Health-Related Inequalities in Life Satisfaction in South Africa: A Decomposition Analysis

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Abstract

While health-related inequalities in subjective well-being have been explored using cross sectional data in developed countries, it has not been well explored within a developing country context. This research paper investigates health-related inequalities in life satisfaction as well as its change over time in South Africa from 2009 to 2017. Evidence from two waves of the National Income Dynamics Survey revealed that health-related inequalities exist in self-reported life satisfaction and that the overall contribution of health-related inequalities had increased inequality in life satisfaction over the period 2009-2017 in South Africa.

Decomposing the health-related inequalities related to life satisfaction provided insights on factors that are associated with health-related inequalities in life satisfaction and provides scope for targeted policy implementation aimed at reducing inequalities in life satisfaction in South Africa. Oaxaca-type decomposition is used to analyse the change in contribution of various health and socio-demographic factors in reducing inequalities in life satisfaction

The results of the analysis found that health-related inequalities exist in self-reported life satisfaction and that the overall contribution of health-related inequalities had a slight widening of inequality of life satisfaction over the period 2009-2017 in South Africa. In particular, notable positive concentration indices in waves I and V were excellent health, ages 15-24, males, and quintile 5 total income groups. The notable negative concentration indices in waves I and V were ages 45-64, females, Africans and inactive employment status factors. The indication is that there is greater life satisfaction among individuals with a lower probability of having poor, fair and good self-reported health status responses in both waves I and V. The concentration curves and indices further indicated that life satisfaction was concentrated more highly on individuals with a higher probability of having an excellent self-reported health status also in both waves I and V.

Results from wave I, saw that notable positive absolute contributions to decreasing inequality in life satisfaction were excellent health status, African race group, employed employment status and the quintile 1 total income group. The most notable negative absolute contribution in wave I was the male factor. Wave V had the only notable positive contribution in the form of excellent health status, while small negative contributions were from individuals aged 25-44 and the African race group possibly explained by a widening inequality in life satisfaction over the

period due to poor policy implementation in reducing inequality that is racially divided because of South Africa’s racially segregated history prior to the country becoming a democracy close to thirty years ago. The decomposition of changes in excellent self-reported health status and inactive employment status indicated a contribution towards the reduction of inequality in life satisfaction. Changes to individuals aged 15-24 and 25-44 years old, individuals classified as African, and quintile 1 total income had contributions towards increased inequality in life satisfaction.

1. Introduction

1.1 Setting

The maximization of the subjective well-being of individuals is considered to be one of the core purposes of governments and policy makers around the world while simultaneously working with a limited resource pool (Ngamaba et al., 2017). Therefore, detecting the key elements that drive subjective well-being plays a key role in helping governments make decisions on policy. Good health and well-being are seen as critical elements of a good life (Subramanian et al., 2005). As a result, governments have looked to improve public health (Ngamaba et al., 2017). Self-reported health as a single measure has the ability to assess the general health and well-being of an individual, accounting for physical, mental and social factors that are outlined by the World Health Organisation (WHO) (Adsanya et al., 2017). The relationship that exists between subjective well-being and health has been found to be positive and statistically significant with regards to the pooled size effect of the association. This gives the indication that a better health status is associated with greater subjective well-being (Ngamaba et al., 2017). However, good health and well-being have marked inequalities in terms of their distributions across population sub-groups and geographic locations (WHO, 2008). Health-related inequalities in subjective well-being exemplify a link between poor health and low subjective well-being insofar as it looks at how subjective well-being is distributed amongst the population relative to their health status (Ryser et al., 2018). With the aforementioned nature of the relationship that exists between subjective well-being and health, focusing on improving the health status of individuals may aid in increasing their well-being, and reducing inequality in well-being as a result. This study sets out to document the nature of health-related inequality in subjective well-being and the factors that contribute to these inequalities and changes over time in such inequality.

At the current time of writing, South Africa has only been a democracy for 26 years. Prior to this, South Africa was racially segregated, as was its healthcare system. Inequality in not only the health system, but the entire country saw a racially white minority gain from sectors highly resourced for their use while the racially black majority was forced to make use of publicly underfunded sectors (Omotoso et al., 2018). Since 1994, the development of the health system in South Africa has shifted towards a primary health care policy with a National Health Insurance scheme in the works as well in a bid to reduce health inequalities in the country (Omotoso et al., 2018). The South African government has also made strides in reducing socio-economic inequality as well by implementing various policies and reforms to reverse the discrimination that endured during the Apartheid era. These policies that aimed to tackle socio-economic inequality include policies targeted towards health care in the country. Although extensions of these policies relate to the health system; the effects of these policies appear to be minimal in reducing inequality (Omotoso et al., 2018). As a result, this paper firstly sets out to derive a latent health index by regressing quasi-objective measures of health on self-reported health using an ordered probit regression. Secondly, using the predicted self-reported health status variable, concentration curves and indices are used to examine health-related inequality in life satisfaction. Thirdly, concentration indices are decomposed for each individual year into the contributions that individual elements make towards health-related inequalities in subjective well-being. Lastly, the concentration index is further decomposed into the contributions that individual elements make towards changes over time in health-related inequalities in subjective well-being. This study therefore seeks to identify socio-economic factors that are health-related and in turn manifest in inequality in life satisfaction so as to recommend more refined socio-economic policy targeting.

1.2 Background literature

Ngamaba, Panagioti and Armitage (2017) investigated the relation that health status has with subjective well-being. A meta-analysis using a random effects model was used after a systematic search from January 1980 to April 2017 was conducted using PRISMA and Cochrane guidelines. A web of medicine, science, Embase and Global Health data was in use. From this selection process only twenty nine studies were used for the analysis. The pooled effect size of the association that was found between health status and subjective well-being was medium, positive and statistically significant.

Study	ES	[95%	CI]	% Weight
An, 2008	0.620	0.573	0.667	3.60
Angner, 2013	0.372	0.274	0.470	3.00
Barger, 2009	0.290	0.243	0.337	3.60
Doherty, 2013	0.333	0.286	0.380	3.60
Dubrovina, 2012	0.730	0.318	1.142	0.65
Fisher, 2010	0.405	0.358	0.452	3.60
Gana, 2013	0.292	0.245	0.339	3.60
Garrido, 2013	0.388	0.341	0.435	3.60
Goldbeck, 2001	0.360	0.313	0.407	3.60
Jacobsson, 2010	0.308	0.261	0.355	3.60
Kim, 2012	0.350	0.303	0.397	3.60
Koots-Ausmees, 2015	0.340	0.297	0.383	3.63
Kulczycka, 2010	0.420	0.373	0.467	3.60
Lacruz, 2012	0.190	0.053	0.327	2.49
Liang, 2014	0.490	0.443	0.537	3.60
Matthews, 2002	0.470	0.423	0.517	3.60
Mukuria, 2013	0.294	0.247	0.341	3.60
Mukuria, 2015	0.390	0.343	0.437	3.60
Ngamaba, 2016	0.498	0.455	0.541	3.63
Ngamaba, 2017	0.290	0.247	0.333	3.63
Patten, 2010	0.160	0.140	0.180	3.78
Sabatini, 2014	0.220	0.161	0.279	3.48
Takeyachi, 2003	0.202	0.155	0.249	3.60
Tuchtenhagen, 2015	0.290	0.243	0.337	3.60
Wang, 2002	0.320	0.273	0.367	3.60
Wang, 2015	0.320	0.300	0.340	3.78
Yildirim, 2013	0.390	0.343	0.437	3.60
Zajacova, 2014	0.244	0.197	0.291	3.60
Zagorski, 2013	0.360	0.313	0.407	3.60
Overall effect (pl)	0.347	0.309	0.385	100.00

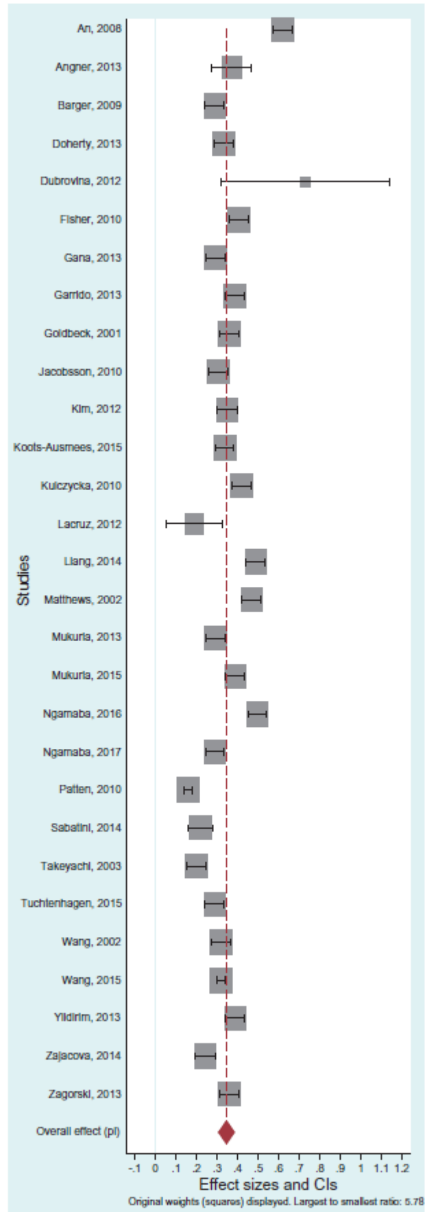


Figure 1: Forest Plot displaying the meta-analysis of the correlations between health status and subjective well-being across the 29 samples (Ngamaba et al. p.883 2017)

Figure 1 above, drawn directly from Ngamaba et al., (2017), illustrates the association from all twenty nine studies analysed. In addition, the correlations, confidence intervals and weights are all displayed from each study investigated.

Additional findings of the paper see the association between health status and subjective well-being becoming stronger when life satisfaction was used instead of happiness as a measure of subjective well-being which plays an influential role in the choice of life satisfaction as the main variable of interest in this analysis. This was because happiness was found to be more closely associated with emotions or feelings, whereas life satisfaction was concerned with individuals' perceptions of their life, which encompasses health, work and relationships among other factors. This association also becomes stronger in studies occurring in developing countries as opposed to developed countries which can be explained by the low levels of health status due to a lack of access to healthcare in developing countries as opposed to developed countries where access to healthcare is far greater. Lastly, when many factors were used to measure health status and subjective well-being instead of single factors the association again becomes stronger between health status and subjective well-being. Concluding remarks saw the suggestion that improving individuals' health status may be a way for governments to improve the subjective well-being of their people (Ngamaba et al., 2017).

Adsanya et al., (2017) provides an analysis into socio-economic factors that contribute to wealth related inequalities in self-rated health and happiness in five Sub-Saharan African countries (namely, Nigeria, Ghana, Rwanda, South Africa and Zimbabwe). The World Values Survey was the data set in use, while the concentration index quantified the socioeconomic inequalities. Additionally regression based decomposition analysis was implemented to find the contribution of each predictor to the magnitude of the concentration index. (Adsanya et al., 2017) found an association between wealth related inequalities and poor self-rated health and unhappiness within the Sub-Saharan African countries investigated. The paper concluded that the warrant of social determinants of health contribute to cultivating equality in health, may be relevant in reducing the one-sided distribution of resources. (Adsanya et al., 2017) notes that knowledge regarding self-rated health and happiness can serve as proxy estimates for the understanding of the distribution of health care access and economic resources needed for well-being in the countries analysed.

Kollamparambil et al., (2020) makes use of an unconditional quantile decomposition analysis to investigate the sources of the reduction in subjective well-being in South Africa between 2008 and 2014. Decomposition of the subjective well-being inequality gap by endowment effect and coefficient effect provide a detailed understanding of the drivers of change. Results from the analysis indicated subjective well-being inequality has decreased in the period 2008-2014 in South Africa. The decomposition analysis over the time period found that the main contributions towards increasing subjective well-being levels were improvements in levels of household per capita income, having employment, higher levels of education and access to essential services such as electricity and bank credit (Kollamparambil et al., 2020). Further, decomposition of the Gini coefficient gap found that the explained endowment and unexplained coefficient effects also contributed to the declining inequality in subjective well-being. The study emphasizes that the reduced inequality in subjective well-being is led by a variety of factors and these very factors differ across the distribution of subjective well-being as well (Kollamparambil et al., 2020).

Kollamparambil (2021) compares Switzerland and South Africa over a ten year period using a concentration index to measure inequality in income related well-being. Oaxaca-Blinder decomposition as well as the Erreygers-corrected concentration index were used to find that the differences in the well-being concentration levels of the two countries are due to both the levels of income and the marginal utility of income. The differences in the coefficients of absolute and relative income contribute more to the differences in well-being concentration in the two countries than the levels of these variables. This indicates that the level of income and relative income is important in understanding the impact of these variables on well-being inequality. The decomposition analysis of the concentration index in gaining an understanding of the relative importance of variables indicated that even though relative income was an important driver of well-being inequality in both observed countries, the absolute income in determining the concentration of well-being was more important. The key takeaway here stems from the findings pointing to the fact that the dominance of absolute and relative income effects is determined by the level of income. In societies with higher mean incomes, the relative income effect is dominant in the absolute income effect. In low mean income countries, the level of income dominates the absolute income effect.

The key argument at hand hinges on the basis that health plays a role in self-evaluated well-being. General health encompasses a broad spectrum of diagnoses and as a result, many of these illnesses need to be taken into account when measuring health. The subjective nature of measuring happiness or satisfaction for individuals has its own challenges for a variety of reasons, including relative and comparative judgements (Diener et al., 2017). Subjective well-being is generally seen as a measure for the overall experience that individuals have in their lives, taking a variety of factors into account, health included.

Many studies analyze the link between subjective well-being and self-reported health, a measure that suffers from subjective bias for the reasons explained above. Objective and quasi-objective measures of health are henceforth used to estimate 'true' levels of self-reported health. Using unadjusted self-reported health status measures in the analysis may lead to different results. By decomposing health into its various diagnoses, the author finds that not all illnesses are equal in its contributions to general health evaluations. With this decomposition at hand, health is then measured against life satisfaction. The entire process captures the overall inequalities in health, health-related inequalities and the association between health and life satisfaction (Ryser et al., 2018).

The background literature provided gives an insight into the topic at hand. The data at hand in the form of the National Income Dynamics Study (NIDS) will however not be of a cross-country nature in comparison to that of the literature mentioned. Ryser et al. (2018) was the only study of a similar nature that could be located. However, developed countries were investigated, as well as an elderly age group sub population. The NIDS data set in use provides scope for new research within the field of interest due to the various chronic conditions that are reported. Additionally, two waves of the NIDS dataset will be studied to take account for factors that explain the changes in health-related inequalities in subjective well-being over time, an additional avenue of inequality research not explored in the paper by Ryser et al. (2018). While health related inequalities in subjective well-being have been explored in developed countries and across countries moreover, it has not been explored within a developing country context, such as is the case in this study, which focuses on South Africa.

2. Methods

2.1 Data

The data used in this study was obtained from two waves of the National Income Dynamic Study (NIDS). NIDS is a panel study that broadly surveys household consumption, employment and education in South Africa. The study ran between 2008 and 2017 with over 28000 participants spanning five waves of surveys to learn about how households within South Africa fare over a given time period. Waves I conducted in 2008 and V conducted in 2017 were chosen from NIDS. Data exists for Waves II, III and IV conducted in 2010, 2012 and 2014 respectively but was not chosen as an extended time period was required to analyse meaningful changes in health-related inequality in life satisfaction in the long run.

NIDS, developed by the Southern African Labour Development Research Unit (SALDRU) and the National Treasury of South Africa, aims to find the trajectory and comprehend the fluctuating aspect of poverty. The study examines the livelihoods of individuals as well as households over time. Information on coping mechanisms households use in the event of both positive and negative shocks such as unemployment of a relative, or the attainment of a job to name a few are provided by the study. Each wave of the study is conducted between two to three years apart, with as many of the same respondents surveyed from the first wave through to the fifth wave as possible via tracking methods. The NIDS survey tracks individuals and shrinks standard errors as a result. Therefore greater precision is realised in determining the change over time of various socio-demographic factors (Omotoso et al., 2018).

The NIDS sample space amounts to over 28,000 individuals surveyed in 7,300 different households. It is worth noting that the number of respondents increased by over 9000 between 2008 and 2017. This was due to attrition occurring from high income earners particularly. As a result, to ensure that the continuous capturing of the changing country was accurate, a sample top-up was undertaken in order to correctly represent all income brackets and population sub-groups.

The survey itself covers broad socio-demographic themes including poverty, well-being, migration, labour market participation, health, education, household composition and structure, economic activity as well as fertility and mortality. Furthermore, in relation to the study at hand, the NIDS survey asked questions on chronic conditions which were aimed directly at the participant. This allows for the use of these chronic conditions within the analysis as well. With more than one wave of the study available, a further decomposition (the Oaxaca-type decomposition) can be added to the study, which sees time trend analysis used by decomposing the changes in health-related inequalities over time (Wagstaff et al. 2003).

2.2 Measures

Life satisfaction data was based on a survey question in Section M which captured well-being and social cohesion. Question M5 asked adult participants to use a scale of 1 to 10 where 1 means “Very dissatisfied” and 10 means “Very satisfied”, and rate how they felt about their life as a whole at that moment. Adult respondents provided direct answers to the survey question.

Health data was collected using a series of short questions that covered health status, conditions that individuals would complain about from time to time such as flu symptoms and persistent coughs to name a few. Chronic conditions, as well as emotional health were also surveyed. Self-reported health status was measured asking respondents to describe their health at that moment. Their response options were “Excellent”, “Very good”, “Good”, “Fair”, and “Poor”, ranked 1-5 respectively.

Chronic health conditions were surveyed asking individuals if they have ever been told by a doctor or nurse that they have tuberculosis, high blood pressure, diabetes or high blood sugar, stroke, asthma, heart problems or cancer. Yes or no responses were required. Other major illnesses surveyed include being physically handicapped, problems with sight, hearing or speech, psychological or psychiatric disorders, HIV/AIDS, epilepsy, emphysema, Alzheimer’s disease or other illness not mentioned. These other major illnesses were ranked from 1 to 8 respectively. The method of questioning also allowed for respondents to reveal whether comorbidities were present in predicting the probability of their self-reported health status. This allowed for the inclusion of multimorbidity as a variable. While it can be viewed as a summary of the variables already included in the analysis, the multimorbidity variable offers an explanation into what a variety of multiple illnesses contribute towards health status, rather than the individual chronic health conditions’ contributions alone.

A Center for Epidemiological Studies Depression Scale (CESD-10) is a 10 item depression screening tool, validated by (Myer et al., 2008) and (Baron et al., 2017) in South Africa, used to detect depression in general populations (Radloff, 1977). The scale was created using Section K- the emotional health section of the NIDS survey. The CESD-10 was found to be a valid, reliable screening tool for depression in Zulu, Xhosa and coloured Afrikaans populations in South Africa (Baron et al., 2017). Ten questions were asked regarding mental or emotional health experiences over the prior week to the survey. This included questions regarding how bothered respondents were by things that usually do not bother them, if the respondent had trouble keeping their mind on what they were doing, had felt depressed, had felt as if everything they were doing was an effort, hopefulness about the future, fearfulness, restless sleep, happiness, loneliness, and if they felt they could not “get going”. All of these questions had response options ranked 1 to 4, where 1 meant ‘rarely’ and represented less than a day or none of the time, 2 was some or little time (1-2 days), 3 was occasionally or a moderate amount of time (3-4 days), and 4 was all of the time (5-7 days). The responses from the ten items effectively gave the interviewer a general understanding of the participant’s well-being over the week prior to the survey. This information was used to construct the CES-D 10 scale of depressive symptoms. The measure derived from this formed a mental health variable in predicting self-reported health outcomes.

Socio-demographic variables that were chosen for the decomposition analysis of life satisfaction were age, gender, employment status, marital status, total income and province. The choices of socio-demographic variables were influenced by authors engaging in decomposition analysis in inequality studies of life satisfaction or subjective well-being. In a cross country study, Ryser et al. (2018) found health status, widowhood and the adaptation process through religious or social activities as the three largest factors that contributed to health-related inequalities in life satisfaction when conducting decomposition analysis on a concentration index for data drawn from the Survey of Health, Age and Retirement in Europe (SHARE). This especially provided motivation for the choice of age and marital status in the current study.

In similar vein to (Kollamparambil et al., 2020) the choice of socio-demographic variables used in the study were informed by (Beccheti et al., 2014) and (Niimi, 2018). According to (Kallamparambil et al., 2020), frequently identified determinants of subjective well-being are in line with the choice of variables for this analysis. Social determinants of health-related inequalities in subjective well-being in South Africa were assessed using decomposition analysis were age, gender; race, education, employment status and provincial location.

Given the use of the National Income Dynamic Survey waves I and V, the ethical considerations regarding informed consent, voluntary participation, confidentiality, anonymity and no harm being done have been adhered to due to the data having already been gathered. However it is worthwhile to note that the data in question was handled in an ethical and responsible manner by assessing only the relevant components of the data set for the study at hand. Post-stratification weights were used to reduce potential non-response bias as well as sampling error.

2.3 Analysis

2.3.1 Ordered Probit Regression Model

The starting point of the analysis is the derivation of a ‘latent index’ variable for health. Jurges (2007) notes that self-reported health status is a poor measure of health, because some people under- and others over-report health. Hence the (Jurges, 2007) uses more objective health indicators to adjust self-reported health status and determine the factors explaining this difference between self-reported and ‘true’ health. It is for this reason that we use a similar approach to derive a latent index variable of health by regressing quasi-objective measures of health on self-reported health status and then predicting people’s self-reported health status was implemented using an ordered probit regression. This is due to the dependent health status variable containing more than two ordered or ranked categories as responses. Various diagnoses that encompass health status such as the chronic conditions mentioned above, have binary response options with yes or no answers and are selected as the independent variables. As a result, these are taken into account and are used when predicting the self-reported health status by estimating the ordered probit regression model suggested by Gujarati et al. (2004) as shown in equation (1) below:

$$Health\ Status_{it} = \alpha_{it} + \beta_1(CESDscore)_{it} + \beta_2(Tuberculosis)_{it} + \beta_3(Diabetes)_{it} + \beta_4(Stroke)_{it} + \beta_5(Asthma)_{it} + \beta_6(HeartProblems)_{it} + \beta_7(Cancer)_{it} + \beta_8(PhysicalHandicap)_{it} + \beta_9(SightSpeechHearingHandicap)_{it} + \beta_{10}(PsychologicalDisorder)_{it} + \beta_{11}(HIV)_{it} + \beta_{12}(Epilepsy)_{it} + \beta_{13}(Emphysema)_{it} + \beta_{14}(Alzeimer's)_{it} + \beta_{15}(OtherIllnesses)_{it} + \beta_{16}(Multi\text{-}morbidity)_{it} + \beta_{17}(Multi\text{-}morbidityCount)_{it} \qquad (1)$$

This prediction of the self-reported health status then acts as the measure of health as the analysis progresses through the second and third stages of the investigation (Ryser et al. 2018).

2.3.2 Concentration Curves and Indices

Concentration curves are used to provide a picture of the share of life satisfaction accounted for by cumulative proportions of individuals in the population ranked from the lowest to the highest probability of self-reported health status. From the concentration curve, differences in life satisfaction across time can also be examined. It acts as a graphical tool for assessing targeted policy towards reducing inequality.

The concentration curve plots the cumulative percentage of the life satisfaction variable on the y-axis against the ranked probability of a given health outcome on the x-axis, starting with the lowest probability of an individual having that health status, and ending with the highest probability (O'Donnell et al. 2008). There is a 45 degree line that runs through the graph which is described as the line of equality.

Interpretation of the concentration curve on the line of equality means that everyone, irrespective of the probability of their self-reported health status outcome, has the exact same value of life satisfaction (O'Donnell et al. 2008). If the concentration curve lies above the line of equality, it means that the life satisfaction variable is concentrated amongst individuals with a lower probability of being classified in the self-reported health status outcome. Conversely, if the concentration curve lies below the line of equality, it means that the life satisfaction variable is concentrated amongst individuals with a higher probability of being classified in the self-reported health status outcome (O'Donnell et al. 2008).

Using the predicted self-reported health status variable, a concentration curve is used to examine inequality in life satisfaction. This is done by plotting the cumulative life satisfaction reported on the y axis against the ranked probability of the predicted health status variable on the x axis.

While concentration curves can be used to identify inequality, it cannot give a measure of the magnitude of inequality for comparisons over time. It is for this reason that the concentration index is calculated. It is derived from the concentration curve and is defined as the area between the concentration curve and the line of equality multiplied by two (O'Donnell et al. 2008). The index value is zero when there is no health-related inequality in life satisfaction. A negative index value is taken when the concentration curve lies above the line of equality, indicating a greater concentration of life satisfaction with lower probabilities of the predicted self-reported health status outcome. A positive index value is taken when the concentration curve lies below the line of equality, indicating a greater concentration of life satisfaction with higher probabilities of the predicted self-reported health status outcome (O'Donnell et al. 2008). The definition for the concentration index is given below in equation (2) and is used when generating the concentration indices and curves within the analysis:

$$C = \frac{2}{n\mu} \sum_{i=1}^{n} y_i R_i - 1 \qquad (2)$$

Where C is defined as the concentration index and is a measure of relative inequality, y is life satisfaction, μ is the mean of the y and R_i is the fractional rank of the *i*th probability of an individual belonging to a self-reported health outcome (Wagstaff et al. 2003). A regression format for the point estimation of the concentration index is provided in equation (4) below:

$$2\sigma_r^2\left(\frac{yi}{\mu}\right) = \alpha + \beta ri + \varepsilon i \qquad (4)$$

Where σ_r^2 is defined as the variance of the fractional rank of the probability of an individual belonging to a self-reported health outcome. The estimate of the concentration index obtained in equation (3) is equivalent to the OLS estimate of β. Here ε is the error term (O'Donnell et al. 2008).

2.3.3 Decomposition of the concentration index.

Wagstaff et al. (2003) demonstrates that the life satisfaction concentration index can be decomposed into the contributions that individual elements make towards health-related inequalities in subjective well-being albeit using decomposition of the causes of health sector inequalities with application to malnutrition inequalities in Vietnam. The contribution that each element makes is the product of the sensitivity of life satisfaction with respect to that element as well as the degree of health-related inequality in that element. For any liner additive regression model of life satisfaction y, such as:

$$y = \alpha + \sum_k \beta_k x_k + \varepsilon, \qquad (5)$$

The concentration index for y, can be written as:

$$C = \sum_k \left(\frac{\beta_k \bar{x}_k}{\mu}\right) C_k + \frac{GC_\varepsilon}{\mu}, \qquad (6)$$

Where μ is the mean of life satisfaction y, $\bar{x}_k$ is the mean of x_k, C_k is the concentration index for x_k, and GC_ε is the generalized concentration index for the error term ε (O'Donnell et al. 2008). Equation (6) can be interpreted as C being equal to a weighted sum of the concentration indices of the k regressors, where the weight for x_k is the elasticity of y with respect to x_k $\left(\eta_k = \beta_k \frac{\bar{x}_k}{\mu}\right)$. Here, equation (6) was used to decompose the concentration indices of health-related inequalities in self-reported life satisfaction. Furthermore, the error term ($\frac{GC_{\varepsilon}}{\mu}$) gives the unexplained systematic variation in the regressors by health that reflects health-related inequality in life satisfaction (O'Donnell et al. 2008).

The absolute contributions to the concentration indices of health-related inequalities in self-reported life satisfaction were calculated through the result of the product of the elasticity and the individual concentration indices (Cordoba et al. 2018).

2.3.4 Decomposing changes in the concentration index

To decompose health-related inequalities in life satisfaction over time, the Oaxaca decomposition method can be applied to equation (6) as is done in (Wagstaff et al. 2003):

$$\Delta C = \sum_k \eta_{kt}(C_{kt} - C_{kt-1}) + \sum_k C_{kt-1}(\eta_{kt} - \eta_{kt-1}) + \Delta(\frac{GC_{\varepsilon t}}{\mu_t}) \qquad (7)$$

$$\Delta C = \sum_k \eta_{kt-1}(C_{kt} - C_{kt-1}) + \sum_k C_k(\eta_{kt} - \eta_{kt-1}) + \Delta(\frac{GC_{\varepsilon t}}{\mu_t}) \qquad (8)$$

where equations (7) and (8) are alternatives, and equation 7 was used within the analysis itself Here, η_{kt} is denoted as the elasticity of the life satisfaction variable y, with respect to x_k at time t, and where Δ is denoted as the first difference (Wagstaff et al. 2003). In equation (7), the difference in concentration indices are weighted by the second period elasticity and the difference in elasticities are weighted by the first period concentration index. Equation (8) acts as an alternative and sees the difference in concentration indices weighted by the first period elasticity and the difference in elasticities weighted by the second period concentration index (Omotoso et al. 2018).

The decomposition followed in equations (7) and (8) provides scope for decomposing the change in health-related inequality in life satisfaction into changes in inequalities in the determinants of life satisfaction. Furthermore, changes in the elasticities of the life satisfaction variable with respect to these determinants are also decomposed (O'Donnell et al. 2008). The first term in equations (7) and (8) gives the distribution effect and measures the change in the concentration index caused by the changes of the concentration indices of the explanatory variables. The second term of the equations gives an indication of the extent to which a change in elasticity has an impact on the concentration index for life satisfaction (Cordoba et al. 2018).

Going even further, following Wagstaff et al. (2003) by investigating the total differential of equation (6) which allows for changes in turn for α, β_k, $\bar{x}_k$, and C_k. Equations (9) and (10) below give a brief mathematical derivation of the total differential of equation (6):

$$dC = \frac{dC}{d\alpha}\, d\alpha + \sum_k \frac{dC}{d\beta_k}\, d\beta_k + \sum_k \frac{dC}{d\bar{x}_k}\, d\bar{x}_k + \sum_k \frac{dC}{dC_k}\, dC_k + \mathrm{d}\frac{GC_\varepsilon}{\mu} \qquad (9)$$

$$= -\frac{C}{\mu} d\alpha + \sum_k \frac{\bar{x}_k}{\mu}(C_k - C) d\beta_k + \sum_k \frac{\beta_k}{\mu}(C_k - C) d\bar{x}_k + \sum_k \frac{\beta_k \bar{x}_k}{\mu} dC_k + d\frac{GC_\varepsilon}{\mu} \qquad (10)$$

Where the effect that a change in $\beta_k$or $\bar{x}_k$ has on C is dependent on whether $\bar{x}_k$ is more or less unequally distributed than the life satisfaction variable y. There are therefore two channels of influence that is reflected in this relation. There is a direct effect of the change in $\beta_k$or $\bar{x}_k$ on C and then the indirect impact that operates through the mean of the regressors, μ. If there is an increase in inequality in $\bar{x}_k$ (therefore a change in C) will increase the degree of inequality in y, the life satisfaction variable. Increasing functions of $\beta_k$and $\bar{x}_k$, and a decreasing function of μ is therefore the relation that exists in equation (10) (O'Donnell et al. 2008).

3. Results

3.1 Description

Table 1 below, provides summary statistics as well as the percentage of respondents in the measurement of self-reported life satisfaction, for waves I and V. When rating their life satisfaction on a scale of 1-10, the average respondent reported a rating of 5.59 in Wave I, and 5.50 in Wave V, seeing a marginal decrease in the average self-reported life satisfaction between the two periods.

Table 1: Life Satisfaction, by Wave

	Life Satisfaction	
	Wave I	**Wave V**
Obs	13777	23772

Mean	5.59	5.50
Std. Dev,	2.54	2.40
Min	1	1
Max	10	10
	Response Percentages	
Measure of Life Satisfaction	**Wave I**	**Wave V**
Level 1	8.29	4.96
Level 2	5.05	6.38
Level 3	7.44	10.00
Level 4	11.26	13.58
Level 5	18.69	17.82
Level 6	12.23	13.64
Level 7	12.61	11.87
Level 8	11.32	9.96
Level 9	3.76	3.78
Level 10	9.35	8.02

The largest percentage of respondents in both Wave I and Wave V reported a life satisfaction level of 5, while level 6 was the next highest percentage of participants. A life satisfaction level of 9 meanwhile, had the smallest percentage of self-reported responses. Comparatively, large responses across waves were reported between a self-reported life satisfaction level of 4 and 7, accounting for almost 50% of all responses in each wave. The largest notable changes in the response percentages across waves in self-reported life satisfaction were level 1 and level 3 with a decreased 3.33% and positive 2.56% of responses respectively. Self-reported life satisfaction was also found to be statistically significantly different over the two waves, with the results shown below in Table 2.

Table 2: Life Satisfaction, by Wave

Life Satisfaction	**Obs**	**Mean**	**Std. Error**	**Std. Dev.**	**Confidence Interval (95%)**	
Wave I	13777	5.463	0.021	2.470	5.423	5.505
Wave V	23773	5.578	0.016	2.466	5.546	5.609
Combined	37550	5.536	0.013	2.468	5.511	5.561
Difference		-0.114	0.013	2.468	5.511	5.561
T-test	-4.3002					

Furthermore, in Figure 2 below, kernel density plots convey the distributional shift of the levels of self-reported life satisfaction displayed across waves.

Figure 2: Kernel Density Plots for Life Satisfaction, by Wave.

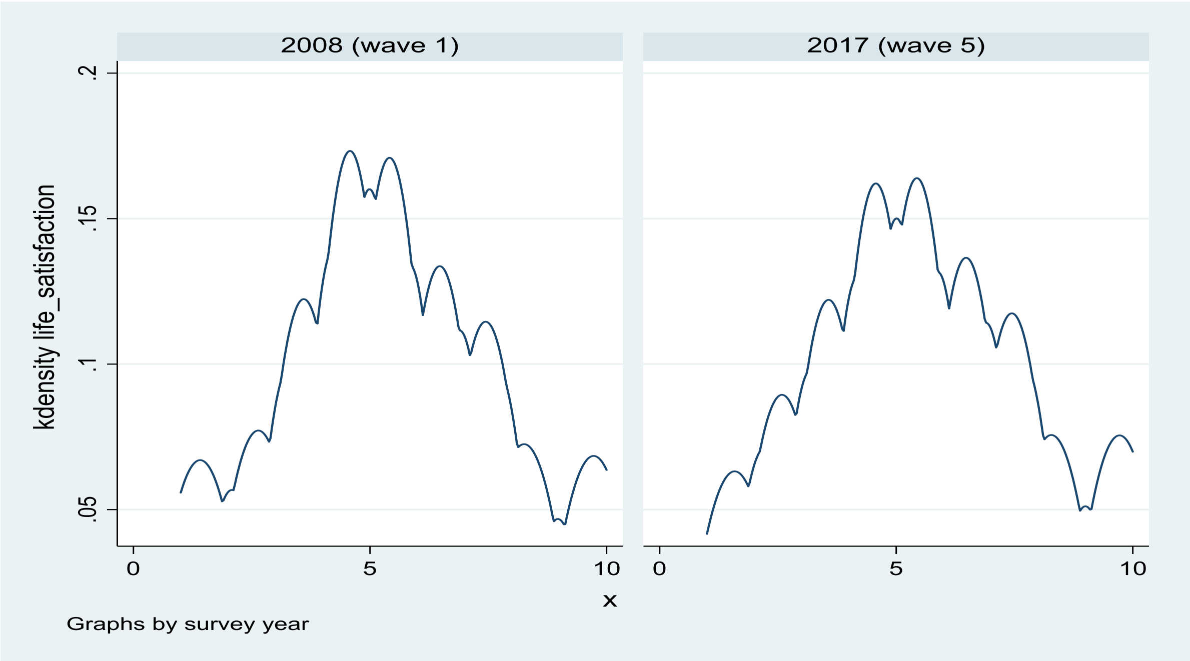


Table 3: Self-Reported Health Status, by Wave

	Response Percentages	
Self-Reported Health	**Wave I**	**Wave V**
Poor	6.36	2.35
Fair	11.38	7.60
Good	22.96	25.41
Very Good	27.17	30.98
Excellent	32.13	33.66

Table 3 presents the percentage of the participants that responded to the various self-reported health outcomes over waves I and V. In both waves, the ‘excellent health’ self-reported health outcome had the largest percentage of respondents, with 32.13% and 33.66% respectively. The ‘poor health’ outcome had the fewest respondents with 6.36% in Wave I and 2.35% in Wave V.

Self-reported health outcome responses ‘good’, ‘very good’ and ‘excellent’ made up over 80% of responses in both waves.

The largest changes in the response percentages across the two reported waves were in the ‘poor’ and ‘very good’ self-reported health outcomes. The ‘poor’ health outcome saw a 4.01% decrease in respondents when comparing response percentages over the two waves. On the other hand, the ‘very good’ health outcome increased by 3.81% respondents over the two reported waves.

Table 4: Independent Variables of Ordered Probit Regression, by Wave

	Wave I		**Wave V**			
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Min**	**Max**
CESD score	7.84	4.73	6.67	4.34	0	30
Tuberculosis	0.04	0.19	0.05	0.22	0	1
Diabetes	0.04	0.18	0.04	0.20	0	1
Stroke	0.01	0.09	0.01	0.10	0	1
Asthma	0.04	0.18	0.03	0.18	0	1
Heart	0.03	0.17	0.02	0.14	0	1
Cancer	0.01	0.09	0.01	0.11	0	1
Handicap 1	0.01	0.09	0.01	0.07	0	1
Handicap 2	0.01	0.10	0.01	0.11	0	1
Psych	0.01	0.07	0.01	0.07	0	1
HIV	0.01	0.01	0.03	0.08	0	1
Epilepsy	0.01	0.09	0.01	0.08	0	1
Emphysema	0.00	0.03	0.00	0.03	0	1
Alzheimer’s	0.00	0.03	0.00	0.03	0	1
Other	0.03	0.18	0.01	0.12	0	1
Multi-morbidity	0.06	0.24	0.08	0.26	0	1
Multi-morbidity count	0.31	0.64	0.37	0.68	0	7

Above, Table 4 provides summary statistics of the independent variables that have been included in the ordered probit regression model used to predict self-reported health. The means and standard deviations for Wave I and Wave V provide an overview of the nature of chronic diseases that encompass health status. The majority of variables included in the analysis have binary yes or no responses where no is given the value of 0 and yes is equal to 1. In Wave I stroke, cancer, physical disability denoted as handicap 1, problems with sight, hearing or speech denoted as handicap 2, psychological or psychiatric problems denoted as psych, HIV/AIDS denoted as HIV and Epilepsy all have mean values of 0.01 indicating that the average respondent did not have any of the mentioned chronic diseases. Diabetes, tuberculosis and asthma all had a mean value of 0.04, while the CESD score had a scale from 0-30 with a mean of 7.84. The multi-morbidity count scaled from 0-7 with a mean of 0.31 in the first wave.

The fifth wave has similar mean results when compared to the first wave. Stroke, cancer, handicaps 1 and 2, psych and epilepsy all have the same mean equal to 0.01. The CESD score and multi-morbidity count have notably increased and decreased mean values respectively in wave five when compared to Wave I.

Table 5: Sociodemographic Characteristics, by Wave

Variables	**Description**	**% Wave I**	**% Wave V**
Age	15-24 years	29.39	24.28
	25-44 years	41.19	46.37
	45-64 years	22.35	22.00
	65+ years	7.07	7.35
Gender	Male	43,98	46.68
	Female	56.02	53.32
Race	African	78.79	81.69
	Coloured	8.21	8.85
	Asian/Indian	2.44	2.06
	White	10.55	7.41
Employment	Inactive	37.99	41.12

	Discouraged	5.20	1.01
	Unemployed	13.61	10.97
	Employed	43,20	46.90
Marital Status	Single	59.29	66.76
	Living together	9.18	5.86
	Married	31.53	27.38
Province	Western Cape	10.15	11.98
	Eastern Cape	12.84	11.14
	Northern Cape	2.34	2.23
	Free State	5.66	5.11
	Kwa-Zulu Natal	18.26	18.63
	North West	7.23	6.87
	Gauteng	25.02	26.01
	Mpumalanga	7.79	7.97
	Limpopo Province	10.69	9.97

Table 5 gives a summary of the sociodemographic characteristics of the same by wave. The percentage of responses within each variable is reported. The age variable has respondents aged between 25 and 44 years as the highest percentage of participants in both waves I and V with 41.19% and 46.37% respectively. Females are the higher proportion of respondents in the gender variable with 56.02% responses in Wave I and 53.32% in Wave V. The race group with the highest percentage of responses was Africans, while Asian or Indian race groups had the lowest percentage of responses in both waves.

Employment status is denoted by employment, where employed responses were made up of 43.2% in wave I and 46.9% in wave V. Inactive responses were 37.99% in wave one and 41.12% in wave five. The marital status variable had its largest responses amongst single respondents over waves I and V. The province variable shows percentage of responses in various locations in South Africa, with Gauteng, Kwa-Zulu Natal, the Western Cape and Eastern Cape making up the four most populated provinces in terms of percentage of responses.

3.2 Predicting Health Outcomes

In order to predict self-reported health status, the array of diagnosis that encompasses health status must be taken into account. An ordered probit regression is used to derive a latent index variable for health outcomes to be predicted, where the diagnoses contain binary response options. Table 6 below, displays the results of the ordered probit regression model for Wave I and V, respectively.

Table 6: Ordered Probit Results for Self-Reported Health, by Wave

	Wave I	Wave V
Self-Reported Health Status	**Coefficient**	**Coefficient**
CESD Score	-0.044*** (0.003)	-0.038*** (0.003)
Tuberculosis	0.074 (0.088)	0.031*** (0.074)
Diabetes	0.003 (0.101)	0.211*** (0.074)
Stroke	-0.018 (0.251)	0.167 (0.124)
Asthma	0.332*** (0.101)	0.310*** (0.071)
Heart	0.213** (0.109)	0.082 (0.103)
Cancer	0.303 (0.285)	0.547*** (0.100)
Handicap 1	-1.072*** (0.161)	-0.392** (0.166)
Handicap 2	-0.566*** (0.168)	-0.562*** (0.097)
Psych	0.165 (0.222)	-0.005 (0.173)
HIV	-0.147 (0.165)	0.133 (0.085)
Epilepsy	-0.209 (0.146)	-0.215 (0.147)
Emphysema	-1.139 (0.869)	-0.471** (0.268)
Alzheimer’s	1.270*** (0.233)	0.226 (0.386)
Other	-0.397*** (0.091)	-0.576*** (0.090)
Multi-morbidity	0.356*** (0.111)	0.213*** (0.075)
Multi-morbidity count	-0.887*** (0.050)	-0.762*** (0.037)
N	14984	23282
Pseudo R^2	0.085	0.064

Robust standard errors are in parenthesis, where *** p<0.01, ** p<0.05, * p<0.1.

The CESD score, handicap 1 and 2, other chronic conditions denoted as ‘other’, and multi-morbidity count were negative and statistically significant in Wave I. This indicates that these variables are likely to be in lower categories of health outcomes. Positive and statistically significant variables in Wave I were asthma, heart disease, Alzheimer’s and multi-morbidity. The indication here is that these variables are likely to be in higher categories of health outcomes. An additional explanation of these results is, given that the question on illness asks about diagnosis, that those diagnosed individuals could also be treated and therefore be in better health when compared to individuals not diagnosed with the particular condition. Tuberculosis, diabetes, stroke, cancer, psych, HIV, epilepsy and emphysema had varying signs but were statistically insignificant in Wave I.

The Wave V results display positive statistical significance in tuberculosis, diabetes, cancer and Alzheimer’s, which are the notable changes observed between the two reported waves. Emphysema also became statistically significant, with a negative coefficient. The remaining variables maintained the same statistical significance and coefficient signs from the first reported wave. Interestingly, multi-morbidity and multi-morbidity count exhibit opposing signs that are statistically significant. However, a negative contribution to predicted health outcomes would have been expected from both diagnoses. The outcome can be explained as individuals with multi-morbidities may only have few diagnoses, while counting multi-morbidities provides negative health outcomes which could indicate that individuals’ have negative psychological responses to acknowledging a large number of chronic diseases to have been diagnosed with.

Table 7 below presents each health outcomes predicted by wave, factoring the various probabilities of the various diagnoses contributing to individuals being in higher or lower health categories. Means and standard deviations are presented with the excellent health status outcome representing the largest average predicted health outcome in waves I and V. The poor health predicted health outcome had the smallest mean value across waves I and V. Furthermore, good, very good and excellent health outcomes made up more than 80 percent of the mean predicted health outcomes over both reported waves.

Table 7: Predicted Health Outcomes, by Wave

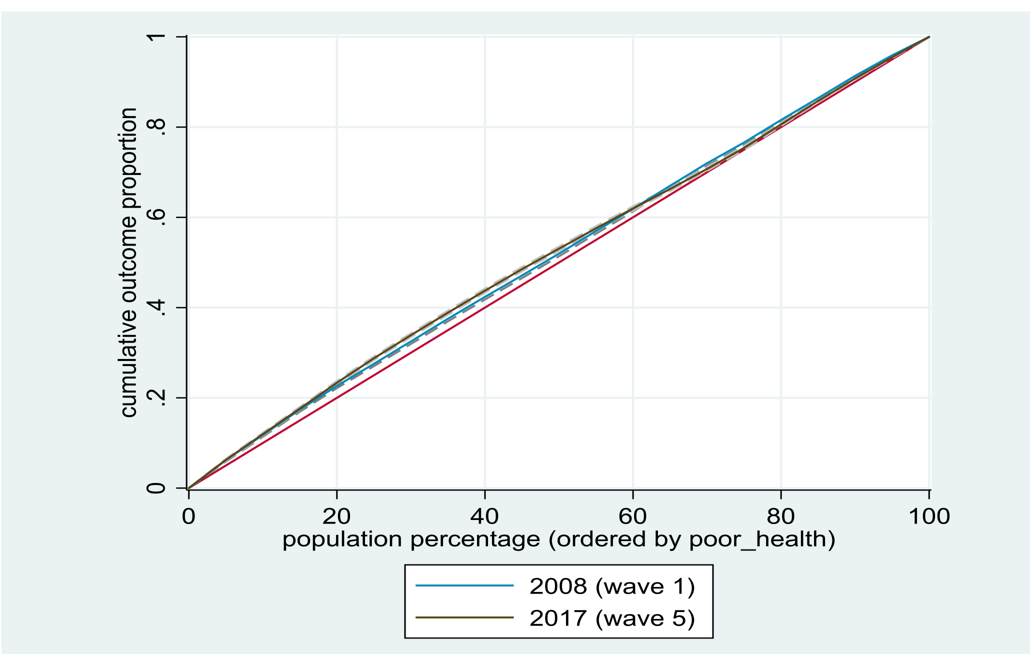
	Wave I	**Wave V**

Variable	Mean	Std. Dev.	Mean	Std. Dev.
Poor Health	0.060	0.103	0.023	0.051
Fair Health	0.112	0.073	0.074	0.062
Good Health	0.236	0.053	0.257	0.073
Very Good Health	0.270	0.057	0.311	0.045
Excellent Health	0.321	0.143	0.335	0.130

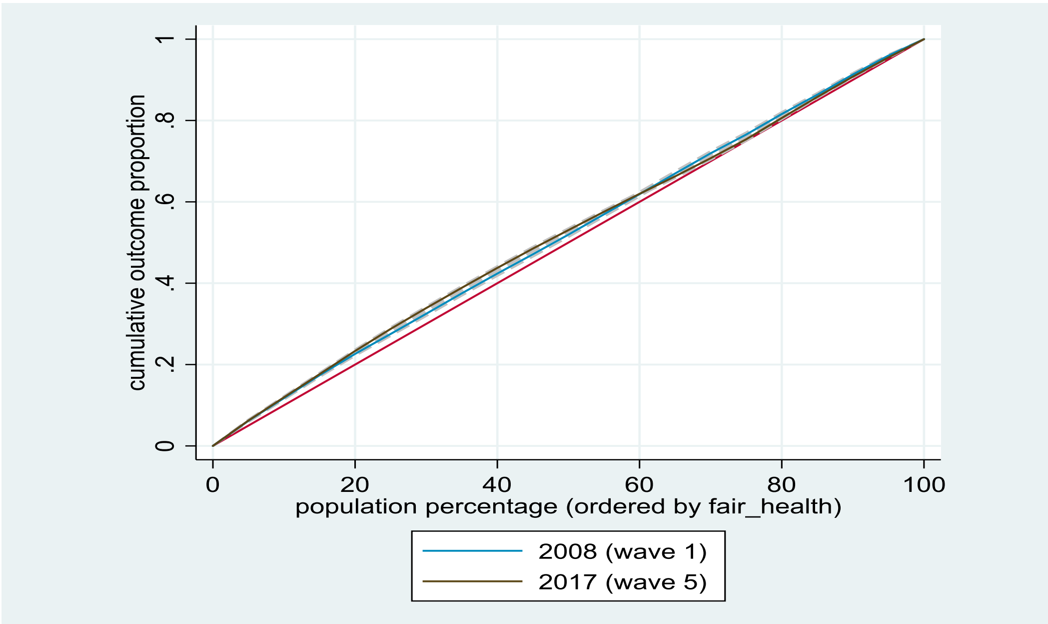
3.3 Concentration Curves and Indices

Once the predicted health outcomes have been generated by wave, concentration curves and concentration indices are created and extracted. Graph 2 through to Graph 6 illustrate concentration curves by wave of the cumulative life satisfaction against the ranked probability of poor, fair, good, very good and excellent health status, respectively. The line of equality is displayed by a red 45 degree line, while the concentration curve for Wave I is displayed in blue and the concentration curve for Wave V is displayed in green for each of the graphs.

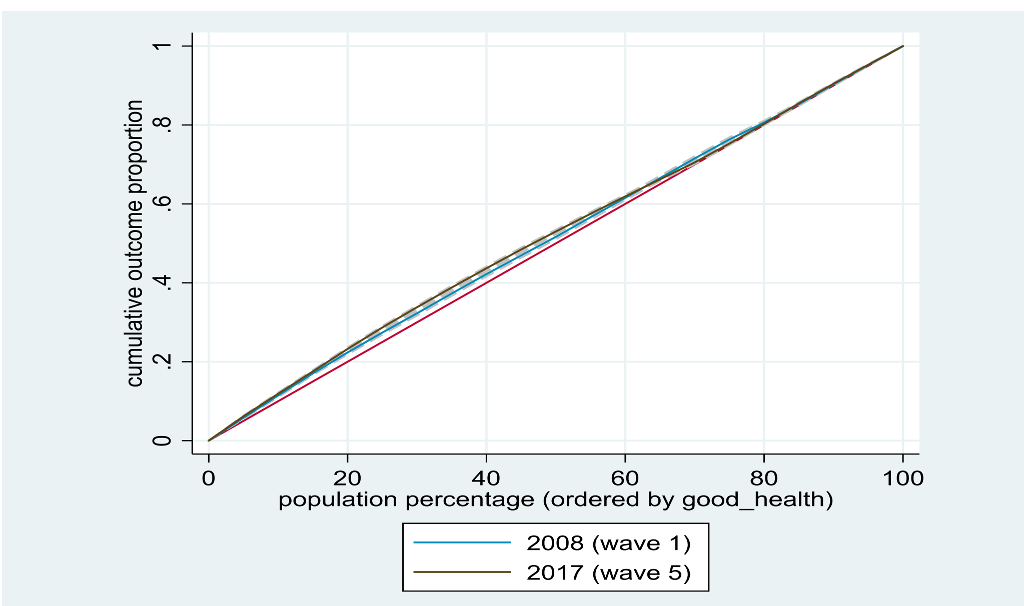
Graph 1: Concentration Curves - Life Satisfaction ranked by Predicted Poor Health Status



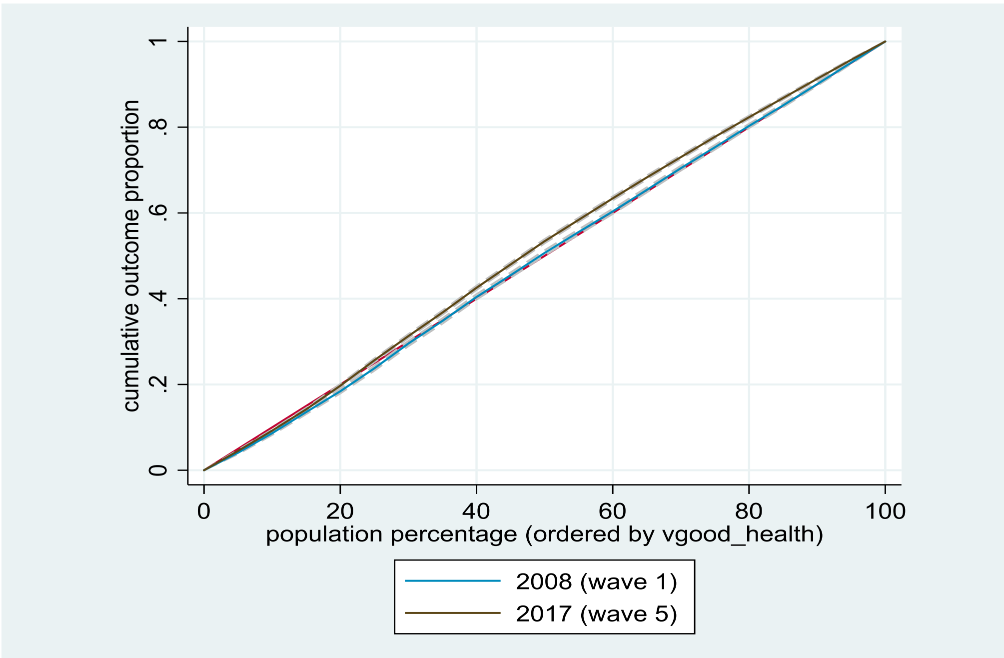
Graph 2: Concentration Curves - Life Satisfaction ranked by Predicted Fair Health Status



Graph 3: Concentration Curves - Life Satisfaction ranked by Predicted Good Health Status



Graph 4: Concentration Curves - Life Satisfaction ranked by Predicted Very Good Health Status



Graph 5: Concentration Curves - Life Satisfaction ranked by Predicted Excellent Health Status

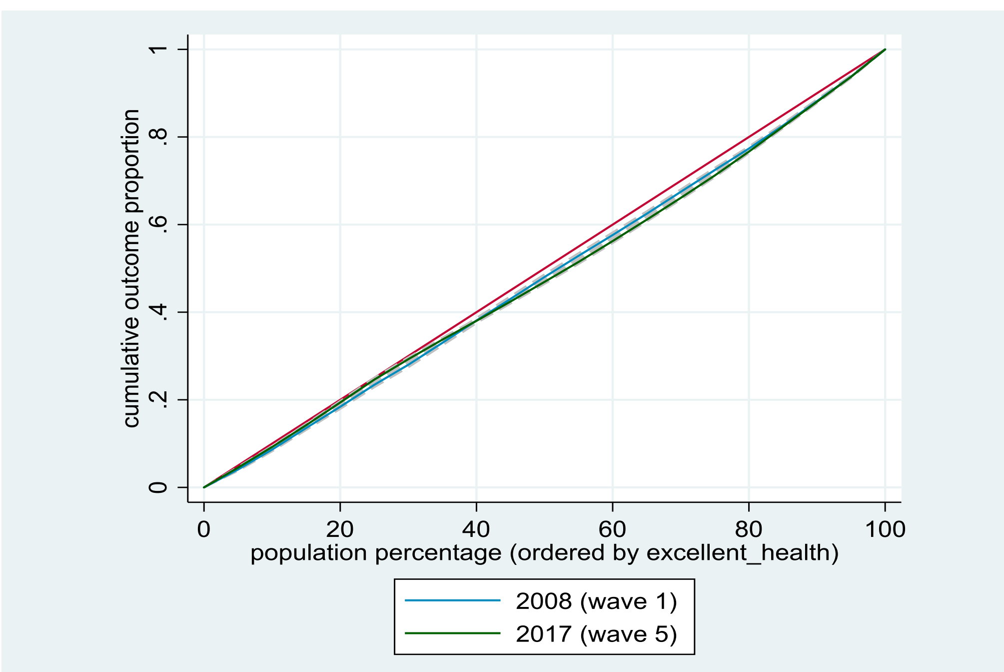


Table 8 gives the calculated concentration indices from the associated concentration curves in graphs 1-6 by wave for comparison purposes. All results were statistically significant over both waves except for the very good health outcome in wave I. Poor, fair and good health status outcomes in both waves had negative values. This indicates that the concentration curve is above the 45 degree line of equality as is visible in graphs 1 to 3. The negative indices can be interpreted as life satisfaction being distributed more among those with a lower ranked probability of individuals having poor, fair and good health outcomes.

Excellent health is positive and statistically significant, indicating that life satisfaction is distributed more amongst individuals with a higher ranked probability of having excellent health outcomes. This is illustrated in Graph 5 where both concentration curves are below the 45 degree line of equality. Very good health status changed between the two reported waves from a positive statistically insignificant index value to a negatively statistically significant index value.

Table 8: Concentration Indices by Self-Reported Health Status, by Wave

	Wave I		**Wave V**	
Variable	**Index Value**	**Std. Error**	**Index Value**	**Std. Error**
Poor Health	-0.206***	0.013	-0.224***	0.009
Fair Health	-0.205***	0.013	-0.224***	0.009
Good Health	-0.159***	0.013	-0.210***	0.009
Very Good Health	0.016	0.013	-0.179***	0.009
Excellent Health	0.206***	0.013	0.224***	0.009

Where *** p<0.01, ** p<0.05, * p<0.1.

3.4 Decomposition Analysis

The results of the decomposition analysis of the concentration indices represented in Table 8 above are reported in Table 9 below with only predicted excellent health used as the largest proportion of the population fell into this category and allowed for a larger sample space for analysis. The concentration index values of each factor, their elasticities, and contributions are all reported in waves I and V and are used further in the analysis to decompose the changes between the two periods observed. The notable positive concentration indices in waves one and five are excellent health, ages 15-24, males, and quintile 5 total income groups. The positive concentration indices indicate that life satisfaction is distributed more among individuals with these factors. The notable negative concentration indices in wave I and V are the ages 45-64, females, Africans and an inactive employment status factors. The negative concentration indices indicate that life satisfaction is distributed less among individuals with these factors.

With regards to the interpretation of the absolute contribution, if the value of the contribution of any of the regressors is positive, then the inequality in life satisfaction would decrease. If the value of the contribution of any of the regressors is negative then the inequality in life satisfaction would increase (Ranari et al. 2017). In Wave I, notable positive absolute contributions to decreasing inequality in life satisfaction were excellent health status, African race group, employed employment status, and the quintile 1 household income group. The most notable negative absolute contribution in wave one was sex, i.e. being male. Wave V had the only notable positive contribution in the form of excellent health status, while small negative contributions were from individuals aged 25-44 and the African race group. Results for the African race group could be explained by ineffective policy implementation in reducing inequality in South Africa amongst race groups over the time period in question. Africans in particular make up the majority of the South African population and as a result of the country's history of unequal racial segregation highlighted at the beginning of the paper, the change in the contribution from positive to negative lends itself to the idea of inequality reducing policies seemingly being ineffective.

The percentage of contributions made by each variable were summed and presented in Graph 6 below to give an illustration of the possible contributing variables. Additionally, the visualization aids in analyzing the distribution of the contributions to the overall concentration of life satisfaction. As a result, the contributions of each variable to health-related inequalities in self-reported life satisfaction are displayed. Here it is evident that large positive contributions are made by excellent health status over both waves, with an increase in the contribution between

Wave I and Wave V. Race had a large negative contribution with an increase in this negative contribution visually evident between waves I and V. Household income also had large negative contributions but had a slight decrease in the negative contribution between wave I and V. Respondents' age had a change in the contribution to life satisfaction inequality between wave I and V. A slight positive contribution in Wave I changed to a larger negative contribution which can be attributed to the large negative contribution that is exhibited from individuals aged 25-44 years in Table 8. Location also had a positive contribution to the inequality in life satisfaction. The province in which respondents live were positive and have a decrease in the magnitude of the positive contribution between Wave I and Wave V.

Table 9: Decomposition Analysis: factor specific elasticities, concentration indices and contributions, by Wave

		Life Satisfaction							
		Wave I				Wave V			
Variable	**Description**	**Elasticity**	**C.I.**	**Absolute Contribution**	**% Contribution**	**Elasticity**	**C.I.**	**Absolute Contribution**	**% Contribution**
Predicted Excellent Health		0.494	0.316	0.156	49.362	0.793	0.286	0.226	79.262
	Total			0.156	**49.362**			0.226	**79.262**
Age	15-24 years	0.079	0.237	0.019	7.853	-0.051	0.226	-0.012	-5.130
	25-44 years	-0.043	0.047	-0.002	-4.308	-0.246	0.134	-0.033	-24.560
	45-64 years	-0.023	-0.188	0.004	-2.311	-0.063	-0.226	0.014	-6.309
	Total			0.021	**1.234**			-0.031	**-35.999**
Gender	Male	-0.062	0.141	-0.009	-6.164	-0.065	0.103	-0.007	-6.502
	Total			-0.009	**-6.164**			-0.007	**-6.502**
Race	African	-0.671	-0.057	0.038	-67.049	-0.877	0.033	-0.029	-87.709
	Coloured	0.002	0.004	0.000	0.209	-0.059	-0.016	0.001	-5.876
	Asian/Indian	0.010	0.014	0.000	0.963	-0.021	0.001	-0.000	-2.128
	Total			0.038	**-65.877**			-0.008	**-95.713**
Employment	Inactive	0.013	-0.071	-0.001	1.328	-0.085	-0.132	0.011	-8.536

	Discouraged	-0.008	-0.004	0.000	-0.833	0.005	0.000	0.000	0.497
	Unemployed	-0.027	-0.020	0.001	-2.669	-0.012	0.026	-0.000	-1.164
	Total			0.000	**-2.174**			0.011	**-9.203**
Marital Status	Single	-0.016	0.041	-0.001	-1.594	-0.163	0.078	-0.013	-16.290
	Living together	-0.006	-0.036	0.000	-0.569	-0.007	-0.001	0.000	-0.684
	Total			-0.001	**-2.163**			-0.013	**-16.974**
Household Income	Quintile 1	-0.290	-0.090	0.026	-28.959	-0.234	-0.034	0.008	-23.410
	Quintile 2	-0.175	-0.040	0.007	-17.493	-0.157	-0.025	0.004	-15.717
	Quintile 3	-0.115	-0.017	0.002	-11.540	-0.112	-0.038	0.004	-11.210
	Quintile 4	-0.038	0.036	-0.001	-3.830	-0.096	0.005	-0.001	-9.603
	Total			0.034	**-61.822**			0.015	**-59.940**
Province	Western Cape	0.051	0.029	0.002	5.104	0.006	-0.029	-0.000	0.592
	Eastern Cape	0.050	-0.027	-0.001	4.946	-0.070	-0.038	0.003	-6.961
	Northern Cape	0.016	-0.003	-0.000	1.593	0.022	0.009	0.000	2.230
	Free State	0.034	-0.030	-0.001	3.432	0.048	-0.001	-0.000	4.756
	Kwa-Zulu Natal	-0.066	-0.052	0.003	-6.571	-0.004	-0.032	0.000	-0.436
	North West	0.043	-0.026	-0.001	4.302	0.066	-0.009	-0.001	6.558
	Gauteng	0.111	0.059	0.007	11.144	0.011	0.033	0.000	1.055
	Mpumalanga	0.074	0.025	0.002	7.353	0.018	0.010	0.000	1.781
	Total			0.11	**31.303**			0.002	**9.575**
	Total				**-56.301**				**-135.494**

	%Contributions								

Graph 6: Percentage absolute contributions to concentration indices of health-related inequalities in self-reported life satisfaction in South Africa, by wave

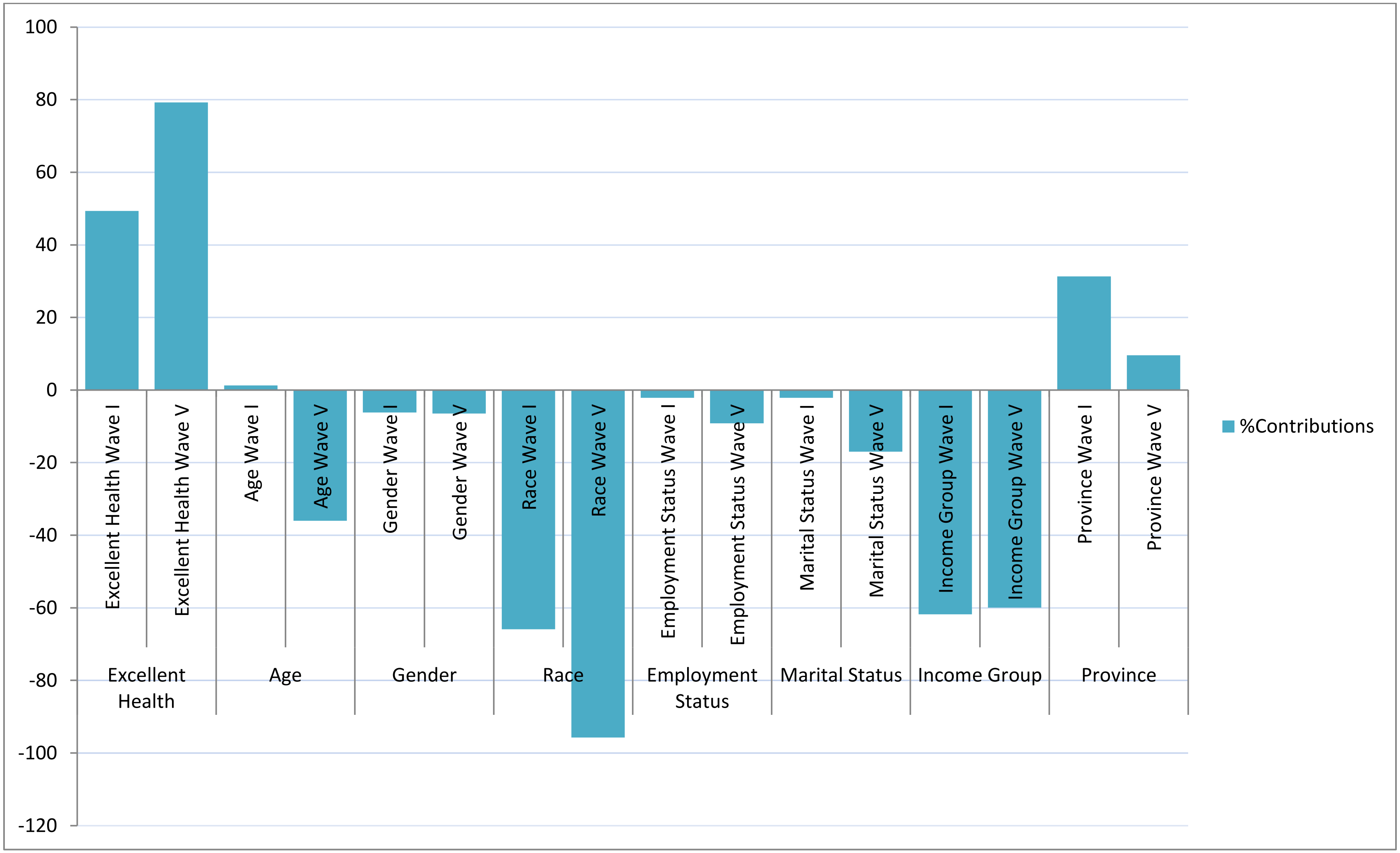


Table 10: Decomposition of Change in Inequality between Wave I and V

	Life Satisfaction			
Variable	**Description**	**Change in Coefficient**	**Change in Elasticity**	**Total Change**
Excellent Health		-0.024	0.095	0.071
Age	15-24 years	0.001	-0.031	-0.030
	25-44 years	-0.021	-0.010	-0.031
	45-64 years	0.002	0.008	0.010
Gender	Male	0.003	-0.001	0.002
Race	African	-0.078	0.012	-0.067
	Coloured	0.001	-0.000	0.001
Employment	Inactive	0.005	0.007	0.012
	Unemployed	-0.001	-0.000	-0.001
Marital Status	Single	-0.006	-0.006	-0.012
Total Income	Quintile 1	-0.013	-0.005	-0.018
	Quintile 2	-0.003	-0.001	-0.003
	Quintile 3	0.002	-0.000	0.002
	Quintile 4	0.003	-0.002	0.001
Province	Western Cape	-0.000	-0.001	-0.002
	Eastern Cape	0.001	0.003	0.004
	Free State	0.001	-0.000	0.001
	Kwa-Zulu Natal	-0.000	-0.003	-0.003

	North West	0.001	-0.001	0.001
	Gauteng	-0.000	-0.006	-0.006
	Mpumalanga	-0.000	-0.001	-0.002

3.5 Oaxaca-Blinder Decomposition Analysis

Table 10 above presents the results of the Oaxaca-type decomposition where the change in inequalities in life satisfaction were examined against the predicted excellent health status between Wave I and Wave V. The results give an indication of the extent to which inequalities in the self-reported excellent health outcome and socio-demographic indicators are due to changes in health-related inequalities in their associated socio-demographic determinants. The results can be interpreted in terms of the contributions from both health and socio-demographic variables to the changes observed in life satisfaction inequalities between Wave I and Wave V.

Table 10 reports the change in coefficient, change in elasticity and the total change between waves I and V for the health outcome and socio-demographic factors. Notable negative changes in coefficients for the health outcome and socio-demographic factors are African and Excellent Health while there were no factors that had notable positive coefficient changes. The positive stand out elasticity change over the decomposed time period was Excellent Health, while the most significant negative change in elasticity was in the form of individuals aged 15-24 years old.

Notable changes can be observed in total positive contributions from excellent self-reported health status and inactive employment status. The positive sign indicates that the contribution in question reduces inequality in life satisfaction between Wave I and Wave V. The total negative contributions that stand out from Table 9 are individuals aged 15-24 and 25-44 years old, individuals classified as African, and quintile 1 household income. The negative sign is an indication that the contribution from the factor in question increases inequality in life satisfaction between waves I and V.

4. Discussion

This paper examines as well as compares the relative changes in health-related inequalities in the distribution of individuals' life satisfaction in South Africa between 2009 and 2017 using waves I and V of NIDS. It appeared that health-related inequalities exist in self-reported life satisfaction and that the overall contribution of health-related inequalities had a slight widening of inequality in life satisfaction over the period 2009-2017. Initially results from the ordered probit regression saw poor, fair and good health status outcomes in both waves had negative values. The expectation was that negative indices for poor and fair health would have been observed, while positive indices for good, very good and excellent health were expected. The results however are quite different and could be an indication of the very subjective nature of responses on health status when considering absolute and relative evaluations of self-reported health.

The concentration curves and indices indicate that there is greater life satisfaction among individuals with a lower probability of having poor, fair and good self-reported health status responses in both waves I and V. The concentration curves and indices further indicated that life satisfaction was concentrated more highly on individuals with a higher probability of having an excellent self-reported health status also in both waves I and V. The magnitude of the concentration indices between waves one and five across all self-reported health status outcomes increased and reinforces the argument and overall result of the paper at hand- which is a widening of health-related inequality in life satisfaction. This falls in line with the intuitive argument that poor or average health is associated with a lower level of life satisfaction. This is similar to the findings of (Ryser et al., 2018) where healthier individuals are seen to 'detain' a more-than-proportional share of the total "stock" of life satisfaction across the countries that were analysed.

The decomposition analysis approach for Wave I indicated the largest positive contributors to reducing inequality in life satisfaction were excellent health status, the African race group, individuals with employed employment status and respondents in the quintile 1 total income group. This can be explained firstly by health status' association with happiness where Ngamaba et al., (2017) investigates the association. Ryser et al., (2018) also finds that health status is statistically significant and positively correlated with life satisfaction where greater health and better life satisfaction is the relation. Further, (Ryser et al., 2018) finds that low relative health is negatively associated with life satisfaction across the countries analysed. Secondly, the African race group is the majority population in the survey as is representative of South Africa's racial demographics, and as a result would have a greater impact in reducing inequality in life satisfaction. Ryser et al., (2018) does not make use of the race group factor as it is not deemed significant within the context of the geographical location (Europe) that was investigated. Employment and quintile 1 income groups' positive contributions indicate that individuals that earn in the lowest 20% of income who are employed, also decrease inequality in life satisfaction.

There were no significantly large negative contributions that widened inequality in life satisfaction in Wave I. The notable positive contributions in the decomposition of the fifth wave showed excellent health status as a life satisfaction inequality reducing factor – the only consistent factor from Wave I. Small negative contributions were reported from individuals aged 25-44 and the African race group indicating a change in the contribution to inequality in life satisfaction. The negative contributions of these factors in Wave V suggest that young individuals classified as African entering the work force are contributing to a widening inequality in life satisfaction in 2017.

Oaxaca-type decomposition revealed that changes in life satisfaction inequalities arise due to the interaction among the inequality determinants. These are factors with positive and negative signs that offset the inequality (Rarani et al. 2016). Changes in excellent self-reported health status and inactive employment status had a positive sign indicating a contribution towards the reduction of inequality in life satisfaction between 2009 and 2017. Changes to individuals aged 15-24 and 25-44 years old, individuals classified as African, and quintile 1 total income earners had negative signs indicating a contribution towards increased inequality in life satisfaction between 2009 and 2017.

In the context of South Africa, the negative contribution of low income earners in particular gives an indication that poverty contributes to increased inequality. Regarding these findings, it could be suggested policy towards improving health status should be considered as a means to enhance people's life satisfaction. Creating policy that could alter the negative contributions from young individuals, who are African that earn in the lowest 20% of income, is an alternative. A suggestion on this type of policy is already in play in South Africa in the form of "Black Economic Empowerment" (BEE) schemes. This is a government policy that aims to increase economic transformation as well as participation from Africans, Coloureds and Indian individuals. The argument is that by increasing direct and indirect empowerment of these identified race groups through ownership and management, will create the opportunity for greater household income, and in turn filter into decreasing health-related inequalities in life satisfaction. Tangri and Southall (2008) investigate BEE in South Africa scheme and discuss various issues regarding the policy due to the political nature associated with it which is not explored in this paper but offers a further avenue for research as a possible income inequality study.

Limitations of this paper stem from the approach that only allows for associations to be investigated. As a result, causal inferences cannot be made about how health status may cause life satisfaction to decline or vice versa. This does pose a weakness of the proposed study, but also provides scope for further research on the topic, with possible policy recommendations for government to implement. Additionally, as highlighted in (Ryser et al., 2018), the potential bias in reporting on self-reported health status can cause problems in the analysis seeing as it is the primary ranking variable of interest. This is due to the subjective nature of self-reported health. Although the use of objective dimensions in the form of chronic diseases are used to measure health outcomes in a probit model, using only objective health measures to estimate health status may yield different results. Furthermore, the result of the opposing signs of multi-morbidity and multi-morbidity count in the ordered probit regression saw no distinction made between those treated or not for the chronic conditions listed in the interview process. In addition, because the question asks if individuals have been diagnosed, some people may have conditions but have not yet been diagnosed via the health system, so the prevalence of these chronic conditions are likely to be underestimated as well and provides avenue for further investigation.

Further limitations to note are from the predicted health status variable displayed in equation (1). Focus is largely drawn towards illnesses and disorders, whereas the consideration for multidimensional factors could be taken into account as health status can encapsulate more than just disease, physical and mental weaknesses. Lastly, the possibility of endogeneity existing as a result of reverse causality in the ordinal regression between mental health (CESD-10 score) and self-reported health forms another limitation of the analysis and could be investigated in further research.

5. Conclusion

Using the first and fifth waves of the NIDS dataset for the period 2009-2017, the analysis observed the relative changes in health-related inequalities in life satisfaction. An explanation for the changes chronic diseases as well as socio-demographic factors of health that also account for changes in life satisfaction for the period was also provided. To achieve the objectives of the paper, an ordered probit regression, concentration index regression model, and Oaxaca-type decomposition of the change in the concentration index were used. Evaluation concentration curves and indices indicate that there is greater life satisfaction among individuals with a lower probability of having poor, fair and good self-reported health status responses in both waves I and V. The concentration curves and indices further indicated that life satisfaction was concentrated more highly on individuals with a higher probability of having an excellent self-reported health status also in both waves I and V. There were no significantly large negative contributions that widened inequality in life satisfaction in Wave I. The notable positive contributions in the decomposition of the fifth wave showed excellent health status as a life satisfaction inequality reducing factor. The decomposition analysis approach for Wave I indicated the largest positive contributors to reducing inequality in life satisfaction were excellent health status, the African race group, individuals with employed employment status and respondents in the quintile 1 total income group. Further results from the Oaxaca-type decomposition analysis saw changes in excellent self-reported health status and inactive employment status contributed towards the reduction of inequality in life satisfaction, while changes to individuals aged 15-24 and 25-44 years old, individuals classified as African, and quintile 1 total income earners contributed towards increased inequality in life satisfaction within the investigated period.

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