Income Related Health Inequality in South Africa

David Khaoya[*], Murray Leibbrandt[†], and Ingrid Woolard[‡]

August 21, 2015

Abstract

Good health is central to human happiness and well-being. It is determined by one's socioeconomic status such as income and education. The uneven distribution of these factors imply that good health may also be disproportionately distributed. To quantify the extent of the distribution of health outcomes, measurement approaches assume the existence of a ratio or cardinal scale for health. However, the health information available in surveys such as ours is collected qualitatively. In this paper we convert the ordinal self assessed health (SAH) to a cardinal scale using predictions of interval regression. These are interpreted as health utilities or quality adjusted life years (QALYS). We then apply the corrected concentration index to estimate the extent of income related health inequality. This is decomposed into contributing factors. We also establish the source of change in this inequality over time. We find that income related health inequality is positive. This implies that good health is distributed in favour of the rich in South Africa. This is attributed to disparities in income and educational attainment.

Key words: Inequality, Health, Interval Regression

JEL Classification: 114

1 Introduction

Interest in the measurement of health inequalities has increased globally. This is because most of the health inequalities across social groups or individuals are considered unjust as they reflect an unfair distribution of the underlying socioeconomic determinants of health (for example access to educational opportunities and income). On the other hand some extreme views exist that deny the role of socioeconomic determinants in the creation of health inequalities and rather point to some examples where health inequalities would not

[*]PhD candidate, University of Cape Town

[†]Prof. of Economics, University of Cape Town, Director; Southern African Labour and Development Research Unit (SALDRU)

[‡]Prof. of Economics, University of Cape Town

normally be considered unjust, such as life stage differences and random genetic mutation (Kawachi et al. 2002). These extreme positions point to the need to clearly understand the sources of health inequalities in order to assist policy-makers and academics alike to solve the problem of inequalities in health outcomes.

Good health is central to human happiness and well-being. Health outcomes are correlated with socioeconomic factors. If these factors are unevenly distributed in the population, we expect health outcomes to be unevenly distributed as well. However, although the presence of a significant determinant is important in explaining its contribution to health inequality, it is not the only consideration. The distribution of socioeconomic determinants also plays a role. In this paper we estimate the extent of income related health inequality which we decompose into factors that contribute to inequality in health outcomes. In doing this we employ the corrected concentration index and the decomposition proposed by Wagstaff.

To estimate inequalities in health, the standard concentration index has been the preferred measure. However, there have been new insights pointing to the unsuitability of this measure. When this index is applied to bounded health outcomes such as self assessed health (SAH), it estimates the health outcome inequality index ambiguously. Depending on whether ill health or good health is used, a different index of health outcome inequality is obtained.[1] Erreygers and Van Ourti (2011) recommend the corrected concentration index as an alternative measure.

The concentration index has dominated as a tool used in the measurement of socioeconomic related health inequalities. It is a rank dependent measure adapted to bivariate analysis. Inherent in rank dependent measures is the bivariate distribution of health and another socioeconomic variable used to rank individuals or households (Van Doorslaer 2012). The most common ranking variable used in bivariate analysis is income. However, a few studies have also used education and consumption expenditure (Cutler and Lleras-Muney 2006, O'Donnell et al. 2008). The most important property required for a ranking variable is ordinal scaling, in order to rank individuals or groups.

We analyze inequalities in health outcomes in relation to the underlying socioeconomic determinants of health. It is logical to believe that countries with high levels of inequality in the socioeconomic determinants of health are likely to also have high levels of inequality in health outcomes. Some of the factors correlated with health outcomes include income, education, and demographic factors. In this study we focus on South Africa.

South Africa presents an appropriate setting for this study because of its high levels of inequality in socioeconomic determinants of health. Some of these inequalities are traced

[1] This property is called the mirror property and is violated by standard concentration index

to the apartheid legacy, which was characterized by policies that exacerbated inequalities in access to resources as well as opportunities in education and employment. These have persisted despite policies aimed at addressing them. This means that without any remedial health interventions the level of income related health inequality, which is our focus, is also expected to be high (McIntyre and J.E. 2012). Very little is known about the relationship between these pervasive inequalities in socioeconomic determinants and inequalities in health outcomes in South Africa. This makes it interesting to investigate the relative association (contribution) of these factors to income related health inequalities.

Our objective in this paper is to estimate an index of income related health inequality using SAH as the measure of health outcome and income as the ranking variable. SAH is a non-specific measure of health that is probably the most feasible and inclusive of health status (Jylhä 2009). It is widely accepted as a strong predictor of morbidity and mortality (Idler and Benyamini 1997, Jylhä 2009). The comprehensive nature of the SAH question allows it to capture elements of health (multidimensional) that more guided questions, specific to a particular illness, cannot (Au and Johnston 2013).

SAH is collected in ordinal scale which poses a challenge in using it directly to estimate inequality as the concentration index requires a cardinal or ratio scale variable. To solve this problem, we use the predicted values of the interval regression to convert it to an interval scale (Van Doorslaer and Jones 2003, Ziebarth 2010). This technique has the added advantage, apart from scaling the ordered SAH, of presenting health outcome on the same scale as health utility[2] or quality adjusted life years (QALY). This makes the scaled SAH outcome directly comparable to a true measure of health utility which is often used to measure quality of life in epidemiological studies (Ziebarth 2010). Other scaling techniques, such as the use of predictions from probit regression, require normalization before they are used in the concentration index and are therefore not appropriate for our purpose.

We apply the corrected concentration index to the scaled health outcome measure to estimate income related health inequality. This study is among the first to use the corrected concentration index rather than the standard concentration index to compute income related health inequality in South Africa. We contribute to the literature in several other ways. First, we use a nationally representative longitudinal survey to estimate income related health inequality in each wave of the panel survey, and generate an index of income related inequality in health outcomes. Second, we decompose the index of income related health inequality into factors associated with (that contribute to) the index. Third, we make use of the panel nature of our data to explore the factors associated with the change in the index across the

[2] Health utility is a unit-less measure of health related quality of life that ranges from a minimum of 0 (death) to a maximum of 1 (perfect health)

waves, using the Oaxaca type decomposition.

Even in the presence of unequal distribution of the socioeconomic determinants of health, it is possible to have fewer inequalities in health outcomes if there are interventions to address them. Since the transition to democracy in 1994, the South African government has undertaken steps aimed at redressing health inequalities particularly for the highly vulnerable groups. These include entrenching health provision in the constitution[3], recruitment of foreign doctors to work in under-served areas, introduction of free health care at all public health facilities for pregnant women and children under six years old (Harrison 2009) and McIntyre et al., 2003), and currently, the roll out of National Health Insurance (NHI) (NDoH 2013). Unfortunately, these interventions have concentrated on supply side factors. However, there are huge differences in health care demand patterns in South Africa that may perpetuate inequalities in health outcomes that are correlated with socioeconomic factors (Skordis-Worrall et al. 2011).

Despite government intervention to redress health inequalities, studies have reported persistent health inequalities in South Africa (Ataguba 2013, Harling et al. 2008, Zere and McIntyre 2003, Case 2004, Bradshaw 2008). Our own exploratory analysis of data from the three waves of NIDS indicates that there are variations in health outcomes. This is the case whether subjective or objective indicators of health are analyzed. The NIDS data shows that about 12% of the sample report poor and fair health while 88% report good health, very good, and excellent health across waves 2 and 3. For wave 1 the figures were 22% and 78% respectively. What is not explicit from the literature on inequality in health outcomes in South Africa is that inequality in health is not quantified. Through an index of health inequality we summarize the extent of income related health inequality and this is decomposed to establish factors driving this inequality.

2 Literature Review

2.1 Theoretical foundations

In this section we highlight theories that are advanced to explain the sources of health inequalities as well as review some of the empirical evidence. Four theories have been advanced in the literature since the Black[4] Report in 1980 that sought to explain sources of health inequalities. These include the artefact theory, the selection theory, the cultural and behavioural theory

[3] This has the implication of giving health expenditure vote preference over other expenditure votes in the event of competing use for resources thereby ensuring prioritization of health provision.

[4] Sir Douglas Black chaired a Research Working Group on Inequalities in Health in England and published the findings in a report that is famously called Black Report of 1980.

and the material/structural theory (McCartney et al. 2013). The artefact theory suggests that the association between markers of social status and health outcomes is explained by statistical artefacts relating to the way in which social status has been classified over time. This theory has been criticized heavily on the grounds that even where different measures of social status are used (such as income, education, and employment status) inequalities in health outcomes are ubiquitous, making it difficult to believe that health outcomes are unrelated to social status.

The selection theory proposes that health selection might explain inequalities in health outcomes. This theory is essentially a reverse causation one where poor health causes social selection which leads to the observed association between ill health and low social status. The selection can be direct or indirect. Indirect selection occurs when factors in early life (genetics, infections, ante/post natal care) set the foundation and cause one to be in a given social position. These early life factors also influence health related behaviour that determine health (Mel Bartley 2005). In order to test this theory however, we would require longitudinal data that measures pre-morbid social status, and test for an association with subsequent morbidity. In our case we use data that spans only four years therefore it is not feasible to use this theory to explain health inequalities in this study.

The third theory advanced to explain health inequality is the cultural and behavioural theory which suggests that differences in behaviour such as smoking, alcohol consumption, diet, physical activity or differences in the dominant cultures between groups explain the source of inequalities in health outcomes. For health behaviour to cause health inequalities however, socioeconomic factors have to be effect modifiers in the relationship. This theory has been criticized on two grounds. One is the finding that when comparing mortality rates of two groups with the same risk exposure but different socioeconomic status, the group with the lower socioeconomic status has higher mortality rates (Smith et al. 1998). Secondly, a simple focus on behaviour ignores how and why individuals in a particular social group adopt a particular unhealthy behaviour (Nettle D. 2009). Some evidence in the literature has shown that the patterning of adult health behaviour can be explained by their earlier exposure to socioeconomically determined situations (Lynch et al 1997).

Another theory that explains the sources of health inequalities is the material or structural theory. This proposes that differences in socioeconomic circumstances of social groups (including differences in income, wealth, power, environment and access) at all stages of the life course, are associated with differences in the health outcome. According to structural theorists the other three theories are subordinate, that is, behaviour and cultures may theorise potential mechanisms linking structural determinants and health outcomes but do not identify the “causal roots” of health inequalities. This theory has further been supported in the literature which has shown that people with the most resources within any society are always the healthiest, regardless of their behaviour (CSDH 2008, Wilkinson and Pickett 2011). In this study we adopt the material or structuralist theory because it provides the dominant frame for analysis in most empirical research (McCartney et al. 2013).

2.2 Empirical literature

Empirical studies assume that health inequalities emanate from differences in socioeconomic determinants of health (income, wealth, education, and demographic characteristics). These studies therefore assume that material or structural theory is the source of inequalities in health outcomes. They therefore first identify the health determinants and evaluate their contribution to health inequality. Many Sub-Saharan African countries have an uneven distribution of socioeconomic factors which translates to uneven distribution of health outcomes. South Africa is one such country which has very high levels of inequalities in income and other socioeconomic factors such educational attainment.

In a study in Uganda, Ssewanyana S. (2012) uses determinants of child nutrition to explain health inequalities. Similar approaches in South Africa include Zere and McIntyre (2003), Charasse-Pouélé and Fournier (2006), Ataguba et al. (2011) and Ataguba (2013). Zere and McIntyre (2003) for example use determinants of self assessed illness and health care to analyze health inequalities in South Africa. They find that the poor reported themselves sick more frequently. Charasse-Pouélé and Fournier (2006) establishes health inequalities based on racial groups while Booysen (2003) establishes health inequalities based on urban rural divide in health care access. Ataguba et al. (2011) and Ataguba (2013) use the standard concentration index to estimate health inequality in self reported acute and chronic illnesses as well as multimorbidity. Inequalities in health outcomes vary in these studies because of differences in the time of study, methods used, and the indicators of health and socioeconomic measures applied.

3 Method of Analysis

3.1 Data and variable definitions

This study uses the NIDS dataset. NIDS is the first nationally representative panel survey in South Africa. It is an initiative of the South African Presidency.[5] This data is aimed at establishing a national panel study to provide an information base to benchmark progress and assist in assessing the effectiveness of policies to promote positive social mobility (SALDRU 2009, 2014a,b). The Southern Africa Labour and Development Research Unit (SALDRU),

[5]Office of the President

based at the School of Economics of the University of Cape Town, undertook the first three waves on behalf of the Presidency (SALDRU 2009, 2014a,b).

The objective of NIDS is to track and explain changes in the well-being of South Africans over time (SALDRU 2009, 2014a,b, Leibbrandt et al. 2009). These changes are tracked for individuals (28, 247) as they move out of their original 7,301 households (Brown et al. 2012). The first wave of NIDS was conducted in 2008 with the second and third in 2010-2011 and 2012 respectively.[6] Data was collected on all household residents in wave 1 (2008) which formed the base sample of individuals. These are called Continuing Sample Members (CSMs) and these individuals are followed in subsequent waves. In the subsequent waves, data is also collected on children born of female CSMs. Our focus is limited to the evaluation of one aspect of well-being, health outcomes.

The salient feature of NIDS is that it contains useful longitudinal data not only on health outcomes but also on other indicators of well-being, such as income, education and employment status. The dataset also has information on the individual characteristics of respondents. Such rich information is useful in the analysis of dynamic interrelationships between health and socioeconomic factors which we use in the decomposition of health inequality.

NIDS collected data on several variables related to health outcomes. One of these is self assessed health status (SAH). For this individuals are asked: "How would you describe your health at present?" This question has five possible responses: Excellent, very good, good, fair, and poor. We use this variable in the estimation of health inequality.

We use household income provided in NIDS to calculate per capita income. We obtain per capita income by dividing the household income by the number of people living in the household and adjust for inflation using the consumer price index (CPI) deflator provided by Statistics South Africa. Household income is self reported income of individuals in the household obtained by summing income data for individuals across all sources of income (Argent 2009).

In the dataset there are two sources of income data. One is a 'one-shot' question asked in the household questionnaire about the total amount of after tax household income received in the previous month. The second source of income data is individual level income questions across all sources of income (Argent 2009). In wave 1 households that did not state their income in the one shot question are asked to select their household income category from 15 income categories. An imputation method is used to assign a household income value to the household based on this category (Yu 2013). In waves 2 and 3, representatives of households

[6] These surveys are henceforth referred to as wave 1, wave 2 and wave 3 respectively.

Table 3.1: Variable Description for Health and Socioeconomic Variables used in the Analysis

Variable	Description
Self Assessed Health	Ordinal with five categories, 1= poor, 2= fair, 3=good, 4=very good 5=excellent
Education	Categorical with five categories, 0=No education, 1=General education, 2=Further education and training, 3=Matric, 4=Higher education
Income	Real per capita monthly income
Race	Four race categories 1=African 2=Coloured 3=Asian 4=White
Geographical type	Categorical with three categories 1=Traditional area 2=Urban 3=Farms
Marital status	Categorical with five categories 1=married, 2=living with partner, 3=Widow/widower, 4=Divorced/separated, 5=Never married
Gender	Binary (Male=1)
Age	Measured in age bands of 10 years from age 15
Province	Categorical 1=Western Cape, 2=Eastern Cape, 3=Northern Cape, 4=Free State, 5=Kwa-Zulu Natal 6=North West, 7=Gauteng 8=Mpumalanga 9=Limpopo

Source: Own compilation. The table shows the description of variables used in this study. HBP is High Blood Pressure

were asked to report whether last month's income was more than, about equal to, or less than a specific amount, and the household income in interval terms is converted into continuous amounts using the mid point Pareto method (Yu 2013). The one shot source is used when the individual income is missing (Argent 2009). For the purpose of our analysis we use the logarithm of th e per capita income variable in our analyses to reduce the effect of outliers in the sample.

For education indicator, we create five categories of educational attainment, with no education as the base category. This variable is constructed from the information regarding the highest grade in school the respondent successfully completed at the time of the survey. Those who have attained grade 1 to grade 9 are categorized as having attained general education. Those with grade 10 and 11, as well as a National Training Certificate (NTC) 1-2 are categorized as having attained further education and training. Respondents with grade 12 and NTC 3 are categorized as having attained Matric. Those with educational attainment above grade 12 are categorized as having attained Higher education.

This categorization is in line with the national department of education which uses similar categories in their reports (NDoE 2013). Previous work on the analysis of Health using NIDS data, by Ardington (2009), uses comparable categories, making it easier for comparison of results. Besides, the use of education categories rather than years of schooling in the regressions provides a flexible functional form, with attention to the key graduation points in the South African education system.

In all our analyses we include demographic variables such as age, gender, race and marital status, as controls. The race variable is particularly important for South Africa because of its

Apartheid history. We also control for geographical type variables, namely traditional area, urban areas, and farms, to cater for the uniqueness of these regions. Regional fixed effects are relevant control variables because of the high regional heterogeneity in health status in South Africa. This is partly due to lack of a uniform health care funding system at provincial level, and differential levels of development that have an influence on the availability of health inputs. For this reason we control for province in all our analysis.

Age is an important explanatory variable because usually health depreciates with age and therefore this variable must be controlled for in the analysis. Age is collected in years in NIDS. We also create 10 year age categories from the continuous age variable in the data. This ensures that we do not impose a functional form a priori but let the data decide. Table 3.1 summarizes the health outcome variables and key explanatory variables used in this study.

3.2 Measurement of health

The WHO defines health as the state of complete physical, mental and social well-being and not just the absence of disease or infirmity (WHO 2010). Thus health is a multidimensional phenomenon and this poses a challenge because it is unlikely that we can find an overall measure which collapses the separate dimensions into one construct. Several index-scoring algorithms have been developed to measure different health profiles, such as SF-36, HUI, and Euroqol-5D. Although these are the ideal measures to use, their availability is limited because they are collected only in health interview surveys which are rare. They are not in NIDS.

SAH is perhaps the closest variable that captures all health dimensions. The idea is that when individuals evaluate their health, they consider all the dimensions before they report themselves in a given health category. For this reason we use SAH to measure health outcome in this study. SAH has also been supported by international literature because of its power to predict mortality and health care utilization (Idler and Benyamini 1997). The former ability has also been confirmed by Ardington (2009) using our dataset.

The SAH variable is collected as an ordinal scale variable, but underlying it is the assumption of a latent health variable that informs the observed responses. We denote the latent health variable by h^* and assume that the SAH categories and the latent health variable (h^*) are related as follows:

$$\begin{gathered} SAH = i \quad if\ \alpha_{i-1} < h^* \leq \alpha_i,\ for\ i = 1,2,3,4,5 \\ Where \quad \alpha_1 = -\infty,\ \ and\ \ \alpha_5 = +\infty \end{gathered} \tag{3.1}$$

SAH is self assessed health, α_i are the thresholds for the health categories. These thresholds are unobservable but have been estimated in various ways in the literature as we will see shortly.

The index of inequality that we use to estimate income related health inequality can not be applied directly to an ordinal scale variable such as SAH. Many previous researchers have dichotomized or converted this to a cardinal scale before using this measure to estimate income related health inequality (Van Doorslaer and Jones 2003, 2004, Van Doorslaer et al. 2004). Unfortunately, dichotomization leads to loss of information between categories that are merged. In addition the choice of cut offs for dichotomization is normally arbitrary and influences the levels of inequality obtained. When different countries or regions are compared dichotomizing SAH categories can lead to rank reversals. Wagstaff and Van Doorslaer (1994) and Van Doorslaer and Jones (2004) have demonstrated rank reversals when comparing health inequalities in the Netherlands and countries in Europe using different dichotomization. We therefore avoid dichotomising the SAH.

In the literature, a number of approaches have been proposed to convert variables captured in ordinal scale such as SAH to cardinal or ratio scales (Van Doorslaer and Jones 2003, O'Donnell et al. 2008). These include the use of predicted values from ordinary least squares (OLS) regression, predicted (linear predictions) values from probit or logit regression applied on SAH after dichotomising it to a binary variable, predictions from ordered probit or logit regression, and predictions from interval regression (Wagstaff and Van Doorslaer 1994, Van Doorslaer and Jones 2003).

It has been shown that predictions from an ordered probit approach overestimate inequality (Van Doorslaer and Jones 2003). The ordered probit predictions also require ex post re-scaling because they are not generated on the same scale as health utility (which is normally bounded between 0 and 1) and hence cannot be used directly as quality weights or utility proxies (Cutler et al. 1997, Van Doorslaer and Jones 2003). In our case we cannot use predicted values of OLS to convert the SAH to cardinal scale because the SAH variable was collected as an ordered variable with only five categories. We therefore use predicted values from interval regression. This has additional advantages, as this approach predicts health outcomes more accurately than predictions from other models (Van Doorslaer and Jones 2003). More importantly, predictions from interval regression are generated on the same scale as health utility[7] making them directly comparable with the health utility index (HUI)

[7]Health utilities are cardinal values that reflect an individual's preferences for different health outcomes. They are measured on an interval scale with zero reflecting states of health equivalent to death and one reflecting perfect health. These utilities can be based on direct patient experience although clinicians and other health professionals are sometimes used as proxies backed by evidence in the literature (Tolley 2009).

which is a true measure of health outcome normally used in health related quality of life studies to measure health states.

The use of interval regression to scale SAH to cardinal scale entails regressing the SAH categories on the covariates of health to predict health outcome and the health outcome variable obtained is therefore conditional on the covariates (Van Doorslaer and Jones 2003).

To implement interval regression, we use thresholds of SAH categories. As mentioned earlier, these are not observed so we estimate them using external information. We use the Canadian health utility index (HUI) to set these thresholds for SAH categories. This is because there is no health survey within South Africa which has simultaneously collected SAH and a true health indicator such as HUI or short form 36 (SF-36). The Canadian HUI has been widely applied with European data and Chinese data to estimate thresholds for SAH (Van Doorslaer and O'Donnell 2008).

We use HUI to set thresholds for SAH because there is a stable mapping from the HUI to the latent variable that determines reported SAH for all individuals (Van Doorslaer and Jones 2003). The implication is that an individual's rank according to HUI corresponds to his rank according to SAH. This is so because SAH is generated in the same scale as HUI, after fixing the lowest and highest bounds of SAH corresponding to those of HUI. This also makes the quantiles in the HUI and SAH correspond to each other, such that the q-th quantile of the distribution of HUI corresponds to the q-th quantile of the distribution of SAH. As mentioned earlier, the lowest bound of HUI is zero which we assign to the lower bound of poor health category and the highest bound of 1 to the higher bound of excellent health. The rest of the thresholds obtained from the Canadian HUI[8] we assign to corresponding thresholds of SAH. We then estimate an interval regression model of SAH categories on the covariates of health outcomes and predict the linear index values as proxy for utility or Quality Adjusted Life Years (QALY) which we use as a continuous indicator of health outcomes. The covariates we include are informed by theory and previous empirical studies.

The interval regression model is linear and this is important because the concentration indices (both standard and corrected concentration indices) calculated using the predictions from a linear model are suitable for decomposition analysis (Van Doorslaer et al. 2004). In effect, the interval regression technique exploits the between SAH category variation to generate some within SAH category variation in HUI, while HUI itself is unobserved.

[8]The Canadian HUI thresholds that correspond to the middle thresholds for SAH are 0.428, 0.756, 0.897 and 0.947. These, together with 0 and 1 form the thresholds of the SAH categories for interval regression purposes.

3.3 Measuring inequality in health

After measurement of health outcome, we now turn to measurement of inequality in the health outcome. Health inequalities have traditionally been measured by rank dependent measures such as the concentration index. This index is bivariate in that it measures inequality in health outcomes conditional on some socioeconomic variable such as income or education (Cutler et al. 1997, Cutler and Lleras-Muney 2006). If we measure inequalities in health per se we would compute a health Gini index. However, because we compute inequalities in health conditional on some other socioeconomic variable (income in our case), the concentration curve and the related concentration index (CI) are the preferred tools in the computation of income related health inequalities (Fleurbaey and Schokkaert 2009).

While the standard CI is common and also popular, new insights have shown that it is not recommended for measuring inequalities for cardinal health indicators that are bounded, such as SAH or HUI (Erreygers and Van Ourti 2011) and also (Van Doorslaer 2012). The health outcome we obtain using predicted values of the interval regression is bounded between 0 and 1 because it is estimated on the same scale as HUI. If the CI is used to measure income related health inequality using bounded health outcomes, it violates some desirable properties of a rank-dependent inequality index, namely, the mirror and scale invariance properties (Erreygers and Van Ourti 2011).

The mirror property requires that for a bounded health outcome like SAH, if h is the good health distribution and s is its associated ill health distribution, then applying the inequality index should yield consistent results in each case i.e. $I(h) = -I(s)$ where I(.) is the inequality index. Unfortunately, the concentration index of health returns a different index from that of ill health.[9] In addition the CI is only meaningful for health variables measured on a ratio scale since the index must remain unchanged under a positive proportional transformation of the health variable. For cardinal variables the value of the CI depends upon the chosen cardinalization since it is not invariant to positive linear transformations (Van Doorslaer and Jones 2004, Erreygers 2009a,b, Erreygers and Van Ourti 2011). Scale invariance property on the other hand requires that the index is invariant to positive affine (linear) transformation.

The bounded nature of the health outcome (SAH) complicates the comparison of health inequalities in the population over time if we apply CI. This is because the bounds of the CI depend upon the lower and upper limit and the mean value of the health outcome[10] in the population (Van Doorslaer and Van Ourti 2012). This means that we cannot compare CI

[9] This is the context in which we argue that the CI is not consistent in ranking socioeconomic related health inequalities when applied to bounded health variables because it depends on whether ill health or health is used.

[10] I.e $-B \leq CI(h) \leq B$ with $B = [(h^{max} - \bar{h})(\bar{h} - h^{min})]/[\bar{h}(h^{max} - h^{min})$

for two populations unless they have equal average population health, as the index will have different bounds.

In light of the above shortcomings, Wagstaff and Van Doorslaer make adjustments on the CI to get the extended concentration index (or Wagstaff index) which unfortunately does not satisfy all the properties (Clarke et al. 2002). Erreygers (2009a) shows that the class of inequality indices that satisfies these two properties (mirror and scale invariance) is given by the general formula:

$$I^{\theta}(h) = \frac{8}{n^2\left[4\mu(h)(1-\mu(h))\right]}\sum_{i=1}^{n} z_i h_i \tag{3.2}$$

Where $I^{\theta}(.)$ is inequality index, θ is inequality aversion parameter, h_i is the health outcome, $\mu(h)$ is the mean of the health outcome and z_i is the fractional rank of the individual. This equation reduces to the Wagstaff index (extended concentration index) if $\theta = 1$ and to Erreygers index (corrected concentration index) if $\theta = 0$.

In addition to the two properties already mentioned (mirror and scale invariance), Erreygers (2009a) and Erreygers and Van Ourti (2011) also impose a convergence property on their index.[11] This condition precludes the suitability of the Wagstaff index from the family of inequality indices shown by equation 3.2 because the convergence condition can only hold if $\theta < 0$.

Following the above explanation, this study adopts the Erreygers index, also called the corrected concentration (CC) index because it satisfies all the desirable properties explained above. This index is given by the formula:

$$CC = \frac{8}{n^2(b_x - a_x)}\sum_{i=1}^{n} z_i x_i \tag{3.3}$$

Where x_i is an indicator of either good health or ill-health, b_x is the upper bound of the health indicator, a_x is the lower bound of the health indicator, z_i is the socioeconomic fractional rank of the individual (income rank in our case). In our case the upper and lower bounds are 1 and 0 respectively which simplifies the above formula even further.

[11] This property requires that $lim_{r\to 0} I(rh) = 0$. This condition examines what happens when a given unequal distribution is gradually reduced to perfectly equal distribution i.e all individual levels reduced to zero by means of a proportional reduction r. When all individuals have zero health, the distribution is equal (even) and so the value of the index should tend to zero.

3.4 The Factor Decomposition Method

In this section we describe how we determine the contributing factors of the CC index. The CC index, like the CI index, is useful in comparing income related health inequality over time or across countries but on its own, it does not tell us much about the factors associated with these inequalities until we decompose it (Van Doorslaer and van Ourti 2010).

The technique to decompose the CC index into contributing factors is proposed by Wagstaff et al. (2003). The technique is meant for decomposing the standard concentration index (CI) but we adapt it to decomposition of the CC index. As we have explained before the CC index is a modification of the standard CI. The modification is aimed at obtaining an index that satisfies the desired properties of a rank dependent index.

In order to decompose the income related health inequality index into contributing factors, we first establish the covariates of the health outcome. The decomposition of income related health inequality relies on the assumption that the underlying health demand/production function is linear. We therefore re-estimate the health demand model using a linear function. To do this we use the parameter estimates of the interval regression model used to estimate conditional health outcome. The intuition is that ceteris paribus, if there are disparities in covariates of health, this is reflected in disparities in health outcome.

We also evaluate the dynamics of income related health inequality. The changes in income related health inequalities are explained by heterogeneous responses of health to the covariates, changes in inequality of covariates, as well as interaction between the two (Jann 2008). Decomposition of income related health inequalities is important because it uncovers the contribution of each factor in CC. It is possible that overall health inequality may be negligible because the contributing factors have opposing effects. In addition decomposition of the CC is useful in addressing why there are differences in income related health inequality in the population at a given time and changes over time (Sahn and Younger 2009).

To implement the decomposition we express the health outcome variable (SAH) as a linear function of socioeconomic, demographic and geographical variables as follows:

$$h_i = \alpha + \sum x_{ki}\beta_k + v_i \tag{3.4}$$

Where h_i is the health outcome for individual i in this case the intervals of SAH categories, x_{ki} is a vector of covariates of health (socioeconomic, demographic and geographical variables), α is the intercept, β_k is a vector of slope coefficients and v_i is the error term. Following Wagstaff et al. (2003), the standard health concentration index (CI) for h_i is written as:

$$CI(h) = \sum_k \frac{\beta_{xk}\bar{x_k}}{\mu} CI_{xi} + \frac{GV_{\varepsilon k}}{\mu} \tag{3.5}$$

Where $CI(h)$ is the standard concentration index, β_{xk} the coefficient of x_{ki} and $\bar{x_k}$ the mean of x_{ki}. Since the corrected concentration has a close relationship with the standard concentration index, the decomposition of the two indices is identical in proportionate terms (Van Doorslaer and Jones 2003). Consequently, given the linear health function in equation 3.4, the decomposition of the corrected concentration index is the weighted sum of the concentration index for each covariate with the weights being the partial effects. This is written as:

$$CC(h) = \sum_k \beta_{xi} CC_{xi} \tag{3.6}$$

Where $CC(h)$ is the health corrected concentration index, CC_{xi} is corrected concentration index for variable x_i, and β_{xi} is coefficient of variable x_i. This analysis implies that a factor can only contribute to inequality if it satisfies two conditions, first it should be associated with health, as indicated by significant coefficients in the linear regression and secondly the factor should be unequally distributed across socioeconomic status (Van Doorslaer and Van Ourti 2010). This approach therefore allows identification of the importance of each of these two components within each factor's total contribution (Van Doorslaer and Jones 2003).

We extend the decomposition approach to explain sources of differences in the income related health inequality over time as in the Oaxaca (1973) and Blinder (1973) as follows:

$$CC^{w3} - CC^{w1} = \sum_k \beta_{xi}^{w1}[CC_{xi}^{w3} - CC_{xi}^{w1}] + \sum_k CC_{xi}^{w1}[\beta_{xi}^{w3} - \beta_{xi}^{w1}] \tag{3.7}$$

Where CC^{w3} is corrected concentration index in wave 3, CC^{w1} is corrected concentration index in wave 1. β_{xi}^{w3} are coefficients of the health covariates in wave 3, β_{xi}^{w1} are coefficients in wave 1. The left hand side of the equation 3.7 is the change in health concentration index between wave 1 and wave 3. The first term on the right hand side is the sum of the change in the CC index attributed to the changes in the distribution of the covariates of health weighted by their partial effects while the second term is the change attributed to heterogeneous responses to covariates (change in coefficients) weighted by the distribution of covariates at the base wave.

While the factor decomposition is enlightening in identifying contributing factors to the health inequality index, we make two caveats. First, decomposition of the index holds only if equation 3.4 is linear. Second, the factor decomposition is descriptive and cannot be interpreted in terms of causal relationships unless equation 3.4 has a causal interpretation (Van Doorslaer and Van Ourti 2010).

4 Results

4.1 Interval regression results

We estimate conditional mean health of the population from linear index predictions of interval regression, as explained earlier in section 4.3.2. These predictions have the same scale as HUI which is unit-less and ranges from 0 to 1 with a score of 0 indicating the worst possible health state (death) and 1 the best possible health state (Tolley 2009). The predictions are conditional on a set of covariates. The results show that conditional mean health was 0.83 in wave 1 and 0.88 and 0.87 in waves 2 and 3 respectively. These results coincide with the good SAH category in the HUI.[12] In other words, on average, South Africans have good self assessed health.

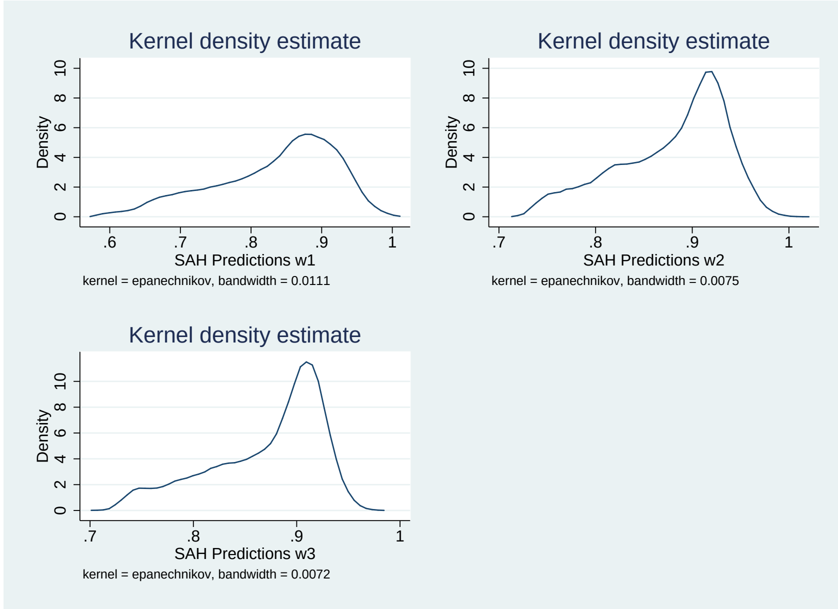
The distribution of the conditional health outcome is presented in figure 4.1. This figure plots the density (frequency) of SAH on the vertical axis and conditional predictions of SAH from an interval regression on the horizontal axis. As we can see the kernel density plots of the conditional health outcomes in each wave are skewed to the left, implying that the majority of South Africans enjoy good health rather than poor health. The conditional health outcome variable (SAH) is bounded between 0 and 1 with a similar scale as that of HUI since it is generated on the scale of HUI.

The interval regression results are presented in table 4.1. These results are separate for each wave. This is meant to capture the dynamics of inequality in health. We therefore discuss these again below. From the results, income is positively correlated with higher values of health utility (better health). The relationship is stable across waves (approximately a significant coefficient of 0.005 across all waves) with the exception of wave 2 where the coefficient is 0.003 but not significant. For wave 1 these results mean that a 1% increase in income is associated with a 0.005 increase in health utility. Put differently, doubling incomes is associated with a 0.5 increase on the health utility index.

In wave 1, respondents with general education (i.e. attained some primary school education) have better health than those with no education. The differences in health increases progressively with increasing levels of education relative to no education. This trend continues

[12]The HUI thresholds are 0-0.428 Poor, 0.428-0.756 Fair, 0.756-0.897 Good, 0.897-0.947 Very Good and 0.947-1 excellent (Van Doorslaer and Jones 2003).

Figure 4.1: Kernel density of SAH health predictions from interval regression



Notes: Kernel density plots for linear predictions of health from interval regressions for waves 1-3. The density plots are skewed to the left implying that the majority of people have good health relative to poor health.

in subsequent waves, however there is no significant difference in health outcomes between those with general education and those with no education in wave 2 and only a difference at 10% level of significance in wave 3. The results are consistent with predictions of the theory of health demand by Grossman which postulates that the more educated are more efficient producers of health. The efficiency effect can take two forms, productive and allocative efficiency. Productive efficiency arises when the more educated obtain a larger health output from given amounts of endogenous inputs. Allocative efficiency on the other hand pertains to a situation in which education increases information about the true effects of health inputs. For example the more educated will on average have accurate information about the harmful effects of what they consume.

Health outcome depreciates over the life cycle, and the young have better health. 25-34 year olds have lower health status in terms of health utility than 15-24 year olds. The differences (decreases) in health status proxied by health utilities progressively increase with increasing age. The pattern is the same across all three waves. However the differences from one age category to another reduces with age. This confirms non linearity of age in explaining health outcomes.

There is evidence of racial differences in health outcomes in wave 1 and 2 where Whites have a higher health utility score than Africans. This difference is significant at 5% in wave 1 and 10% level of significance in wave 2. There is no statistically significant health outcome difference between Coloureds and Asians relative to Africans in wave 1 and wave 2. However in wave 3, Coloureds have higher health utility score while Asians report lower health utility score than Africans. This is significant at 5% and 10% level respectively.

Widows and widowers are less likely to report a high health utility score than married people. However there is no statistically significant differential in health outcomes between divorcees and married individuals. Those who had never married at the time of the survey reported lower health utility scores than those who were married. There was however no evidence of differential health outcomes between different marital status in wave 2 and only those never married reported lower health outcomes relative to married in wave 3.

In wave 1 respondents in Western Cape reported better health utility scores relative to all the other provinces except Eastern Cape and Limpopo, where there was no statistically significant difference. However these results were not stable across waves. Respondents in Gauteng and Limpopo provinces reported statistically significant better health utility scores than those in the Western Cape province in wave 2. In wave 3, respondents in the Western Cape province reported poorer health than those of the other provinces. Living in different area types (traditional areas, urban areas or on farms) also resulted in health differences. Those in urban areas reported poorer health outcomes than those in traditional areas in waves 1 and 2 but no differential health outcomes were reported in wave 3. The reversal of signs for province dummies is surprising, with possible explanation being the roll-out of anti retro-viral treatment across the provinces in South Africa that may have changed peoples' perception about their health. This however remains speculative for now.

Gender differences in health outcomes were significant. Men had higher health utility scores across the waves and these differences were statistically significant at 1% level of significance. These results confirm that there are health differences in South Africa based on socioeconomic and demographic and on geography. The next challenge is to quantify the differences in health outcomes highlighted in the regression as an index. This has the advantage of showing who is favoured by these health outcomes.

4.2 The Factor Decomposition Results

Table 4.2 presents the results of the income related health inequality index (CC) and its decomposition. From the table the CC index is 0.0359 in wave 1, 0.0144 and 0.0194 in wave 2 and wave 3 respectively. Since the index is positive, this means that better health is distributed in favour of the rich across the waves of NIDS in South Africa. In addition the index has standard errors of 0.0036 in wave 1, 0.0023 in wave 2 and 0.0018 in wave 3. This implies that income related health inequality actually decreases in later waves. We

Table 4.1: Interval Regression of SAH on its covariates.

VARIABLES	(1)	(2)	(3)
Log of real pc income	0.00581***	0.00260	0.00548***
	(0.00185)	(0.00166)	(0.00197)
General Education (rel. to No educ.)	0.0437***	0.0128	0.0160*
	(0.00881)	(0.00807)	(0.00903)
Further Education and Training	0.0651***	0.0289***	0.0318***
	(0.00934)	(0.00873)	(0.00835)
Matric	0.0856***	0.0437***	0.0433***
	(0.00984)	(0.00857)	(0.00911)
Higher education	0.108***	0.0564***	0.0486***
	(0.0112)	(0.00948)	(0.00894)
25-34 (rel. to 15-24)	-0.0359***	-0.0238***	-0.0209***
	(0.00493)	(0.00294)	(0.00455)
35-44	-0.0681***	-0.0442***	-0.0464***
	(0.00687)	(0.00469)	(0.00554)
45-54	-0.109***	-0.0747***	-0.0698***
	(0.00855)	(0.00595)	(0.00513)
55-64	-0.149***	-0.103***	-0.0958***
	(0.0109)	(0.00913)	(0.00855)
65+	-0.180***	-0.138***	-0.134***
	(0.0128)	(0.0115)	(0.00966)
Coloureds (rel to Africans)	-0.00532	0.00226	0.0174**
	(0.00835)	(0.0108)	(0.00724)
Asians	0.000448	-0.0127	-0.0253*
	(0.0128)	(0.0151)	(0.0146)
Whites	0.0212**	0.0187*	0.00288
	(0.00905)	(0.00981)	(0.00832)
With partner (rel. to married)	-0.0263***	-0.0104	-0.00699
	(0.00880)	(0.00653)	(0.00701)
Widow	-0.0409***	-0.0154	-0.0142*
	(0.00912)	(0.00975)	(0.00841)
Divorced	-0.0128	0.000325	-0.000338
	(0.0155)	(0.0155)	(0.0102)
Never married	-0.0121**	-0.00761*	-0.00966*
	(0.00538)	(0.00426)	(0.00496)
Eastern Cape (rel. to Western Cape)	0.00765	0.0102	0.0197**
	(0.0106)	(0.0103)	(0.00947)
Northern Cape	-0.0172*	-0.000448	-0.00308
	(0.00958)	(0.00847)	(0.0102)
Free State	-0.0327***	0.0109	0.00922
	(0.0108)	(0.0120)	(0.0103)
Kwa-Zulu Natal	-0.0593***	0.00577	0.0220***
	(0.00917)	(0.0110)	(0.00805)
North West	-0.0271**	0.0120	0.0222**
	(0.0115)	(0.0108)	(0.00946)
Gauteng	-0.0168**	0.0258**	0.0257***
	(0.00822)	(0.0105)	(0.00797)
Mpumalanga	-0.0306***	0.00910	0.0170*
	(0.0113)	(0.0101)	(0.00891)
Limpopo	0.00403	0.0362***	0.0306***
	(0.0107)	(0.0112)	(0.00919)
Male	0.0222***	0.0133***	0.0138***
	(0.00363)	(0.00320)	(0.00251)
Urban (rel. to Traditional area)	-0.0155**	-0.0112**	-3.11e-05
	(0.00674)	(0.00517)	(0.00444)
Farms	0.00907	-0.0102	0.00539
	(0.00982)	(0.00883)	(0.00828)
Constant	0.842***	0.881***	0.835***
	(0.0179)	(0.0164)	(0.0180)
Observations	15,446	17,323	18,673

Notes: The dependent variable is self assessed health (intervals). Robust standard errors that allow for correlation in un-observables for each individual drawn from the same primary sampling unit are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

note however that the standard errors are quite small and this could be partly because the predictions from interval regression smooth out some of the variation we would expect from health outcomes. In addition, the range of health utility predictions is small (0 to 1) with majority clustered towards the higher levels of health utility.

In addition to summarizing the extent of income related health inequalities, we also decompose the index into factors associated with the inequalities. A positive (negative) contribution for a variable implies that the variable increases (decreases) income-related health inequalities favouring the rich. The decomposition results show that disparities in income and education have the highest positive contribution to income related health inequality across the waves except in wave 3, where health differences due to marital status play a prominent role. Age differences decrease income related health inequalities favouring the rich across all waves. In addition, differences due to race, province of residence and in marital status increase income related health inequalities favouring the rich except in wave 3 when differences in provinces of residence decrease income related health inequalities favouring the rich. Gender differences in health outcome also increase the income related health inequality in favour of the rich. Differences in health outcomes due to geographical are type of residence (Traditional area, in urban areas or on farms) reduce income related health inequality favouring the rich in wave 1 and 2 but do not have any influence in wave 3.

The index is enlightening and is used to compare levels of inequality in health outcomes from one time period to another. However, it is more useful when it is decomposed over time to identify the factors associated with changes in the index. To do so, we use Oaxaca type decomposition of the income related inequality index. We note, however, that the dataset we use represents only four years between the first and the third wave. This may not show noticeable differences in income related health inequalities. Our objective here is to address the fundamental question of why income related health inequality decreased over this short time period. Table 4.3 presents the Oaxaca type decomposition results for this exercise.

Following Jann (2008), we decompose the change in income related health inequality into three components. The first is a change in inequality due to a change in the distribution of socioeconomic determinants. The second is a change in inequality due to changes in the coefficients. Finally, a change due to the interaction or change in both coefficients and distribution of covariates. The results in table 4.3 show that the biggest contribution to the change in income related health inequality is the interaction (in some literature this is also referred to as, unexplained) (Jann 2008). The change in income related health inequality due to the distribution of covariates is higher than the change due to coefficients, although the difference between the two is small.

Table 4.2: Decomposition of the corrected concentration index

		Wave 1		Wave 2		Wave 3	
Variable		**CC**	**Aggregate CC**	**CC**	**Aggregate CC**	**CC**	**Aggregate CC**
Income		0.0172	0.0172	0.0076	0.0076	0.0148	0.0148
Education	General Education	-0.0123		-0.0035		-0.0045	
	FET	-0,0026		-0.0013		-0.0024	
	Matric	0.0134		0.0062		0.0054	
	Higher education	0.0300	0.0285	0.0149	0.0163	0.0153	0.0138
Age	25-34	-0.0019		-0.0003		-0.0006	
	35-44	-0.0047		-0.0038		-0.0039	
	45-54	-0.0035		-0.0035		-0.0027	
	55-64	-0.0049		-0.0039		-0.0035	
	65+	-0.0030	-0.0180	-0.0031	-0.0146	-0.0022	-0.0129
Race	Coloureds	-0.0003		0.0002		0.0006	
	Asians	0		-0.0007		-0.0012	
	Whites	0.0065	0.0062	0.0054	0.0049	0.0008	0.0002
Marital status	With partner	0		0.0001		0.0001	
	Widow	0.0008		0.0002		0.0001	
	Divorced	-0.0005		0		0	
	Never married	0.0031	0.0034	0.0020	0.0023	0.0022	0.024
Province	Eastern Cape	-0.0011		-0.0008		-0.0020	
	Northern Cape	0		0		0	
	Free State	0		0		-0.0001	
	Kwa-Zulu Natal	0.0080		-0.0007		-0.0023	
	North West	-0.0003		0.0001		0	
	Gauteng	-0.0039		0.0054		0.0060	
	Mpumalanga	-0.0001		-0.0001		-0.0001	
	Limpopo	-0.0003	0.0023	-0.0032	0.0007	-0.0025	-0.0010
Male		0.0032	0.0032	0.0019	0.0019	0.0021	0.0021
Geographical types	Urban	-0.0070		-0.0048		0	
	Farms	0.0001	-0.0069	0.0001	-0.0047	0	0
Total (CC)		**0.0359**		**0.0144**		**0.0194**	

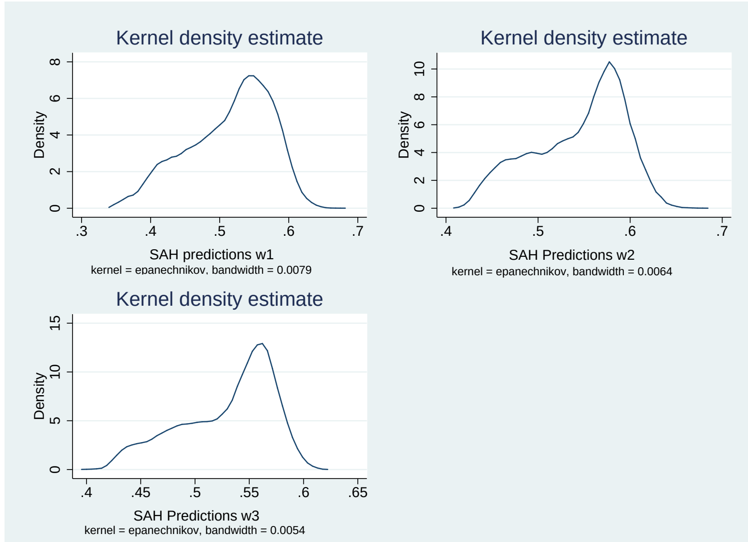
Notes: The table shows magnitudes and direction of contribution of each factor in the income related health inequality index (corrected concentration index). The aggregate contribution of categorical variables is invariant to the base category although contribution of specific categories such as specific provinces may vary with the base category. Positive (negative) values indicate that the factor increases (decrease) income related health inequality favouring the rich.

Table 4.3: Factor Decomposition over time (Oaxaca Type decomposition)

		1	2	3	4	5	6	7	8	9
Variable		CC_{w1}	CC_{w3}	β_{w1}	CC_{w3}-CC_{w1}	β_{w3}	$\beta_{w3} - \beta_{w1}$	$CC_{w1}(\beta_{w3} - \beta_{w1})$	$\beta_{w1}(CC_{w3}$-$CC_{w1})$	Interaction
Income		0.0172	0.0148	0.006	-0.002	0.006	0.000	0.0000	0.0000	-0.0024
Education	General Education	-0.0123	-0.0045	0.044	0.008	0.016	-0.028	0.0003	0.0003	0.0071
	FET	-0,0026	-0.0024	0.065	0.000	0.032	-0.033	0.0001	0.0000	0.0001
	Matric	0.0134	0.0054	0.086	-0.008	0.043	-0.042	-0.0006	-0.0007	-0.0067
	Higher education	0.0300	0.0153	0.108	-0.015	0.048	-0.060	-0.0018	-0.0016	-0.0113
Age	25-34	-0.0019	-0.0006	-0.036	0.001	-0.021	0.015	0.0000	0.0000	0.0014
	35-44	-0.0047	-0.0039	-0.068	0.001	-0.046	0.022	-0.0001	-0.0001	0.0010
	45-54	-0.0035	-0.0027	-0.109	0.001	-0.070	0.039	-0.0001	-0.0001	0.0010
	55-64	-0.0049	-0.0035	-0.149	0.001	-0.096	0.053	-0.0003	-0.0002	0.0019
	65+	-0.0030	-0.0022	-0.180	0.001	-0.134	0.046	-0.0001	-0.0001	0.0011
Race	Coloureds	-0.0003	0.0006	-0.005	0.001	0.017	0.023	0.0000	0.0000	0.0009
	Asians	0	-0.0012	0.000	-0.001	-0.025	-0.026	0.0000	0.0000	-0.0012
	Whites	0.0065	0.0008	0.021	-0.006	0.003	-0.018	-0.0001	-0.0001	-0.0055
Marital status	With partner	0	0.0001	-0.026	0.000	-0.007	0.019	0.0000	0.0000	0.0001
	Widow	0.0008	0.0001	-0.041	-0.001	-0.014	0.027	0.0000	0.0000	-0.0007
	Divorced	-0.0005	0	-0.013	0.001	0.000	0.013	0.0000	0.0000	0.0005
	Never married	0.0031	0.0022	-0.012	-0.001	-0.010	0.002	0.0000	0.0000	-0.0009
Province	Eastern Cape	-0.0011	-0.0020	0.008	-0.001	0.020	0.012	0.0000	0.0000	-0.0009
	Northern Cape	0	0	-0.017	0.000	-0.003	0.014	0.0000	0.0000	0.0000
	Free State	0	-0.0001	0.033	0.000	0.009	0.042	0.0000	0.0000	-0.0001
	Kwa-Zulu Natal	0.0080	-0.0023	0.059	-0.010	0.022	-0.037	-0.0003	-0.0006	-0.0094
	North West	-0.0003	0	-0.027	0.000	0.022	0.049	0.0000	0.0000	0.0003
	Gauteng	-0.0039	0.0060	-0.017	0.010	0.026	0.043	-0.0002	-0.0002	0.0102
	Mpumalanga	-0.0001	-0.0001	-0.031	0.000	0,017	0.048	0.0000	0.0000	0.0000
	Limpopo	-0.0003	-0.0025	0.004	-0.002	0.031	0.027	0.0000	0.0000	-0.0022
Male		0.0032	0.0021	0.022	-0.001	0.014	-0.008	0.0000	0.0000	-0.0010
Regions of residence	Urban	-0.0070	0	-0.016	0.007	0.000	0.016	-0.0001	-0.0001	0.0072
	Farms	0.0001	0	0.009	0.000	0.005	-0.004	0.0000	0.0000	-0.0001
Total (CC)		**0.0359**	**0.0194**					-0.0033	-0.0035	-0.0096

Notes: The table shows magnitudes and direction of contribution of each factor to the corrected concentration index in wave 1 and wave 3. Positive values indicate that the factor increases income related health inequalities favouring the rich and vice versa. Column 7 shows inequality attributed to change in coefficients while column 8 shows inequality attributed to change in covariates. The last column captures inequality due to interaction.

Figure 4.2: Kernel density of SAH health predictions using SF-12



Notes: Kernel density plots for linear predictions of health from interval regressions for waves 1-3. Thresholds for SAH categories are set by thresholds from SF-12 index. The kernel density plots are skewed to the left implying that majority of the people have better health.

4.3 Sensitivity Analysis

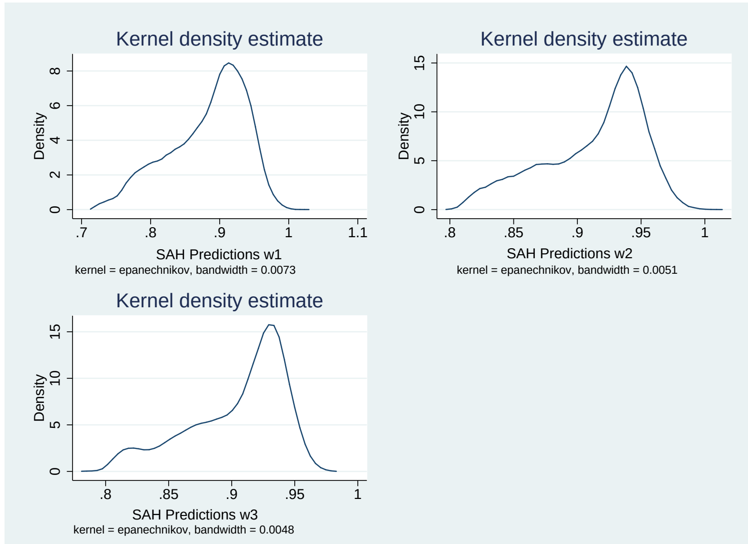
We check for robustness of the results using alternative generic[13] measures of health in setting the thresholds for the SAH categories. The alternative generic measures we use to set the thresholds are the SF-12 and the EuroQo-15D. These are generic measures of health which are collected in continuous scale like the HUI. We use these alternative measures to set thresholds for SAH and then generate predicted values from the interval regressions in the same way as we generated the cardinalized SAH health using HUI. We also keep the regressors the same to make the predicted values comparable.

We find that the patterns of kernel densities for predicted interval regressions using these alternative generic health measures do not deviate from the ones we obtained from the HUI. For example, figure 4.2 shows kernel densities of predicted values from interval regression where we use SF-12 index to set thresholds for the three waves in NIDS. Figure 4.4 shows predicted values from interval regression where we use EuroQo-15D index to set thresholds for the three waves in NIDS. In all cases the densities are skewed to the left implying that the majority of the individuals have better health outcomes according to these measures. These results confirm that whichever generic health measure we use our initial results do not change.

We also estimate income related health inequality using the corrected concentration index applied on these cardinalized SAH measures. We find that the index is positive implying

[13]Health measures can be classified as i) Subjective health (e.g. SAH) ii) Generic health (e.g. HUI, SF12, EQ-15D) iii)Vignettes based health iv) Objective health (e.g. height for age, weight for height).

Table 4.4: Kernel density of SAH predictions using EQ-15D



Notes: Kernel density plots for linear predictions of health from interval regressions for waves 1-3. Thresholds for SAH categories are set by thresholds from EuroQo-15D (EQ-15D) index. The kernel density plots are skewed to the left, implying that the majority of people have better health.

Table 4.5: Corrected concentration indices for health

	Corrected concentration index	
Generic measures of health	**Wave 1**	**Wave 3**
Health Utility Index (HUI)	0.0359	0.0194
	(0.00365)	(0.00193)
Short Form (SF)-12	0.026	0.016
	(0.0025)	(0.00161)
EuroQo 15D	0.023	0.013
	(0.00238)	(0.00143)

Notes: The table shows the corrected health concentration index for SAH when the SAH category thresholds are fixed using three different generic health. The standard deviations are shown in parentheses. The health concentration index decreases from wave 1 to wave 3 in all cases showing that our results are robust to the different ways of setting SAH thresholds.

that better health is concentrated among the well off. This is consistent with the results we find with the predictions from interval regression where we used the HUI index to set SAH category thresholds. The results of these indices together with their standard errors are shown in table 4.5 as well as the index we obtained earlier using HUI to set SAH category thresholds. As we can see income related health inequality decreased from wave 1 to wave 3 irrespective of the generic health we use to set thresholds. The results are therefore robust to the use of alternative generic measures to set SAH category thresholds.

5 Conclusion

In this paper we set out to estimate the extent of income related health inequalities in South Africa and decompose this into contributing factors. We do this by computing the corrected concentration index because of its desirable properties over other indices (such as the standard concentration index and Wagstaff index). The suitability of the corrected concentration index arises from the boundedness of the health outcome variable we use. We use SAH as our indicator of health outcome because the international literature prefers this indicator due to its predictive power regarding mortality and subsequent use of health services. This variable predicted two year mortality for South Africa using NIDS data, further adding credence to its suitability for our purpose (Ardington and Gasealahwe 2012).

SAH is a qualitative indicator of health that does not directly lend itself to the calculation of a health concentration index. We scaled it from ordinal to cardinal scale using predicted values of interval regression, a method we borrowed from Van Doorslaer and Jones (2004). The advantage of scaling the SAH using predictions of interval regression is that the health outcome obtained is measured on the same scale as health utilities, which are true measures of quality of life. Although the health utility index is unit-less it has clear bounds where 0 reflects the worst health status (death) and 1 the best health status and can be interpreted as quality adjusted life years (QALYs).

We also utilized the rich socioeconomic data in NIDS such as income that we used as a socioeconomic ranking variable in the computation of the corrected concentration index. The panel nature of NIDS data allows us to counter check one of the most important characteristic of SAH, that is, whether it predicts mortality. We find a positive corrected concentration index across all waves of NIDS implying that better health in South Africa is concentrated among the rich. This is the case irrespective of the generic health measure we use in setting the threshold for SAH for the purpose of cardinalizing it.

We decompose the index to identify the factors associated with inequalities in health outcomes. It turns out that the most consistent factors associated with income related health inequality in South Africa are disparities in income and educational attainment. These factors are associated with increase in income related health inequality, while disparities in age are associated with a decrease in inequality. These findings are important for policymakers who want to solve the problem of inequalities in health. Inequalities in health outcomes can be solved partly by reducing inequalities in the factors that determine health, such as income and education. For example, increasing the opportunity for education among low income groups, will improve their health outcomes thereby reducing the income related health inequalities.

References

Ardington, C. & Case, A.: 2009, Health: Analysis of the NIDS wave 2 dataset. NIDS discussion paper, no. 2.

Ardington, C. and Gasealahwe, B.: 2012, Health: Analysis of the NIDS wave 1 and 2 datasets.

Argent, J.: 2009, Household income: Report on NIDS wave 1, technical paper no. 3.

Ataguba, J.: 2013, Inequalities in multimorbidity in South Africa.

Ataguba, J. E., Akazili, J. and McIntyre, D.: 2011, Socioeconomic-related health inequality in South Africa: evidence from General Household Surveys.

Au, N. and Johnston, D. W.: 2013, An econometric analysis of self-assessed health: what does it mean and what is it hiding?, *Technical report*, HEDG, c/o Department of Economics, University of York.

Blinder, A. S.: 1973, Wage discrimination: reduced form and structural estimates, *Journal of Human resources* pp. 436–455.

Booysen, F.: 2003, Urban rural inequalities in health care delivery in South Africa, *Development Southern Africa, 20:5,659-673* .

Bradshaw, D.: 2008, Determinants of health and their trends: Primary health care: in context, *South African Health Review* pp. 51–69.

Brown, M., Daniels, R. C., De Villiers, L., Leibbrandt, M. and Woolard, I.: 2012, National Income Dynamics Study wave 2 Beta Release User Manual. Cape Town.

Case, A.: 2004, Does money protect health status? Evidence from South African pensions, *Perspectives on the Economics of Aging*, University of Chicago Press, pp. 287–312.

Charasse-Pouélé, C. and Fournier, M.: 2006, Health disparities between racial groups in South Africa: a decomposition analysis, *Social Science & Medicine* **62**(11), 2897–2914.

Clarke, P. M., Gerdtham, U.-G., Johannesson, M., Bingefors, K. and Smith, L.: 2002, On the measurement of relative and absolute income-related health inequality, *Social Science & Medicine* **55**(11), 1923–1928.

CSDH: 2008, Closing the gap in a generation: health equity through action on the social determinants of health. Final report of the Commission on Social Determinants of Health, *Technical report*, Geneva, World Health Organization.

Cutler, D. M. and Lleras-Muney, A.: 2006, Education and health: evaluating theories and evidence, *Technical report*, National Bureau of Economic Research.

Cutler, D. M., Richardson, E., Keeler, T. E. and Staiger, D.: 1997, Measuring the health of the US population, *Brookings papers on economic activity. Microeconomics* pp. 217–282.

Erreygers, G.: 2009a, Correcting the concentration index, *Journal of health economics* **28**(2), 504–515.

Erreygers, G.: 2009b, Correcting the concentration index: a reply to Wagstaff, *Journal of Health Economics* **28**(2), 521–524.

Erreygers, G. and Van Ourti, T.: 2011, Measuring socioeconomic inequality in health, health care and health financing by means of rank-dependent indices: a recipe for good practice, *Journal of Health Economics* **30**(4), 685–694.

Fleurbaey, M. and Schokkaert, E.: 2009, Unfair inequalities in health and health care, *Journal of health economics* **28**(1), 73–90.

Harling, G., Ehrlich, R. and Myer, L.: 2008, The social epidemiology of tuberculosis in South Africa: a multilevel analysis, *Social science & medicine* **66**(2), 492–505.

Harrison, D.: 2009, An overview of health and health care in South Africa 1994–2010: Priorities, progress and prospects for new gains, *Washington, DC: Henry J Kaiser Family Foundation* .

Idler, E. L. and Benyamini, Y.: 1997, Self-rated health and mortality: a review of twenty-seven community studies, *Journal of health and social behavior* pp. 21–37.

Jann, B.: 2008, A stata implementation of the blinder-oaxaca decomposition, *Stata Journal* **8**(4), 453–479.

Jylhä, M.: 2009, What is self-rated health and why does it predict mortality? Towards a unified conceptual model, *Social science & medicine* **69**(3), 307–316.

Kawachi, I., Subramanian, S. and Almeida-Filho, N.: 2002, A glossary for health inequalities, *Journal of epidemiology and community health* **56**(9), 647–652.

Leibbrandt, M., Woolard, I. and Villiers, d. L.: 2009, Methodology: Report of NIDS wave 1, Technical paper number 1, NIDS.

McCartney, G., Collins, C. and Mackenzie, M.: 2013, What (or who) causes health inequalities: Theories, evidence and implications?, *Health Policy* **113**(3), 221–227.

McIntyre, D. and J.E., A.: 2012, What do we know about poverty, inequality and health in South Africa and what are the health system reforms implications? an overview of recent research, *Conference paper in Carnegie III* .

NDoH: 2013, Annual report 2012/2013.

Oaxaca, R.: 1973, Male-female wage differentials in urban labor markets, *International economic review* pp. 693–709.

O'Donnell, O. A., Wagstaff, A. et al.: 2008, *Analyzing health equity using household survey data: a guide to techniques and their implementation*, World Bank Publications.

Sahn, D. E. and Younger, S. D.: 2009, Measuring intra-household health inequality: explorations using the body mass index, *Health Economics* **18**(S1), S13–S36.

SALDRU: 2009, *National Income Dynamics Study 2008, wave 1 [dataset]. version 5.2. Cape Town:*, Southern Africa Labour and Development Research Unit [producer]: Cape Town DataFirst [distributor].

SALDRU: 2014a, *National Income Dynamics Study 2010-2011, wave 2 [dataset]. version 2.2. Cape Town:*, Southern Africa Labour and Development Research Unit [producer]: Cape Town DataFirst [distributor].

SALDRU: 2014b, *National Income Dynamics Study 2012, wave 3 [dataset]. version 1.2. Cape Town:*, Southern Africa Labour and Development Research Unit [producer]: Cape Town DataFirst [distributor].

Skordis-Worrall, J., Hanson, K. and Mills, A.: 2011, Estimating the demand for health services in four poor districts of Cape Town, South Africa, *International health* **3**(1), 44–49.

Ssewanyana S., K. I.: 2012, Causes of health inequalities in Uganda: Evidence from the demographic and health surveys: 1995-2006, Economic Policy Research Centre Uganda.

Tolley, K.: 2009, What are health utilities, *Hayward Medical Communications, London* .

Van Doorslaer, E. and Jones, A. M.: 2003, Inequalities in self-reported health: Validation of a new approach to measurement, *Journal of health economics* **22**(1), 61–87.

Van Doorslaer, E. and Jones, A. M.: 2004, Income-related inequality in health and health care in the European Union, *Health Economics* **13**(7), 605–608.

Van Doorslaer, E., Koolman, X. and Jones, A. M.: 2004, Explaining income-related inequalities in doctor utilisation in Europe, *Health Economics* **13**(7), 629–647.

Van Doorslaer, E. and O'Donnell, O.: 2008, *Measurement and explanation of inequality in health and health care in low-income settings*, number 2008/04, WIDER Discussion Papers, World Institute for Development Economics (UNU-WIDER).

Wagstaff, A. and Van Doorslaer, E.: 1994, Measuring inequalities in health in the presence of multiple-category morbidity indicators, *Health Economics* **3**(4), 281–291.

Wagstaff, A., Van Doorslaer, E. and Watanabe, N.: 2003, On decomposing the causes of health sector inequalities with an application to malnutrition inequalities in vietnam, *Journal of Econometrics* **112**(1), 207–223.

WHO: 2010, *World Health Statistics 2010*, World Health Organization.

Wilkinson, R. G. and Pickett, K.: 2011, *The Spirit Level: Why Greater Equality Makes Societies Stronger*, Bloomsbury Press.

Yu, D.: 2013, Poverty and inequality estimates of National Income Dynamics Study revisited, *Technical report*.

Zere, E. and McIntyre, D.: 2003, Equity in Self-reported Adult Illness and Use of Health Service in South Africa: Inter-temporal Comparison, *Journal of Health, Population and Nutrition* **21**(3), 205.

Ziebarth, N.: 2010, Measurement of health, health inequality, and reporting heterogeneity, *Social Science & Medicine* **71**(1), 116–124.