Explaining the demand for medical scheme membership in South Africa: implications for National Health Insurance (NHI)

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Abstract

Against the backdrop of the proposed National Health Insurance (NHI) and the move to universal health coverage, this paper examines the factors associated with selection into medical scheme membership. We explore the role of price and perceptions of the quality of care amongst other considerations motivating individuals to insure themselves against catastrophic health expenditure. This allows for a tentative assessment of the scope for financing the expansion of insurance coverage via user contributions and the importance of the quality of care for securing such contributions.

Medical schemes are the main vehicle through which the formal risk pooling of health expenditure in South Africa occurs. The transition into post-apartheid South Africa created the expectation that medical scheme membership would expand commensurate with the new economic opportunities open to all races. However, during the period 2000 to 2011 medical scheme membership experienced limited growth. Despite some growth in membership due to roll-out of the Government Employees Medical Scheme (GEMS), the total growth in scheme membership has been small. It is therefore important to identify the main factors that determine selection into medical schemes with a view to inform future policy.

This paper explores the relationship between medical scheme membership and a number of variables including income, employment, race, gender, age, household coverage and structure, asset ownership, chronic disease, illness and quality of healthcare. It also considers whether and how shifts in South African society may have impacted medical scheme membership. A pooled version of the Labour Force Surveys (2000-2007) and Quarterly Labour Force Surveys (2008-2011) and a pooled version of the General Household Survey

(2002-2011) provide the basis to track trends and explore associations between the above variables using a Linear Probability Model approach.

JEL codes: I13, I18

Keywords: medical schemes; National Health Insurance; universal health coverage

1. Introduction

Health insurance is an important tool in achieving universal health coverage. Although evidence on the impact on health outcomes of health insurance remains elusive, there exists increasing evidence that health insurance helps households mitigate the impact of catastrophic health expenditure by reducing the burden on household finances while also improving access to healthcare (Finkelstein et al, 2012; Baicker et al., 2013).

Medicals schemes are the main vehicle[1] through which the formal risk pooling of health expenditure in South Africa occurs. It takes the form of private health insurance that is community-rated and subject to comprehensive regulation and that typically provides for access to private health services. It thus has the potential to be an important tool in South Africa's move towards universal health coverage which is currently planned to occur through the implementation of a National Health Insurance (NHI) scheme. Although a green paper on the plans for NHI has been published the much awaited white paper has not yet been made public. A recent overview of the first eighteen months of the implementation of NHI makes it clear that health system reforms under this banner have until now mainly focused on health services and that experimentation with the funding mechanism is yet to start (Matsotso & Fryatt, 2013).

While some uncertainty remains about the role and position of medical schemes in the NHI, a better understanding of sectoral coverage and the factors associated with medical scheme membership provide important background information about affordability and individual preferences that can help to inform the design and implementation of the NHI.

Much of the recent literature on health financing in South Africa focuses on the inequity present in the relatively high per capita expenditure on medical schemes, purchasing access to mainly private healthcare for those who have this type of cover, compared to the relatively low per capita expenditure on healthcare in the public sector (see, for example, Mills et al., 2012). The majority of medical scheme cover, however, can be considered an employment benefit helping to ensure social security for South Africans in formal employment. Inequity in health financing can therefore be considered a reflection of the inequity present in the income and labour markets in larger South African society.

South Africa has a voluntary health insurance system with the majority of medical scheme cover originating from employers as an employment benefit. In the past this cover was typically extend through "closed ", employer-based funds only open to employees and their family members. Only since the early 1980's did "open" funds start to play a more important role in medical scheme coverage (Söderlund & Hansl, 2000).

[1] Apart from medical schemes, hospital cash plan insurance is the only other form of insurance that provides insurance cover for the expenses associated with hospitalisation. While households are able to purchase hospital cash plan insurance, this insurance does not indemnify (cover at actual cost) their medical expenses and there is much uncertainty about whether these products are legal.

Employers who provide medical scheme cover as an employment benefit either cover the cost in full or make a contribution towards the premium. Depending on the nature of the benefit provided by the employer, the main member of the medical scheme has the option to extend cover to family members. While some employers may pay for the full cost of covering the employee and her beneficiaries, other employers fully fund or subsidise the medical scheme cost of only the employee with the employee having to fund the cost of cover for family members.

Various data sources confirm an increase in the total medical scheme membership, albeit small, from 2006 (see Figure 1 in the next section). Despite this increase in total membership and an increase in black main membership through employers from slightly more than 1 million in 2000 to almost 2 million, a far lower percentage of black South Africans relative to white, Indian and coloured South Africans are members of medical schemes. Data from the General Household Survey (GHS) shows that in 2002 only 8.02% of black South Africans were members of medical schemes. By 2010, this had increased to 10.2% but decreased to 8.82% in 2011.

The increase in both total medical scheme membership and black medical scheme membership has been attributed to the launch of the Government Employees Medical Scheme (GEMS) in 2006 and the extension of cover from this scheme to previously uncovered medical scheme members (Van Eeden, 2009). However, as this paper shows, analysis of total medical scheme cover provided by employers to their employees indicates an increase in excess of what can be explained by the extension of membership by only one medical scheme. A more granular understanding of medical scheme membership is required.

This paper considers the main demographic and socio-economic changes in medical scheme membership over the twelve years from 2000 to 2011. It demonstrates that changes (or the lack thereof) in medical scheme membership mainly mirror broader socio-economic and demographic change in South African society. We use data on medical scheme membership from the labour market as our starting point as the majority of medical scheme cover originates from this market and is then extended to family members.

Our analysis examines why medical scheme membership grew only moderately and significantly less than expected. To better understand the role of individual preferences, affordability and access to a formal labour market job, we consider the correlates of demand for medical scheme cover by first investigating the labour market attributes associated with medical scheme membership (of the main member) and then undertake a more generic analysis including all medical scheme members. We start by describing socio-economic and demographic trends in medical scheme membership over the period 2000-2011 by drawing on data from labour market surveys and household survey data.

2. Trends from survey data

Figure 1 below summarises the parallels between medical scheme cover data from labour force surveys and administrative data, on the one hand (Columns A and B), and a household survey and administrative data, on the other hand (Columns C and D). Data from a combination of the Labour Force Survey (2000-2007) and Quarterly Labour Force Survey (2008-2011) mirror administrative data on the total number of medical scheme members, while data from the General Household Survey is closely aligned to administrative data on the total number of medical scheme beneficiaries (members and their dependents). In some years survey data over-estimates the administrative data while in other years the survey data lends itself to under-estimation. In 2002 and 2003 the deviation of the LFS from administrative data was very large, over-estimating medical scheme membership by about 630,000 in 2002, almost 500,000 in 2003 and 360,000 in 2004. By 2005 the gap had reduced to 102,000 with the Labour Force Survey under-estimating medical scheme membership.

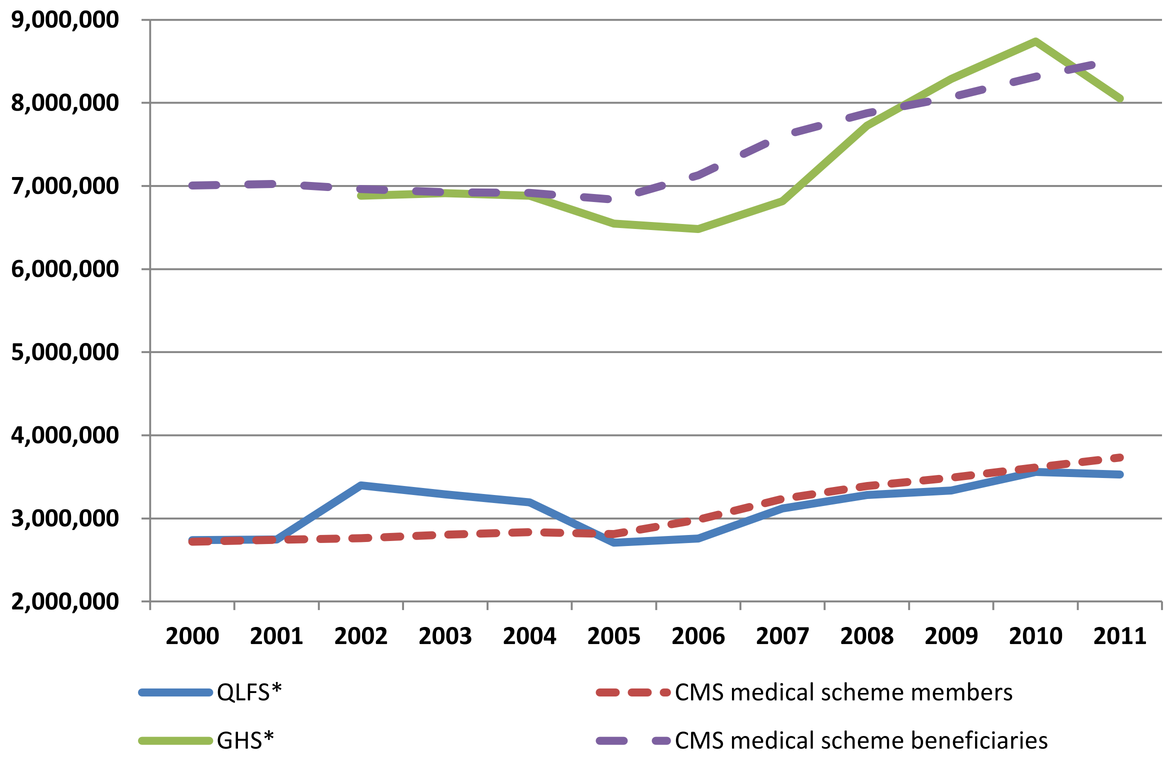

Figure 1: Number of medical scheme main members and members from the combined Labour Force Surveys (LFS) and Quarterly Labour Force Surveys (QLFS), the Council for Medical Schemes and the General Household Surveys (GHS)

**The Labour Force survey is a bi-annual survey while the Quarterly Labour Force Survey is conducted quarterly. To provide annually comparable data we used data collected in September for both the Labour Force Survey and Quarterly Labour Force Survey.*

While one would expect discrepancies between the administrative and survey data, by and large the surveys do not perform too poorly at capturing main member and total medical scheme membership and at least do not appear to systematically under-capture a large proportion of members. We therefore proceed to use the survey data for the analysis of the characteristics and correlates of membership.

The survey data provides us with many additional variables not available in the administrative data. It allows us to consider how the racial composition of medical schemes has changed over time. This, in turn, provides some indication of the degree to which socio-economic mobility is occurring in the labour market: are South Africans formerly excluded from formal and skilled employment positions obtaining access to what is considered a social security benefit? We answer this question by considering changes in medical scheme cover for black and white South Africans, the two largest race groups in terms of medical scheme membership. Total medical scheme cover by race over the period 2002-2011 has been summarised in Table 1 below. We refer back to this table during the discussion that follows.

Year	**Total black medical scheme cover**	**Total coloured medical scheme cover**	**Total Indian medical scheme cover**	**Total white medical scheme cover**
2002	2,884,583	754,166	325,221	2,919,353
2003	2,961,277	799,373	398,121	2,756,033
2004	2,662,157	752,879	410,351	3,058,338
2005	2,620,160	749,623	373,836	2,805,103
2006	2,718,192	675,205	339,045	2,750,198
2007	2,782,495	798,691	365,738	2,870,593
2008	3,220,111	941,086	487,026	3,077,405
2009	3,499,852	941,131	542,074	3,303,134
2010	4,040,810	970,821	608,086	3,115,080
2011	3,529,959	914,642	538,297	3,068,036

Table 1: Total medical scheme coverage by race

Source: General Household Survey, 2002-2011

While total black medical scheme membership did not increase at such a large scale given the base from which it was growing, the provision of medical scheme cover by employers to black employees grew by 82% from only more than 1 million employees having cover to almost 2m during the 2000-2011 period (Table 2). The change in medical scheme cover for black employees can be considered the result of two dynamics: more black South Africans moving into formal positions that are typically associated with medical scheme cover in *both* the public and private sector (Table 2) and the extension of medical scheme cover as an employment benefit to previously uncovered black South Africans working in the public sector.

Year	Black formal sector employees	Black public sector employees	Black employees with medical scheme cover	Black public sector employees with medical scheme cover	Black private sector employees with medical scheme cover
2000	4,093,213	1,171,555	1,082,301	557,772	524,529
2001	3,948,157	1,082,434	1,179,693	541,377	638,316
2002	4,079,575	1,059,075	1,698,953	750,077	948,876
2003	4,188,531	1,070,016	1,575,938	734,136	841,802
2004	4,485,638	1,060,415	1,430,469	684,507	745,962
2005	4,739,737	1,116,400	1,221,203	597,052	624,151
2006	5,075,698	1,147,161	1,264,598	607,350	657,248
2007	5,670,493	1,325,646	1,545,731	755,180	790,551
2008	5,913,554	1,287,963	1,799,808	897,857	901,951
2009	5,668,963	1,296,069	1,787,165	966,164	821,001
2010	5,636,035	1,310,419	1,922,281	1,003,217	919,064
2011	6,049,111	1,382,120	1,974,918	1,013,164	961,754

Table 2: Black employment and medical scheme cover

Source: Labour Force Survey and Quarterly Labour Force Survey, September 2000-2011

In contrast, medical scheme cover for white South Africans obtained through their employer decreased by 23.2% between 2000 and 2011, moving from cover for almost 1.2m employees to cover for only 915,000. Much of this decrease can be attributed to a decrease in employment of whites in the public sector as well as a decrease in the number of white private sector employees with medical scheme cover (see Table 3 below).

Year	White formal sector employees	White public sector employees	Medical scheme cover to white employees	White public sector employees with medical scheme cover	White private sector employees with medical scheme cover
2000	1,792,377	331,969	1,192,503	272,491	919,018
2001	1,845,376	282,585	1,053,005	211,090	841,915
2002	1,813,731	260,050	1,119,272	198,049	921,223
2003	1,871,835	286,900	1,152,706	225,341	927,365
2004	1,836,961	302,378	1,153,368	253,370	898,847
2005	1,803,905	291,235	1,001,457	217,130	784,327
2006	1,819,208	235,871	938,875	173,865	765,010
2007	1,889,466	215,233	1,081,955	184,945	897,010
2008	2,070,651	218,209	913,847	190,169	723,678
2009	1,995,814	239,709	927,432	208,471	718,961
2010	2,008,718	234,569	957,800	211,580	746,220
2011	2,002,586	218,493	915,359	201,124	714,235

Table 3: White employment and medical scheme cover

Source: Labour Force Survey and Quarterly Labour Force Survey, September 2000-2011

Using data from the Council for Medical Schemes, Mcleod (2012b) estimates that 36% of all medical scheme members in 2009 were covered by some public sector-related medical scheme. The portion of public sector employees with medical scheme cover has gradually been increasing. Between 2007 and 2008 total public sector employees who indicated that their employer provides medical scheme cover increased from 59% to 73%, stabilising around 77% in 2011. At the same time, medical scheme cover for black formal sector employees increased from 57% in 2007 to 70% in 2008. By 2011, 77% of black public sector workers indicated that they had some form of medical scheme cover through their employer (Figure 2). The public sector’s role in the provision of medical scheme cover, especially through the establishment and extension of GEMS, has thus been a major driver of employment-based medical scheme cover increases.

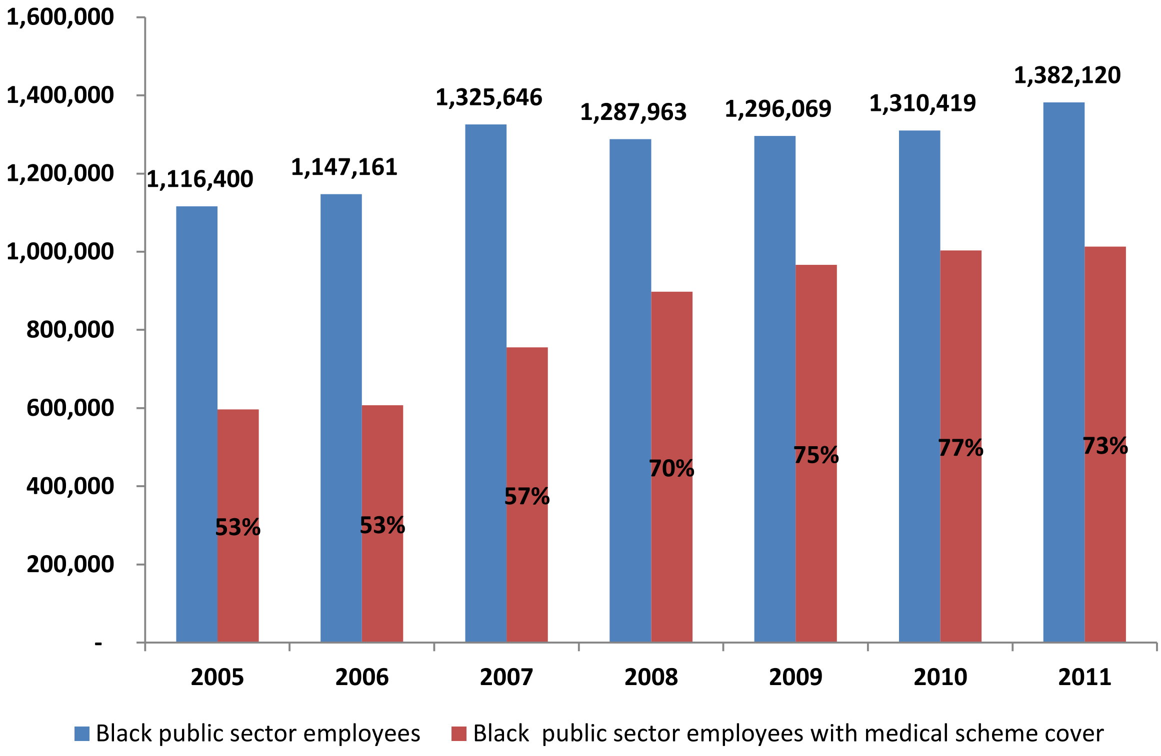

Figure 2: Black employees with medical scheme cover in the public sector

Source: Labour Force Survey and Quarterly Labour Force Survey, September 2005-2011

Data on total medical scheme membership (i.e. including family members or dependents in addition to the main member) from the GHS shows that white medical scheme membership stayed almost constant between 2000 and 2011, despite a decrease in cover provided by employers (Table 1 and Table 3). In contrast, total black membership grew less than expected despite the fact that medical scheme cover from employers almost doubled. This begs the question of what determines medical scheme membership demand. If the extension of employer-based medical scheme cover did not generate the same multiplier effect for black employees as white employees, what are the ultimate determinants of medical scheme demand?

Labour force and household survey data allow us to not only consider labour market dynamics but also analyse broader economic, social and demographic factors in the extension of medical scheme cover to other household members. One such factor is the proportion of households members that have medical scheme cover if there is at least one person with medical scheme cover present in the household. Figure 3 below shows that in 2011 82.2% of white households with at least one medical scheme member present had medical scheme cover for all household members. This was the case for only 38.8% of black households where there was at least one medical scheme member present. In 2011, 42.7% of black households where there was at least one medical scheme member present had less than 60% of household members covered by a medical scheme. These coverage statistics potentially point towards differences in both household size and household structure (i.e. who lives in the household) between different races.

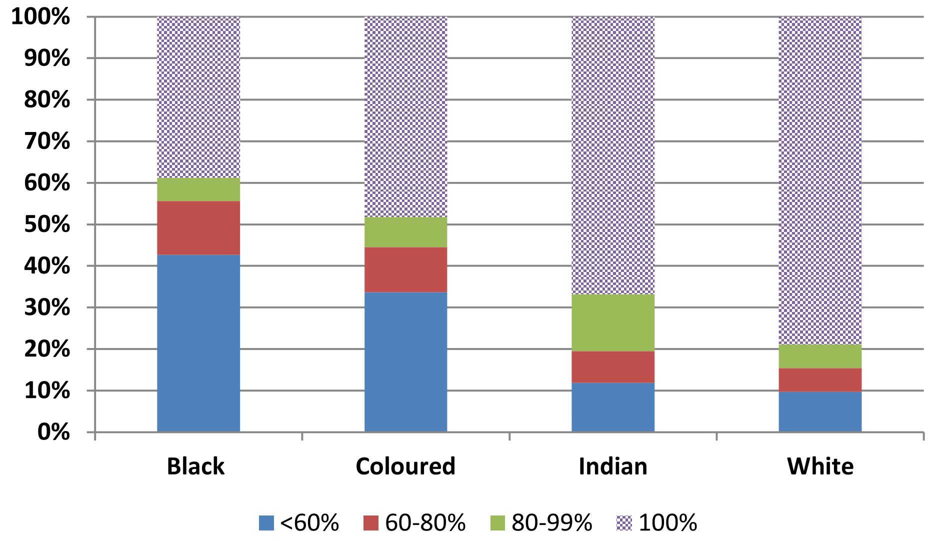

Figure 3: Percentage of household members with medical scheme according to race in households with at least one medical scheme member in 2011

Source: General Household Survey 2011

Below we provide a brief overview of some of the factors likely to influence the demand for healthcare and health insurance.

3. Literature on the demand for health services and health insurance

The demand for health insurance is influenced by both the demand for healthcare and the demand for financial risk management tools to assist in meeting the costs of ill health. Arrow (1963) distinguishes between two fundamental risks associated with health: the risk of ill health which implies health care expenditure, decreased quality of life, loss of income generating ability and potentially even death; and complete, partial or delayed recovery. The financial losses associated with the former risk can be partly managed through health insurance and loss of income insurance, while the latter risk can be partly managed with disability insurance.

There exists well-developed international literature on the demand for health care (Grossman, 1972; Grossman, 1999) the topic has only recently started to be explored in the South African context (Havemann and Van der Berg, 2003; Grobler and Stuart, 2007; Van Eeden, 2009). We summarise just a few of the theoretical propositions made by Grossman (1972) before moving to the South African literature on the demand for health and then the demand for health insurance. Grossman's (1972) key theoretical proposition is that health or "good health" should be viewed as a durable capital stock which depletes over the course of a lifetime and therefore requires investments to maintain the capital stock. As individuals age, the depreciation rate of health status increases, implying that the rate of investment will also have to increase if the capital stock is to be maintained. He also argues that higher education levels imply lower investments in health status as more educated people are likely to be more efficient "producers" of health stock.

Havemann and Van der Berg (2003) use a multinomial logit model to explore the factors that influence the type of health provider selected in the context of health demand in South Africa. The demand for three types of healthcare is considered: self-treatment, public healthcare and private healthcare. The majority (46%) of respondents who reported recent illness chose to use a private healthcare provider. Given that the demand for private care increases with an increase in income, they conclude that within the constraints of their demand model public healthcare is an inferior good.

Grobler and Stuart (2007) build on the work of Havemann and Van der Berg (2003) by using the approach of "out-of-sample imputation" to link income data from the 2000 Income and Expenditure Survey and Labour Force Survey with health service utilisation and other demographic and household data in the 2004 General Household Survey.

Unlike Havemann and Van der Berg (2003), they find that the majority of respondents used a public healthcare provider and ascribe this contrasting finding to the fact that access to public primary healthcare (i.e. clinics) had been made free to South Africans since 1993, the year when the survey data used by Havemann and Van der Berg (2003) was collected. Similar to Havemann and Van der Berg (2003) they model the demand for healthcare as the outcome of a process with multiple steps and use a multinomial logit model to explore demand for care from a public hospital, public clinic, private hospital or clinic, private doctor and self-treatment. The authors note that while they explored the possibility of estimating separate demand models for medical scheme and non-medical scheme members it adds little to their understanding of broad healthcare demand in South Africa. They therefore do not report the findings in their paper.

Grobler and Stuart (2003) find income to have a significant influence on the type of healthcare selected. Individuals from all income quintiles use private healthcare but individuals up to the fourth quintile are more likely to use public healthcare, while individuals in the fifth quintile mostly used private care. Other individual factors that have a significant relationship with the type of healthcare used include age, relationship to the household head, level of education and the nature of the health problem experienced. Individuals in the age band of twenty five to forty five made the highest number of visits to private hospitals or clinics. Controlling for a long list of income, demographic, geographic and health service utilisation-specific factors, they find that while race has a significantly influence on the type of health service used, its influence is relatively small. Medical scheme members are found to be less likely to use public care or self-treat their illness (Grobler & Stuart, 2003).

Grobler and Stuart (2003) also find geography to be an important factor in utilisation patterns. Individuals living in rural areas were found to be more likely to use healthcare from public facilities than private facilities. This is ascribed to both lower access to private facilities in and lower incomes in rural areas. The distribution of the type of healthcare utilised also differed amongst provinces. The use of private hospitals was found to be the most common in the Northern Cape, Gauteng and the Western Cape, while the use of private hospitals was lowest in the Eastern Cape, Kwazulu-Natal and North West. People living in the Western Cape were found to be least likely to consult a public clinic.

While the determinants of demand for health insurance are well-explored in international literature, it has not yet been examined to the same extent in the South African context. Kirigia et al. (2005) consider the relationship between health insurance ownership and demographic, economic and education variables as obtained from the 1994 Health Inequalities Survey. The survey sampled 3,796 respondents of which the majority (3,489) were women. Their analysis therefore focuses on the factors that influence health insurance ownership amongst South African women. Given the timing of the survey, the data does not reflect the full extent of labour market and socio-economic dynamics in post-Apartheid South Africa and provides a snapshot of the factors that determined health insurance ownership amongst women at the time.

The authors use a binary logit model to explore the association between health insurance ownership, which includes both medical scheme and other private health insurance ownership due to the phrasing of the survey question, and health status, economic, demographic, social, spatial and environmental and behavioural factors. While the nature of the relationship of employment (employed vs. unemployed) and occupation (blue vs. white collar worker) with health insurance ownership are considered, the nature of the employer (size of firm) and sector of employment (public vs. private or, for example, financial sector) is not explored. Due to the limitations of the survey the relationship of health insurance ownership with the cost (price) of health insurance and health service quality is also not considered.

Kirigia et al. (2005) find that health insurance cover amongst South African women is positively and significantly ($p<=0.05$) associated with higher income, being employed, being employed in a white collar occupation, a minimum education level of matric, being married, living in an urban formal area, a good perception of the surrounding residential environment and smoking. Health insurance cover is negatively and significantly associated with household size, the use of contraceptives and consumption of alcohol.

Over the longer period 2000-2011, both income and employment of black South Africans grew. Van der Berg (2010, 2012) finds that during the period 1994-2008, black South Africans in households earning more than R40,000 per capita per annum (in 2000 Rand) increased from 0.4 million to 1.9 million. Visagie (2011) focuses on the so-called "middle class affluent", defined as individuals who live in households with a per capita household income (in 2008 prices) of R1,400 to R10,000 per month. During the period between 1993 and 2008 2.7 million black South Africans moved into this group. It is thus surprising that the medical scheme membership of Black South Africans has not increased to the same degree as employment and income and remains at almost the same level of ten years ago. We now proceed to uncover some possible explanations for this by examining the correlates of medical scheme demand.

4. Data and methodology

South Africa has limited administrative data on the characteristics of medical scheme members. While publically available administrative data from the Council of Medical schemes allows us to track trends in total membership and beneficiary numbers, as well as average age and distribution across age bands, no further information on medical scheme members is made publically available by the sector regulator. This study therefore uses two nationally representative datasets to examine the correlates of medical scheme demand: data from the Labour Force Surveys (2000-2007) and the Quarterly Labour Force Surveys (2008-2011) pooled into one dataset and pooled data from consecutive General Household Surveys (2002-2011). Collectively these two pooled data sets allow us to robustly estimate the correlates of having medical scheme cover through an employer when employed (LFS/QLFS) and the correlates to total medical scheme membership for both main members and their dependents when we consider a data set that includes is representative of the national population (GHS).

The two sets of labour force surveys ask all respondents who indicate that they are employed whether the employer provides medical scheme cover. The LFS/QLFS thus allows us to tease out the variables associated with having medical scheme cover for all *employed* South Africans as both the LFS and QLFS are nationally representative surveys. In contrast, the GHS asks all respondents are whether they have medical scheme cover. As the GHS is also a nationally representative survey the population of interest thus is *all South Africans*.

While the two pooled datasets provide a sufficiently large number of observations to allow for the identification of robust statistical relationships between variables, the data remains subject to at least two major constraints. The pooled datasets were created by merging data for different years for those variables that had been most consistently asked across years. Despite variables only being included in the pooled set if they had been asked for at least two years (for specific variables of interest, e.g. health) or longer for other variables, there are a number of variables that were not available for the full period and when these variables are included in the analysis, we consequently work with a much smaller sample.

We use linear probability models (LPMs) to explore the relationship between being a member of a medical scheme and four categories of variables: labour market, socio-economic, demographic variables and variables on health status and use of health services. While both datasets contain most of the categories of variables, the nature of variables varies across the two datasets. The combined LFS/QLFS dataset does not contain any variables on health status while opposite is true for the GHS dataset. The LFS/QLFS dataset contains more detailed labour market variables (e.g. formal employment, skills level, public vs. private sector employment) while we only control for employment (in the broad sense) when we use the GHS dataset.

While LPMs are prone to the problem of heteroskedasticity, this is not the case with probit models, Angrist and Pischke (2008) conclude that this has a relatively small effect on the empirical results produced. As a robustness check we experimented with probit models and the results were in line with what is reported here.

The demand for health insurance or, more specifically in South Africa, medical scheme cover, is likely to be influenced by factors that determine both the demand for healthcare and those unique to the demand for health insurance. Below we provide a brief explanation of some of the variables used in our linear probability models and the likely direction of the relationship between these variables and the probability of being a medical scheme member.

Labour market variables:

The LFS/QLFS dataset provides a rich source of variables on the characteristics of the employed and the organisations by which they are employed. We therefore include binary variables on formal employment, skilled employment, public sector employment and union membership. It is anticipated that being employed in the formal sector (relatively to the informal sector) is likely to increase the probability of having medical scheme cover through your employer while being in a skilled position is also likely to have a positive relationship with the probability of having medical scheme cover.

Socio-economic variables:

We use different variables to control for the socio-economic correlates of medical scheme demand. While we are unable to control for any income variables in LPMS run with the QLFS/LFS dataset as this data had not been collected. We calculate per capita expenditure from a household expenditure variable in the GHS dataset to control for income and the concept of affordability.

In addition to the per capita household expenditure variable, we include a binary asset and municipal services index threshold that is constructed through multiple correspondence analysis (MCA) applied to various municipal services and asset variables in the GHS dataset. This variable provides additional nuance to the model by contributing information on the non-income dimensions of deprivation. Due to the low number of indicators that are available across all years of the pooled data set, we opt to use it as a dummy variable to distinguish the top two quintiles from the rest of the population.

Apart from implicitly controlling for household size through use of the per capita expenditure variable in the GHS dataset, we also include it as a separate variable in the LPMs for both the GHS and LFS/QLFS data.

We also control for education by including binary variables for 12-14 years of education and 15 years or more of education in the LPMs using the LFS/QLFS data. For the LPMs using the GHS data we control for the presence of someone in the household with an education of 15 years or more. While education can also be included as a continuous variable binary variables lend itself to easier interpretation in LPMs. Initial data exploration indicated a small association with education levels of 12 years or less. We therefore decided to rather estimate the association of years of education in excess of the minimum number of years to complete matric.

Demographic variables:

We control for the enduring effect of race with a dummy for white individuals. Aligned with the general medical scheme member structure discussed in earlier sections, we hypothesise that race remains linked to the probability of having medical scheme cover. Similarly, we also include a male dummy to control for gender.

According to Grossman (1978) the demand for healthcare is likely to increase as the stock of health depletes as individuals age, implying an expected positive association between the demand for healthcare and insurance and age. It is possible, however, that individuals may want to hold insurance for certain health events for which they prefer to use private health services. In South Africa there exists anecdotal evidence of households or individuals obtaining medical scheme membership in anticipation of child birth and medical services that will be required for both the mother and child (Econex, 2012).

If it is assumed that scheme membership is determined mainly by need rather than affordability, one would membership to increase with age but that there may also be increased demand during the sexually reproductive years of women. The age distribution of medical scheme beneficiaries in the GHS dataset indicates a distribution slightly contrary to our expectation. While there is indeed a sharp increase in medical scheme membership that coincides with the typical childbearing age period of women, this age period is also closely associated with the start of the economically active years of both male and female members. Contrary to the expectation create by Grossman's conclusion on the direction of the age relationship, the age distribution displays a "twin peak" profile with the first peak, occurring during the childhood years but decreasing sharply around 18 years of age, followed by the start of the second peak at the beginning of the economically active years that also coincide with the childbearing years of women. Contrary to Grossman's (1978) view on the demand for healthcare increasing with the stock of age, medical scheme membership starts to rapidly decrease from around 50 years of age.

Figure 4: Kernel density function of age of all medical scheme members

Source: General Household Survey, 2002-2011

If we consider the age distribution of the two largest race groups of medical scheme members, black and white members, separately, two different pictures emerge. There is no such prominent twin peak in the age distribution visible for white members and far more white older persons are members of medical schemes compared to black members, although medical scheme membership for white older members still decreases. The twin peak distribution is even more prominent for black members with a peak in membership for both male and female members shortly after 40 years of age followed by a sharp decline in membership.

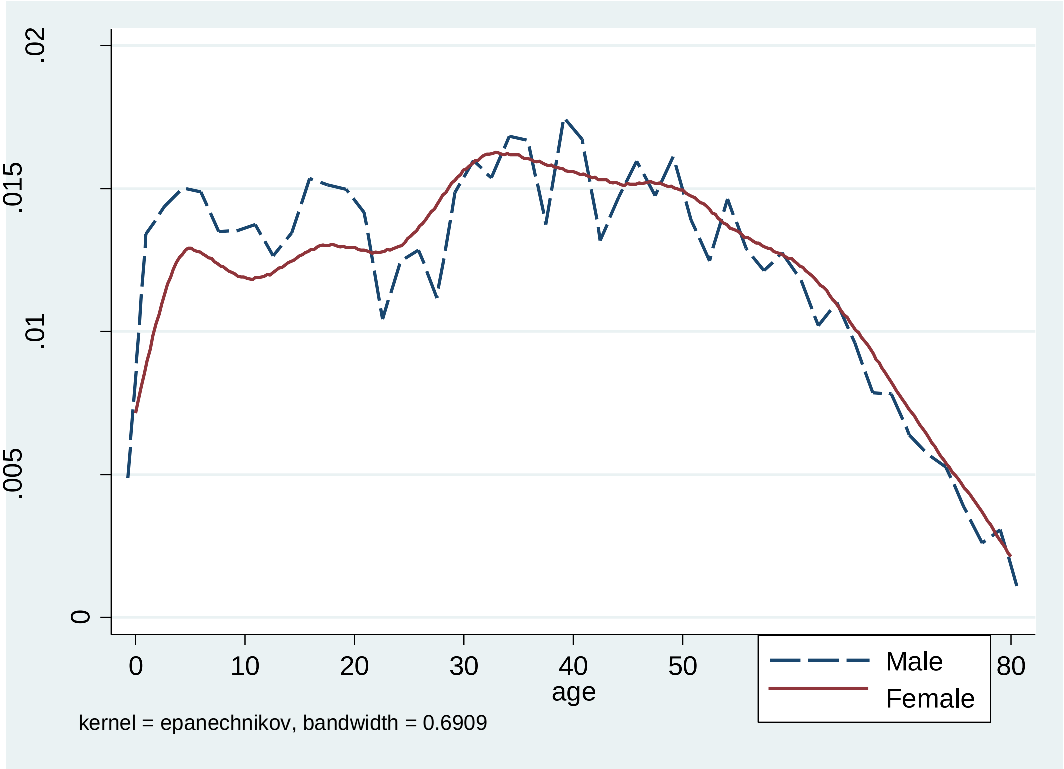

Figure 5: Kernel density function of age of white medical scheme members

Source: General Household Survey, 2002-2011

We firstly control for age as a continuous variable to determine the direction and significance of the relationship and secondly as a binary variable for various age groups in order to capture the threshold effects associated with certain age groups. We do this for both the QLFS/LFS and GHS data.

Figure 6: Kernel density function of age of black medical scheme members

Source: General Household Survey, 2002-2011

Health and health service variables:

The GHS data set allows us to control for two health-status related variables: an injury or illness in the four weeks preceding the survey and prevalence of chronic disease. The latter variable is constructed to identify individuals that indicated they have been diagnosed with one of a number of chronic diseases, including diabetes, hypertension, arthritis, asthma, HIV, cancer and an "other" category of chronic diseases. While these variables are potentially important in explaining the take-up of medical scheme cover we take cognisance of the potential problem of endogeneity associated with the inclusion of these variables. Illness and chronic disease may have a higher likelihood of diagnosis because of access to health insurance. No impact of these variables on the demand for medical scheme cover can be inferred.

Private health insurance is able to provide the insured with access to private health services or services not normally provided by the public sector or provided at different quality levels. Quality differentials between the services provided by the public and private sector can thus form an important explanation of the demand for health insurance. Waiting lists or waiting times for accessing health services have often been used interchangeably as a health service quality variable in the literature on the demand for private health insurance. In the absence of data on waiting times for health care, Besley, Hall and Preston (1999) use data on waiting lists as a proxy for waiting times and find it to be a significant determinant for private health insurance. However, once data on both waiting lists and waiting times are considered, waiting lists become an insignificant variable with only waiting times having a significant impact on the demand for health insurance (Johar et al, 2013).

Although quality differentials in healthcare services between the public and private sector are potentially a quite important correlate of the demand for medical scheme cover in South Africa, we are unable to control for this with the available data. This will be explored during a second phase of the research as it is likely to require that data from an additional data source be merged into the GHS data set.

5. Empirical results

The aim of the paper is to determine which generalizable factors are associated with medical scheme membership. Due to endogeneity concerns relating to income and reported illness, coefficients cannot be interpreted as representing an estimate of the causal impact. Below we discuss the variables estimated to be the largest correlates of the probability of having medical scheme cover, both for employees and any other medical scheme member. The regression results for the LFS/QLFS and GHS datasets are reported separately and parallels or differences between these two sets of results highlighted where appropriate. The full results can be found in Appendix B.

Factors associated with medical scheme cover:

All variables included in the five different LPM models of medical scheme cover through an employer are statistically significant (Table B1). In the third specification we add a binary asset and municipal services index threshold, which is excluded again in the fourth model where we include a chronic disease variable (in addition to the illness variable which is included in all five specifications). In the last specification we add an urban variable.

The variables with the largest associations with medical scheme membership are the white dummy and post-high school education (15 years or more). Across the five models, being white (as opposed to black, coloured or Indian) is associated with a probability of medical scheme cover of at least 24.4%. Living in a household with someone who was has 15 years or more is associated with a probability of medical scheme cover of at least 25%.

As in the models for the QLFS/LFS data, the continuous age variable displays a negative sign. We use the age group of 61 and older as a base variable through its omission. The age categories of 0-4, 5-14 and 15-20 have the largest association with the dependent variable. Being a child is associated with a probability of medical scheme cover of at least 7.2%. This is in contrast to probabilities of medical scheme cover of less than 2.3% associated with the age groups of 21-40 and 41-60. Interestingly and contrary to our expectation of a higher probability of medical scheme cover in the child-bearing years, falling in the age category of 41-60 is associated with a medical scheme probability of almost twice the size of falling in the 21-40 age category.

Per capita expenditure has a positive although small association with the probability of having a medical scheme, while the asset and municipal services index dummy also has a positive and relatively large association with the probability of medical scheme cover. Falling into the top two quintiles of the asset and municipal services index is associated with a probability of 11.4% of medical scheme cover.

Household size is statistically significant and negatively associated with medical scheme cover. Regressions with the GHS data also control for household size through inclusion of per capita household expenditure by adjusting expenditure for the number of household members, irrespective of whether adults or children. An alternative approach would be to control for number of adult and child household members separately.

The health status variables, illness and chronic disease, both have a positive relationship with medical scheme cover. Having been ill or injured in the month preceding the survey implies a probability of needing medical scheme cover almost double the size of the probability of needing cover when having been diagnosed with a chronic disease.

As expected, living an in urban area has a positive associated with the probability of medical scheme cover while being employed (in the broad sense) implies an association of at least 4.4% of medical scheme cover.

Factors associated with medical scheme cover through an employer:

All variables included in the four different LPM models of medical scheme cover through an employer are statistically significant (Table B2). In the first model we control for age as a continuous variable. In the second model the continuous age variable is replaced with three binary age variables (ages 21-40, 41-60 and ages 61 and older), while in the third model a binary variable for union membership is added. While the labour union variable is likely to suffer from endogeneity issues it may allude to the effect of labour unions in being able to negotiate greater social security benefits for their members. We therefore proceed cautiously to interpret the meaning of any association between labour union membership and the probability of medical scheme cover. In the last model we also add a rural dummy variable. The size of some of the largest correlates of medical scheme cover show large changes when the additional variables are added.

In the initial two models, public employment and large firm size have the largest association with medical scheme membership. These variables are followed in size by having education of 15 years or more, being a white employee and having been employed in a skilled position (as opposed to an unskilled or semi-skilled). However, when a dummy for union membership is added in the third model, it emerges as the largest correlate of medical scheme cover. In fact, being a union member increases a worker's probability of having medical scheme cover by 24%. Post-high school education increases a worker's probability of having medical scheme membership through their employer by 23.6%.

Including the union dummy causes a number of shifts in other coefficients due to the web of relationships connecting the labour market variables. The probability of medical scheme cover increases from around 14% for a white employee to 18%, while public sector employment now has a smaller association with medical scheme cover. In the first two regressions being a public sector employee implies a probability of 32.8% of having medical scheme cover. When union membership is also controlled for, the contribution of being a public sector employee decreases by 11 percentage points to a probability of 21.6% of having medical scheme cover.

In the fourth and final model we add area rural dummy. The rural variable has a relatively small coefficient and in the direction expected, i.e. living in a rural area makes an employee less likely to have medical scheme cover. The negative relationship is most likely due to more limited access to private health services in rural areas. The addition of this variable has a fairly small impact on the size of the other variables' coefficients.

As the medical scheme cover question is only asked to employed individuals, the available age variable is limited to the economically active age period of 15-65. The continuous age variable is negative associated with the probability of medical scheme cover. The three age binary variables also show association patterns slightly contrary to what we had expected. We omit the 15-20 age range to serve as the base case for comparing the coefficients of the other age categories. It is an age group slightly younger than the ages when most South Africans typically become economically active. Relative to the base variable, being in the age group 41-60 years most likely matters most for having medical scheme cover. It is associated with an increase in the probability of medical scheme cover by between 4.7% and 8.5%, considerably larger associations than that of the other age categories.

Across all LPM models, being formally (as opposed to informally) employed has a relatively small association with having medical scheme cover.

6. Conclusion

In this paper we explore how medical scheme membership has changed over the period 2000 to 2011 and how this may be influenced by the correlates of the demand for medical scheme cover. We do this by describing broad trends in the racial composition of medical scheme membership and how this has been driven by employment changes in different sectors (public vs. private) of workers of different race groups. By relating the increase in medical scheme cover extended by employers to especially black workers back to total medical scheme cover for black South Africans, we uncover the puzzle of a seemingly lower medical scheme multiplier effect for black compared to white workers. Black workers do not appear to extend medical scheme cover to as many household members as white workers do. In order to solve the puzzle, we estimate LPMs for medical scheme cover and four categories of variables (labour market, socio-economic, demographic and health status) using two large pooled data sets.

Despite an initial exploration of the factors associated with having medical scheme membership we are unable to explain why black workers who obtain medical scheme cover through their employers do not extend the cover to their dependents to the same degree as white workers do. We do, however, have some clues. Being employed in a formal sector, skilled position especially when this is based in the public sector is associated with having medical scheme cover through the employer. More education than the minimum number of high school years also displays a large association with medical scheme cover. The association becomes even larger when a worker has three years or more of post-matric education. We also know that household size is negatively associated with medical scheme coverage, while being white, in the context of cover for both main members and their dependents, has the largest association with medical scheme membership.

The empirical results also seem to indicate that affordability and risk matter. Both income and position in the municipal and services index is positively associated with medical scheme membership, while there is a positive association between medical scheme cover and having at least one chronic disease or illness or injury in the month preceding data collection. The implications of affordability for contributions to NHI and health risk for utilisation of the services to be provided will have to be carefully considered.

To fully answer the question on the apparently different insurance behaviour of white and black South Africans, we will have to source additional data that allows us to control for factors we are unable to explore now. This includes perceptions or experiences of health service quality (public vs. private sector) that may drive health service preferences and more comprehensive and detailed data on household income and expenditure. It is possible that being white emerges as such a large correlate of medical scheme membership simply because we are unable to control for income and affordability to the necessary degree.

The extension of medical scheme cover to formerly uncovered black employees and more black workers moving into positions associated with medical scheme cover emphasises the role of employers as implementation partner in the proposed NHI. Employer subsidies and their involvement in funding the health of their workers will be central to the extension of medical scheme coverage.

Appendix A

Table A1: Number of medical scheme main members and members from the combined Labour Force Surveys (LFS) and Quarterly Labour Force Surveys (QLFS), the Council for Medical Schemes and the General Household Surveys (GHS)

Year	LFS* (2000-2007) and QLFS* (2008-2011) (Column A)	CMS medical scheme members* (Column B)	GHS (Column C)	CMS medical scheme beneficiaries (Column D)
2000	2,739,167	2,718,301	-	7,004,636
2001	2,744,551	2,740,572	-	7,025,262
2002	3,397,083	2,762,392	6,883,323	6,963,189
2003	3,289,203	2,802,815	6,914,804	6,924,686
2004	3,194,747	2,833,322	6,883,725	6,915,666
2005	2,709,580	2,812,083	6,548,722	6,835,621
2006	2,758,400	2,985,350	6,482,640	7,127,343
2007	3,119,865	3,233,490	6,817,517	7,605,236
2008	3,280,759	3,388,582	7,725,628	7,874,826
2009	3,335,213	3,488,009	8,286,191	8,068,505
2010	3,559,055	3,612,062	8,737,797	8,315,718
2011	3,526,707	3,730,565	8,050,934	8,526,409

Appendix B

Table B1: Output of linear probability model using GHS (2002-2011)

	Dependent variable: covered by a medical scheme				
	Regression 1	**Regression 2**	**Regression 3**	**Regression 4**	**Regression 5**
Per capita expenditure	0.0000901*** (0.000000336)	0.0000899*** (0.000000335)	0.0000797*** (0.000000599)	0.0000873*** (0.000000531)	0.000086*** (0.000000645)
Male	-0.0073978*** (0.0006064)	-0.0117827*** (0.0006073)	-0.0109927*** (0.0009429)	-0.0121471*** (0.0011622)	-0.0127227*** (0.0014054)
Married	0.045782*** (.0007683)	0.0641451*** (0.0008254)	0.0578137*** (0.0012512)	0.0692562*** (0.0015932)	0.0665147*** (0.0019283)
Age (continuous)	-0.0005349*** (0.0000121)				
Ages 0-4		0.0836014*** (0.0015443)	0.0798119*** (.0024001)	0.0873176*** (0.0031227)	0.0828215*** (0.0037811)
Ages 5-14		0.0910504*** (0.0013838)	0.0892635*** (0.0021474)	0.0928938*** (0.0028209)	0.0889416*** (0.0034113)
Ages 15-20		0.0745704*** (0.0014575)	0.0729937*** (0.0022149)	0.0735993*** (0.002982)	0.0722404*** (0.0036018)
Ages 21-40		0.0170969*** (.0012871)	0.0178763 (0.001947)	0.0081375*** (0.0026275)	0.0008225*** (0.0031774)
Ages 41-60		0.0234122*** (0.0013874)	0.0272931 (0.0020981)	0.0155597*** (0.0027047)	0.0122277*** (0.0032644)
Maximum education level in household 15 year plus	0.2580247*** (0.0014062)	0.2558835*** (0.0014022)	0.2389154*** (.002209)	0.2600965*** (0.0026793)	0.2497522*** (.0031903)
Employment	0.0438664*** (.0007704)	0.0632287*** (0.0008483)	0.054496*** (0.0012857)	0.0668006*** (0.0016403)	0.0657713*** (0.0019907)
Household size	-0.0013986*** (0.0001072)	-0.0021266*** (0.0001072)	-0.0015736*** (0.0001702)	-.0017101*** (0.0002003)	0.00000457 *** (0.0002382)
White	0.3093463*** (.0012564)	0.306342*** (0.0012586)	0.2811063*** (0.001961)	0.2798596*** (0.0024576)	0.2441114*** (0.0030082)
Illness	0.0266591*** (.0009166)	0.0293713*** (0.0009197)	0.0305241*** (0.001429)	0.0226264*** (0.0017461)	0.0215072*** (0.002326)
Top two asset index quintiles			0.1144215*** (0.00104)		
Any chronic disease				0.0125636*** (0.0019454)	0.0122023*** (0.0023587)
Urban					0.058243*** (0.0015097)
Constant	0.0504921*** (0.0008969)	-0.0141016*** (0.001388)	-0.0508185*** (0.0021394)	-0.0160515*** (0.0028687)	-0.0526718***
Observations	945,755	945,395		272,702	184,496
Years covered	2002-2011	2002-2011	2004, 2006-2008	2009-2011	2010-2011
R-squared	0.335	0.340	0.362	0.357	0.359

***, ***, *: Statistically significant at the 1%, 5% and 10% levels.

Table B2: Output of linear probability model using LFS and QLFS data (2000-2011)

		Dependent variable: medical scheme cover through employer		
	Regression 1	**Regression 2**	**Regression 3**	**Regression 4**
Formal employment	0.0972054*** (0.001186)	0.0960752*** (0.0011884)	0.0514183*** (0.0013659)	0.0498419*** (0.0016197)
Skilled employment	0.1307855*** (0.0013099)	0.1323259*** (0.0013098)	0.1275632*** (0.001514)	0.1287421*** (0.0017275)
Public sector employment	0.3277039*** (0.0013629)	0.3304002*** (0.001361)	0.2182733*** (0.0016713)	0.2161982*** (0.0018862)
White	0.1386696*** (0.0013818)	0.1403323*** (0.001387)	0.182822*** (0.0015842)	0.1778232*** (0.0018018)
12-14 years education	0.1319925*** (0.0010978)	0.12901*** (0.0010977)	0.1147127*** (0.0012702)	0.1156269*** (0.0014592)
15 years plus education	0.2462948*** (0.0021384)	0.243767*** (0.0021404)	0.235568*** (0.0024515)	0.2301187*** (0.002785)
Male	0.0212611*** (0.0009196)	0.0212321*** (0.0009209)	0.0143646*** (0.0010556)	0.0150647*** (0.0012051)
Age (continuous)	0.0028519*** (0.0000448)			
Ages 21-40		0.0298018*** (0.0027201)	0.0124409*** (0.0030477)	0.011644*** (0.0034961)
Ages 41-60		0.0853211*** (0.0028035)	0.0479725*** (0.0031395)	0.047022*** (0.0036005)
Ages 61 plus		0.0528993*** (0.0041083)	0.0256248*** (0.0045294)	0.0250173*** (0.0052047)
Married	0.0603989*** (0.00098460)	0.066184*** (0.0009681)	0.0456787*** (0.0011028)	0.0473279*** (0.0012531)
Household size	-0.0061054*** (0.000292)	-0.0067391*** (0.0002946)	-0.0032175*** (0.000336)	-0.0039719*** (0.0003795)
Number of children in household	0.0024906*** (0.0005162)	0.0034606*** (0.00052)	0.0014961** (0.0005884)	0.0028064*** (0.000669)
Firm size 20-49	0.0695989*** (0.0013155)	0.0689404*** (0.0013163)	0.0569404*** (0.001536)	0.054639*** (0.0017611)
Firm size 50 plus	0.197561*** (0.0011089)	0.1971291*** (0.0011099)	0.1506754*** (0.0013213)	0.1491172*** (0.0014962)
Union member			0.2430985*** (0.0013882)	0.2485416*** (0.0015771)
Rural				-0.0271279*** (0.0014127)
Constant	-0.1502283 (0.0020602)	-0.0921788 (	-0.067987 (0.0032448)	-0.0526827 (0.0037961)
Observations	645,767	645,767	459,575	359,638
Years covered	2000-2011	2000-2011	2000-2007, 2010-2011	2000-2005, 2010-2011
R-squared	0.3804	0.3796	0.4107	0.4149

***, ***, *: Statistically significant at the 1%, 5% and 10% levels.

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