medical schemes are in long-run disequilibrium as reflected by E-statistic scores of -0.06, -0.14, -0.11 and -0.15 respectively.

For the most part, similar results are found as above when the H-statistic is estimated using random effects. Tables 6.14 and 6.15 show, by including the SFA technical efficiency scores into the analysis, the Model One estimated H-statistics for open and restricted medical schemes are equal to 0.8 and 0.7 respectively, suggesting monopolistic competition for both open and restricted medical scheme markets. In regard to Model Two, estimated H-statistic scores of 0.8 and 0.7 are found for both open and restricted medical schemes respectively, also implying monopolistic competition. In addition, the equilibrium test reveals that for both Model One and Model Two, open and restricted medical schemes are in long-run disequilibrium as reflected by E-statistic estimates of -0.17, -0.25, -0.2 and -0.3 respectively.

More so, Tables 6.16 and 6.17 reveal that, by including the SFA technical efficiency scores into the analysis, the fixed effects estimated H-statistics for both open and restricted medical schemes are equal to 0.6 and 0.4 respectively for Model One, indicating monopolistic competition. In regard to Model Two, the results show estimated H-statistic scores of 0.8 and 0.6 for both open and restricted medical schemes respectively, also implying monopolistic competition. Further, the equilibrium test reveals that for both Model One and Model Two, open and restricted medical schemes are in long-run disequilibrium as reflected by E-statistic estimates of -0.2, -0.4, -0.3 and -0.4 respectively

Furthermore, Tables 6.18 and 6.19 reveal that, by including the SFA technical efficiency scores into the analysis, the GMM estimated H-statistics for open and restricted medical schemes are equal to 0.4 and 0.3 respectively for Model One, which points to monopolistic competition for both open and restricted medical schemes. In regard to Model Two, the results show estimated H-statistics of 0.3 and 0.2 for both open and restricted medical schemes respectively, also implying monopolistic competition. In addition, the equilibrium test reveals that for both Model One and Model Two, open and restricted medical schemes are in long-run disequilibrium as reflected by E-statistic estimates of -0.42, -0.41, -0.4 and -0.44 respectively.

Table 6.12: Model One medical scheme H-statistics pooled OLS with SFA technical efficiencies

	Open schemes		Restricted schemes	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
Price of labour	0.797***	0.435***	0.503***	0.221***
	(0.0250)	(0.0181)	(0.0185)	(0.0156)
Price of capital	0.102	-0.102*	-0.00783	-0.154***
	(0.0849)	(0.0615)	(0.0587)	(0.0493)
Price of debt	0.102	-0.402***	0.283***	-0.203***
	(0.0889)	(0.0644)	(0.0581)	(0.0488)
Beneficiaries	1.025***	0.00471	1.048***	0.0470***
	(0.00464)	(0.00336)	(0.00545)	(0.00458)
Leverage	-0.0497	-0.435***	0.296***	-0.164***
	(0.109)	(0.0791)	(0.0706)	(0.0593)
SFA technical efficiency	2.762***	1.488***	2.821***	1.157***
	(0.148)	(0.107)	(0.0563)	(0.0473)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	1.967***	2.427***	3.535***	2.304***
	(0.223)	(0.162)	(0.150)	(0.126)
H-Statistics	1***	-0.0690581***	0.7783017***	-0.1360603***
	(0.0254501)	(0.018421)	(0.0155125)	(0.0130269)
Observations	162	162	434	434
$Prob >$ F	0.0000	0.0000	0.0000	0.0000
R-squared	0.998	0.979	0.991	0.885

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

Table 6.13: Model Two medical scheme H-statistics pooled OLS with SFA technical efficiencies

	Open schemes		Restricted schemes	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
Price of labour	0.737***	0.400***	0.494***	0.217***
	(0.0269)	(0.0194)	(0.0233)	(0.0160)
Price of equity	0.202**	-0.0484	-0.00935	-0.163***
	(0.0946)	(0.0683)	(0.0739)	(0.0507)
Price of debt	-0.00923	-0.462***	0.252***	-0.209***
	(0.0989)	(0.0714)	(0.0729)	(0.0501)
Beneficiaries	1.030***	0.00726*	1.042***	0.0444***
	(0.00516)	(0.00372)	(0.00686)	(0.00471)
Leverage	-0.166	-0.498***	0.268***	-0.165***
	(0.122)	(0.0878)	(0.0887)	(0.0609)

SFA technical efficiency	1.467***	0.754***	1.597***	0.676***
	(0.0930)	(0.0671)	(0.0421)	(0.0289)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	2.460***	2.716***	3.843***	2.441***
	(0.241)	(0.174)	(0.189)	(0.130)
H-Statistics	0.9299263***	-0.1104858***	0.7360668***	-0.154665***
	(0.0269243)	(0.0194413)	(0.0195947)	(0.013456)
Observations	162	162	434	434
$Prob >$ F	0.0000	0.0000	0.0000	0.0000
R-squared	0.997	0.975	0.986	0.879

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

Table 6.14: Model One medical scheme H-statistics random effects with SFA technical efficiencies

	Open schemes		**Restricted schemes**	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
Price of labour	0.637***	0.327***	0.402***	0.178***
	(0.0371)	(0.0263)	(0.0244)	(0.0161)
Price of capital	-0.0400	-0.231***	0.278***	0.0629**
	(0.0799)	(0.0556)	(0.0389)	(0.0247)
Price of debt	0.240***	-0.262***	-0.0156	-0.491***
	(0.0859)	(0.0599)	(0.0333)	(0.0207)
Beneficiaries	1.028***	0.00633	1.018***	-0.00969
	(0.00984)	(0.00714)	(0.0123)	(0.00914)
Leverage	0.135	-0.264***	-0.121***	-0.523***
	(0.106)	(0.0739)	(0.0449)	(0.0282)
SFA technical efficiency	1.845***	0.853***	1.388***	0.453***
	(0.132)	(0.0916)	(0.0736)	(0.0490)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	3.037***	3.018***	4.696***	3.906***
	(0.354)	(0.252)	(0.263)	(0.187)
H-Statistics	0.8369412***	-0.1658265***	0.6647044***	-0.2508918***
	(0.0376785)	(0.0267023)	(0.0255521)	(0.017628)
Observations	162	162	434	434
$Prob >$ F	0.0000	0.0000	0.0000	0.0000
R-squared	0.9969	0.9723	0.9778	0.7559

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

Table 6.15: Model Two medical scheme H-statistics random effects with SFA technical efficiencies

	Open schemes		Restricted schemes	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
Price of labour	0.581***	0.287***	0.313***	0.160***
	(0.0418)	(0.0289)	(0.0251)	(0.0160)
Price of capital	0.0373	-0.205***	0.268***	0.0602**
	(0.0874)	(0.0589)	(0.0389)	(0.0247)
Price of debt	0.174*	-0.280***	-0.0265	-0.494***
	(0.0940)	(0.0635)	(0.0324)	(0.0206)
Beneficiaries	1.034***	0.00889	0.995***	-0.0161*
	(0.0120)	(0.00860)	(0.0148)	(0.00957)
Leverage	0.0804	-0.275***	-0.111**	-0.519***
	(0.116)	(0.0784)	(0.0443)	(0.0281)
SFA technical efficiency	1.140***	0.488***	0.639***	0.251***
	(0.100)	(0.0681)	(0.0522)	(0.0333)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	3.298***	3.215***	5.602***	4.105***
	(0.412)	(0.289)	(0.301)	(0.194)
H-Statistics	0.7923078***	-0.1980631***	0.554566***	-0.2736277***
	(0.0429474)	(0.0298096)	(0.0280148)	(0.0179502)
Observations	162	162	434	434
$Prob > \chi^2$	0.0000	0.0000	0.0000	0.0000
R-squared	0.9962	0.9678	0.9667	0.7333

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

Table 6.16: Model One medical scheme H-statistics fixed effects with SFA technical efficiencies

	Open Schemes		Restricted Schemes	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
Price of abour	0.430***	0.202***	0.244***	0.116***
	(0.0524)	(0.0377)	(0.0221)	(0.0153)
Price of capital	-0.0361	-0.248***	0.194***	0.00489
	(0.0769)	(0.0553)	(0.0322)	(0.0224)
Price of debt	0.209**	-0.244***	-0.0225	-0.494***
	(0.0916)	(0.0658)	(0.0257)	(0.0178)
Beneficiaries	0.970***	-0.0200	0.911***	-0.0889***
	(0.0310)	(0.0223)	(0.0170)	(0.0118)

Leverage	0.150	-0.224***	-0.0841**	-0.501***
	(0.108)	(0.0775)	(0.0357)	(0.0248)
SFA technical efficiency	1.403***	0.601***	0.692***	0.198***
	(0.136)	(0.0981)	(0.0692)	(0.0480)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	5.395***	4.192***	7.497***	5.591***
	(0.813)	(0.584)	(0.314)	(0.218)
H-Statistics	0.6036968***	-0.2895291***	0.4159247***	-0.3723398***
	(0.0642817)	(0.0462105)	(0.0268819)	(0.0186557)
Observations	162	162	434	434
$Prob >$ F	0.0000	0.0000	0.0000	0.0000
R-squared	0.967	0.942	0.967	0.898

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

Table 6.17: Model Two medical scheme H-statistics fixed effects with SFA technical efficiencies

	Open schemes		**Restricted schemes**	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
Price of labour	0.382***	0.168***	0.199***	0.102***
	(0.0587)	(0.0403)	(0.0236)	(0.0154)
Price of capital	0.0210	-0.225***	0.191***	0.00369
	(0.0860)	(0.0590)	(0.0350)	(0.0228)
Price of debt	0.175*	-0.263***	-0.0266	-0.495***
	(0.102)	(0.0699)	(0.0278)	(0.0181)
Beneficiaries	0.983***	-0.0202	0.905***	-0.0911***
	(0.0360)	(0.0247)	(0.0185)	(0.0120)
Leverage	0.126	-0.235***	-0.0766**	-0.499***
	(0.120)	(0.0825)	(0.0386)	(0.0251)
SFA technical efficiency	0.877***	0.333***	0.302***	0.0822**
	(0.113)	(0.0774)	(0.0517)	(0.0336)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	5.414***	4.407***	7.878***	5.712***
	(0.952)	(0.653)	(0.344)	(0.224)
H-Statistics	0.5778762***	-0.3195611***	0.3633674***	-0.3887619***
	(0.0750335)	(0.0514517)	(0.0294239)	(0.0191541)
Observations	162	162	434	434
$Prob >$ F	0.0000	0.0000	0.0000	0.0000
R-squared	0.959	0.934	0.961	0.895

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

Table 6.18: Model One medical scheme H-statistics GMM with SFA technical efficiencies

	Open schemes		Restricted schemes	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
L.ln_TREV / L.ln_ROA	0.0471*	0.0643*	0.134**	0.0357
	(0.0283)	(0.0339)	(0.0633)	(0.0323)
Price of labour	0.315***	0.147***	0.197***	0.118***
	(0.0628)	(0.0466)	(0.0390)	(0.0248)
Price of capital	0.0964	-0.0188	0.0786*	-0.0565*
	(0.143)	(0.0938)	(0.0443)	(0.0331)
Price of debt	-0.0402	-0.550***	0.0397	-0.477***
	(0.164)	(0.111)	(0.0285)	(0.0146)
Beneficiaries	0.873***	-0.0886***	0.801***	-0.123***
	(0.0484)	(0.0312)	(0.0805)	(0.0337)
Leverage	-0.0417	-0.542***	0.0362	-0.452***
	(0.191)	(0.127)	(0.0404)	(0.0240)
SFA technical efficiencies	0.908***	0.367***	0.529***	0.166
	(0.261)	(0.136)	(0.186)	(0.122)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	7.379***	6.082***	6.483***	6.237***
	(1.121)	(0.789)	(0.650)	(0.512)
H-Statistics	0.3711128***	-0.4211601***	0.3151594***	-0.4151386***
	(0.0852693)	(0.0598236)	(0.0602374)	(0.0337886)
Observations	111	111	288	288
$Prob > \chi^2$	0.0000	0.0000	0.0000	0.0000
$Wald\ \chi^2(12)$	29296.62	3463.72	3859.35	13471.37
$\boldsymbol{m1\ p-value}$	0.3998	0.5255	0.0664	0.2906
$\boldsymbol{m2\ p-value}$	0.7502	0.6620	0.7396	0.4682

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

Table 6.19: Model Two medical H-statistics GMM with technical efficiencies

	Open schemes		Restricted schemes	
	Model One (lnTrev)	Model Two (ln ROA)	Model One (lnTrev)	Model Two (ln ROA)
L.ln_TREV / L.ln_ROA	0.0641*	0.0852**	0.130*	0.0424
	(0.0339)	(0.0403)	(0.0681)	(0.0347)
Price of labour	0.262***	0.140***	0.138***	0.0958***
	(0.0612)	(0.0519)	(0.0382)	(0.0237)
Price of capital	0.109	-0.0198	0.0768	-0.0571*

	(0.144)	(0.0935)	(0.0482)	(0.0342)
Price of debt	-0.0397	-0.525***	0.0324	-0.480***
	(0.171)	(0.109)	(0.0296)	(0.0136)
Beneficiaries	0.858***	-0.0765**	0.795***	-0.127***
	(0.0557)	(0.0313)	(0.0860)	(0.0357)
Leverage	-0.0208	-0.509***	0.0410	-0.451***
	(0.194)	(0.124)	(0.0433)	(0.0238)
SFA technical efficiencies	0.550***	0.266***	0.104***	0.0182
	(0.123)	(0.101)	(0.0391)	(0.0344)
Year dummy variables	Yes	Yes	Yes	Yes
Constant	7.448***	5.754***	7.019***	6.430***
	(1.310)	(0.859)	(0.739)	(0.555)
H-Statistics	0.3306515***	-0.4044387***	0.2473013***	-0.4409048***
	(0.09517)	(0.0687535)	(0.0619363)	(0.0366727)
Observations	111	111	288	288
$Prob > \chi^2$	0.0000	0.0000	0.0000	0.0000
$Wald\ \chi^2(12)$	13452.51	8152.44	3278.91	14256.12
$\boldsymbol{m1\ p-value}$	0.1981	0.3268	0.1174	0.2840
$\boldsymbol{m2\ p-value}$	0.3755	0.5332	0.5578	0.2998

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

6.6 Conclusions and Policy Recommendations

This chapter has assessed the relationship between competition and efficiency in South Africa's medical scheme industry. The DEA and SFA approaches were used to estimate the technical efficiency scores of both open and restricted medical schemes for the period 2011 to 2017. In addition, competition was assessed for both open and restricted medical schemes using the Panzar-Rosse model.

The empirical results suggest that for the most part, open medical schemes are operating in conditions of monopolistic competition. Further, by incorporating efficiency in the model, open medical schemes still appear to be operating under conditions of monopolistic competition. In regard to restricted medical schemes, the empirical results reveal the existence of monopolistic competition. Similarly to the open medical scheme market, once efficiency is incorporated in the model, the empirical findings still reveal conditions of monopolistic competition. These findings seem to support the Competition Commission's view that the South African private medical schemes operate in uncompetitive market environments. Given this, policymakers

should formulate policies that will encourage more vigorous competition in both open and restricted medical schemes.

7 Chapter Seven: Conclusions and Policy Recommendations

7.1 Introduction

This thesis has included empirical research papers related to the themes of competition and efficiency within the South African medical scheme industry. More specifically, this research study assessed: (i) the relative efficiencies of South African medical schemes; (ii) the efficiency, returns to scale and productivity of South African medical schemes; and (iii) the competition dynamics of the South African medical industry. This study employed firm-level annual financial data in the empirical analysis. This data covered all the medical schemes which were in operation during the period 2011 to 2017. This translates to 26 open medical schemes and 71 restricted medical schemes. This dataset was obtained from the Council of Medical Schemes.

This thesis is comprised of seven chapters, four of which are empirical studies. The researcher employed different methodologies in order to measure the key concepts and as a result, different conclusions were reached. Chapters One and Two presented the introduction and overview of the South African medical scheme industry. The first empirical topic was in Chapter Three which presented the relative efficiencies of both open and restricted medical schemes that the researcher assessed by employing both the data envelopment analysis and stochastic frontier analysis approaches.

Chapter Four discussed how the researcher had empirically assessed the efficiency, returns to scale and productivity of South African medical schemes. Chapter Five presented the researcher's examination of the competition dynamics within South African medical scheme industry through which he employed traditional structural approaches in the form of the market, conduct and performance paradigm. The last empirical paper was in Chapter Six which presented the non-structural approaches employed in the form of New Empirical Industrial Organization tools in order to further assess the competition dynamics within the South African medical industry. More specifically, the Panzar-Rosse H-statistic was employed to assess the competitive conditions within both open and restricted medical scheme markets. This last

chapter of the thesis summarises the conclusions of the empirical chapters and discusses the policy implications of these conclusions. In addition, this last chapter outlines the key benefits in terms of contributions made to the empirical literature on competition and efficiency in the South African medical scheme industry and also outlines areas for future research.

7.2 Summary of Key Findings

The study first measured the relative efficiency scores of both open and restricted medical schemes by employing both the data envelopment analysis and stochastic frontier analysis techniques over the period 2011 to 2017. The DEA empirical findings suggest that open medical schemes tended to be more efficient than restricted medical schemes in terms of technical, scale and pure technical efficiency over the sample period. The same conclusions were arrived at 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.

The next empirical study examined the efficiency, returns to scale and productivity of South African medical Schemes. Similar to the results in the first empirical study, the empirical results revealed that open medical schemes tend to be more efficient than restricted medical schemes. Indeed, open medical schemes achieved, on average, efficiency scores of 75%, 94% and 80% for technical, scale and pure technical efficiency, respectively. Whereas in regard to restricted medical schemes, on average they achieved efficiency scores of 47%, 87% and 55% for technical, scale and pure technical efficiency, respectively. In regard to the efficiency determinants, the empirical results revealed that restricted medical schemes do not encounter issues of monitoring and control as they grow larger which was in contrast to open medical schemes. In regard to the determinants of scale efficiency, the results revealed that the age of the medical scheme appeared to be inversely related to the probability of a medical scheme operating with constant returns to scale for both open and restricted medical schemes. Furthermore, in regard to efficiency divergence, the empirical results revealed that unconditional β-Convergence exists in both open and restricted medical schemes, implying that both inefficient open and restricted medical schemes have been able to catch up with best-practised medical schemes over the period assessed. However, the empirical results did not reveal evidence of σ-convergence in either the open and or restricted medical scheme markets,

implying that there is no reduction in the variability of efficiency and conversion towards a common level. Overall, the empirical results revealed that there is room for improvement in terms of efficiencies for both open and restricted medical schemes. This is specifically true for restricted medical schemes. In addition, the empirical results seem to support the view that firms with market power, operating in highly concentrated markets, will limit competition and will operate under a reduced efficiency level. The empirical results appear to contradict the view that market concentration is a result of competition from firms that enjoy low cost structures that increase profits by reducing their prices, implying that the better performance achieved from firms which have market power is a result of the efficiencies they enjoy.

The third empirical study aimed to assesses the competition dynamics within the South African medical scheme industry by employing traditional structural approaches. The empirical findings revealed that both the structure-conduct-performance and efficient structure hypothesis can be rejected in relation to South African medical schemes. The empirical evidence further revealed support for differing hypotheses for open and restricted medical schemes. Moreover, the empirical evidence suggests that the market for restricted medical schemes is highly concentrated and operating under a reduced efficiency level which produces less than desirable outcomes. In regard to open medical schemes, the empirical results reveal strong support for the relative market power hypothesis which suggests that medical schemes with more differentiated product and/or service offerings will achieve higher market share, be in a position to exercise market power and thus able to set higher prices and earn higher profits.

The last empirical study also assessed the competition dynamics within the South African medical scheme industry by employing non-structural approaches. The empirical findings suggest that open medical schemes are operating in conditions of monopolist competition. Further, by incorporating efficiency in the model, open medical schemes still appear to be operating in conditions of monopolistic competition. In regard to restricted medical schemes, the empirical results reveal the existence of monopolistic competition. Similar to open medical schemes, once efficiency is incorporated in the model, the empirical findings still reveal conditions of monopolistic competition. These findings seem to support the Competition Commission's view that the South African medical schemes operate in uncompetitive market environments. Importantly, these findings appear to support the findings of the third empirical study which suggested less competitive market structures.

7.3 Policy Implications and Recommendations

The empirical findings of the study have a number of policy implications that are a result of the key themes examined in this study. First, the empirical findings suggest that there is room for improvement in terms of efficiencies for both open and restricted medical schemes. Managerial effort could be improved in this instance in order to seek to reduce resource wastages. This will aid medical schemes in moving closer to their individual optimum capacity. More so, managerial effort should focus on the adoption of new technologies that seek to improve operations and achieve efficiency in resource utilisation. Further, policymakers and regulators should ensure that they have regulations in place which enable medical scheme efficiency as there is room for improvement in terms of efficiency, specifically for restricted medical schemes. This could be achieved by introducing various efficiency measures that medical schemes need to abide by.

Second, the empirical findings reveal that both the open and restricted medical scheme markets are highly concentrated and dominated by single medical schemes respectively. Discovery Health Medical Scheme in the open medical scheme market has enjoyed an average market share of 53% over the sample period, and the Government Employees Medical Scheme has enjoyed an average market share of 46% in the restricted medical scheme market over the sampler period. This suggests a lack of competitive pressure from other competitors within both the open and restricted medical scheme markets. Given this, polices should be formulated which aim at improving the current competitive conditions within both the open and restricted medical schemes. These policies can be in the form of unrestricting membership within restricted medical schemes as the incentive to compete is limited for this type of medical scheme, given that these medical schemes are restricted to certain designated groups of the population. Whereas in contrast, open medical schemes are open to the general South African public. More so, the findings from the third empirical study appear to support the findings of the fourth empirical study in regard to the view that the South African medical schemes operate in uncompetitive market environments Given this conclusion, policymakers should be focused on policies that spur competition in both open and restricted medical scheme markets.

7.4 Limitations of the Study

One limitation of the study is that the findings indicate 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. This comparison is self-evident from the study's findings. However, the study did not delve deeper into the complex terrain of understanding efficiencies within both open and restricted medical schemes. This type of analysis is proposed for future research.

7.5 Contributions and Proposed Future Research

As far as the author is aware, this study is the first comprehensive assessment and empirical analysis of South Africa's medical scheme industry. Given this, the author believes this study makes several contributions to the empirical literature in regard to South African insurance markets. First, the study assessed the relative efficiency scores of South Africa medical schemes. The relevance of this contribution can help measure and evaluate the efficiencies of South African medical schemes and aid in improving industry performance. To the best of the author's knowledge, this study is the first to do so. In addition, this study extends the growing efficiency literature by adopting the growth theory of convergence to assess the relative medical scheme efficiency scores. This can also aid in formulating regulatory policies and improving industry performance. Second, the study assessed the competitive dynamics of the South African medical scheme industry by employing both structural and non-structural approaches in assessing competition. To the best of the author's knowledge, this is the first study to do so in regard to South African medical schemes. The contribution will aid policymakers and regulators in the formulation of appropriate and effective polices as the competition within the medical schemes industry is better understood.

Furthermore, the empirical analysis conducted in this study aims at extending the limited but growing academic literature on insurance markets in South Africa and more generally Africa. This is still an emerging research topic in South Africa and more importantly, Africa. Further studies can be conducted on such aspects which were not addressed in this study. One such study is employing other New Empirical Industrial Organization tools when assessing the competitive dynamics within insurance markets. Tools such as the Lerner index, the Conjectural Variation model and the Boone indicator can also be investigated and used. This would make the comparisons between structural and non-structural approaches to competition more complete.

Appendices

Appendix A: Theoretical Framework

The Economics of Competition

The subsection below outlines the basic theoretical framework regarding the economics of competition. For an extensive discussion on the economics of competition see Jehle and Reny (2011), Pepall et al. (2014), Carlton and Perloff (2015), Krugman and Wells (2015), Lipczynski et al. (2017), Varian (2014), Pindyck and Rubinfeld (2018), Case et al. (2018) and Frank et al. (2019) which offer a more complete overview of the theory in general. The theoretical framework outlined below draws on these various sources.

Perfect competition

Economic theory defines perfect competition as a market outcome whereby:

i. All firms within a market produce homogenous, perfectly divisible output;
ii. Consumers have full information, incur no transactions costs and are price takers; and
iii. They are no externalities.

More so, in perfectly competitive markets, it is assumed that there is a large number of buyers and sellers. Indeed, if a market contains a large number of similar firms, it is believed that no firm can charge a price above the market price without running the risk of losing customers. Moreover, it they are a few firms within a market, no firm can successfully increase its prices without losing customers from potential new entrants that can enter the market and undercut them. Given this, it can be said that all firms within perfectly competitive markets are price-takers.

Further, the primary objective of firms is the maximisation of its profits or the minimisation of its losses. This is also true for firms which compete in competitive markets. Indeed, a competitive firm's profits can be illustrated by the following:

$$\pi = pq - C(q) \qquad \text{(A1)}$$

Where π represents profits, p represents the price, q represents output and $C(q)$ is a representation of total cost. Given that firms in competitive markets are price takers, a firm would be able to sell its output at price p and will not be able to influence the market price. This suggests that firms in competitive markets face a horizontal demand curve at price p. It would only be profitable for a firm that operates in a competitive market to increase output as long as the additional revenue from selling an additional unit is greater than the extra cost of producing that unit.

Given this, the optimal profit maximising production rule for a competitive firm operating in a competitive market is to increase its output to the point whereby marginal cost equals price. Figure A1 below is a graphical illustration of the discussion above.

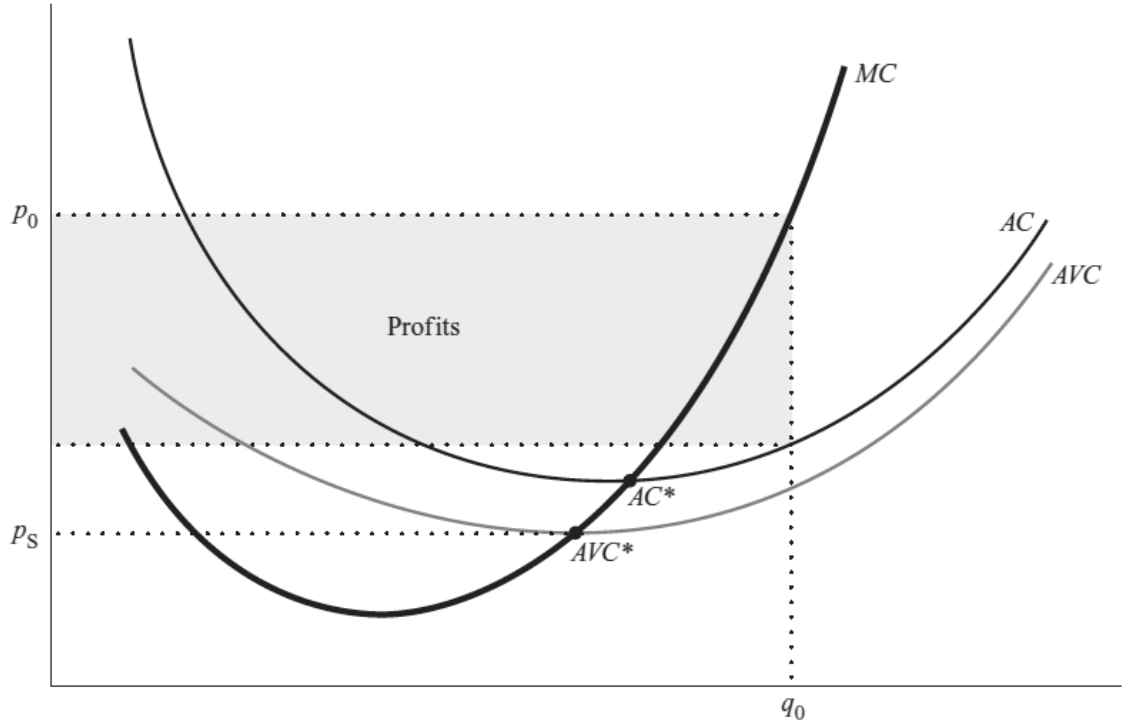

Figure A1: Perfect competition

Source: Carlton and Perloff (2015)

Figure A1 above illustrates the profit-maximising decisions of a firm operating in a competitive market. p_0 represents the market price whereas q_0 represents the firm's output. If a firm were producing output greater than q_0, p_0 is believed to be less than marginal cost (MC) suggesting that the firm would be able to increase its profits by decreasing its output. Conversely, if a firm were producing less than q_0, p_0 is believed to be higher than MC suggesting that a firm would

be able to increase its profits by increasing its output. This suggests that at output q_0, the price will equal marginal costs. This is a point where profits are seen to be maximized.

Monopoly

A monopoly is a situation whereby a particular market has only one firm operating in it. Given this, a monopolist recognises that it has influence over the market and will choose a price level or output level that allows it to maximise profits. The more a monopolist sells, the lower the price it gets given that a monopolist faces a downward sloping demand curve. Indeed, it is believed that the market demand curve constrains a monopolist. In order to maximise profits, a monopolist can only choose to set price or the quantity of output but not both.

If a monopolist chooses to set price, the quantity is determined by the downward sloping demand curve. If the monopolist decides to set the quantity, the market price is determined by the downward sloping demand curve. Figure A2 below further illustrates this point.

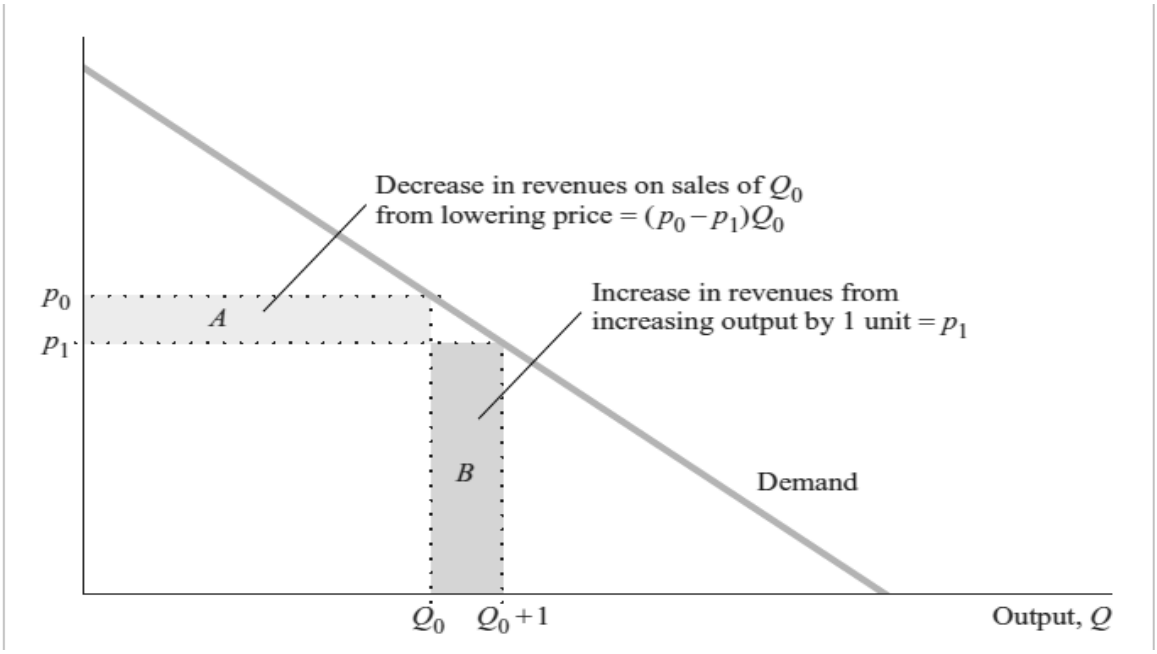

Figure A2: Monopoly

Source: Krugman and Wells (2015)

In order for the monopolist to sell q_0 units, it would have to charge p_0. If it requires to sell an additional unit, the monopolist would have to decrease the price to p_1. Lowering its prices may result in increases or decreases in revenue. It would be able to gain revenue on the additional unit at p_1, illustrated by Area B. Indeed, in order to be able to sell an additional unit, the

monopolist has to the decrease its price from p_0 to p_1 which results in a loss of revenue of $(p_0 - p_1)Q_0$, illustrated by Area A in Figure A2 above.

If Area B is bigger than Area A, selling the additional unit will lead to revenue increases. The additional revenue received from producing an additional unit is referred to as marginal revenue. Marginal revenue equals the difference between Area B and Area A. Therefore, it is accepted that a monopolist will maximise its profit when the revenue earned from selling an additional unit equals the additional cost of producing that unit. That being, when marginal revenue equals marginal cost.

Monopolistic competition

Monopolistic competitive markets are those in which each firm can set their price for their individual differentiated product and/or service. How high these prices can be set will depend on the limited competition a firm faces from existing and potential competitors that produce close but not identical products and/or services. It is assumed that there are many firms within a monopolistic competitive market, such that that market does not resemble a monopoly nor an oligopoly. In such markets, each firm offers a product and/or service that customers or consumers somewhat view as distinct from products and/or services from competitors. This allows each firm to set its own price to an extent.

As a result of each firm offering a somewhat distinct product, firms operating in monopolistic competitive markets face a downward-sloping demand curve. The extent to which they can set their own price will lie within the limits of their market power. For further illustration, consider Figure A3 below.

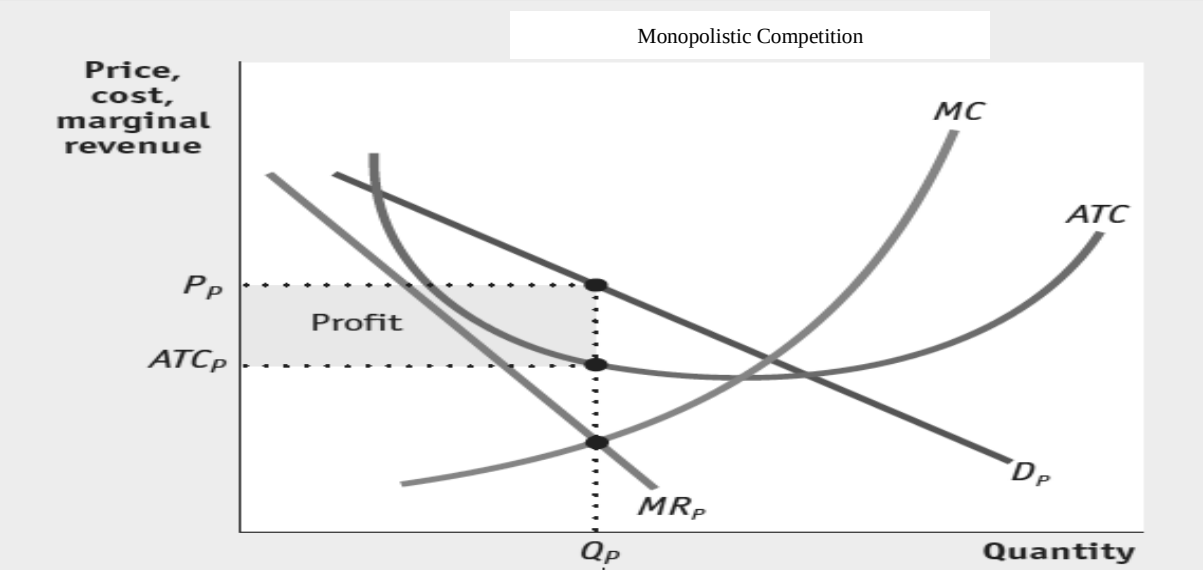

Figure A3: Monopolistic competition

Source: Krugman and Wells (2015)

As illustrated in Figure A3 above, a firm operating in a monopolistic competitive market will face a downward-sloping demand curve, a downward-sloping marginal revenue curve and an upward-sloping marginal cost curve. Similar to a monopolist, a firm operating in a monopolistic market structure will set marginal cost equal to marginal revenue in order to maximise profits. Indeed, when the firm faces demand curve D_p and marginal revenue curve MR_p, it will be able to produce output that maximised profit at Q_0. At this point marginal revenue is equal to marginal cost. At this particular point, the firm will be able to sell at price P_0, where the price is above its average total cost of production.

Oligopoly theory

Oligopolistic markets are those characterised by a limited number of firms. Strategic interdependencies exist within these markets, whereby the behaviour of a single firm will depend on the behaviour of other firms within the market. Five assumptions are found within these markets:

i. Customers and/or consumers are price takers.
ii. Firms within the market produce homogenous products that customers and/or consumers perceive no differences among them.
iii. There is no entry within the market, such that the number of firms remains constant over time.

iv. Firms within the market collectively have market power and set price above marginal cost.
v. Each firm within the market sets its own price or output.

Indeed, the equilibrium price within oligopolist markets tends to lie between that of competitive markets and monopolistic markets. In oligopolistic markets, firms maximise their profits given their belief in how their competitors will behave. A firm will maximise its profit when its expected marginal revenue is equal to its marginal costs. More so, a firm operating in an oligopolistic market's marginal revenue will depend on the residual demand curve facing that particular firm.

Oligopoly models are built upon a non-cooperative game theory that utilises formal methods to assess the strategic decisions among firms. A key concept of non-cooperative game theory is the Nash equilibrium which is a set of strategies whereby by holding constant the strategies of other firms, no firm can be seen to achieve a better payoff by choosing a different strategy. There are different types of oligopoly models which differ in terms of the actions firms may take, such as setting prices or setting outputs. There are two main oligopoly models, namely the Cournot model and the Bertrand model. In Cournot competition models the strategies taken by firms are about setting output quantities. In Bertrand competition models, firms set prices rather than quantities of output. These are outlined further below.

Cournot competition

The Cournot model developed by Augustin Cournot in 1838, postulates that each firm within a market will act independently in the pursuit of maximising profits by choosing its own output. Indeed, under Cournot competition, firms decide on the optimal level of output and let the price be determined by market. For further illustration, consider a market with J identical firms, where entry by additional firms is restricted and each firm is faced with the same cost structure, such that the following can be derived:

$$C(q^j) = cq^j, \quad c \geq 0 \quad and\ j = 1, \dots, J. \tag{A2}$$

Where cq^j represents the cost structure of firm j. Accordingly, firms produce output to be sold to a common market. Therefore the market price will depend on the total output sold within the market. Inversing market demand to be in linear form produces the following:

$$p = a - b\sum_{j=1}^{j} q^j \tag{A3}$$

Where a and b are the representations of the intercept and slope parameters. p is the market price whereas q is the output. Further, the profit for firm j can be derived by the following:

$$\Pi^j\left(q^1, \dots, q^j\right) = \left(a - b\sum_{k=1}^{j} q^k\right)q^j - cq^j \tag{A4}$$

In addition, $(\bar{q}1, \dots, \bar{q}J)$ are vector of outputs that represent each firm's output choice that is profit-maximising given the output choices of competitors. This is referred to as the Cournot-Nash equilibrium. Given the Cournot-Nash equilibrium, $\bar{q}J$maximizes equation A4 above when $q_k - \ \bar{q}_k$ for all $k \neq j$. Furthermore, the derivative of equation A4 above with respect to $\bar{q}_j$ needs to be zero when $q_k = \ \bar{q}_k$ for all $k = 1$, therefore the following can be derived:

$$a - 2b\bar{q}_j - b\sum_{k\neq j} \bar{q}_k - c = 0, \tag{A5}$$

The above equation can be rewritten as

$$b\bar{q}_j = a - c - b\sum_{k=1}^{j} q^k \tag{A6}$$

Further, by allowing $\bar{q}$ denote the common equilibrium, equation 3.6 becomes the following:

$$b\bar{q} \ = a - c - Jb\bar{q} \tag{A7}$$

Suggesting that

$$\bar{q} = \frac{a - c}{b(J + 1)} \tag{A8}$$

Given this, by continuing with the calculations, the market equilibrium values of firm output, total output, market price and firm profits can be derived as follows:

$$\bar{q}^j \ = \frac{a - c}{b(J + 1)}, \qquad j = 1, \dots, J, \tag{A9}$$

$$\bar{p} = a - \frac{J(a-c)}{J+1} < a,$$

$$\bar{\Pi}^{j} = \frac{(a-c)^2}{(J+1)^2 b}.$$

More so, the deviation of price from marginal cost can be calculated as follows:

$$\bar{p} - c = \frac{a-c}{b(J+1)} > 0 \qquad \text{(A10)}$$

Given the above equation, it can be seen that the equilibrium price will tend to be higher than marginal cost for each firm. More so, when the number of firms is infinite the following equation can be derived:

$$\lim_{j \to \infty} (\bar{p} - c) = 0 \qquad \text{(A11)}$$

Equation A11 above suggests that price will tend to move toward marginal cost as the number of competitors within a market expand.

Bertrand competition

Approximately 45 years after Cournot, Joseph Bertrand in 1883 argued that it was much easier to assume that firms in oligopolistic markets set prices rather than output. Bertrand argued that it was difficult to see who sets prices in these markets if the firms themselves do not set them. Indeed, if customers and/or consumers had complete information and are aware that firms produce identical products, they would rather buy those with the cheapest prices. To illustrate this, consider a Bertrand duopoly, whereby two competing firms produce a homogenous good. These two firms have identical marginal costs $c > 0$ and no fixed costs. A market with linear demand can be derived as follows:

$$Q = \alpha - \beta p \qquad \text{(A12)}$$

Where p represents the market price whereas Q represents the total market output. In Bertrand competition firms will simultaneously set their prices and supply the output for what is demanded for that particular price. Consumers will then purchase from the firm with the cheaper price. Given this, the firm with the cheapest price will supply the entire market,

whereas the firm with the higher price will get no customers. However, if both firms have the same price, the firms will share the market equally.

For further illustration, consider the following equation which relates to the profit of firm 1 when all non-negative prices are below α/β:

$$\prod^1(p^1, p^2) = \begin{cases} (p^1 - c)(\alpha - \beta p^1), & c < p^1 < p^2, \\ \frac{1}{2}(p^1 - c)(\alpha - \beta p^1) & c < p^1 = p^2, \\ 0, & otherwise. \end{cases} \quad \text{(A13)}$$

Where $\prod^1$ represents the profit for firm 1 and p^1 and p^2 are the prices for firm 1 and firm 2 respectively. It is believed that firm 1's profit will be positive so long as its price is higher than that of its marginal cost. Further, firm 1's profit will be higher should it, all else being equal, have the lowest price and half as large if the two firms charge the same price. Given that firm 1 can charge a price equal to its marginal cost, it can be assumed that firm i restricts prices to $p^1 \geq c$. Therefore it is believed that the Nash equilibrium for both firms is setting prices equal to marginal cost and thus both firms will earn zero profit. This suggests that in Bertrand competition, if one firm's price is above marginal cost it will be undercut by the other and thus in a Bertrand model competition is driven by price.

The Economics of Efficiencies

Concepts of economic efficiency

Economic efficiency relates to both technical and allocative elements. The technical elements relate to the ability not to waste, that being either producing as much output as available technology and inputs allow or by utilising as little inputs as required by available technology and output production. Indeed, the assessment of technical efficiency can both have a output-augmenting orientation or an input-conserving orientation. Moreover, the allocative element of efficiency relates to the ability to combine both inputs and outputs in optimal proportions under prevailing prices.

According to Koopmans (1951), a firm can be seen as technically efficient if an increase in output requires a reduction in at least one other output or an increase in at least one input. Further, a firm can be seen as technically efficient if a reduction in an input requires an increase in at least one other input or a reduction in at least one output (Koopmans, 1951). Debreu

(1951) and Farrell (1957) were the first to develop a way to measure technical efficiency. Indeed, for an input-conserving orientation, the measure is referred to as the maximum radial reduction in all inputs which is feasible given the available technology and output (Fried and Schmidt, 2008). In regards to an output-augmenting orientation, the measure is referred to as the maximum radial expansion in outputs which is feasible given the available technology and inputs.

For further illustration, consider a firm with the following inputs $x = (x_1, \dots, x_n) \in R_+^n$ which are used to produce the following outputs $y = (y_1, \dots, y_m \in R_+^m$. The production function can be represented by the following production set:

$$T = \{(y, x): x\ can\ produce\ y\} \tag{A14}$$

Given the above, technical efficiency can be formally referred to as $(y, x) \in T$ if, $(y', x') \notin T$ for $(y', x') \geq (y, x)$. Further, technology can be illustrated by the following input sets:

$$L(y) = \{x : (y, x) \in T \tag{A15}$$

For every $\in R_+^m$ the following input isoquants can be found:

$$I(y) = \{x: x \in L(y), \lambda x \notin L(y), \lambda < 1\} \tag{A16}$$

With the following input efficient subsets:

$$E(y) = \{x: x \in L(y), x' \notin L(y), x' \leq x\} \tag{A17}$$

Where the three sets satisfy the following $E(y) \subseteq I(y) \subseteq L(y)$. In addition, Shephard (1953) developed an input distance function in order to provide a functional representation of the production technology. The input distance function is illustrated by the following:

$$D_I(x, y) = \max \{\lambda: (x/\lambda) \in L(y)\}. \tag{A18}$$

For $x \in L(y), D_1(y, x) \geqq 1$, and for $x \in I(y)$, $D_I(y, x) = 1$. It is assumed that the input distance function $D_I(y, x)$ is nonincreasing in y and nondecreasing, homogenous of degree+1, and concave in x. Therefore the Debreu-Farrell input-oriented measure of technical efficiency TE_1 can be illustrated as follows:

$$TE_I(y, x) = \min \{\theta : \theta x \in L(y)\} \tag{A19}$$

Further the following can be derived:

$$TE_I(y,x) = 1/D_I(y,x) \quad \text{(A20)}$$

Where $x \in L(y), TE_I(y,x) \leqq 1$, and for $x \in I(y), TE_I(y,x) = 1$.

Furthermore, in regard to the output-oriented measure, the following production technology can be shown by the following output sets:

$$P(x) = \{y: (x,y) \in T\}, \quad \text{(A21)}$$

Where $\in R_+^n$ has the following output isoquants:

$$I(x) = \{y: y \in P(x), \lambda y \notin P(x), \lambda > 1\} \quad \text{(A22)}$$

With the following output efficient subsets:

$$E(x) = \{y: y \in P(x), y' \notin P(x), y' \leq y\} \quad \text{(A23)}$$

Which satisfy the following, $E(x) \subseteq I(x) \subseteq P(x)$.

Similarly to the input distance function, the output distance function can be derived as:

$$D_0(x,y) = \min \{\lambda: (y/\lambda) \in P(x)\}. \quad \text{(A24)}$$

For $y \in P(x), D_0(x,y) \leqq 1$, and for $y \in I(x), D_0(x,y) = 1$.

Further, the Debreu-Farrell output measure of technical efficiency TE_0 can be illustrated as follows:

$$TE_0(x,y) = \max \{\phi : \phi y \in P(x)\} \quad \text{(A25)}$$

Further the following can be derived:

$$TE_0(x,y) = [D_0(x,y)]^{-1} \quad \text{(A26)}$$

Where $y \in P(x), TE_0(x,y) \geqq 1$, and for $y \in I(x), TE_0(x,y) = 1$.

Measurement of economic efficiency

Measuring economic efficiency entails a comparison on actual performance against optimal performance located on the relevant efficiency frontier (Davis and Garces, 2010). Indeed, the

actual true frontier is unknown therefore an empirical approximation in required (Davis and Garces, 2010). This approximation is referred to as a "best-practice" frontier (Davis and Garces, 2010). Below are two most commonly used techniques to arrive at "best-practice frontiers, that being, the data envelop analysis technique and the stochastic frontier analysis technique.

Data envelop analysis

The data envelop analysis approach to measure economic efficiency is a nonparametric frontier model whereby, given the basic one-input and one-output DEA model, considers the maximal or frontier output that can be produced for each amount of input (Fried and Schmidt, 2008). The DEA model seeks to find the frontier which envelops the relevant data (Davis and Garces, 2010).

For further illustration, continuing with the one-input and one-output example, consider the output of firm i which is denoted q_i and where a vector of J inputs are used by firm i, $\underline{I_J} = (I_{1i}, \dots, I_{ji})$. Given this, the DEA estimate for efficiency for individual firm k, θ_k can be constructed by solving the following minimisation problem:

$$\min_{\theta, y_1, \dots, y_J} \{\theta | \frac{q_k}{\theta} \leq \sum_{i=1}^{n} \gamma_i q_i;\ I_{jk} \geq \sum_{i=1}^{n} \gamma_i I_{ji},\ \ j = 1, \dots, J;\ \ \theta > 0; \gamma_i \geq 0, \quad i = 1, \dots, n\}. \tag{A27}$$

Where the observed data are the relevant input and output levels for each firm and where the nonnegative weighted sums $\sum_{i=1}^{n} \gamma_i q_i$ and $\sum_{i=1}^{n} \gamma_i I_{ji}$ for $j = 1, \dots, J$ represent a firm's level of outputs and inputs. Further, by decreasing θ in $\frac{q_k}{\theta}$ scales up actual output for firm k. Therefore, the optimisation program indicates that scaling up actual output from firm k is possible subject to the requirement of finding the smallest firm which could have produced that higher level of output given the actual combinations of inputs and outputs observed in the data. To do so, the Farrell Efficiency Index θ_k is estimated for each individual firm.

Stochastic frontier analysis

The stochastic frontier model is a parametric approach to measuring economic efficiency (Davis and Garces, 2010). This approach estimates a frontier model by minimising the sum of squared residuals subject to the constraint that a model's predicted output is higher than its observed output (Davis and Garces, 2010). For further illustration, consider the following Cobb-Douglas Frontier model:

$$InQ_i = \beta_0 + \beta_L InL_i + \beta_K InK_i + \beta_F InF_i - u_i \quad \text{(A28)}$$

This model can fit a single cross-sectional data set consisting of observations on n firms, $i = 1, \dots, n$, by solving the following:

$$\min_{\beta_0, \beta_L, \beta_K, \beta_F} \sum_{i=1}^{n} u_i(\beta_o, \beta_L, \beta_K, \beta_F) \; subject\ to \;\; u_i(\beta_o, \beta_L, \beta_K, \beta_F) \geq 0, i = 1, \dots, n, \quad \text{(A29)}$$

Where $u_i(\beta_o, \beta_L, \beta_K, \beta_F) = \beta_0 + \beta_L InL_i + \beta_K InK_i + \beta_F InF_i - InQ_i$, in which this equation is positive in order to ensure that the predicted production frontier model lies above the actual output achieved.

Econometrics

This study used econometrics which can be seen as statistical tools used to assess the relationship between economic variables and the possible changes to those economic variables based on observed data. In particular, these statistical tools were employed in order to assess a panel dataset in the form of a panel analysis. The nature of the panel dataset and the techniques employed to analyse it are discussed briefly below.

Panel data

This study employed a panel dataset which can be also be referred to as a cross-sectional time-series dataset. This dataset offers repeated measurements of a number of variables over a period of time for both open and restricted medical schemes. Panel datasets can be conceptualised as a three-dimensional structure for each particular variable, that being the vertical dimension as time and the horizontal dimension as multiple observations for each variable (Miller and Yang, 2017). Indeed, observations in the sample can be the same across all periods or observations in the sample may not be the same across all periods. The former of this is referred as a balanced

panel dataset whereas the latter is referred to as unbalanced panel dataset. Given the nature of the data, this study employed a number of panel data analysis models which are briefly discussed below.

Estimation techniques

In general, panel data contains information on both temporal and spatial dimensions. The temporal dimension contains the period in which the repeated measures are given and can be month, quarter, and the year. The spatial dimension contains the unit of observations and can represents individuals, firms and countries. The standard regression model of panel data can be derived as follows:

$$y_{it} = \beta_0 + \beta_1 x_{it,1} + \beta_2 x_{it,2} + \cdots + \beta_k x_{it,k} + v_{it,}\ i = 1 \ldots, N; t = 1, \ldots, T; k = 1, \ldots, K \quad \text{(A30)}$$

Where i represents the unit of an observation, t represents the period of time, k represents the kth explanatory variable, β_0 represents the intercept, β_k represents the coefficient of each explanatory variable whereas v_{it} represents the composite error term. More so, the error term can be further decomposed into two elements, that being the cross-sectional unit-specific error a_i and the idiosyncratic error u_{it}. This can be further illustrated below.

$$v_{it} = a_i + u_{it} \quad \text{(A31)}$$

Accordingly, it is believed that the cross-sectional unit-specific error does not change over time whereas the idiosyncratic error term varies over the cross-sectional units and time (Greene, 2018). By incorporating the above equation into the initial equation, the following can be derived:

$$y_{it} = \beta_0 + \beta_1 x_{it,1} + \beta_2 x_{it,2} + \cdots + \beta_k x_{it,k} + a_i + u_{it} \quad \text{(A32)}$$

Where equation A32 above is referred to as an error component model and whereby the time-constant and unit-specific errors terms are unobserved factors. The estimation methods of the error component models can be differentiated by how the error term is treated. The pooled OLS model fails to distinguish the different types of errors whereas the fixed effects model considers them as coefficients to be estimated (Greene, 2018). The random effects model however considers them as random variables (Stock and Watson, 2020). These different estimation techniques are briefly discussed below.

Pooled ordinary least square (OLS) model

The pooled OLS estimation technique is the simplest method to estimate panel data. This technique involves pooling the data and applying ordinary least squares estimation techniques. When estimating, this method assumes that the composite error term is not correlated with the explanatory variables. This implies that the pooled OLS estimation model can be employed when they are neither cross-sectional nor temporal effects. The pooled OLS estimation model can be expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + v \quad \text{(A33)}$$

Further, there are additional limitations in using the pooled OLS estimation technique. As indicated above, panel data contains information that pertains to both time and cross-sectional dimensions. However, the pooled OLS estimation technique tends to disregard the information of panel data (Miller and Yang, 2017). More so, the assumptions of OLS tend not to be realistic as it is not possible to measure all time-constant and unit-specific effects and thus include them in the model (Miller and Yang, 2017). Given this, employing OLS in assessing panel data will lead to the OLS estimator being biased and inconsistent (Miller and Yang, 2017)**.**

Fixed effects model

The fixed effects estimation technique is often employed when there is a need to control for omitted variables that tend to be constant over time and vary across measurement units (Pesaran, 2015). This is often referred to as unobserved heterogeneity or fixed effects a_i. When estimating panel data using the fixed effects estimation technique, it is assumed that the unobserved heterogeneity is correlated with the explanatory variables. Moreover, it is assumed that the idiosyncratic error u_{it} is independent of the explanatory variables (Greene, 2018). Indeed, by removing the unobserved effect and reducing the omitted variable biases, the fixed effect estimation technique arrives at more robust estimates (Greene, 2018).

Random effects model

Furthermore, when the unobserved heterogeneity a_i is independent of each explanatory variable, estimating using the fixed effects estimation technique to remove a_i will lead to inefficient estimators (Miller and Yang, 2017). Given this, the random effects estimation technique also referred to as the variance components model considers the unobserved

heterogeneity a_i as random variables rather than fixed ones (Studenmud, 2016). Given this, the random effects estimation technique is advocated when the cross-sectional units are randomly selected from a large population (Miller and Yang, 2017). More so, if the variance structure among groups is known, the random effects estimation model is estimated by employing generalised least squares whereas if it is not known the random effects model is estimated using feasible generalised least squares.

Hausman test

Given the above, the question becomes which model to employ between the fixed effects and random effects estimation techniques. The key element to this debate is on how to treat the unobserved heterogeneity and which estimation technique is more efficient in treating the unobserved heterogeneity (Miller and Yang, 2017). The fixed effects estimation technique assumes that the unobserved heterogeneity is correlated with the explanatory variables whereas the random effects estimation technique does not (Miller and Yang, 2017).

Given this, the decision on which technique to employ will depend on whether or not the unobserved heterogeneity a_i is independent of the explanatory variables. One approach which aids in this decision is employing the Hausman specification test which was developed by Hausman (1978). The Hausman test requires estimating both the fixed effects and random effects models and then testing the statistical significance of the differences in the coefficients on the time-varying explanatory variables (Hausman, 1978). The Hausman specification test will then compare the fixed effects against the random effects under the null hypothesis that the individual effects a_i are independent of the other explanatory variables within the model (Hausman, 1978). If the null hypothesis is rejected, then the fixed effects estimation technique is preferred as it produces more efficient estimators (Hausman, 1978).

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Appendix I: Chapter Three Tables

Table 7.1: Summary of literature on DEA inputs and Outputs

Author (s)	Inputs	Output
Diacon and O'Brien (2002)	Staff and capital resources.	Investment income and premiums
Brockett et al. (2004)	Wages, capital, investment income and premiums.	Claims paid to policyholders and profits paid to owners.
Kasman and Turgutlu (2007)	Labour, business services and financial capital.	Benefits incurred net of reinsurance plus additions to reserves.
Cummins et al. (2010)	Real invested assets and the present values of real losses incurred for short and long-tail personal and commercial lines. Administrative labour, agent labour, materials and business services and financial equity capital	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.
Chen and Chang (2010)	Equity capital and total expenses.	Premium income.
Barros et al. (2010)	Labour costs, non-labour costs and equity capital.	invested assets losses incurred, reinsurance reserves and own reserves
Biener and Eling (2011)	labour, business services, debt capital and equity capital	value of current losses paid plus additions to reserves.
Biener and Eling (2012)	Labour, business services and material, debt capital and equity capital	Current losses paid plus additions to reserves.
Bai-qing et al. (2012)	Total assets, expenditure and the number of employees.	Net premiums, final reserves, investment income and underwriting profit.
Barros and Dumbo (2014)	Operating costs, the number of employees, wages and capital.	Claims paid, profits paid, premiums earned and ceded reinsurance.
Depotis et al. (2016)	Operation expenses and insurance expenses.	Direct written premiums, reinsurance premiums, underwriting profit and investment profit.
Biener et al. (2016)	Operating costs, the number of employees, wages and capital.	Claims paid, profits paid, premiums earned and ceded reinsurance.
Akhtar (2018)	Financial capital, net claims incurred and general administrative expenses.	Investment income, net premium earned and investment and management fee income.

Table 7.2: DEA efficiency results for open medical schemes

Medical Scheme	Year	Technical efficiency	Bias corrected technical efficiency	Technical efficiency lower bound	Technical efficiency upper bound	Scale efficiency	Pure technical efficiency
Bestmed Medical Scheme	2011	0,6420377	0,6270967	0,608128	0,6388514	0,9863315	0,635787
Bestmed Medical Scheme	2012	0,6686177	0,6486806	0,626931	0,6632146	0,9935102	0,6529179
Bestmed Medical Scheme	2013	0,7587253	0,7313652	0,7078713	0,7512966	0,9989457	0,7321371
Bestmed Medical Scheme	2014	0,8162315	0,7839465	0,7578747	0,8073288	0,9995708	0,7842831
Bestmed Medical Scheme	2015	0,9428784	0,8996158	0,8688822	0,929361	0,99397	0,9050733
Bestmed Medical Scheme	2016	0,9330969	0,9066966	0,8781192	0,9265794	0,9946671	0,9115579
Bestmed Medical Scheme	2017	0,9414881	0,9192985	0,889933	0,9378558	0,9850399	0,9332601
Bonitas Medical Fund	2011	0,7412708	0,7103608	0,6770769	0,7347946	0,8049446	0,8824965
Bonitas Medical Fund	2012	0,7377917	0,6970456	0,66268	0,7272645	0,7441402	0,9367127
Bonitas Medical Fund	2013	0,7291645	0,7018402	0,6716015	0,7238122	0,843324	0,8322308
Bonitas Medical Fund	2014	0,7941651	0,7488118	0,7137445	0,7831359	0,807386	0,927452
Bonitas Medical Fund	2015	0,9633853	0,9075842	0,8739074	0,9438996	0,9633853	0,9420781
Bonitas Medical Fund	2016	0,9630221	0,9098727	0,8746353	0,9455645	0,9630221	0,9448098
Bonitas Medical Fund	2017	1	0,959049	0,9271123	0,986061	1	0,959049
Cape Medical Plan	2011	0,6544887	0,6188294	0,5936724	0,64582	0,9139547	0,6770898
Cape Medical Plan	2012	0,6771485	0,6306799	0,6022262	0,6670202	0,9090204	0,6938018
Cape Medical Plan	2013	0,8006406	0,7635578	0,7286842	0,7959655	0,934445	0,8171244
Cape Medical Plan	2014	0,8108013	0,7725475	0,7379556	0,8060651	0,9373425	0,8241892
Cape Medical Plan	2015	0,8713905	0,8239014	0,786054	0,8629957	0,940879	0,875672
Cape Medical Plan	2016	0,729348	0,6841373	0,6542422	0,7182094	0,9360706	0,7308608
Cape Medical Plan	2017	0,7804148	0,7364056	0,7030561	0,7723743	0,945624	0,7787509
Community Medical Aid Scheme (COMMED)	2011	0,8673188	0,8295019	0,7984961	0,8522487	0,9988806	0,8304315
Community Medical Aid Scheme (COMMED)	2012	0,7068629	0,6790286	0,6559313	0,6989655	0,9722441	0,6984137
Community Medical Aid Scheme (COMMED)	2013	0,6233418	0,6058147	0,5863087	0,6182482	0,9628969	0,6291584
Community Medical Aid Scheme (COMMED)	2014	0,6249096	0,5926234	0,5702546	0,6130137	0,9604366	0,6170354
Compcare Wellness Medical Scheme	2011	0,6230424	0,6084968	0,5901142	0,6201973	0,9608337	0,6333009
Compcare Wellness Medical Scheme	2012	0,5840561	0,569243	0,551767	0,581148	0,9730129	0,5850312
Compcare Wellness Medical Scheme	2013	0,568944	0,551366	0,5354363	0,5631601	0,9859918	0,5591994
Compcare Wellness Medical Scheme	2014	0,572669	0,5558181	0,5400121	0,5684841	0,9857846	0,5638332
Compcare Wellness Medical Scheme	2015	0,7352169	0,6946075	0,6702801	0,7197003	0,9977929	0,696144
Compcare Wellness Medical Scheme	2016	0,8195676	0,7698181	0,7382895	0,8042815	0,9887604	0,7785689

Compcare Wellness Medical Scheme	2017	0,7874177	0,744499	0,7175947	0,7714418	0,999342	0,7449892
Discovery Health Medical Scheme	2011	0,6618384	0,6448354	0,6254143	0,6575334	0,6618384	0,9743094
Discovery Health Medical Scheme	2012	0,6644365	0,6463739	0,6259831	0,6604547	0,6644365	0,9728151
Discovery Health Medical Scheme	2013	0,6698909	0,6521083	0,6309844	0,6661448	0,6698909	0,9734544
Discovery Health Medical Scheme	2014	0,6705719	0,653683	0,6330479	0,6673213	0,6705719	0,9748142
Discovery Health Medical Scheme	2015	0,7818154	0,7648969	0,7463759	0,7777901	0,7818154	0,9783599
Discovery Health Medical Scheme	2016	0,7784376	0,7585117	0,73683	0,7730658	0,7784376	0,9744026
Discovery Health Medical Scheme	2017	0,7646675	0,7443831	0,7212446	0,7593916	0,7646675	0,973473
Fedhealth Medical Scheme	2011	0,6878127	0,6737347	0,656911	0,6845735	0,9992783	0,6742213
Fedhealth Medical Scheme	2012	0,6781398	0,6577839	0,6343907	0,6745368	0,9998788	0,6578636
Fedhealth Medical Scheme	2013	0,6819972	0,6510416	0,6229131	0,6726301	0,9995235	0,651352
Fedhealth Medical Scheme	2014	0,7005542	0,655005	0,6236246	0,6837568	0,9710515	0,6745317
Fedhealth Medical Scheme	2015	0,8332976	0,7690789	0,7317066	0,8110116	0,9946369	0,7732257
Fedhealth Medical Scheme	2016	0,8430355	0,7900922	0,7575883	0,8220099	0,9833165	0,8034973
Fedhealth Medical Scheme	2017	0,7851301	0,7620054	0,7387946	0,7786766	0,9990383	0,7627389
Genesis Medical Scheme	2011	0,614162	0,5899999	0,5605181	0,6122224	0,9384409	0,6287022
Genesis Medical Scheme	2012	0,6354665	0,6075715	0,574146	0,6336407	0,9429038	0,6443621
Genesis Medical Scheme	2013	0,6071218	0,5776491	0,5432945	0,6055178	0,945248	0,6111085
Genesis Medical Scheme	2014	0,6286834	0,6068347	0,5793812	0,6263759	0,9566293	0,6343467
Genesis Medical Scheme	2015	0,6406998	0,6214024	0,5963268	0,6381261	0,9645265	0,6442564
Genesis Medical Scheme	2016	0,6695263	0,6521789	0,6295401	0,666709	0,9715756	0,671259
Genesis Medical Scheme	2017	0,6350371	0,6210158	0,6043704	0,6322985	0,980401	0,6334305
Hosmed Medical Aid Scheme	2011	0,975571	0,9498357	0,9211004	0,9695023	0,975571	0,9736202
Hosmed Medical Aid Scheme	2012	0,9692855	0,9302148	0,8977159	0,9577262	0,9692855	0,9596912
Hosmed Medical Aid Scheme	2013	0,8769763	0,8460249	0,8167434	0,8684308	0,9964586	0,8490316
Hosmed Medical Aid Scheme	2014	0,9340142	0,8898243	0,8601824	0,920793	0,9719664	0,9154887
Hosmed Medical Aid Scheme	2015	1	0,9259823	0,8881128	0,972609	1	0,9259823
Hosmed Medical Aid Scheme	2016	1	0,912396	0,872122	0,9696146	1	0,912396
Hosmed Medical Aid Scheme	2017	0,914852	0,8863967	0,8504943	0,9098607	0,9998727	0,8865096
Keyhealth	2011	0,9870625	0,9606878	0,9180313	0,9825814	0,9870625	0,9732796
Keyhealth	2012	1	0,9818659	0,9541471	0,9966431	1	0,9818659
Keyhealth	2013	0,9295291	0,9120833	0,889414	0,9252322	0,9969638	0,914861
Keyhealth	2014	0,8952859	0,8653582	0,8338615	0,888571	0,9976166	0,8674256
Keyhealth	2015	1	0,9311723	0,8972441	0,9737048	1	0,9311723
Keyhealth	2016	1	0,9433307	0,9083229	0,9814951	1	0,9433307
Keyhealth	2017	0,9920963	0,9713531	0,9384201	0,9892945	0,9963995	0,9748631
Liberty Medical Scheme	2011	0,6696016	0,6301785	0,6034218	0,6585301	0,9674423	0,6513861

Liberty Medical Scheme	2012	0,6454297	0,6161799	0,594434	0,6345476	0,9779763	0,6300561
Liberty Medical Scheme	2013	0,6444613	0,6252347	0,6056985	0,6390661	0,9597034	0,6514875
Liberty Medical Scheme	2014	0,7571913	0,7146502	0,6693861	0,7440882	0,9247736	0,7727839
Liberty Medical Scheme	2015	1	0,9039712	0,8435625	0,9712841	1	0,9039712
Makoti Medical Scheme	2011	1	0,886937	0,7712752	0,9671866	1	0,886937
Makoti Medical Scheme	2012	0,6341614	0,5793933	0,5467963	0,6135193	0,6713939	0,8629708
Makoti Medical Scheme	2013	0,8863883	0,7978929	0,6746647	0,8674256	0,9207491	0,8665693
Makoti Medical Scheme	2014	1	0,6449068	0,5311525	0,9281977	1	0,6449068
Makoti Medical Scheme	2015	0,950723	0,8642407	0,7078193	0,943801	0,9996327	0,8645582
Makoti Medical Scheme	2016	0,7480603	0,6827292	0,6387725	0,7364908	0,7815636	0,8735427
Makoti Medical Scheme	2017	0,6437457	0,5738198	0,5377175	0,6279936	0,77595	0,7395061
Medihelp	2011	0,9254333	0,8823273	0,836255	0,9152786	0,9400336	0,9386125
Medihelp	2012	0,8270223	0,7623821	0,7213953	0,8041682	0,9723123	0,7840918
Medihelp	2013	0,806843	0,7483808	0,7105719	0,7826049	0,9315838	0,8033425
Medihelp	2014	0,8999016	0,851519	0,8176895	0,8820553	0,9130871	0,9325715
Medihelp	2015	0,9879079	0,9331269	0,8892196	0,9698064	0,9879079	0,9445484
Medihelp	2016	1	0,9063388	0,8553131	0,9650036	1	0,9063388
Medihelp	2017	1	0,8797598	0,8265519	0,9659839	1	0,8797598
Medimed Medical Scheme	2011	0,8154445	0,7956758	0,771216	0,8115037	0,9126828	0,8717988
Medimed Medical Scheme	2012	0,7724711	0,7458751	0,7185504	0,7644042	0,9198267	0,8108865
Medimed Medical Scheme	2013	0,7826561	0,7425238	0,7108787	0,770432	0,9315572	0,797078
Medimed Medical Scheme	2014	0,8018916	0,7778103	0,7486754	0,795541	0,9414887	0,8261494
Medimed Medical Scheme	2015	0,9445117	0,8850743	0,8384936	0,9275628	0,9804527	0,9027201
Medimed Medical Scheme	2016	1	0,9321908	0,8822275	0,9794036	1	0,9321908
Medimed Medical Scheme	2017	1	0,9459644	0,8970093	0,9846203	1	0,9459644
Medshield Medical Scheme	2011	0,8074415	0,7532071	0,7248813	0,7860134	0,9974796	0,7551103
Medshield Medical Scheme	2012	0,7334164	0,7040403	0,6719774	0,7305335	0,9982097	0,7053031
Medshield Medical Scheme	2013	0,7705035	0,7363674	0,7074621	0,7642061	0,9910652	0,743006
Medshield Medical Scheme	2014	0,7292841	0,6836926	0,6552571	0,7165602	0,9930642	0,6884677
Medshield Medical Scheme	2015	0,9590068	0,9100993	0,8734328	0,9503374	0,9789623	0,9296572
Medshield Medical Scheme	2016	0,8817822	0,8311843	0,7960792	0,8715489	0,9841225	0,8445944
Medshield Medical Scheme	2017	0,8813956	0,833784	0,7987777	0,8749192	0,976987	0,8534239
Momentum Health	2011	0,7051363	0,6869115	0,6657861	0,7008432	0,9286276	0,7397061
Momentum Health	2012	0,6778324	0,6618526	0,6423919	0,6740087	0,9414149	0,7030403
Momentum Health	2013	0,6656507	0,6475959	0,6242628	0,6621522	0,9219855	0,7023928
Momentum Health	2014	0,6537458	0,6355287	0,612902	0,6501318	0,9133793	0,6957994
Momentum Health	2015	0,7390344	0,7154839	0,6909656	0,7344152	0,9258083	0,7728208
Momentum Health	2016	0,7427737	0,7129323	0,6924103	0,7329413	0,9105108	0,7830026

Momentum Health	2017	0,7351777	0,7134077	0,6918762	0,7298784	0,8966144	0,7956683
National Independent Medical Aid Society (NIMAS)	2011	1	0,9180246	0,8783488	0,9712716	1	0,9180246
Pharos Medical Plan	2011	0,8348925	0,7798078	0,7172455	0,8248295	0,9958469	0,7830599
Pharos Medical Plan	2012	0,8483442	0,8019	0,7448663	0,8414324	0,9912415	0,8089855
Pharos Medical Plan	2013	0,7321106	0,7080458	0,6735826	0,729786	0,9825205	0,7206423
Pro Sano Medical Scheme	2011	0,8064885	0,7673149	0,7379329	0,7941207	0,9948063	0,7713209
Pro Sano Medical Scheme	2012	0,6786028	0,6373544	0,6077864	0,66774	0,9754434	0,6533997
Resolution Health Medical Scheme	2011	1	0,9560555	0,8365303	0,9949241	1	0,9560555
Resolution Health Medical Scheme	2012	1	0,7493244	0,5944101	0,9633694	1	0,7493244
Resolution Health Medical Scheme	2013	1	0,9168217	0,8054442	0,9759636	1	0,9168217
Resolution Health Medical Scheme	2014	0,9557257	0,8998039	0,8179376	0,9386784	0,9997133	0,900062
Resolution Health Medical Scheme	2015	1	0,9209811	0,8603337	0,9791911	1	0,9209811
Resolution Health Medical Scheme	2016	0,9876799	0,9324079	0,8705823	0,9754685	0,9981865	0,9341019
Resolution Health Medical Scheme	2017	0,9455495	0,9051117	0,8626165	0,9364884	0,9955464	0,9091607
Selfmed Medical Scheme	2011	0,6827285	0,6430982	0,6017158	0,6804845	0,9573199	0,6717694
Selfmed Medical Scheme	2012	0,7595775	0,6833856	0,6385891	0,7462529	0,9745122	0,7012591
Selfmed Medical Scheme	2013	0,6911607	0,6245031	0,584731	0,6787017	0,9865287	0,6330309
Selfmed Medical Scheme	2014	0,6776891	0,6025372	0,5648517	0,6611036	0,9619935	0,6263422
Selfmed Medical Scheme	2015	0,8145364	0,7413909	0,701746	0,8031082	0,9629429	0,769922
Selfmed Medical Scheme	2016	0,8713462	0,7980786	0,7533469	0,8624817	0,9678229	0,8246122
Selfmed Medical Scheme	2017	0,842033	0,7770933	0,736487	0,8336983	0,9723601	0,7991827
Sizwe Medical Fund	2011	0,8280408	0,7730261	0,740946	0,8100681	0,9174945	0,8425403
Sizwe Medical Fund	2012	0,8570823	0,8027068	0,7731991	0,8414453	0,9347114	0,858775
Sizwe Medical Fund	2013	0,8436443	0,8152331	0,7799647	0,838244	0,9559899	0,8527632
Sizwe Medical Fund	2014	0,9089384	0,8781956	0,8355481	0,9003789	0,9408719	0,9333848
Sizwe Medical Fund	2015	0,8947164	0,8399576	0,786218	0,8871632	0,9906999	0,8478426
Sizwe Medical Fund	2016	0,7822555	0,724916	0,6772714	0,7741718	0,9959108	0,7278925
Sizwe Medical Fund	2017	0,7748815	0,7144363	0,6681651	0,7657422	0,9914238	0,7206164
Spectramed	2011	0,6723408	0,6525314	0,6255614	0,668848	0,9890853	0,6597322
Spectramed	2012	0,5550319	0,5410526	0,5247036	0,5526249	0,9999673	0,5410703
Spectramed	2013	0,445797	0,4370387	0,4242359	0,4441981	0,9999859	0,4370448
Spectramed	2014	0,4262464	0,413382	0,3992278	0,4230345	0,9985319	0,4139897
Spectramed	2015	0,5300198	0,4958912	0,4723854	0,5248112	0,9748427	0,5086884
Spectramed	2016	0,7083111	0,6718802	0,6432491	0,6994867	0,9893323	0,6791249
Spectramed	2017	0,7942231	0,7577037	0,7258247	0,7870267	0,9938284	0,762409
Suremed Health	2011	0,5019056	0,4951321	0,481544	0,5009583	0,5019056	0,9865046
Suremed Health	2012	0,5418837	0,5345021	0,5203716	0,5406897	0,5806708	0,9204908
Suremed Health	2013	0,7498481	0,7146366	0,6928394	0,7393625	0,7920092	0,9023085
Suremed Health	2014	0,7615673	0,7183213	0,6908145	0,7456378	0,8037126	0,8937539

Suremed Health	2015	0,6691797	0,6597363	0,6434594	0,6671056	0,6691797	0,985888
Suremed Health	2016	0,7328682	0,7213636	0,7042269	0,7305603	0,7328682	0,984302
Suremed Health	2017	0,7149374	0,6926166	0,6715776	0,7075453	0,7312244	0,9472012
Thebemed	2011	1	0,8388802	0,7570295	0,9449937	1	0,8388802
Thebemed	2012	1	0,918156	0,8349839	0,9777957	1	0,918156
Thebemed	2013	0,952634	0,9228594	0,8833539	0,9484231	0,952634	0,9687449
Thebemed	2014	0,9096037	0,8730885	0,8460995	0,8979487	0,9148893	0,9543105
Thebemed	2015	0,8767846	0,8373088	0,7974112	0,8640876	0,9617819	0,8705807
Thebemed	2016	0,9472306	0,8930872	0,8402874	0,9337091	0,9943435	0,8981677
Thebemed	2017	1	0,8961485	0,839075	0,9672952	1	0,8961485
Topmed Medical Scheme	2011	0,6195949	0,5705264	0,543148	0,6101475	0,9679985	0,5893877
Topmed Medical Scheme	2012	0,6346508	0,5850155	0,5547003	0,6279784	0,9704984	0,602799
Topmed Medical Scheme	2013	0,6115241	0,5792247	0,5530656	0,606637	0,9857769	0,5875819
Topmed Medical Scheme	2014	0,6495715	0,5903707	0,5574039	0,6411895	0,9852587	0,5992037
Topmed Medical Scheme	2015	0,7824222	0,7308937	0,6975315	0,7715306	0,9948239	0,7346966
Topmed Medical Scheme	2016	0,8046252	0,7592991	0,7257276	0,7961501	0,9960927	0,7622775
Topmed Medical Scheme	2017	0,8366855	0,7950704	0,7603872	0,8323751	0,9973157	0,7972103

Table 7.3: DEA efficiency results for restricted medical schemes

Medical Scheme	Year	Technical efficiency	Bias corrected technical efficiency	Technical efficiency lower bound	Technical efficiency upper bound	Scale efficiency	Pure technical efficiency
AECI Medical Aid Society	2011	0,6679283	0,6063222	0,6520121	0,8982139	0,6750309	0,8834279
AECI Medical Aid Society	2012	0,692863	0,6284806	0,671036	0,8929041	0,7038612	0,8950566
AECI Medical Aid Society	2013	0,8103443	0,7373974	0,7851896	0,9490075	0,7770196	0,8994572
AECI Medical Aid Society	2014	0,7701229	0,7052363	0,7490216	0,916421	0,7695549	0,8149948
AECI Medical Aid Society	2015	0,7615696	0,6818959	0,749701	0,7990071	0,853429	0,9054069
AECI Medical Aid Society	2016	0,759338	0,6754698	0,7525299	0,807613	0,836378	1
AECI Medical Aid Society	2017	0,6507712	0,5417322	0,6330788	0,7428105	0,7293007	0,9178053
Afrox Medical Aid Society	2011	0,5097746	0,4668707	0,5020003	0,966572	0,4830169	0,7682711
Afrox Medical Aid Society	2012	0,4418479	0,3877126	0,4313481	0,9859732	0,3932283	0,8187037
Afrox Medical Aid Society	2013	0,8226237	0,770955	0,8082628	0,9609495	0,8022847	1
Alliance Midmed Medical Scheme	2011	0,4068512	0,3725746	0,39826	0,815941	0,4566195	0,840973
Alliance Midmed Medical Scheme	2013	0,4190136	0,3949985	0,415094	0,846351	0,4667077	0,7883983
Alliance Midmed Medical Scheme	2014	0,4617813	0,4252383	0,4519775	0,8563779	0,4965545	0,9090505
Alliance Midmed Medical Scheme	2015	0,5169905	0,4775119	0,5056067	0,8714827	0,5479304	0,9354853
Alliance Midmed Medical Scheme	2016	0,4833213	0,4539565	0,4779997	0,881461	0,5150047	0,8900141

Alliance Midmed Medical Scheme	2017	0,5199302	0,4784542	0,5087166	0,8984736	0,532519	1
Altron Medical Aid Scheme	2011	0,4801204	0,4268795	0,4734355	0,8087168	0,5278479	1
Altron Medical Aid Scheme	2012	0,5150734	0,4741936	0,5113338	0,8594694	0,5517284	0,9469911
Altron Medical Aid Scheme	2013	0,4860491	0,4498616	0,4821824	0,8866576	0,507368	0,8572276
Anglo Medical Scheme	2011	0,3494248	0,3175894	0,3457806	0,8041219	0,3949518	0,9752824
Anglo Medical Scheme	2012	0,3419626	0,3106369	0,3382474	0,799278	0,3886468	0,9482222
Anglo Medical Scheme	2013	0,3166758	0,287677	0,3132353	0,8080565	0,356011	0,8777757
Anglo Medical Scheme	2014	0,2897049	0,2627754	0,2859683	0,8008649	0,3281145	0,8807995
Anglo Medical Scheme	2015	0,4714281	0,4302422	0,4676044	0,7913395	0,5436885	0,9722297
Anglo Medical Scheme	2016	0,4950142	0,4518597	0,4909992	0,7860957	0,5748151	1
Anglo Medical Scheme	2017	0,4850956	0,4424909	0,481161	0,7849567	0,5637138	0,9599144
Anglovaal Group Medical Scheme	2011	0,2800511	0,2628284	0,2756065	0,9404171	0,2794807	0,8070955
Anglovaal Group Medical Scheme	2012	0,2692283	0,2542931	0,2653065	0,9450066	0,2690914	0,7471454
Anglovaal Group Medical Scheme	2013	0,2655702	0,2434767	0,2582669	0,9495888	0,2564023	0,8000497
Anglovaal Group Medical Scheme	2014	0,2706004	0,250304	0,264649	0,9611002	0,2604348	0,82061
Anglovaal Group Medical Scheme	2015	0,3187176	0,2905741	0,3137186	0,9866772	0,2944976	0,8464901
Anglovaal Group Medical Scheme	2016	0,3491965	0,3214423	0,3438313	0,9833272	0,3268925	1
Anglovaal Group Medical Scheme	2017	0,3395314	0,3107842	0,3321687	0,9900951	0,3138933	0,9983481
BMW Employees Medical Aid Society	2011	0,4852598	0,4403845	0,477848	0,921949	0,4776669	0,7502236
BMW Employees Medical Aid Society	2012	0,5300798	0,4744591	0,5186613	0,9251239	0,51286	0,6923781
BMW Employees Medical Aid Society	2013	0,6109279	0,5473424	0,5901683	0,9462362	0,5784416	0,7828128
BMW Employees Medical Aid Society	2014	0,5595178	0,4948445	0,5480886	0,9862088	0,5017644	0,8489361
BMW Employees Medical Aid Society	2015	0,7323112	0,6476157	0,7162977	0,9950537	0,6508349	1
BMW Employees Medical Aid Society	2016	0,8995341	0,8247778	0,8787851	0,9822312	0,8396983	0,7990594
BMW Employees Medical Aid Society	2017	0,7925264	0,7231056	0,7797424	0,9652907	0,7491065	0,7169737
BP Medical Aid Society	2011	0,528701	0,4628042	0,5233769	0,9614385	0,4813664	0,9005117
BP Medical Aid Society	2012	0,5835474	0,5221952	0,5784545	0,969828	0,5384411	0,8879827
BP Medical Aid Society	2013	0,6388437	0,5814035	0,631117	0,9731432	0,5974491	0,8241833
BP Medical Aid Society	2014	0,7600312	0,6996915	0,7497991	0,9826614	0,7120372	0,8975626
BP Medical Aid Society	2015	0,779056	0,6773103	0,772299	0,9842482	0,6881499	1
BP Medical Aid Society	2016	0,639052	0,552371	0,6290648	0,9863937	0,5599904	0,8388578
BP Medical Aid Society	2017	0,6080393	0,5210621	0,5999339	0,9640262	0,5405061	0,8082096
Bankmed	2011	0,3651238	0,3392937	0,358651	0,8622785	0,393485	0,7475554
Bankmed	2012	0,3682395	0,3413631	0,3618802	0,8481776	0,4024665	0,7346513
Bankmed	2013	0,3725347	0,3475826	0,3662229	0,8579656	0,4051242	0,7573249
Bankmed	2014	0,3746541	0,3430637	0,3657637	0,8603616	0,3987436	0,8000937
Bankmed	2015	0,4657605	0,4253614	0,4521941	0,8375653	0,5078546	0,9085482
Bankmed	2016	0,5274435	0,4827649	0,5131348	0,8266743	0,5839844	0,9652883
Bankmed	2017	0,5944892	0,5465479	0,5791623	0,7790407	0,7015653	1
Barloworld Medical Scheme	2011	0,4779612	0,4530365	0,4707394	0,9126628	0,4963898	0,8193635

Barloworld Medical Scheme	2012	0,4590775	0,4352497	0,4527619	0,8717223	0,4992986	0,8094051
Barloworld Medical Scheme	2013	0,4404235	0,4049778	0,4349158	0,8102654	0,4998088	0,7036142
Barloworld Medical Scheme	2014	0,4478064	0,3805625	0,4372375	0,7896855	0,4819165	0,8527868
Barloworld Medical Scheme	2015	0,6204315	0,5426498	0,6111186	0,785907	0,6904759	1
Barloworld Medical Scheme	2016	0,6223445	0,5531038	0,6111447	0,8006526	0,6908162	0,9946682
Barloworld Medical Scheme	2017	0,6153872	0,553537	0,6012001	0,820196	0,6748838	0,9824778
Building & Construction Industry Medical Aid Fund	2011	0,3791194	0,3281042	0,3659075	0,8482422	0,3868049	0,967176
Building & Construction Industry Medical Aid Fund	2012	0,3837062	0,3382208	0,3739576	0,865474	0,3907926	0,8757634
Building & Construction Industry Medical Aid Fund	2013	0,3348162	0,2935127	0,3251715	0,895578	0,3277355	0,8652719
Building & Construction Industry Medical Aid Fund	2014	0,3428656	0,3032393	0,3344977	0,9190292	0,3299561	0,8275238
Building & Construction Industry Medical Aid Fund	2015	0,4249749	0,3836142	0,4149348	0,9537936	0,4021983	0,9568
Building & Construction Industry Medical Aid Fund	2016	0,3979611	0,3589543	0,384891	0,9443951	0,3800892	1
Building & Construction Industry Medical Aid Fund	2017	0,3436067	0,3076023	0,3364342	0,976557	0,3149865	0,9320364
Chartered Accountants (SA) Medical Aid Fund (CAMAF)	2011	0,3483604	0,3288857	0,3432562	0,9396111	0,3500232	0,7772135
Chartered Accountants (SA) Medical Aid Fund (CAMAF)	2012	0,3516285	0,3326029	0,3464178	0,9312381	0,3571621	0,80717
Chartered Accountants (SA) Medical Aid Fund (CAMAF)	2013	0,3522415	0,3311446	0,3467857	0,9248582	0,3580491	0,824392
Chartered Accountants (SA) Medical Aid Fund (CAMAF)	2014	0,3487206	0,3286339	0,3432476	0,9290169	0,3537437	0,8555165
Chartered Accountants (SA) Medical Aid Fund (CAMAF)	2015	0,3712229	0,3347645	0,3607171	0,9213216	0,3633524	0,9570051
Chartered Accountants (SA) Medical Aid Fund (CAMAF)	2016	0,388179	0,3533981	0,3800374	0,9257993	0,3817222	1
Chartered Accountants (SA) Medical Aid Fund (CAMAF)	2017	0,3973863	0,3680025	0,3914096	0,9226403	0,3988581	0,9578047
De Beers Benefit Society	2011	0,4400618	0,4003713	0,428451	0,8551339	0,4681972	0,9704854
De Beers Benefit Society	2012	0,3963606	0,3563424	0,3840447	0,8428574	0,422779	0,9337273
De Beers Benefit Society	2013	0,4008335	0,3645785	0,3908156	0,8417578	0,4331158	0,9010208
De Beers Benefit Society	2014	0,4174901	0,3774815	0,4052273	0,8572879	0,4403206	0,9583006
De Beers Benefit Society	2015	0,3942366	0,3531835	0,3816124	0,8242416	0,4284951	0,9521858
De Beers Benefit Society	2016	0,4836228	0,4408491	0,4740489	0,8650573	0,5096183	0,9947578
De Beers Benefit Society	2017	0,4829843	0,4407212	0,4737231	0,8561816	0,514752	1
Edcon Medical Aid Scheme	2011	0,3687107	0,3525832	0,364412	0,8154835	0,4323609	
Engen Medical Benefit Fund	2011	0,4344852	0,409548	0,4270452	0,9732156	0,4208194	0,8555023
Engen Medical Benefit Fund	2012	0,409996	0,3881868	0,4036976	0,9832942	0,3947819	0,7805292
Engen Medical Benefit Fund	2013	0,4363618	0,4029006	0,4234475	0,9930971	0,4057011	0,9195429
Engen Medical Benefit Fund	2014	0,4186878	0,3841895	0,404519	0,9877916	0,3889378	0,9086961
Engen Medical Benefit Fund	2015	0,5772432	0,520224	0,564984	0,9613763	0,5411242	0,9693131
Engen Medical Benefit Fund	2016	0,6039217	0,5453257	0,5947317	0,9376081	0,5816137	1
Engen Medical Benefit Fund	2017	0,6114682	0,56835	0,6070988	0,9192027	0,6183075	0,8693081
Eyethumed Medical Scheme	2011	0,2891603	0,2742361	0,284217	0,6162626	0,4449988	0,9103171
Eyethumed Medical Scheme	2012	0,3329716	0,3039991	0,326854	0,5917929	0,5136917	1
Fishing Industry Medical Scheme (Fishmed)	2011	0,2297396	0,205274	0,2241088	0,2297396	0,8935072	0,6426097
Fishing Industry Medical Scheme (Fishmed)	2012	0,2407314	0,2234809	0,2374204	0,2464698	0,9067273	0,6578363

Fishing Industry Medical Scheme (Fishmed)	2013	0,2756464	0,2412763	0,2676924	0,2890608	0,8346903	0,7222847
Fishing Industry Medical Scheme (Fishmed)	2014	0,2957063	0,2558072	0,2864101	0,3301125	0,7749093	0,7626697
Fishing Industry Medical Scheme (Fishmed)	2015	0,3288081	0,3029621	0,324131	0,3976962	0,7617929	0,891524
Fishing Industry Medical Scheme (Fishmed)	2016	0,3383445	0,3202899	0,3334479	0,4626342	0,6923178	0,9498177
Fishing Industry Medical Scheme (Fishmed)	2017	0,3515974	0,3325695	0,3465136	0,5216237	0,6375659	1
Food Workers Medical Benefit Fund	2011	0,6344957	0,5584495	0,6265636	0,6344957	0,880147	1
Food Workers Medical Benefit Fund	2012	0,6318896	0,556524	0,6244937	0,6518422	0,8537711	0,8717747
Food Workers Medical Benefit Fund	2013	0,4466316	0,3933552	0,441404	0,643559	0,6112186	0,7583708
Food Workers Medical Benefit Fund	2014	0,5512495	0,485501	0,5447974	0,6702217	0,7243887	0,7627249
Food Workers Medical Benefit Fund	2015	0,4464479	0,3933927	0,4419881	0,6961768	0,5650759	0,6922481
Food Workers Medical Benefit Fund	2016	0,2555436	0,2248389	0,2529908	0,6320797	0,3557129	0,5576177
Food Workers Medical Benefit Fund	2017	0,4991582	0,43975	0,4941718	0,7280777	0,6039878	0,7253308
Glencore Medical Scheme	2014	0,8748525	0,7861748	0,8400574	0,9442098	0,8326272	0,8153247
Glencore Medical Scheme	2015	0,8241363	0,7193608	0,8058156	0,8241363	0,8728664	1
Glencore Medical Scheme	2016	0,7791511	0,6781945	0,7620932	0,7838323	0,8652291	0,8550203
Glencore Medical Scheme	2017	0,7141099	0,6133601	0,6998571	0,762756	0,8041368	0,8087594
Gold Fields Medical Scheme	2011	0,4563102	0,413817	0,4475774	0,993512	0,4165194	0,9681272
Gold Fields Medical Scheme	2012	0,473799	0,4096082	0,4553314	0,955442	0,4287107	0,9756504
Gold Fields Medical Scheme	2013	0,4685911	0,4022164	0,4477359	0,9424748	0,4267662	1
Golden Arrow Employees Medical Benefit Fund	2012	0,3734806	0,3474933	0,3669159	0,7436224	0,467298	
Golden Arrows Employees Medical Benefit Fund	2011	0,3897226	0,3697411	0,3833289	0,7298083	0,5066277	0,9947975
Golden Arrows Employees Medical Benefit Fund	2013	0,4004787	0,3554192	0,3891083	0,7685668	0,4624441	0,9637182
Golden Arrows Employees Medical Benefit Fund	2014	0,4075073	0,3680699	0,4007278	0,7907866	0,4654479	0,9203582
Golden Arrows Employees Medical Benefit Fund	2015	0,424904	0,3744948	0,4170779	0,8457727	0,4427842	1
Golden Arrows Employees Medical Benefit Fund	2016	0,4869635	0,445413	0,4804514	0,8646253	0,5151514	0,9605297
Golden Arrows Employees Medical Benefit Fund	2017	0,3767753	0,3365984	0,3736643	0,8742836	0,3849991	0,8260047
Government Employees Medical Scheme (GEMS)	2011	0,9746538	0,9147149	0,9670731	0,9991705	0,9154743	0,8323295
Government Employees Medical Scheme (GEMS)	2012	0,9198912	0,8009679	0,9027354	0,9994044	0,8014453	0,8663232
Government Employees Medical Scheme (GEMS)	2013	0,994345	0,9522123	0,9866502	0,994345	0,9576277	0,7901143
Government Employees Medical Scheme (GEMS)	2014	1	0,9095272	0,9747749	1	0,9095272	0,8846577
Government Employees Medical Scheme (GEMS)	2015	1	0,8464984	0,9622716	1	0,8464984	0,9304702
Government Employees Medical Scheme (GEMS)	2016	1	0,8313581	0,9631386	1	0,8313581	1
Government Employees Medical Scheme (GEMS)	2017	0,835579	0,7584372	0,8247451	0,835579	0,9076785	0,6259203
Grintek Electronics Medical Aid Scheme	2011	0,5120118	0,4593357	0,4997706	0,7382682	0,62218	0,9220241
Grintek Electronics Medical Aid Scheme	2012	0,447952	0,3967785	0,4360158	0,669927	0,5922712	0,6931685
Grintek Electronics Medical Aid Scheme	2013	0,4626307	0,4182868	0,4502417	0,6282827	0,6657621	0,619807
Grintek Electronics Medical Aid Scheme	2014	0,6390559	0,5957642	0,6277141	0,6868689	0,8673623	0,8125014

Grintek Electronics Medical Aid Scheme	2015	0,7411738	0,6846989	0,7282414	0,7411738	0,9238034	1
Grintek Electronics Medical Aid Scheme	2016	0,4784967	0,4389872	0,4664938	0,6803051	0,6452798	0,8476044
Grintek Electronics Medical Aid Scheme	2017	0,5455093	0,5056909	0,5337732	0,7335869	0,6893401	1
Horizon Medical Scheme	2011	0,2906606	0,2568151	0,283609	0,5271648	0,4871628	0,603191
Horizon Medical Scheme	2012	0,3772007	0,3245766	0,3657603	0,5377393	0,6035947	0,6414922
Horizon Medical Scheme	2013	0,333407	0,2886154	0,3239926	0,6015131	0,4798156	0,6379945
Horizon Medical Scheme	2014	0,3516871	0,2988725	0,339781	0,642552	0,4651336	0,7867179
Horizon Medical Scheme	2015	0,4340287	0,3807897	0,422083	0,6978545	0,5456578	0,7325987
Horizon Medical Scheme	2016	0,3394904	0,3212691	0,3343607	0,7672121	0,4187487	0,8222193
Horizon Medical Scheme	2017	0,4119771	0,376298	0,4048004	0,8203957	0,4586786	1
IBM (SA) Medical Scheme	2011	0,3409219	0,3167051	0,3362208	0,7206633	0,4394633	1
IBM (SA) Medical Scheme	2012	0,3148046	0,2893702	0,3103197	0,6931856	0,4174499	0,9547462
Impala Medical Plan	2011	0,9230505	0,8302358	0,9083753	0,9230505	0,8994479	0,8868918
Impala Medical Plan	2012	0,9446217	0,8590582	0,9297581	0,9446217	0,9094203	0,8749931
Impala Medical Plan	2013	0,9221211	0,8532426	0,9013436	0,9504489	0,897726	0,8064631
Impala Medical Plan	2014	1	0,8106979	0,9589742	1	0,8106979	1
Impala Medical Plan	2015	0,9197457	0,8440535	0,8974395	0,9673952	0,8725013	0,803669
Impala Medical Plan	2016	0,9554312	0,8640584	0,9300091	0,9789741	0,8826162	0,8145515
Impala Medical Plan	2017	1	0,8871503	0,9630013	1	0,8871503	0,8655191
Imperial Group Medical Scheme	2011	0,4601701	0,4069701	0,451926	0,8836929	0,4605334	0,8090978
Imperial Group Medical Scheme	2012	0,466123	0,4089445	0,4541903	0,848554	0,481931	0,8203939
Imperial Group Medical Scheme	2013	0,652337	0,5956548	0,6325063	0,9313138	0,6395856	0,923391
Imperial Group Medical Scheme	2014	0,8361589	0,7687452	0,8131198	0,9934379	0,7738231	0,9909165
Imperial Group Medical Scheme	2015	0,7652298	0,6935799	0,7410725	0,8727406	0,7947148	1
Imperial Group Medical Scheme	2016	0,6201428	0,55269	0,6087049	0,8068272	0,6850166	0,942703
Imperial Group Medical Scheme	2017	0,5104219	0,4453705	0,5065075	0,7609056	0,5853164	0,8224554
LA Health Medical Scheme	2011	0,398156	0,3769092	0,3933091	0,9959424	0,3784448	0,9868004
LA Health Medical Scheme	2012	0,3991576	0,3785134	0,3940081	0,9983791	0,3791279	1
LA Health Medical Scheme	2013	0,3969472	0,3763011	0,3925618	0,9837307	0,3825245	0,9494084
LA Health Medical Scheme	2014	0,384817	0,3645856	0,3797396	0,9645375	0,3779901	0,9047723
LA Health Medical Scheme	2015	0,3996955	0,3713953	0,3941999	0,9325138	0,3982733	0,9589761
LA Health Medical Scheme	2016	0,3826961	0,3530456	0,377029	0,9258228	0,3813317	0,9311398
LA Health Medical Scheme	2017	0,3794427	0,3515548	0,3738941	0,9128466	0,3851193	0,9008864
Libcare Medical Scheme	2011	0,3045199	0,287466	0,3009334	0,9754643	0,2946966	0,8256478
Libcare Medical Scheme	2012	0,291341	0,2769623	0,2878628	0,9995641	0,277083	0,7576464
Libcare Medical Scheme	2013	0,2908248	0,2774724	0,2877527	0,937952	0,295828	0,7546374
Libcare Medical Scheme	2014	0,287841	0,2719441	0,2847422	0,9039935	0,3008253	0,7785261
Libcare Medical Scheme	2015	0,3701097	0,3455999	0,3657254	0,9040923	0,3822618	0,8441527
Libcare Medical Scheme	2016	0,3730094	0,3444599	0,3676277	0,8855129	0,3889948	0,8391021
Libcare Medical Scheme	2017	0,4104035	0,3675891	0,3996156	0,8677287	0,4236221	1

Lonmin Medical Scheme	2011	0,625049	0,5075389	0,6109564	0,8451347	0,600542	0,3996201
Lonmin Medical Scheme	2012	0,6899642	0,5423959	0,6721935	0,8886574	0,6103543	0,5095084
Lonmin Medical Scheme	2013	0,5601404	0,4886504	0,5469697	0,8735209	0,5594032	0,4688102
Lonmin Medical Scheme	2014	0,7031705	0,5880927	0,6821032	0,8919714	0,6593179	0,5891562
Lonmin Medical Scheme	2015	0,6434141	0,5773085	0,6289335	0,9263887	0,6231816	0,6193601
Lonmin Medical Scheme	2016	1	0,9563599	0,9886902	1	0,9563599	1
Lonmin Medical Scheme	2017	1	0,9150988	0,9822773	1	0,9150988	0,8352225
MBMed Medical Aid Fund	2011	0,7628468	0,6868377	0,7349765	0,9248697	0,7426319	0,8877
MBMed Medical Aid Fund	2012	0,4631278	0,4165887	0,4521521	0,974131	0,4276516	0,7972445
MBMed Medical Aid Fund	2013	0,4682202	0,4098024	0,4559343	0,9874517	0,4150101	0,7605709
MBMed Medical Aid Fund	2014	0,8806272	0,7747518	0,8444678	0,9346353	0,828935	0,914227
MBMed Medical Aid Fund	2015	0,8381366	0,7646611	0,8174969	0,9945077	0,768884	0,9375026
MBMed Medical Aid Fund	2016	0,8041478	0,7386567	0,7859874	0,9999744	0,7386757	1
MBMed Medical Aid Fund	2017	0,5704637	0,4940643	0,5635475	0,8926454	0,5534833	0,9692454
Malcor Medical Scheme	2011	0,6047132	0,5699093	0,5945206	0,9735981	0,585364	0,7195629
Malcor Medical Scheme	2012	0,6621672	0,589619	0,6433771	0,9393945	0,6276586	0,7851439
Malcor Medical Scheme	2013	0,6951382	0,636036	0,6808534	0,9699569	0,6557364	0,8152456
Malcor Medical Scheme	2014	0,7953579	0,7459804	0,7807915	0,9969146	0,7482892	0,8945018
Malcor Medical Scheme	2015	0,8111841	0,7396828	0,7924859	0,9933431	0,7446398	0,908276
Malcor Medical Scheme	2016	0,9469309	0,8908311	0,9282728	0,9860812	0,9034054	1
Malcor Medical Scheme	2017	0,9082565	0,8457538	0,8888634	0,9779844	0,8647928	0,9639401
Massmart Health Plan	2011	0,3371927	0,3196411	0,3343747	0,8756176	0,3650464	0,5815076
Massmart Health Plan	2012	0,3173946	0,3013889	0,3149613	0,8988211	0,3353158	0,5664257
Massmart Health Plan	2013	0,3165629	0,300653	0,3143391	0,9204252	0,3266457	0,6125394
Massmart Health Plan	2014	0,3490911	0,3302729	0,3460773	0,9596788	0,3441494	0,7036046
Massmart Health Plan	2015	0,4417087	0,4184231	0,4379723	0,9996628	0,4185643	0,910836
Massmart Health Plan	2016	0,4274259	0,4026964	0,4233341	0,9968934	0,4039513	0,9550189
Massmart Health Plan	2017	0,4412899	0,4158242	0,4369922	0,9596171	0,433323	1
Medipos Medical Scheme	2011	0,4420464	0,4120082	0,435617	0,8155673	0,5051798	0,5896606
Medipos Medical Scheme	2012	0,4478421	0,413393	0,4406895	0,8009892	0,516103	0,6200656
Medipos Medical Scheme	2013	0,6724341	0,6098278	0,6571699	0,8273379	0,7370964	0,7856954
Medipos Medical Scheme	2014	0,6155372	0,5579714	0,605441	0,8282419	0,6736817	0,8244698
Medipos Medical Scheme	2015	0,697901	0,6218071	0,6914709	0,7947192	0,7824237	0,9592695
Medipos Medical Scheme	2016	0,6130179	0,5465657	0,6023262	0,7655473	0,7139542	0,9233532
Medipos Medical Scheme	2017	0,6032763	0,5321962	0,5939934	0,7473076	0,7121515	1
Metrocare	2011	0,9161723	0,8586335	0,9021873	0,9161723	0,9371964	
Metropolitan Medical Scheme	2011	0,5732511	0,5151652	0,5554421	0,9941192	0,5182127	0,7455872
Metropolitan Medical Scheme	2012	0,495737	0,4361427	0,4801843	0,9796093	0,4452211	0,7183937
Metropolitan Medical Scheme	2013	0,9050041	0,8278572	0,8980587	0,9635671	0,8591588	0,8652298
Metropolitan Medical Scheme	2014	0,7775158	0,7181983	0,7641875	0,983826	0,7300054	0,8733199
Metropolitan Medical Scheme	2015	0,9252783	0,8644724	0,9092697	0,9982223	0,866012	1
Metropolitan Medical Scheme	2016	0,7965431	0,7390229	0,7828098	0,9949813	0,7427505	0,9309457

Minemed Medical Scheme	2011	0,7851945	0,7387402	0,7739978	0,9363106	0,7889905	1
Minemed Medical Scheme	2012	0,7308751	0,6915828	0,7202243	0,9817933	0,7044078	0,7647752
Motohealth Care	2011	0,405838	0,3860018	0,3997027	0,9105548	0,4239194	0,9087236
Motohealth Care	2012	0,3738291	0,3549434	0,3676934	0,9111645	0,3895493	0,8624825
Motohealth Care	2013	0,3624089	0,3421069	0,3564935	0,9127027	0,3748284	0,8471093
Motohealth Care	2014	0,3550352	0,3235412	0,3472432	0,9147617	0,3536891	0,871421
Motohealth Care	2015	0,4153945	0,3820173	0,4033485	0,8983521	0,4252422	0,9174012
Motohealth Care	2016	0,4138667	0,3752692	0,3991367	0,8992187	0,4173281	0,9287255
Motohealth Care	2017	0,451014	0,4105968	0,4386478	0,9049519	0,4537222	1
Nampak SA Medical Scheme	2011	0,4378827	0,3959624	0,43037	0,9686661	0,4087707	1
Nampak SA Medical Scheme	2012	0,3870834	0,3555572	0,3804871	0,9765129	0,364109	0,9291053
Naspers Medical Fund	2011	0,2990767	0,2785234	0,2945635	0,9634215	0,2890981	0,7247673
Naspers Medical Fund	2012	0,2907781	0,2699057	0,2864608	0,9766102	0,27637	0,7151769
Naspers Medical Fund	2013	0,3003349	0,2798283	0,2952515	0,9750031	0,2870025	0,7786475
Naspers Medical Fund	2014	0,3089281	0,2881478	0,3043645	0,9929281	0,2902001	0,7616518
Naspers Medical Fund	2015	0,3876125	0,3644772	0,3810525	0,972334	0,3748478	0,9361427
Naspers Medical Fund	2016	0,3851363	0,3519044	0,3723262	0,9883609	0,3560484	0,9949641
Naspers Medical Fund	2017	0,3876813	0,3552029	0,3738253	0,9690438	0,3665498	1
Nedgroup Medical Aid Scheme	2011	0,4493615	0,4059719	0,4397093	0,9894044	0,4103195	0,4086598
Nedgroup Medical Aid Scheme	2012	0,4500635	0,4070494	0,4404066	0,97912	0,4157298	0,4098273
Nedgroup Medical Aid Scheme	2013	0,4388438	0,3961559	0,4296184	0,9782733	0,4049542	0,4175338
Nedgroup Medical Aid Scheme	2014	0,5934567	0,5638526	0,5825372	0,9460579	0,5960022	1
Nedgroup Medical Aid Scheme	2015	0,5704075	0,5281044	0,5551911	0,9174203	0,5756406	0,9416247
Nedgroup Medical Aid Scheme	2016	0,5585267	0,5036024	0,5423906	0,933489	0,539484	0,969597
Nedgroup Medical Aid Scheme	2017	0,5856001	0,5306129	0,5689719	0,9411404	0,5637978	0,9737543
Netcare Medical Scheme	2011	0,4991289	0,4557471	0,4894969	0,9682937	0,4706703	0,865221
Netcare Medical Scheme	2012	0,5143241	0,4797074	0,5083527	0,9270735	0,5174426	0,9076162
Netcare Medical Scheme	2013	0,5114149	0,480614	0,5062175	0,8966435	0,5360147	0,8206511
Netcare Medical Scheme	2014	0,4987341	0,4577475	0,4871227	0,9001244	0,508538	0,8491004
Netcare Medical Scheme	2015	0,6726323	0,6207184	0,6587704	0,8482185	0,7317907	0,9606522
Netcare Medical Scheme	2016	0,6796426	0,6249549	0,6640881	0,8411193	0,7430038	1
Netcare Medical Scheme	2017	0,6955914	0,6424959	0,6806458	0,8012277	0,8018892	0,9878001
Old Mutual Staff Medical Aid Fund	2011	0,3973975	0,3666736	0,391583	0,9944516	0,3687195	0,7442448
Old Mutual Staff Medical Aid Fund	2012	0,3912575	0,3598321	0,38366	0,9705309	0,370758	0,7685748
Old Mutual Staff Medical Aid Fund	2013	0,3872818	0,3554974	0,3804747	0,9741431	0,3649334	0,7936063
Old Mutual Staff Medical Aid Fund	2014	0,4123486	0,38439	0,4051226	0,9713183	0,3957405	0,8582417
Old Mutual Staff Medical Aid Fund	2015	0,4518823	0,4186126	0,4448659	0,9450936	0,4429325	0,8665701
Old Mutual Staff Medical Aid Fund	2016	0,4562767	0,4104692	0,4422389	0,9776233	0,4198644	0,9725047
Old Mutual Staff Medical Aid Fund	2017	0,4602251	0,4111581	0,4446944	0,9873692	0,4164178	1
PG Bison Medical Aid Society	2011	0,516219	0,478643	0,5060896	0,5796226	0,8257838	0,8882545
PG Bison Medical Aid Society	2012	0,3921137	0,3411196	0,3864213	0,5091456	0,6699845	1

PG Bison Medical Aid Society	2013	0,3209178	0,2933735	0,3163597	0,4338596	0,6761945	0,7786092
PG Group Medical Scheme	2011	0,2896786	0,2646869	0,2865407	0,8491997	0,3116899	0,6431291
PG Group Medical Scheme	2012	0,3111019	0,283049	0,3081823	0,8770482	0,3227291	0,7438166
PG Group Medical Scheme	2013	0,3275316	0,2972935	0,324045	0,8788152	0,338289	0,7338975
PG Group Medical Scheme	2014	0,3405958	0,3100241	0,3373994	0,8878493	0,3491855	0,8211064
PG Group Medical Scheme	2015	0,4479918	0,4075548	0,4437822	0,9068255	0,4494303	0,8938947
PG Group Medical Scheme	2016	0,4681099	0,4259214	0,4637169	0,9196928	0,4631127	0,9881229
PG Group Medical Scheme	2017	0,3984967	0,3607858	0,3931249	0,8864192	0,4070149	1
Parmed Medical Aid Scheme	2011	0,6060694	0,5431805	0,589966	0,9896497	0,5488614	0,8088073
Parmed Medical Aid Scheme	2012	0,5874941	0,5383641	0,5741225	0,9545063	0,5640236	0,7627057
Parmed Medical Aid Scheme	2013	0,5893791	0,5301369	0,574329	0,9516043	0,5570981	0,7759448
Parmed Medical Aid Scheme	2014	0,5764673	0,5308633	0,5672826	0,8716013	0,6090667	0,7892385
Parmed Medical Aid Scheme	2015	0,6634125	0,6066214	0,648076	0,9007879	0,6734343	0,8130421
Parmed Medical Aid Scheme	2016	0,7206258	0,6506639	0,7080828	0,8833426	0,7365929	0,9137756
Parmed Medical Aid Scheme	2017	0,7635451	0,6939561	0,750126	0,8837972	0,7851984	1
Pick & Pay Medical Scheme	2011	0,2114398	0,1952652	0,207993	0,9949651	0,1962533	0,8179433
Pick & Pay Medical Scheme	2012	0,2120684	0,1965008	0,2091769	0,9593495	0,2048271	0,7668953
Pick & Pay Medical Scheme	2013	0,2144205	0,1980948	0,2111367	0,9224983	0,2147373	0,8031904
Pick & Pay Medical Scheme	2014	0,214776	0,1921708	0,2091305	0,917653	0,2094155	0,864863
Pick & Pay Medical Scheme	2015	0,3194804	0,2902302	0,3161918	0,8871455	0,3271506	1
Pick & Pay Medical Scheme	2016	0,3236095	0,301386	0,3220396	0,8568474	0,3517383	0,9136187
Pick & Pay Medical Scheme	2017	0,3139263	0,2934385	0,3124189	0,8535773	0,343775	0,8204076
Platinum Health	2011	0,5889437	0,5520697	0,5839748	0,930486	0,5933132	0,5956597
Platinum Health	2012	0,6038739	0,5479174	0,5872408	0,9320236	0,5878793	0,7321683
Platinum Health	2013	0,5959426	0,541163	0,5810534	0,9428511	0,5739645	0,7727154
Platinum Health	2014	0,6326792	0,5767383	0,6181235	0,9302102	0,6200085	0,8223476
Platinum Health	2015	0,6526018	0,5812717	0,6350737	0,9738451	0,5968832	1
Platinum Health	2016	0,6630236	0,6093401	0,6547194	0,9451045	0,644733	0,9125248
Platinum Health	2017	0,6316329	0,5695344	0,6163307	0,9395082	0,6062049	0,9703221
Profmed	2011	0,4911108	0,4383897	0,4810844	0,9144793	0,4793872	0,8658623
Profmed	2012	0,5098959	0,4340882	0,4893432	0,9130055	0,4754497	0,8791798
Profmed	2013	0,5099556	0,4377154	0,4901454	0,9147577	0,4785042	0,8457554
Profmed	2014	0,4277649	0,3671049	0,4099205	0,8536972	0,4300177	0,7809671
Profmed	2015	0,5316409	0,4647847	0,5144277	0,8397666	0,5534689	0,9222565
Profmed	2016	0,4879863	0,4180719	0,4660355	0,7988685	0,5233301	0,9599911
Profmed	2017	0,5013002	0,4377601	0,4824035	0,7847717	0,5578184	1
Quantum Medical Aid Society	2011	0,2512623	0,2198193	0,2433686	0,9966363	0,2205612	0,8161908
Quantum Medical Aid Society	2012	0,2725548	0,251121	0,2680918	0,9980462	0,2516126	0,9023603
Quantum Medical Aid Society	2013	0,2844878	0,2629381	0,2794864	0,9996011	0,263043	0,9476295
Quantum Medical Aid Society	2014	0,2551362	0,2331853	0,2501154	0,9897702	0,2355954	0,8346785
Quantum Medical Aid Society	2015	0,3201497	0,2890187	0,3137202	0,9737182	0,2968196	0,9899859
Quantum Medical Aid Society	2016	0,3242626	0,290821	0,3171656	0,9584605	0,3034251	1

Quantum Medical Aid Society	2017	0,3233584	0,2904427	0,3193425	0,933535	0,3111214	0,9497471
Rand Water Medical Scheme	2011	0,4923022	0,4350281	0,4824421	0,9884429	0,4401145	0,8416442
Rand Water Medical Scheme	2012	0,5667094	0,4814058	0,5533394	0,9332116	0,5158592	1
Rand Water Medical Scheme	2013	0,5145899	0,4786455	0,5072767	0,946878	0,5054986	0,7298288
Rand Water Medical Scheme	2014	0,6496468	0,5828719	0,642239	0,9121739	0,6389921	0,9041615
Rand Water Medical Scheme	2015	0,8184352	0,7354434	0,8079231	0,899375	0,8177273	0,9916185
Rand Water Medical Scheme	2016	0,6621681	0,5931519	0,6541054	0,8490552	0,6986023	0,88348
Rand Water Medical Scheme	2017	0,8386463	0,7467626	0,8333065	0,8386463	0,8904381	0,9312072
Remedi Medical Aid Scheme	2011	0,4439142	0,4208926	0,438271	0,8463504	0,497303	0,7454236
Remedi Medical Aid Scheme	2012	0,4198211	0,3996188	0,4142684	0,8342586	0,4790107	0,7394825
Remedi Medical Aid Scheme	2013	0,3930189	0,3690287	0,3860239	0,8415765	0,4384969	0,8144451
Remedi Medical Aid Scheme	2014	0,4137362	0,3904128	0,4067326	0,8335707	0,4683619	0,8484895
Remedi Medical Aid Scheme	2015	0,4892829	0,4589129	0,4829946	0,7792937	0,5888832	0,9283405
Remedi Medical Aid Scheme	2016	0,4876359	0,4518204	0,4781208	0,774888	0,5830783	0,9606679
Remedi Medical Aid Scheme	2017	0,4985722	0,459851	0,4872555	0,7736843	0,5943652	1
Retail Medical Scheme	2011	0,231016	0,215838	0,2278788	0,9666342	0,2232882	0,8033236
Retail Medical Scheme	2012	0,234781	0,2187305	0,231381	0,9829048	0,2225347	0,8009465
Retail Medical Scheme	2013	0,240456	0,2245203	0,2368506	0,9992025	0,2246995	0,8173165
Retail Medical Scheme	2014	0,2333976	0,218791	0,2301864	0,9669535	0,2262684	0,7372574
Retail Medical Scheme	2015	0,2740177	0,2544268	0,2692657	0,9202952	0,2764622	1
Retail Medical Scheme	2016	0,2836599	0,2661301	0,2801328	0,8867244	0,3001272	0,9649411
Retail Medical Scheme	2017	0,2835579	0,2669723	0,2796111	0,8701488	0,3068122	0,9626734
Rhodes University Medical Scheme	2011	0,4568345	0,4093276	0,4508781	0,6900016	0,593227	0,8267728
Rhodes University Medical Scheme	2012	0,5310273	0,4831252	0,5219271	0,718814	0,6721144	0,8112367
Rhodes University Medical Scheme	2013	0,4602118	0,4136159	0,4535273	0,736627	0,5614998	0,8590223
Rhodes University Medical Scheme	2014	0,4182434	0,3681632	0,4134145	0,7317459	0,5031299	0,8805141
Rhodes University Medical Scheme	2015	0,4848729	0,4197392	0,4787671	0,6909003	0,6075249	0,8959116
Rhodes University Medical Scheme	2016	0,5773424	0,5176954	0,5717975	0,8038934	0,6439851	0,9388499
Rhodes University Medical Scheme	2017	0,5025584	0,4189614	0,489935	0,7513402	0,5576187	1
SABC Medical Aid Scheme	2011	0,3919812	0,3703274	0,388194	0,9763455	0,3792996	0,9037802
SABC Medical Aid Scheme	2012	0,3983307	0,376864	0,394646	0,9892389	0,3809636	0,9232293
SABC Medical Aid Scheme	2013	0,3829106	0,3630576	0,3795703	0,9983515	0,3636571	0,8904041
SABC Medical Aid Scheme	2014	0,3736978	0,3546717	0,3720041	0,9239632	0,3838591	0,8282821
SABC Medical Aid Scheme	2015	0,5007592	0,4674278	0,4983361	0,8714824	0,5363595	0,8882812
SABC Medical Aid Scheme	2016	0,4811661	0,4426108	0,4766097	0,8622288	0,5133333	0,9175087
SABC Medical Aid Scheme	2017	0,5194831	0,4711144	0,5137368	0,8620607	0,546498	1
SAMWUMed	2011	0,4172102	0,39202	0,4115463	0,8210524	0,4774604	0,686729
SAMWUMed	2012	0,4262789	0,3948461	0,4191211	0,827222	0,4773158	0,8256108
SAMWUMed	2013	0,4996108	0,4553002	0,4873033	0,8205488	0,5548728	1
SAMWUMed	2014	0,6705453	0,6060849	0,659237	0,78579	0,7713065	0,9449378
SAMWUMed	2015	0,571954	0,5089162	0,5666594	0,7080194	0,7187885	0,8714572

SAMWUMed	2016	0,5198729	0,448248	0,5127143	0,7033067	0,6373435	0,9223195
SAMWUMed	2017	0,4988863	0,4559008	0,4928039	0,7259291	0,6280239	0,7741841
Sappi Medical Aid Scheme	2011	0,5135015	0,466943	0,5015191	0,9304405	0,5018516	0,6963015
Sappi Medical Aid Scheme	2012	0,6523334	0,6112496	0,6375659	0,971691	0,6290576	1
Sasolmed	2011	0,6456752	0,5871071	0,6312618	0,8159898	0,719503	0,8618381
Sasolmed	2012	0,6641486	0,6085394	0,6475957	0,8173063	0,7445671	0,9100491
Sasolmed	2013	0,6967185	0,6371207	0,6813942	0,8285441	0,7689641	0,9504552
Sasolmed	2014	0,6727465	0,5925581	0,6516719	0,7675852	0,7719769	0,8790977
Sasolmed	2015	0,7350456	0,6520555	0,7201087	0,7553102	0,863295	0,9937469
Sasolmed	2016	0,7406829	0,6400328	0,7243811	0,7406829	0,8641118	1
Sasolmed	2017	0,7297329	0,6467558	0,7136754	0,7380872	0,8762593	0,9745741
Sedmed	2011	0,7528873	0,6783832	0,7401914	0,7528873	0,9010422	0,6212088
Sedmed	2012	0,589422	0,5448147	0,5780836	0,5894716	0,9242426	0,7124414
Sedmed	2014	0,4808314	0,439638	0,472276	0,5965838	0,7369257	0,7031496
Sedmed	2015	0,5151011	0,470765	0,5059179	0,6251594	0,753032	0,7539311
Sedmed	2016	0,6935285	0,6357987	0,6813436	0,6935285	0,9167593	0,9564008
Sedmed	2017	0,6970886	0,6375303	0,6847997	0,708842	0,899397	1
Siemens Medical Scheme	2011	0,4205219	0,3825409	0,4093339	0,8707201	0,4393385	
Sisonke Health Medical Scheme	2014	0,4452678	0,3973777	0,4348803	0,9183963	0,4326866	0,8161139
Sisonke Health Medical Scheme	2015	0,4592968	0,4215668	0,4520025	0,8717285	0,4835988	0,8465236
Sisonke Health Medical Scheme	2016	0,5012848	0,4505004	0,4887831	0,8649306	0,5208516	0,9554853
Sisonke Health Medical Scheme	2017	0,5236419	0,4608403	0,5068775	0,8553935	0,5387465	1
South African Breweries Medical Aid Scheme (SABMAS)	2011	0,3253517	0,3065802	0,3208367	0,9279107	0,3303984	0,8674629
South African Breweries Medical Aid Scheme (SABMAS)	2012	0,3181659	0,2988915	0,3127453	0,8877332	0,3366906	0,8668279
South African Breweries Medical Aid Scheme (SABMAS)	2013	0,3158611	0,2992105	0,3127406	0,8602907	0,3478017	0,8407723
South African Breweries Medical Aid Scheme (SABMAS)	2014	0,2951655	0,277561	0,2922552	0,842074	0,3296159	0,7790913
South African Breweries Medical Aid Scheme (SABMAS)	2015	0,3680933	0,3304165	0,3589986	0,8104207	0,4077099	0,930939
South African Breweries Medical Aid Scheme (SABMAS)	2016	0,3644041	0,3256243	0,3544627	0,7981426	0,4079776	0,94598
South African Breweries Medical Aid Scheme (SABMAS)	2017	0,3578391	0,3207285	0,3475443	0,8081255	0,3968796	1
South African Police Service Medical Scheme (POLMED)	2011	0,6243055	0,5825712	0,6148939	0,7363053	0,7912087	0,7906762
South African Police Service Medical Scheme (POLMED)	2012	0,568517	0,5287653	0,5604467	0,7628767	0,6931202	0,7706305
South African Police Service Medical Scheme (POLMED)	2013	0,5968673	0,5485836	0,5853766	0,6896146	0,795493	0,8411458
South African Police Service Medical Scheme (POLMED)	2014	0,5936027	0,5415609	0,5810368	0,6806975	0,795597	0,8501059
South African Police Service Medical Scheme (POLMED)	2015	0,6717907	0,6199698	0,6521012	0,7645661	0,8108779	0,8699625
South African Police Service Medical Scheme (POLMED)	2016	0,6618056	0,6050369	0,6457239	0,7137145	0,8477296	0,9282095

South African Police Service Medical Scheme (POLMED)	2017	0,7870933	0,725963	0,7707177	0,7870933	0,9223341	1
TFG Medical Scheme	2011	0,662677	0,5781226	0,6365656	0,8772004	0,6590542	1
TFG Medical Scheme	2012	0,703994	0,6170269	0,6799079	0,8773074	0,703319	0,9147298
TFG Medical Scheme	2013	0,7223617	0,6358202	0,6940949	0,8913645	0,7133111	0,9021182
TFG Medical Scheme	2014	0,6006141	0,5452971	0,5859712	0,9439351	0,5776849	0,6536841
TFG Medical Scheme	2015	0,7229469	0,6598925	0,7101741	0,9798809	0,6734415	0,7278761
TFG Medical Scheme	2016	0,8989238	0,8257877	0,8750727	0,9703286	0,8510392	0,7803168
TFG Medical Scheme	2017	0,7996166	0,732107	0,7793407	0,9842781	0,7438009	0,7566224
Tiger Brands Medical Scheme	2011	0,5634162	0,5158417	0,552959	0,9396251	0,5489867	0,7357442
Tiger Brands Medical Scheme	2012	0,5757352	0,5274818	0,5639539	0,9444243	0,558522	0,7691063
Tiger Brands Medical Scheme	2013	0,635373	0,5596487	0,6170968	0,9131792	0,6128575	0,7618909
Tiger Brands Medical Scheme	2014	0,6054263	0,5320234	0,5891518	0,8931467	0,5956731	0,797851
Tiger Brands Medical Scheme	2015	0,7690891	0,6566459	0,7585498	0,8260611	0,794912	0,96499
Tiger Brands Medical Scheme	2016	0,8044875	0,7444494	0,7883382	0,8912554	0,8352817	1
Tiger Brands Medical Scheme	2017	0,7577074	0,6687957	0,7423439	0,8468325	0,7897615	0,9901886
Transmed Medical Fund	2011	0,7493527	0,6749651	0,7418286	0,9732515	0,6935157	0,858645
Transmed Medical Fund	2012	0,5824704	0,5459199	0,5758424	0,9836434	0,5549977	0,6030761
Transmed Medical Fund	2013	0,7633144	0,692627	0,741692	0,9948377	0,6962211	0,7040036
Transmed Medical Fund	2014	0,8311349	0,725053	0,7988219	0,9877249	0,7340637	0,7309303
Transmed Medical Fund	2015	1	0,8679048	0,9574535	1	0,8679048	1
Transmed Medical Fund	2016	1	0,7595061	0,9432232	1	0,7595061	0,8233948
Transmed Medical Fund	2017	0,6972756	0,6685221	0,689056	0,9986736	0,66941	0,6637757
Tsogo Sun Group Medical Scheme	2011	0,2627158	0,2434368	0,2578303	0,8168287	0,2980267	0,7319006
Tsogo Sun Group Medical Scheme	2012	0,2776617	0,2596987	0,2732663	0,8722509	0,297734	0,7970718
Tsogo Sun Group Medical Scheme	2013	0,2712347	0,2537452	0,2669114	0,887816	0,2858083	0,8327523
Tsogo Sun Group Medical Scheme	2014	0,2659473	0,2481063	0,2617243	0,8923165	0,2780475	0,8896316
Tsogo Sun Group Medical Scheme	2015	0,3166436	0,2980937	0,3114718	0,9244457	0,3224567	0,9814227
Tsogo Sun Group Medical Scheme	2016	0,315235	0,2953252	0,3100622	0,9265968	0,3187203	1
Tsogo Sun Group Medical Scheme	2017	0,3088168	0,2909572	0,30393	0,9458244	0,3076228	0,932932
Umvuzo Health Medical Scheme	2011	0,5195205	0,482541	0,5170494	0,8411726	0,5736527	0,9147068
Umvuzo Health Medical Scheme	2012	0,5481445	0,5134194	0,544979	0,903	0,5685707	1
Umvuzo Health Medical Scheme	2013	0,4637982	0,438637	0,4580151	0,9325384	0,4703688	0,8125951
Umvuzo Health Medical Scheme	2014	0,4274381	0,4038401	0,4246338	0,9673818	0,4174568	0,7679828
Umvuzo Health Medical Scheme	2015	0,4473753	0,4182001	0,4422506	0,9938354	0,4207941	0,7464517
Umvuzo Health Medical Scheme	2016	0,516838	0,4930936	0,5109893	0,9904138	0,4978662	0,8258766
Umvuzo Health Medical Scheme	2017	0,5214445	0,4977885	0,5151367	0,9821575	0,5068317	0,8643622
University of KwaZulu-Natal Medical Scheme	2011	0,2704242	0,2547144	0,2676745	0,8813311	0,289011	0,9145312
University of KwaZulu-Natal Medical Scheme	2012	0,2766351	0,2539805	0,2696843	0,902404	0,2814488	0,9576726
University of KwaZulu-Natal Medical Scheme	2013	0,287606	0,2731548	0,2853484	0,9277146	0,2944384	0,8722296

University of KwaZulu-Natal Medical Scheme	2014	0,2755507	0,2622663	0,2741007	0,9409109	0,2787366	0,8315287
University of KwaZulu-Natal Medical Scheme	2015	0,3530954	0,3187822	0,3475571	0,9808623	0,325002	0,9798925
University of KwaZulu-Natal Medical Scheme	2016	0,3459482	0,3214525	0,343628	0,9858059	0,3260809	0,9768749
University of KwaZulu-Natal Medical Scheme	2017	0,3506562	0,3248039	0,3483129	0,9916631	0,3275345	1
University of the Witwatersrand Staff Medical Aid Scheme	2011	0,6304814	0,557769	0,6092724	0,9720738	0,5737929	1
University of the Witwatersrand Staff Medical Aid Scheme	2012	0,6024594	0,5371826	0,5819567	0,9829814	0,546483	0,9174591
University of the Witwatersrand Staff Medical Aid Scheme	2013	0,6691604	0,6083419	0,6506573	0,9778132	0,6221454	0,8587331
University of the Witwatersrand Staff Medical Aid Scheme	2014	0,7337722	0,6665763	0,7072729	0,9717718	0,6859392	0,8583229
University of the Witwatersrand Staff Medical Aid Scheme	2015	0,7057762	0,6373333	0,6874459	0,9995331	0,6376311	0,8872586
University of the Witwatersrand Staff Medical Aid Scheme	2016	0,7657745	0,6855044	0,7551212	0,9489734	0,7223642	0,9767523
University of the Witwatersrand Staff Medical Aid Scheme	2017	0,7323693	0,660994	0,7226437	0,9460247	0,6987069	0,9598958
Witbank Coalfields Medical Aid Scheme	2011	0,4278263	0,3890888	0,4238062	0,8732016	0,4455887	1
Witbank Coalfields Medical Aid Scheme	2012	0,408237	0,3676975	0,4012252	0,8575889	0,4287573	0,9689963
Witbank Coalfields Medical Aid Scheme	2013	0,4270748	0,3974061	0,4248462	0,8221666	0,4833645	0,9044754
Witbank Coalfields Medical Aid Scheme	2014	0,3924485	0,3607091	0,3885477	0,8143249	0,4429547	0,8951766
Witbank Coalfields Medical Aid Scheme	2015	0,4077553	0,3712658	0,4023151	0,8098458	0,4584402	0,8925163
Witbank Coalfields Medical Aid Scheme	2016	0,3772883	0,3406313	0,3717877	0,8267533	0,4120108	0,8919912
Witbank Coalfields Medical Aid Scheme	2017	0,3642059	0,3298207	0,3600645	0,8311201	0,3968388	0,8485458
Wooltru Healthcare Fund	2011	0,5627407	0,4999455	0,539526	0,9941976	0,5028633	0,738176
Wooltru Healthcare Fund	2012	0,5190048	0,4613217	0,4993543	0,9617164	0,4796858	0,7230322
Wooltru Healthcare Fund	2013	0,6853512	0,6314471	0,6680058	0,9932926	0,6357111	0,798656
Wooltru Healthcare Fund	2014	0,65429	0,6022344	0,6411922	0,9993487	0,6026269	0,8708085
Wooltru Healthcare Fund	2015	0,7344216	0,6738142	0,7173325	0,9574577	0,7037535	0,9803328
Wooltru Healthcare Fund	2016	0,622156	0,551587	0,6080551	0,8971233	0,6148397	1
Wooltru Healthcare Fund	2017	0,5331014	0,4721108	0,5167931	0,8674033	0,5442806	0,9039258
Xstrata Medical Aid Scheme	2011	0,7524983	0,7000657	0,7415255	0,9847406	0,7109138	1
Xstrata Medical Aid Scheme	2012	0,8222614	0,7236767	0,7998705	0,9330308	0,7756193	0,9177848
Xstrata Medical Aid Scheme	2013	0,7977909	0,7078524	0,7722732	0,9472153	0,7472983	0,8628663

Table 7.4: SFA efficiency results for open medical schemes

Year	Medical Scheme	Model One SFA Technical Efficiencies	Model Two SFA Technical Efficiencies
2011	Bestmed Medical Scheme	0,9172208	0,8827112
2012	Bestmed Medical Scheme	0,9204531	0,8897043
2013	Bestmed Medical Scheme	0,9364567	0,9164359
2014	Bestmed Medical Scheme	0,9410899	0,9230298
2015	Bestmed Medical Scheme	0,9536139	0,9428468
2016	Bestmed Medical Scheme	0,9503459	0,9304546
2017	Bestmed Medical Scheme	0,9471185	0,9201801
2011	Bonitas Medical Fund	0,9421018	0,9254327
2012	Bonitas Medical Fund	0,9342318	0,9169608
2013	Bonitas Medical Fund	0,9262031	0,8994544
2014	Bonitas Medical Fund	0,936618	0,9198202
2015	Bonitas Medical Fund	0,9541216	0,9487498
2016	Bonitas Medical Fund	0,952359	0,9423238
2017	Bonitas Medical Fund	0,9551883	0,9389464
2011	Cape Medical Plan	0,9246305	0,9067928
2012	Cape Medical Plan	0,9201499	0,9081396
2013	Cape Medical Plan	0,9178931	0,9322529
2014	Cape Medical Plan	0,9248851	0,9274849
2015	Cape Medical Plan	0,9304906	0,9381166
2016	Cape Medical Plan	0,9130594	0,887812
2017	Cape Medical Plan	0,8972335	0,8999389
2011	Community Medical Aid Scheme (COMMED)	0,9434063	0,9271709
2012	Community Medical Aid Scheme (COMMED)	0,9088243	0,8636791
2013	Community Medical Aid Scheme (COMMED)	0,8606517	0,8095432
2014	Community Medical Aid Scheme (COMMED)	0,8114361	0,7768959
2011	Compcare Wellness Medical Scheme	0,9240299	0,881503
2012	Compcare Wellness Medical Scheme	0,9054874	0,8352678
2013	Compcare Wellness Medical Scheme	0,8803184	0,8364878
2014	Compcare Wellness Medical Scheme	0,8542026	0,7886248
2015	Compcare Wellness Medical Scheme	0,9271233	0,9145625
2016	Compcare Wellness Medical Scheme	0,9384174	0,9293687
2017	Compcare Wellness Medical Scheme	0,9316128	0,9097656
2011	Discovery Health Medical Scheme	0,8736692	0,8041885
2012	Discovery Health Medical Scheme	0,8695347	0,7895802
2013	Discovery Health Medical Scheme	0,8695099	0,7729107
2014	Discovery Health Medical Scheme	0,862161	0,7629309

2015	Discovery Health Medical Scheme	0,9199221	0,8761247
2016	Discovery Health Medical Scheme	0,9114018	0,8629771
2017	Discovery Health Medical Scheme	0,8994558	0,8273466
2011	Fedhealth Medical Scheme	0,935717	0,9022483
2012	Fedhealth Medical Scheme	0,9316386	0,8898504
2013	Fedhealth Medical Scheme	0,9257047	0,9006163
2014	Fedhealth Medical Scheme	0,9221749	0,9008017
2015	Fedhealth Medical Scheme	0,9494011	0,9380585
2016	Fedhealth Medical Scheme	0,9396179	0,9292715
2017	Fedhealth Medical Scheme	0,9277167	0,8881403
2011	Genesis Medical Scheme	0,9223893	0,8205412
2012	Genesis Medical Scheme	0,9221312	0,8074725
2013	Genesis Medical Scheme	0,9013014	0,7334254
2014	Genesis Medical Scheme	0,894968	0,7324176
2015	Genesis Medical Scheme	0,8874334	0,7047443
2016	Genesis Medical Scheme	0,888298	0,7219753
2017	Genesis Medical Scheme	0,8479484	0,6460638
2011	Hosmed Medical Aid Scheme	0,9581899	0,946041
2012	Hosmed Medical Aid Scheme	0,9588662	0,9465355
2013	Hosmed Medical Aid Scheme	0,9476912	0,9341983
2014	Hosmed Medical Aid Scheme	0,9527466	0,9379038
2015	Hosmed Medical Aid Scheme	0,9613841	0,9528618
2016	Hosmed Medical Aid Scheme	0,9607484	0,9548407
2017	Hosmed Medical Aid Scheme	0,9502007	0,9289612
2011	Keyhealth	0,9647858	0,9577953
2012	Keyhealth	0,968706	0,9606929
2013	Keyhealth	0,9636615	0,9516081
2014	Keyhealth	0,9595589	0,9474856
2015	Keyhealth	0,9636378	0,9591459
2016	Keyhealth	0,9614496	0,9531419
2017	Keyhealth	0,9588061	0,9414781
2011	Liberty Medical Scheme	0,9241231	0,9095894
2012	Liberty Medical Scheme	0,8993431	0,8743243
2013	Liberty Medical Scheme	0,8782665	0,8301031
2014	Liberty Medical Scheme	0,8977881	0,8848441
2015	Liberty Medical Scheme	0,9490346	0,9445145
2011	Makoti Medical Scheme	0,9640452	0,9594163
2012	Makoti Medical Scheme	0,905708	0,8845125
2013	Makoti Medical Scheme	0,9459624	0,9338679
2014	Makoti Medical Scheme	0,9481057	0,938632
2015	Makoti Medical Scheme	0,9441878	0,9175914
2016	Makoti Medical Scheme	0,9407882	0,9126818

2017	Makoti Medical Scheme	0,9003223	0,8613313
2011	Medihelp	0,965407	0,9589767
2012	Medihelp	0,9537096	0,9494283
2013	Medihelp	0,9434087	0,9339983
2014	Medihelp	0,932884	0,9208714
2015	Medihelp	0,9543469	0,9420826
2016	Medihelp	0,958829	0,9524587
2017	Medihelp	0,9630409	0,9542415
2011	Medimed Medical Scheme	0,9569159	0,9377369
2012	Medimed Medical Scheme	0,948653	0,9282209
2013	Medimed Medical Scheme	0,942897	0,9304969
2014	Medimed Medical Scheme	0,9454584	0,9137759
2015	Medimed Medical Scheme	0,9569299	0,9428328
2016	Medimed Medical Scheme	0,9586826	0,9444723
2017	Medimed Medical Scheme	0,9569572	0,9346928
2011	Medshield Medical Scheme	0,9566489	0,9521807
2012	Medshield Medical Scheme	0,9446962	0,9229247
2013	Medshield Medical Scheme	0,9448328	0,9257959
2014	Medshield Medical Scheme	0,9313015	0,9099874
2015	Medshield Medical Scheme	0,9551728	0,9478533
2016	Medshield Medical Scheme	0,9442093	0,9331965
2017	Medshield Medical Scheme	0,9355569	0,9275196
2011	Momentum Health	0,9218072	0,8701998
2012	Momentum Health	0,9123366	0,8341447
2013	Momentum Health	0,90047	0,8176168
2014	Momentum Health	0,8818976	0,799771
2015	Momentum Health	0,9163331	0,8759182
2016	Momentum Health	0,9030806	0,862147
2017	Momentum Health	0,89157	0,8271555
2011	National Independent Medical Aid Society (NIMAS)	0,970953	0,96911
2011	Pharos Medical Plan	0,9265398	0,9072285
2012	Pharos Medical Plan	0,9255472	0,8933565
2013	Pharos Medical Plan	0,8817919	0,8090685
2011	Pro Sano Medical Scheme	0,9534191	0,9458279
2012	Pro Sano Medical Scheme	0,9226323	0,9064454
2011	Resolution Health Medical Scheme	0,9129698	0,9097545
2012	Resolution Health Medical Scheme	0,9243603	0,9218886
2013	Resolution Health Medical Scheme	0,9404681	0,9204878
2014	Resolution Health Medical Scheme	0,9352298	0,9161981
2015	Resolution Health Medical Scheme	0,9517263	0,9412587
2016	Resolution Health Medical Scheme	0,9488975	0,9358667
2017	Resolution Health Medical Scheme	0,9419053	0,9216021

2011	Selfmed Medical Scheme	0,9428676	0,9082631
2012	Selfmed Medical Scheme	0,9453674	0,9401916
2013	Selfmed Medical Scheme	0,9274079	0,9142912
2014	Selfmed Medical Scheme	0,92366	0,9022155
2015	Selfmed Medical Scheme	0,9477015	0,9294297
2016	Selfmed Medical Scheme	0,9383284	0,9369283
2017	Selfmed Medical Scheme	0,9225561	0,9244571
2011	Sizwe Medical Fund	0,9506726	0,9463504
2012	Sizwe Medical Fund	0,9538416	0,9477425
2013	Sizwe Medical Fund	0,9528953	0,9310736
2014	Sizwe Medical Fund	0,9463589	0,9083971
2015	Sizwe Medical Fund	0,9549212	0,9413143
2016	Sizwe Medical Fund	0,9376127	0,9121706
2017	Sizwe Medical Fund	0,9317342	0,8976318
2011	Spectramed	0,9330651	0,8799094
2012	Spectramed	0,8798491	0,7840616
2013	Spectramed	0,7185743	0,6179727
2014	Spectramed	0,6684535	0,5968507
2015	Spectramed	0,7283735	0,7289921
2016	Spectramed	0,8777807	0,8606522
2017	Spectramed	0,906999	0,8883016
2011	Suremed Health	0,8717859	0,8062862
2012	Suremed Health	0,8892905	0,7843334
2013	Suremed Health	0,9435078	0,9324508
2014	Suremed Health	0,9238827	0,9145731
2015	Suremed Health	0,9201913	0,8666132
2016	Suremed Health	0,9275706	0,8677719
2017	Suremed Health	0,9198154	0,869251
2011	Thebemed	0,9363174	0,890549
2012	Thebemed	0,9438598	0,9291787
2013	Thebemed	0,9480428	0,926131
2014	Thebemed	0,9488991	0,9137258
2015	Thebemed	0,9261463	0,886795
2016	Thebemed	0,9239082	0,8981493
2017	Thebemed	0,9297709	0,9154467
2011	Topmed Medical Scheme	0,9049603	0,8892477
2012	Topmed Medical Scheme	0,8821005	0,8827012
2013	Topmed Medical Scheme	0,8357852	0,8437905
2014	Topmed Medical Scheme	0,9008766	0,8780817
2015	Topmed Medical Scheme	0,9268639	0,9179527
2016	Topmed Medical Scheme	0,9221159	0,9157308
2017	Topmed Medical Scheme	0,9213607	0,913371

Table 7.5: SFA efficiency results for restricted medical schemes

Year	Medical Scheme	Model One SFA Technical Efficiencies	Model Two SFA Technical Efficiencies
2011	AECI Medical Aid Society	0,8959103	0,8678825
2012	AECI Medical Aid Society	0,8924772	0,8674075
2013	AECI Medical Aid Society	0,8863102	0,8490933
2014	AECI Medical Aid Society	0,8798488	0,8359007
2015	AECI Medical Aid Society	0,9038913	0,8802235
2016	AECI Medical Aid Society	0,8971947	0,8839937
2017	AECI Medical Aid Society	0,894317	0,874306
2011	Afrox Medical Aid Society	0,8466823	0,8429717
2012	Afrox Medical Aid Society	0,8468875	0,8489164
2013	Afrox Medical Aid Society	0,8681639	0,8573155
2011	Alliance Midmed Medical Scheme	0,8599445	0,8376255
2013	Alliance Midmed Medical Scheme	0,859454	0,8008837
2014	Alliance Midmed Medical Scheme	0,8649217	0,8380426
2015	Alliance Midmed Medical Scheme	0,8821203	0,8509854
2016	Alliance Midmed Medical Scheme	0,8625921	0,8136073
2017	Alliance Midmed Medical Scheme	0,8606929	0,8257094
2011	Altron Medical Aid Scheme	0,8797811	0,8609653
2012	Altron Medical Aid Scheme	0,8838313	0,852964
2013	Altron Medical Aid Scheme	0,8711156	0,8255866
2011	Anglo Medical Scheme	0,7639322	0,7485415
2012	Anglo Medical Scheme	0,744951	0,7189015
2013	Anglo Medical Scheme	0,6897941	0,6651647
2014	Anglo Medical Scheme	0,6213894	0,6129304
2015	Anglo Medical Scheme	0,7141361	0,7395195
2016	Anglo Medical Scheme	0,7037233	0,7347274
2017	Anglo Medical Scheme	0,7034221	0,7029602
2011	Anglovaal Group Medical Scheme	0,8132088	0,7607829
2012	Anglovaal Group Medical Scheme	0,7926207	0,709565
2013	Anglovaal Group Medical Scheme	0,7805051	0,7307143
2014	Anglovaal Group Medical Scheme	0,7710783	0,7191203
2015	Anglovaal Group Medical Scheme	0,8179134	0,7575637
2016	Anglovaal Group Medical Scheme	0,8129855	0,7767991
2017	Anglovaal Group Medical Scheme	0,8039879	0,7521826
2011	BMW Employees Medical Aid Society	0,8908152	0,8783252
2012	BMW Employees Medical Aid Society	0,8867413	0,8521139

2013	BMW Employees Medical Aid Society	0,8793708	0,8437427
2014	BMW Employees Medical Aid Society	0,8757966	0,8522891
2015	BMW Employees Medical Aid Society	0,9069021	0,8878491
2016	BMW Employees Medical Aid Society	0,8967866	0,8399455
2017	BMW Employees Medical Aid Society	0,893353	0,8328975
2011	BP Medical Aid Society	0,8900995	0,8905745
2012	BP Medical Aid Society	0,8833894	0,8837067
2013	BP Medical Aid Society	0,880026	0,870684
2014	BP Medical Aid Society	0,8749254	0,8744115
2015	BP Medical Aid Society	0,8993898	0,902501
2016	BP Medical Aid Society	0,8861384	0,8805058
2017	BP Medical Aid Society	0,8657096	0,8622644
2011	Bankmed	0,8299331	0,8021425
2012	Bankmed	0,8217012	0,7922791
2013	Bankmed	0,8139235	0,7734852
2014	Bankmed	0,8023629	0,7681192
2015	Bankmed	0,8413955	0,8182803
2016	Bankmed	0,855074	0,8323931
2017	Bankmed	0,8732067	0,849632
2011	Barloworld Medical Scheme	0,8954037	0,8640373
2012	Barloworld Medical Scheme	0,8889467	0,8576558
2013	Barloworld Medical Scheme	0,8830671	0,8340631
2014	Barloworld Medical Scheme	0,8700771	0,8422154
2015	Barloworld Medical Scheme	0,899703	0,8850601
2016	Barloworld Medical Scheme	0,8939136	0,879146
2017	Barloworld Medical Scheme	0,8877174	0,8711534
2011	Building & Construction Industry Medical Aid Fund	0,8170947	0,6971661
2012	Building & Construction Industry Medical Aid Fund	0,7944243	0,6364491
2013	Building & Construction Industry Medical Aid Fund	0,7707872	0,6239186
2014	Building & Construction Industry Medical Aid Fund	0,7494181	0,570039
2015	Building & Construction Industry Medical Aid Fund	0,7880883	0,643328
2016	Building & Construction Industry Medical Aid Fund	0,7549343	0,6601799
2017	Building & Construction Industry Medical Aid Fund	0,7322439	0,602123
2011	Chartered Accountants (SA) Medical Aid Fund (CAMAF)	0,8089447	0,7384501
2012	Chartered Accountants (SA) Medical Aid Fund (CAMAF)	0,7976836	0,729193
2013	Chartered Accountants (SA) Medical Aid Fund (CAMAF)	0,7905203	0,7199522
2014	Chartered Accountants (SA) Medical Aid Fund (CAMAF)	0,7688944	0,7021543
2015	Chartered Accountants (SA) Medical Aid Fund (CAMAF)	0,7944217	0,7532144
2016	Chartered Accountants (SA) Medical Aid Fund (CAMAF)	0,7928906	0,740618
2017	Chartered Accountants (SA) Medical Aid Fund (CAMAF)	0,7873687	0,7123536

2011	De Beers Benefit Society	0,8823704	0,8588618
2012	De Beers Benefit Society	0,8624994	0,8336722
2013	De Beers Benefit Society	0,8551168	0,8189003
2014	De Beers Benefit Society	0,8491021	0,8199638
2015	De Beers Benefit Society	0,8349117	0,7940856
2016	De Beers Benefit Society	0,8472223	0,8225509
2017	De Beers Benefit Society	0,8316707	0,8085643
2011	Edcon Medical Aid Scheme	0,816009	0,7365276
2011	Engen Medical Benefit Fund	0,8855699	0,858961
2012	Engen Medical Benefit Fund	0,8733121	0,8339817
2013	Engen Medical Benefit Fund	0,8723748	0,8507528
2014	Engen Medical Benefit Fund	0,8583516	0,8283153
2015	Engen Medical Benefit Fund	0,9054001	0,8849698
2016	Engen Medical Benefit Fund	0,9013313	0,8839653
2017	Engen Medical Benefit Fund	0,8991157	0,8627047
2011	Eyethumed Medical Scheme	0,7714968	0,7002895
2012	Eyethumed Medical Scheme	0,8002336	0,7748207
2011	Fishing Industry Medical Scheme (Fishmed)	0,685178	0,5550292
2012	Fishing Industry Medical Scheme (Fishmed)	0,6823629	0,5271813
2013	Fishing Industry Medical Scheme (Fishmed)	0,7012261	0,5199257
2014	Fishing Industry Medical Scheme (Fishmed)	0,7058505	0,5074672
2015	Fishing Industry Medical Scheme (Fishmed)	0,7553958	0,5967118
2016	Fishing Industry Medical Scheme (Fishmed)	0,7594655	0,6013048
2017	Fishing Industry Medical Scheme (Fishmed)	0,7562971	0,5940581
2011	Food Workers Medical Benefit Fund	0,595024	0,365854
2012	Food Workers Medical Benefit Fund	0,5035032	0,2794493
2013	Food Workers Medical Benefit Fund	0,4421283	0,2404549
2014	Food Workers Medical Benefit Fund	0,367635	0,2004097
2015	Food Workers Medical Benefit Fund	0,402363	0,193606
2016	Food Workers Medical Benefit Fund	0,3035627	0,1431938
2017	Food Workers Medical Benefit Fund	0,330621	0,166344
2014	Glencore Medical Scheme	0,8952463	0,8703943
2015	Glencore Medical Scheme	0,9133934	0,9064668
2016	Glencore Medical Scheme	0,9122853	0,8948166
2017	Glencore Medical Scheme	0,9056854	0,8852631
2011	Gold Fields Medical Scheme	0,8487641	0,8055134
2012	Gold Fields Medical Scheme	0,8477086	0,7939971
2013	Gold Fields Medical Scheme	0,8361554	0,7850094
2012	Golden Arrow Employees Medical Benefit Fund	0,681096	0,7712184
2011	Golden Arrows Employees Medical Benefit Fund	0,7090231	0,8035748
2013	Golden Arrows Employees Medical Benefit Fund	0,667549	0,7728639
2014	Golden Arrows Employees Medical Benefit Fund	0,6359981	0,7416799

2015	Golden Arrows Employees Medical Benefit Fund	0,7175062	0,8094057
2016	Golden Arrows Employees Medical Benefit Fund	0,6907322	0,7759223
2017	Golden Arrows Employees Medical Benefit Fund	0,642255	0,7300706
2011	Government Employees Medical Scheme (GEMS)	0,9223334	0,9171665
2012	Government Employees Medical Scheme (GEMS)	0,9185987	0,9151528
2013	Government Employees Medical Scheme (GEMS)	0,9062687	0,8968873
2014	Government Employees Medical Scheme (GEMS)	0,9016607	0,896231
2015	Government Employees Medical Scheme (GEMS)	0,920601	0,9160817
2016	Government Employees Medical Scheme (GEMS)	0,9126018	0,9080122
2017	Government Employees Medical Scheme (GEMS)	0,89697	0,8748978
2011	Grintek Electronics Medical Aid Scheme	0,8665557	0,854048
2012	Grintek Electronics Medical Aid Scheme	0,8607956	0,8104187
2013	Grintek Electronics Medical Aid Scheme	0,8461174	0,7851471
2014	Grintek Electronics Medical Aid Scheme	0,8446064	0,821082
2015	Grintek Electronics Medical Aid Scheme	0,8774664	0,8616859
2016	Grintek Electronics Medical Aid Scheme	0,8674949	0,8408417
2017	Grintek Electronics Medical Aid Scheme	0,8694612	0,8412033
2011	Horizon Medical Scheme	0,738327	0,5912008
2012	Horizon Medical Scheme	0,7524536	0,585807
2013	Horizon Medical Scheme	0,7323244	0,5623096
2014	Horizon Medical Scheme	0,7276525	0,6062734
2015	Horizon Medical Scheme	0,7716165	0,5840066
2016	Horizon Medical Scheme	0,7516249	0,6418629
2017	Horizon Medical Scheme	0,7697145	0,6586674
2011	IBM (SA) Medical Scheme	0,832986	0,7671728
2012	IBM (SA) Medical Scheme	0,8119844	0,7464449
2011	Impala Medical Plan	0,9403396	0,9323938
2012	Impala Medical Plan	0,9417584	0,9338263
2013	Impala Medical Plan	0,9394709	0,9307089
2014	Impala Medical Plan	0,9414927	0,9333153
2015	Impala Medical Plan	0,9355435	0,9255004
2016	Impala Medical Plan	0,9355206	0,9251127
2017	Impala Medical Plan	0,9361924	0,9252364
2011	Imperial Group Medical Scheme	0,8712586	0,8512205
2012	Imperial Group Medical Scheme	0,8724604	0,846122
2013	Imperial Group Medical Scheme	0,8720719	0,8436027
2014	Imperial Group Medical Scheme	0,8719687	0,8393848
2015	Imperial Group Medical Scheme	0,8886922	0,8589457
2016	Imperial Group Medical Scheme	0,8805986	0,8473747
2017	Imperial Group Medical Scheme	0,8676893	0,8181083
2011	LA Health Medical Scheme	0,8210354	0,7567075
2012	LA Health Medical Scheme	0,8070375	0,7329186

2013	LA Health Medical Scheme	0,7962627	0,7012635
2014	LA Health Medical Scheme	0,7765719	0,6688588
2015	LA Health Medical Scheme	0,795742	0,7125335
2016	LA Health Medical Scheme	0,7730677	0,6790368
2017	LA Health Medical Scheme	0,7539586	0,6414188
2011	Libcare Medical Scheme	0,8286662	0,7656732
2012	Libcare Medical Scheme	0,8121652	0,7154951
2013	Libcare Medical Scheme	0,8037828	0,6909384
2014	Libcare Medical Scheme	0,7956281	0,6943843
2015	Libcare Medical Scheme	0,8354074	0,7627367
2016	Libcare Medical Scheme	0,8267531	0,7561747
2017	Libcare Medical Scheme	0,8327243	0,7912074
2011	Lonmin Medical Scheme	0,8435925	0,7184798
2012	Lonmin Medical Scheme	0,839122	0,7718693
2013	Lonmin Medical Scheme	0,8177885	0,7476138
2014	Lonmin Medical Scheme	0,8224923	0,7689061
2015	Lonmin Medical Scheme	0,8866992	0,8801771
2016	Lonmin Medical Scheme	0,9044662	0,9015849
2017	Lonmin Medical Scheme	0,9049734	0,8862749
2011	MBMed Medical Aid Fund	0,8958454	0,867494
2012	MBMed Medical Aid Fund	0,8806784	0,858316
2013	MBMed Medical Aid Fund	0,8758379	0,8422408
2014	MBMed Medical Aid Fund	0,8782647	0,8356613
2015	MBMed Medical Aid Fund	0,9006635	0,8690037
2016	MBMed Medical Aid Fund	0,8875378	0,8621687
2017	MBMed Medical Aid Fund	0,8798606	0,8579244
2011	Malcor Medical Scheme	0,8890516	0,8838968
2012	Malcor Medical Scheme	0,9062619	0,9015607
2013	Malcor Medical Scheme	0,9027227	0,8970904
2014	Malcor Medical Scheme	0,9048368	0,8998981
2015	Malcor Medical Scheme	0,9087082	0,9035147
2016	Malcor Medical Scheme	0,9132712	0,9069896
2017	Malcor Medical Scheme	0,9116794	0,9013692
2011	Massmart Health Plan	0,8413485	0,7535542
2012	Massmart Health Plan	0,824436	0,720735
2013	Massmart Health Plan	0,8170795	0,7350014
2014	Massmart Health Plan	0,8159811	0,7138712
2015	Massmart Health Plan	0,8564513	0,7954032
2016	Massmart Health Plan	0,8337415	0,768329
2017	Massmart Health Plan	0,8283688	0,7543352
2011	Medipos Medical Scheme	0,8873839	0,8476999
2012	Medipos Medical Scheme	0,8808748	0,8490338

2013	Medipos Medical Scheme	0,8852385	0,8554685
2014	Medipos Medical Scheme	0,8672328	0,844897
2015	Medipos Medical Scheme	0,8892764	0,8755364
2016	Medipos Medical Scheme	0,8842287	0,8724717
2017	Medipos Medical Scheme	0,8818557	0,8662482
2011	Metrocare	0,8639094	0,8836315
2011	Metropolitan Medical Scheme	0,8718084	0,8463407
2012	Metropolitan Medical Scheme	0,8604769	0,8304323
2013	Metropolitan Medical Scheme	0,8625478	0,8303601
2014	Metropolitan Medical Scheme	0,852194	0,8239182
2015	Metropolitan Medical Scheme	0,881576	0,8726372
2016	Metropolitan Medical Scheme	0,8601863	0,8485838
2011	Minemed Medical Scheme	0,9199721	0,9078501
2012	Minemed Medical Scheme	0,9152409	0,8915681
2011	Motohealth Care	0,8363145	0,794368
2012	Motohealth Care	0,8091974	0,761916
2013	Motohealth Care	0,7981703	0,7437758
2014	Motohealth Care	0,7980956	0,7554182
2015	Motohealth Care	0,8337434	0,7984008
2016	Motohealth Care	0,8216097	0,7838311
2017	Motohealth Care	0,8234659	0,7925919
2011	Nampak SA Medical Scheme	0,8885671	0,8778464
2012	Nampak SA Medical Scheme	0,875708	0,8488433
2011	Naspers Medical Fund	0,8027562	0,7203709
2012	Naspers Medical Fund	0,7821804	0,6879431
2013	Naspers Medical Fund	0,7791807	0,7131063
2014	Naspers Medical Fund	0,7732891	0,6709836
2015	Naspers Medical Fund	0,8301723	0,772185
2016	Naspers Medical Fund	0,8167084	0,7706403
2017	Naspers Medical Fund	0,8089662	0,757211
2011	Nedgroup Medical Aid Scheme	0,8320625	0,811747
2012	Nedgroup Medical Aid Scheme	0,8285936	0,7971666
2013	Nedgroup Medical Aid Scheme	0,8125502	0,7757701
2014	Nedgroup Medical Aid Scheme	0,8599163	0,8464725
2015	Nedgroup Medical Aid Scheme	0,8704045	0,8487818
2016	Nedgroup Medical Aid Scheme	0,8621718	0,845015
2017	Nedgroup Medical Aid Scheme	0,8667396	0,8468155
2011	Netcare Medical Scheme	0,8744013	0,8662018
2012	Netcare Medical Scheme	0,8864358	0,8638335
2013	Netcare Medical Scheme	0,8799461	0,8475342
2014	Netcare Medical Scheme	0,8684107	0,843146
2015	Netcare Medical Scheme	0,8999758	0,8856676

2016	Netcare Medical Scheme	0,8979615	0,880089
2017	Netcare Medical Scheme	0,8992169	0,8777792
2011	Old Mutual Staff Medical Aid Fund	0,8553715	0,8098392
2012	Old Mutual Staff Medical Aid Fund	0,8434198	0,8021174
2013	Old Mutual Staff Medical Aid Fund	0,830088	0,7869788
2014	Old Mutual Staff Medical Aid Fund	0,8247502	0,7830368
2015	Old Mutual Staff Medical Aid Fund	0,8476459	0,8017707
2016	Old Mutual Staff Medical Aid Fund	0,835928	0,8054945
2017	Old Mutual Staff Medical Aid Fund	0,830694	0,7930343
2011	PG Bison Medical Aid Society	0,8538139	0,8245661
2012	PG Bison Medical Aid Society	0,8363297	0,8557492
2013	PG Bison Medical Aid Society	0,811322	0,8056226
2011	PG Group Medical Scheme	0,819307	0,7637451
2012	PG Group Medical Scheme	0,8033167	0,7818536
2013	PG Group Medical Scheme	0,8099446	0,7745585
2014	PG Group Medical Scheme	0,7998301	0,7776098
2015	PG Group Medical Scheme	0,8444071	0,8194578
2016	PG Group Medical Scheme	0,8464398	0,8216398
2017	PG Group Medical Scheme	0,825304	0,7798659
2011	Parmed Medical Aid Scheme	0,9188245	0,9091434
2012	Parmed Medical Aid Scheme	0,9137653	0,8976777
2013	Parmed Medical Aid Scheme	0,9103124	0,89488
2014	Parmed Medical Aid Scheme	0,9044862	0,8798854
2015	Parmed Medical Aid Scheme	0,9103693	0,8905435
2016	Parmed Medical Aid Scheme	0,9033418	0,8981196
2017	Parmed Medical Aid Scheme	0,9073325	0,8989294
2011	Pick & Pay Medical Scheme	0,7438647	0,6751097
2012	Pick & Pay Medical Scheme	0,7283086	0,6271836
2013	Pick & Pay Medical Scheme	0,7151957	0,6167882
2014	Pick & Pay Medical Scheme	0,6914778	0,6268492
2015	Pick & Pay Medical Scheme	0,768328	0,7351257
2016	Pick & Pay Medical Scheme	0,7807901	0,6807784
2017	Pick & Pay Medical Scheme	0,7549393	0,6066493
2011	Platinum Health	0,9039348	0,8727006
2012	Platinum Health	0,9005975	0,8891324
2013	Platinum Health	0,8930722	0,8822604
2014	Platinum Health	0,8971366	0,8810914
2015	Platinum Health	0,8929896	0,8787885
2016	Platinum Health	0,8901947	0,867407
2017	Platinum Health	0,8787932	0,8523477
2011	Profmed	0,8401326	0,7867402
2012	Profmed	0,8234687	0,7749016

2013	Profmed	0,8064395	0,7463039
2014	Profmed	0,783881	0,7101905
2015	Profmed	0,7910912	0,7375857
2016	Profmed	0,7804376	0,723723
2017	Profmed	0,7783332	0,7191646
2011	Quantum Medical Aid Society	0,7469318	0,6968127
2012	Quantum Medical Aid Society	0,7254657	0,7076916
2013	Quantum Medical Aid Society	0,7330225	0,6977304
2014	Quantum Medical Aid Society	0,7177428	0,6476251
2015	Quantum Medical Aid Society	0,8067899	0,7588843
2016	Quantum Medical Aid Society	0,802852	0,7471414
2017	Quantum Medical Aid Society	0,7967275	0,7177166
2011	Rand Water Medical Scheme	0,9080293	0,8919297
2012	Rand Water Medical Scheme	0,9100101	0,8949557
2013	Rand Water Medical Scheme	0,9028292	0,8690208
2014	Rand Water Medical Scheme	0,9021634	0,8718973
2015	Rand Water Medical Scheme	0,9131774	0,8899496
2016	Rand Water Medical Scheme	0,9062415	0,8799396
2017	Rand Water Medical Scheme	0,9119857	0,8801079
2011	Remedi Medical Aid Scheme	0,8841867	0,8378419
2012	Remedi Medical Aid Scheme	0,872815	0,8249567
2013	Remedi Medical Aid Scheme	0,851092	0,8178955
2014	Remedi Medical Aid Scheme	0,8511886	0,8095827
2015	Remedi Medical Aid Scheme	0,8814321	0,8500845
2016	Remedi Medical Aid Scheme	0,8747383	0,8457041
2017	Remedi Medical Aid Scheme	0,8712134	0,8403185
2011	Retail Medical Scheme	0,7311488	0,6310878
2012	Retail Medical Scheme	0,7186375	0,5947403
2013	Retail Medical Scheme	0,7020504	0,5623886
2014	Retail Medical Scheme	0,6668223	0,4906031
2015	Retail Medical Scheme	0,7497104	0,6778004
2016	Retail Medical Scheme	0,7472675	0,6323962
2017	Retail Medical Scheme	0,7317456	0,609235
2011	Rhodes University Medical Scheme	0,8875359	0,8324524
2012	Rhodes University Medical Scheme	0,8811175	0,8144631
2013	Rhodes University Medical Scheme	0,8705406	0,8209326
2014	Rhodes University Medical Scheme	0,8638337	0,8187419
2015	Rhodes University Medical Scheme	0,8878486	0,8447219
2016	Rhodes University Medical Scheme	0,8843783	0,8368155
2017	Rhodes University Medical Scheme	0,875683	0,8422338
2011	SABC Medical Aid Scheme	0,8602743	0,8196922
2012	SABC Medical Aid Scheme	0,8572458	0,8119702

2013	SABC Medical Aid Scheme	0,8428668	0,7826832
2014	SABC Medical Aid Scheme	0,8408508	0,7620092
2015	SABC Medical Aid Scheme	0,8729541	0,816354
2016	SABC Medical Aid Scheme	0,8592128	0,8108934
2017	SABC Medical Aid Scheme	0,8531132	0,8222724
2011	SAMWUMed	0,87337	0,8280603
2012	SAMWUMed	0,8601906	0,8329995
2013	SAMWUMed	0,8773403	0,8583734
2014	SAMWUMed	0,8879939	0,8369947
2015	SAMWUMed	0,894933	0,8551221
2016	SAMWUMed	0,8794125	0,8497852
2017	SAMWUMed	0,8645329	0,8140388
2011	Sappi Medical Aid Scheme	0,8904359	0,8777446
2012	Sappi Medical Aid Scheme	0,9037178	0,8903579
2011	Sasolmed	0,9040717	0,8917366
2012	Sasolmed	0,9008796	0,8898032
2013	Sasolmed	0,8986338	0,8832019
2014	Sasolmed	0,8916336	0,8670253
2015	Sasolmed	0,912963	0,9022263
2016	Sasolmed	0,9126762	0,8990626
2017	Sasolmed	0,9086987	0,8932279
2011	Sedmed	0,9326528	0,9224913
2012	Sedmed	0,9014531	0,8974541
2014	Sedmed	0,85751	0,849231
2015	Sedmed	0,8641397	0,8516326
2016	Sedmed	0,8910903	0,8864903
2017	Sedmed	0,8899003	0,880155
2011	Siemens Medical Scheme	0,8568159	0,831933
2014	Sisonke Health Medical Scheme	0,8322239	0,7782264
2015	Sisonke Health Medical Scheme	0,8589187	0,8199942
2016	Sisonke Health Medical Scheme	0,8554729	0,8224841
2017	Sisonke Health Medical Scheme	0,8499394	0,8109958
2011	South African Breweries Medical Aid Scheme (SABMAS)	0,837962	0,7877332
2012	South African Breweries Medical Aid Scheme (SABMAS)	0,8295965	0,7815539
2013	South African Breweries Medical Aid Scheme (SABMAS)	0,8234863	0,7648436
2014	South African Breweries Medical Aid Scheme (SABMAS)	0,8000801	0,7259155
2015	South African Breweries Medical Aid Scheme (SABMAS)	0,8384166	0,7970061
2016	South African Breweries Medical Aid Scheme (SABMAS)	0,8286299	0,7820285
2017	South African Breweries Medical Aid Scheme (SABMAS)	0,805721	0,7681234
2011	South African Police Service Medical Scheme (POLMED)	0,9038455	0,883257

2012	South African Police Service Medical Scheme (POLMED)	0,8925628	0,8765675
2013	South African Police Service Medical Scheme (POLMED)	0,8908048	0,8771661
2014	South African Police Service Medical Scheme (POLMED)	0,8851165	0,8706822
2015	South African Police Service Medical Scheme (POLMED)	0,9026098	0,8908169
2016	South African Police Service Medical Scheme (POLMED)	0,8910768	0,8788167
2017	South African Police Service Medical Scheme (POLMED)	0,9069227	0,8984255
2011	TFG Medical Scheme	0,9013388	0,8798919
2012	TFG Medical Scheme	0,8843803	0,843685
2013	TFG Medical Scheme	0,8760189	0,8329021
2014	TFG Medical Scheme	0,8642098	0,7680937
2015	TFG Medical Scheme	0,8928894	0,8368704
2016	TFG Medical Scheme	0,8900442	0,8381897
2017	TFG Medical Scheme	0,8784111	0,8286282
2011	Tiger Brands Medical Scheme	0,9062485	0,89156
2012	Tiger Brands Medical Scheme	0,9015062	0,8898634
2013	Tiger Brands Medical Scheme	0,8991136	0,8764225
2014	Tiger Brands Medical Scheme	0,8943527	0,8767092
2015	Tiger Brands Medical Scheme	0,9195712	0,9091397
2016	Tiger Brands Medical Scheme	0,9162614	0,9085804
2017	Tiger Brands Medical Scheme	0,9142731	0,8982347
2011	Transmed Medical Fund	0,8947586	0,8854121
2012	Transmed Medical Fund	0,88144	0,8507587
2013	Transmed Medical Fund	0,8741044	0,8528126
2014	Transmed Medical Fund	0,8662163	0,8430134
2015	Transmed Medical Fund	0,882461	0,8816178
2016	Transmed Medical Fund	0,8941728	0,8646128
2017	Transmed Medical Fund	0,8563364	0,8346416
2011	Tsogo Sun Group Medical Scheme	0,7789291	0,630111
2012	Tsogo Sun Group Medical Scheme	0,7774436	0,6370595
2013	Tsogo Sun Group Medical Scheme	0,7550656	0,6299901
2014	Tsogo Sun Group Medical Scheme	0,7296048	0,6222018
2015	Tsogo Sun Group Medical Scheme	0,7864116	0,7004225
2016	Tsogo Sun Group Medical Scheme	0,7704142	0,6843191
2017	Tsogo Sun Group Medical Scheme	0,747099	0,6177539
2011	Umvuzo Health Medical Scheme	0,8507032	0,7955351
2012	Umvuzo Health Medical Scheme	0,8442479	0,7933529
2013	Umvuzo Health Medical Scheme	0,8319037	0,7463004
2014	Umvuzo Health Medical Scheme	0,8153858	0,7292063
2015	Umvuzo Health Medical Scheme	0,8248312	0,7447481
2016	Umvuzo Health Medical Scheme	0,8185051	0,7468776
2017	Umvuzo Health Medical Scheme	0,8116006	0,7424249

2011	University of KwaZulu-Natal Medical Scheme	0,7850379	0,7163971
2012	University of KwaZulu-Natal Medical Scheme	0,7808663	0,7313882
2013	University of KwaZulu-Natal Medical Scheme	0,7875037	0,6773521
2014	University of KwaZulu-Natal Medical Scheme	0,7698383	0,649227
2015	University of KwaZulu-Natal Medical Scheme	0,8224421	0,7672656
2016	University of KwaZulu-Natal Medical Scheme	0,8130931	0,7268969
2017	University of KwaZulu-Natal Medical Scheme	0,8027816	0,7161422
2011	University of the Witwatersrand Staff Medical Aid Scheme	0,8956792	0,8756364
2012	University of the Witwatersrand Staff Medical Aid Scheme	0,8883102	0,8610023
2013	University of the Witwatersrand Staff Medical Aid Scheme	0,882028	0,8432262
2014	University of the Witwatersrand Staff Medical Aid Scheme	0,8759417	0,8356656
2015	University of the Witwatersrand Staff Medical Aid Scheme	0,888052	0,8607117
2016	University of the Witwatersrand Staff Medical Aid Scheme	0,9000532	0,8804379
2017	University of the Witwatersrand Staff Medical Aid Scheme	0,8851882	0,8621771
2011	Witbank Coalfields Medical Aid Scheme	0,8589423	0,8489301
2012	Witbank Coalfields Medical Aid Scheme	0,8569865	0,8291802
2013	Witbank Coalfields Medical Aid Scheme	0,85641	0,8040959
2014	Witbank Coalfields Medical Aid Scheme	0,8324814	0,7795918
2015	Witbank Coalfields Medical Aid Scheme	0,8269356	0,7732701
2016	Witbank Coalfields Medical Aid Scheme	0,7943409	0,7417732
2017	Witbank Coalfields Medical Aid Scheme	0,7630346	0,7061703
2011	Wooltru Healthcare Fund	0,8621162	0,8266861
2012	Wooltru Healthcare Fund	0,855887	0,8181806
2013	Wooltru Healthcare Fund	0,8512103	0,8173646
2014	Wooltru Healthcare Fund	0,835314	0,8083079
2015	Wooltru Healthcare Fund	0,8677952	0,8412081
2016	Wooltru Healthcare Fund	0,864151	0,8368193
2017	Wooltru Healthcare Fund	0,849211	0,8067032
2011	Xstrata Medical Aid Scheme	0,9114501	0,8937255
2012	Xstrata Medical Aid Scheme	0,908766	0,8789153
2013	Xstrata Medical Aid Scheme	0,8947614	0,861242