Dynamics of Health Among Adults in South Africa

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Research

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DYNAMICS OF HEALTH AMONG ADULTS IN SOUTH AFRICA

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***Availability of data and material**

The datasets generated and analysed during the current study are available at DataFirst repository, https://www.datafirst.uct.ac.za/dataportal/index.php/catalog/central#_r=1599436134372&collection=&country=&dtype=&from=1947&page=1&ps=&sk=NIDS&sort_by=nation&sort_order=&to=2020&topic=&view=s&vk=

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***Authors' contributions**

Usengimana Mutembereza had the idea of the paper and searched for appropriate data and the research questions. He also discussed the model, run the models, too care interpretation, and provided recommendations.

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Abstract

Background: This paper estimates trend of health mobility in South Africa using National Income Dynamic Study (NIDS) and investigate whether the patterns of health mobility differs within socioeconomic groups created by income and gender. Health is measured by SRHS, which correlates with mortality and morbidity; thus, it is the best measure of health.

Methods: Using five waves of NIDS and various econometric models, this research estimates health mobility in the period between 2007 and 2017. This study will use transition matrix as descriptive analysis of health mobility and Conditional Maximum Likelihood Estimations to analyse health mobility, trend of health mobility and relationship between health mobility and health inequality within NIDS.

Results: The study shows that, among poor males, health mobility neither follows a health selection or health constraint mobility trend; the high health mobility with ambiguous trends has not decreased health inequality. Among the poor females, a negative health mobility trend is observed; this research also found that health inequality has not creased. Among the non-poor males, it is found that health mobility follows a gradient constraint trend which has decreased health inequality. Among non-poor females, it is found that health mobility follows a health selection trend which has not decreased health inequality. The results suggest that policy makers should target both social determinants of health and health campaigns to deal with health inequality among the poor males.

Conclusions: The trend of health mobility among poor females suggest that policy makers should target the social determinants of health to combat health inequality. The trend of health mobility among the non-poor males suggests that health mobility will eliminate health inequality. Lastly, the trend of health mobility suggests that policymakers should target health campaigns to deal with health inequality.

Key words: SRHS, health dynamic, gradient constraint, health selection, health inequality

Introduction

Health mobility has implications for the health inequality (Umuhoza and Ataguba, 2018). The people in excellent or very good health statuses can recover from the health shocks, while the people in poor and fair health statuses have very little chances of recovering from health shocks; because the latter's bodies have lower immunity to fight illnesses. Therefore, the South African government has implemented a number of policies to lift the people out of bad health. The most notable policy is the free primary healthcare at delivery, and some aspects of the tertiary healthcare (Mayosi et al., 2012). However, health inequality continues persists as reported by previous literature such as Obaku-Igwe (2015). This enigma has inspired this research to investigate the patterns of health mobility in different Socio-Economic Statuses (SES). The results of this research give indication on whether, in the long run, the current patterns of health mobility will reduce the health inequality that exists in South Africa.

The previous research has studied the patterns of health mobility in the developed countries. For example, Contoyannis et al. (2004) studies the health mobility in the UK; they found that on average, among the British, the people that had previously reported poor health status had higher probability of reporting different health status than the people that had reported excellent health status. Their finding suggests that the patterns of health mobility will equalise health in the long run for Britons.

However, such blessings are not for all countries. Previous literature reports that health mobility has a parabolic relationship with the health inequality (Deaton, 2013); at the low levels of health inequality, health inequality is declining as the health mobility increases; but at high levels of health inequality, health mobility is associated with an increase in health inequality. The countries with very high health inequality such as Russia, in early 2000, had an increasing health inequality when health mobility increased (Heggebø, 2015 and Bobak et al., 2000).

Mackbenbach (2012) and van Kippersluis et al. (2010) suggests that the relationship between health mobility and health inequality should be analysed in the lenses of the health gradient. They both used the data from the Netherlands, which is an egalitarian country and they found that the relationship between health inequality and health mobility is complex and there is a need to investigate conditions upon which health mobility decreases health inequality. The previous literature show that health mobility has different effect on health inequality in different groups of

people that are in the same country. Health mobility may also have different impact in a particular group of people in different periods.

The negative relationship between health inequality and health mobility is either explained by gradient constraint of health or health selection (Mutyambizi, et al., 2019 and Mackbenbach 2012). The people in better health status have developed the network and lifestyle that keep them healthy. They eat nutritious food and they abstain from unhealthy behaviour. While the people in bad health have also developed unhealthy behaviour (Mutyambizi, et al., 2019). Health selection hypothesis states that the people in bad health are not economically productive, and they are deprived of the resources (Haas, 2006); the people in bad health will remain in bad health in the long run. Therefore, when the relationship between health inequality and health mobility is driven by health selection, policies that encourage change of behaviour need to be implemented for all people to develop good behaviour. For example, sugar tax has been charged on beverages in many countries including South Africa with a hope of decreasing sugar consumption. The campaign and policies hope that people below the health threshold will move away from poor health status or decreases the number of new cases of diabetes (Mutyambizi, et al., 2019).

In some countries, for example countries that have high inequality in access to healthcare, increasing access to healthcare will increase health mobility for people previously reported poorer health statuses more than for people that had previously reported better health statuses. In such countries, mobility will decrease health inequality (Ro et al., 2016). This phenomenon is known as gradient constraint (Elstad, 2001). The literature argues that when gradient constraint is present, the determinants of health mobility should be boosted to eliminate health inequality in the long run (Haas, 2006).

The literature on the gradient in South Africa has highlighted the issues that have kept a large portion of the population in poor health and others in relatively better health statuses. Literature has tested for the presence of the gradient constraint (Ro et al., 2016). However, the approach has encountered numerous modelling challenges because health and income have an endogenous relationship. For example, income causes improvement in health and health causes the improvement in income. The deficiency is laid bare for example, Boyler et al (2009) and Warren (2009) both use the data from the UK, but they reach a different conclusion. Warren (2009) finds no evidence for the health inequality decreasing but Boyler et al (2009) finds evidence for health inequality widening. Their results could not indicate what causes health inequality to

increase over the time. Likewise, in South Africa, literature is not conclusive (Mayosi & Benatar, 2014).

Ro et al. (2016) argue that the paradox in the relationship between health inequality and health mobility that has dominated the literature for decades is caused by the failure to recognize the effect that health threshold has on the relationship between health mobility and health inequality. The threshold on health mobility is evident if the health of people in health status below certain health status is immobile (Moscelli et al., 2012).

In South Africa, policy makers have implemented a number of policies without recognising health threshold. When health threshold is significant, people below the threshold will not recover from health shocks. An example of the threshold is people with compromised immune systems that they cannot recover from minor illnesses like a flu. When a large portion of people are constrained by the health threshold, the health policies need to deal with such threshold because health mobility will increase health inequality if the threshold is not addressed. For example, in the 1990s, South Africa was deeply affected by HIV/AIDS. Large portion of the population had health below the threshold, but the threshold was not addressed which caused an increase in health inequality up to 2006 when AIDS reached its peak in South Africa (Marmot, 2017 and Obaku-Igwe, 2015).

The relationship between health mobility and health inequality need to be invested because the increase in health inequality could have been driven by the health threshold on health mobility. Health threshold is tested using Self-Reported Health Status (SRHS) because SRHS is the holistic measure of health. The people in poor health status have little chance of moving from their ill-health if the threshold is present (Marmot, 2017).

Health immobility may be related to health threshold when chronical illnesses are predominantly clustered in the group of people that have low access to the social determinants of health. In such an environment, health inequality increases radically. In this case the safety net and government interventions are necessary for the health inequality to decrease over the years. The health inequality is caused by a health damaging environment. People in poor health have a double burden, thus the government interventions must target people in poor health that are struggling to access social determinants of health. However, the policy interventions that do not include all the people in ill-health will be futile in the long run. The people that currently have essential needs will eventually be pulled into poverty (Marmot, 2017).

Therefore, there first objective of this research is to evaluate the patterns of health and the implication of the patterns on health inequality. The investigation indicates if there is a need for policy intervention and whether the intervention is to cover all people or first intervene for people in ill-health that do not have essential determinants of health. In South Africa, there is limited literature on the relationship between health mobility and health inequality. The literature has used different approaches. For example, Lau and Ataguba (2015) used two waves of NIDS, they estimate the relationship between social capital and health over the first two waves. The research investigates the implied relationship between health inequality and health mobility and assumed that health improves as the social capital increases.

Lau and Ataguba (2015) suggest that there has been a reduction in health inequality, because the factors that are associated with health have improved. However, in South Africa, there is evidence that social improvement does not imply a reduction in health inequality because economic development has been skewed in favour of the affluent communities. For example, in 2012, the Marikana incident where national police force shot 36 people dead showed that the affluent can use their political connections to marginalise the poor people; while poor people are increasingly being frustrated by lack of opportunity (Mabena, 2017). The resources and power are disproportionately more in the affluent community. In this research a person is classified poor, if the person had income per capita that is below R577 in 2011 prices (The Presidency, 2012; Stats SA, 2017 and Rossouw, et al., 2018).

Therefore, the second objective for this research is to investigate the nature of observed relationship between health inequality and health mobility. This study analyses the existence and impact of health gradient and health threshold on health mobility to give insight into the relationship between health mobility and health inequality. If health mobility has gradient constraint, health inequality is decreasing because people in lower health status have higher probability of improving health compared to people in higher health status. When health mobility is driven by health selection hypothesis, health mobility has implication in the long run health inequality; the people in higher health statuses have higher probability of improving their health than the people in bad health statuses (Mutyambizi, et al., 2019; Deaton, 2013 and Haas, 2006).

The insights from this research are important. In 2012, the commission on development in South Africa found that the nation will need to address the problem of health inequality for South Africa to achieve the goals that set for national vision 2030. Furthermore, policymakers have applied enormous amounts of effort to reduce the health inequality, but to a large degree, the results have

been disappointing. Among the developing countries, South Africa spends the largest portion of her GDP (Obuaku-Igwe, 2015); however, the health indicators lag other developing countries. This problem, large spending without desired results, is speculated to be linked to biases methods used in research that guide the policy makers. These methods will be discussed under methods section.

This research investigates the current health patterns of health mobility and assess if current patterns can address the problem of health inequality in South Africa. The patterns of health mobility in different SES groups indicate which group is having the greatest health mobility and the analysis explores the gap in literature on health inequality. This is done by estimating the trend of health mobility after controlling for social determinants of health. This allows the researcher to indicate which SES group needs policy intervention. In addition, this insight enables the researcher to recommend whether the policy makers should intervene within social determinants of health or health behaviour campaigns.

Methods

Data

To achieve the objectives, this research uses the National Income Dynamic Study (NIDS) data set. The data set currently has five waves available, which were collected starting from 2007 to 2017. The data is managed by the Southern Africa Labour and Development Research Unit (SALDRU) and is collected using two-stage cluster sample design. At the first stage, 400 Primary Sampling Unit (PSU) were randomly selected from 3000 PSUs that were recognized by Statistics South Africa in 2003. At the second stage, 24 to 48 households are selected from each of the selected PSU for the interview (Ardington and Gasealahwe, 2012).

The data set has a number of questionnaires, there is a questionnaire for the adults, children, proxy and the household; the adult questionnaire is answered by an individual that is above 15 years of age and lives in the household. The questionnaire for children and proxy questionnaire are answered by an individual that is familiar with the particular individual. The household questionnaire is answered by the oldest female in the house or any other person that is familiar with the household spending. Therefore, this research uses the data collected through the adult and household questionnaires. These are the only questionnaires where the individual answers for themselves or for the household; this research is concerned with the self-reported health status

(Brown et al., 2012). Individual person has knowledge to assess their own health and the assessment that they give is more accurate than the objective measures of health.

Table 1: The number of people in the survey

	Number of people
Wave1	16 872
Wave 2	21 874
Wave 3	22 457
Wave 4	26 804
Wave 5	30 110

Source: NIDS

The table shows that the number of the people in the survey has been increasing over time. In reality, the people come in and drop out of the survey. The NIDS data has two types of participants (Ardington and Gasealahwe, 2012). The first type is the Continuing Sampling Members (CSM), and the second is the Temporary Sampling Members (TSM). The CSMs are the people that are interviewed in every wave. They got the status from being in the initial interview or being born to a CSMs woman (Ardington and Gasealahwe, 2012). The TSMs are the people that live with CSM at the time of the interview and represent the most changes in the number of the sample. In 2017, the sample was extended through the recruitment of an additional 1008 responding households to correct for people that have dropped out, prime-age males, for example.

Attrition

The other cause for change in the numbers of people in the sample is attrition and retention. Participating in NIDS is not enforced by law and some people may not be traced. Therefore, information on some people, as the number of waves increase, is lost. If people drop out at a certain pattern, the sample is no longer unbiased because the people that drop out of the survey have a predictable health pattern. For example, if all the people dropped out of the survey were in poor health status, the sample would have become biased; the population in poor health status will be underrepresented. Therefore, there is a need to use the weight to adjust for the underrepresentation (Ardington and Gasealahwe, 2012); this research investigates the nature of attrition before analysing the relationship between health inequality and health mobility.

The analysis of attrition regresses the attrition variable on health variables and other control variables. The attrition variable takes on one if the person drops out of the survey and zero if the person is re-interviewed. The variable for attrition is the dependent variable in the probit model and the other variables, including health, are the explanatory in the model. The other variables

are included to prevent coefficient on health from being biased and inconsistent. The model assesses if dropping out of the sample have significant relationship with health (Jones and Schurer, 2011).

Significant relationship indicates that the attrition is not at random. In the probit regression, the coefficient on the variables for health in the previous wave assesses the nature of the relationship between attrition and health. If the coefficients on previous health variables are statistically significant and positive (negative), then the people in that health status have a higher (lower) probability of dropping out of the survey than people that had reported health which is the base category. The people previously in that health status are significantly likely to drop out of the survey or stay because of their health condition (Jones and Schurer, 2011).

Table 2: Attrition test using probit method

	Full sample	Poor female	Non-poor female	Poor male	Non-poor male
Health (Poor health status is the base category)					
Excellent	0.028	-0.148	0.376	-0.063	0.051
Very good	-0.041	-0.322	0.058	-0.129	0.02
Good	0.026	-0.101	0.075	-0.07	0.076
Fair	0.057	-0.365	0.215	-0.046	0.119
Household size	-0.019	-0.016	-0.047	-0.011	-0.02***
Log of income	0.083***	0.016	0.146**	0.072*	0.081***
Community violence	-0.011***	0.008	0.036	-0.007***	-0.021
Urban	0.184***	0.279	0.544***	-0.04326**	0.228***
Marital status (Single is base category)					
Married	-0.047	-0.42*	-0.214	-0.28682	-0.013
Divorced or widow	-0.061	0.039	-0.003	0.011831	-0.026
Population group (African is base category)					
Coloured	0.489***	1.132***	0.255	0.132468***	0.425***
Asian/Indian	0.887***			0.274572***	0.899***
White	1.093***	3.048***	2.395***	-0.17962***	1.113***
Education	0.017***	-0.043	-0.076***	0.015**	0.027***
Good home	-0.043	-0.384**	-0.012	-0.058***	-0.008
Province (Mpumalanga is base category)					
Western Cape	-1.584***	-1.646***	-1.505***	-1.481***	-1.62***
Eastern Cape	-1.641***	-1.73***	-1.727***	-1.447***	-1.78***
Northern Cape	-1.716***	-2.926***	-1.67***	-1.545***	-1.802***

Free State	-1.858***	-1.583***	-2.075***	-1.677***	-2.017***
KwaZulu-Natal	-1.542***	-1.687***	-1.378***	-1.379***	-1.64***
North West	-1.544***	-1.531***	--1.834***	-1.428***	-1.647***
Gauteng	-1.356***	-1.597***	-1.231***	-1.239***	-1.421***
Limpopo	-1.679***	-1.792***	-1.652***	-1.465***	-1.834***
Age	-0.005	0.006	-0.019	0.018**	-0.017***
Age square	0	-0.019	-0.006	-0.026***	0.016**
Constant	-1.088***	0.342	-0.623	-1.219***	-1.091***
N	45 474	1 353	2 226	16 224	24 794
Rho	0.487***	0.433**	0 .446***	0.426***	0.529***
log	-11773.618	-350.645	-408.626	-4812.398	-5882.372

Note: * shows the significance at 1% ** shows the significance at 5% and * shows the significance at 10%. The control variables were adopted from Baigrie and Eyal (2014). Note that in data used to analyse attrition, there were only 3 Indian poor males and no poor female, therefore variable for Indian was omitted in poor male and poor females groups. where €it is i.i.d. Gaussian distributed with mean zero and variance* $\theta_{\epsilon} = 1$*, independently of* υ_i*. Rho is the proportion of the total variance contributed by the panel-level variance component and likelihood-ratio tests show that panel-level variance component is important. quadchk test also shows that it does not differ substantially.*

Table shows that coefficients on the health variables are not significant. In the full sample, the attrition status is not significantly dependent on the previous health status. The previous literature has argued that males report health different to females (Leibbrandt et al., 2009). There is also evidence in South African literature that the poor people report health differently compared to non-poor people (Rossouw et al., 2018). Therefore, the data set was split into poor males, poor females, non-poor males, and non-poor females. It remains that the health variables in the previous wave does not determine who attrit in the current wave.

The results are not affected by individual heterogeneity, and likelihood-ratio tests show that panel-level variance component is important. The results show that health attrition is random. Therefore, the NIDS data set which is used in this research is appropriate to assess the individual health mobility; attrition does not depend on the previous health status. Therefore, the analysis on dynamics of health using the SRHS produces reliable results.

The literature has argued that SRHS is correlated with morbidity and mortality. Thus, it is an appropriate measure of health because it is more reliable than objective measures of health. The literature observes that a person that reports poor health status has higher probability of being dead in the next wave than a person that had previously reported excellent health status (Shulman et al., 2006). SRHS is derived from the adult questionnaire in NIDS (Brown et al., 2012). The participants were asked to describe their current health;

they can rate their health as excellent, very-good, good, fair, or poor (Leibbrandt et al., 2009). The current SRHS is correlated with mortality and morbidity because it contains all health shocks that occurred in the past and the influence of the exogenous variables (van Kippersluis et al., 2010; Contoyannis et al., 2004 and Deaton and Paxson, 1998).

Therefore, SRHS is a good measure of health (Shulman et al., 2006 and Idler and Kasl, 1995). SRHS meets definition by the World Health Organization (WHO); WHO defines health as a state of complete physical, mental and social well-being and not just the absence of disease and infirmity. SRHS is a general measure of health at the point of time and it accounts for the physical, mental and social well-being (Deaton and Paxson, 1998). People have knowledge of their medical history and the conditions of their health; therefore, SRHS is the best measure of general health. When people report their health, they account for the past condition of their health.

The SRHS was included in the Panel Study of Income Dynamics (PSID), which is among the prominent dynamic data sets in the USA that started in the 1980s. However, the academics debated the reliability of the variable for a decade. In mid 1990s, academics concluded that the SRHS is correlated with objective measures of health (Shulman et al., 2006 and Idler and Kasl, 1995). The literature also argued that SRHS suffers problems of individual heterogeneity; different people that have exactly the same objective health will report different health status. Although this argument is persuasive and exposes the weakness of SRHS, the previous literature has proven that the reporting error can be addressed (van Kippersluis et al., 2010).

Lindeboom and van Doorslaer (2004) use the McMaster Health Utility Index Mark 3 (HUI3) to distinguish the cut-point shift from the index shift. HUI3 is available for the Canadian National Population Health Survey data. The literature found that male population reported their health differently compared to the female population (Lindeboom and van Doorslaer, 2004). Literature suggests that the heterogeneity can be mitigated by splitting the sample into two groups, one for males and another for females, and analysis computed separately.

Grol-Prokopczyk et al., (2011) suggest that anchoring vignettes is another possible methodology to investigate the heterogeneity problem. The anchoring vignettes work like the HUI3 and most countries including South Africa have the indices (Rossouw et al., 2018). Once the cut-point shift has been distinguished, the analysis can compare the people that have similar reporting patterns. The literature found that poor people in South Africa have different thresholds to the non-poor (Rossouw et al, 2018 and Shulman et al., 2006). Therefore, to mitigate heterogeneity in South Africa, we split the sample into four groups. Health that is reported using the same scale is analysed together (Contoyannis et al., 2004 and

Hauck and Rice, 2004). The first two for poor males and non-poor males and the other two are the poor females and non-poor females.

Since the conclusion of the debate, SRHS has been widely used in literature (Carro and Traferri, 2014; Halliday, 2008; Contoyannis et al., 2004 and Deaton and Paxson, 1998). Hauck and Rice (2004) use SRHS to study health mobility per Socioeconomic Status (SES) in Britain. Lau and Ataguba (2015) use SRHS to study the determinants of health in South Africa; SRHS has been used in both the developed and developing countries. Literature has found that once individual heterogeneity is mitigated by splitting the data into different groups, SRHS is the most reliable measure of health (Abdulrahim and El Asmar, 2012 and van Kippersluis et al., 2010).

However, Lindeboom and van Doorslaer (2004) cautions about using SRHS in short panel data. Literature argues that SRHS suffers from individual heterogeneity even within these homogenous groups such as the poor female group (Arellano and Bond, 1991). People of different cultures and languages assess their health differently. The individuals may have different interpretation of true health outcome which may lead them to report different health status as the other person (Jones and Schurer, 2011). However, the reporting style which may differ between two people is consistent over time for each person.

Table 3: Number of people reported each health status in each wave

	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
Poor male					
Excellent health	174	257	181	196	178
Very good health	129	208	174	166	157
Good health	130	110	151	153	124
Fair health	58	36	42	41	41
Poor health	43	24	10	14	20
Non-poor males					
Excellent health	1963	2711	2293	2928	3022
Very good health	1533	1918	1946	2551	2807
Good health	1238	1262	1802	2235	2171
Fair health	616	403	462	579	617
Poor health	358	189	182	205	166

Poor females					
Excellent health	217	327	228	208	229
Very good health	230	258	266	257	247
Good health	219	202	267	292	238
Fair health	109	87	86	98	89
Poor health	67	43	29	35	41
Non-poor females					
Excellent health	2193	3166	2695	3220	3472
Very good health	2036	2681	2853	3543	3944
Good health	2171	2054	2976	3659	3687
Fair health	1273	891	1032	1205	1282
Poor health	779	410	383	400	388

Source: NIDS, table shows the sample size after all the restriction.

Therefore, inclusion of variable for initial health status would mitigate individual heterogeneity that is not corrected by splitting the sample, because the scale that a person uses to report health status does not change within the panel (Arellano and Bond, 1991). When a person experiences a decline/improvement in health, they will report worse/better health than the previous reported health status. Therefore, initial health status adjusts for unobserved heterogeneity, and splitting the sample adjust for systematic heterogeneity (Hauck and Rice, 2004). The coefficients on the variable for previously reported health status and initially reported health status are explained further in section: conditional maximum likelihood methods.

Descriptive analysis

The transition matrices are suitable to describe health mobility. The matrix analyses mobility between two periods; it shows the probability of reporting health status reported in the initial wave (Chen and Cowell, 2017). The matrix requires a longitudinal data set, and NIDS data set are longitudinal. Therefore, NIDS data set are suited to analyse the dynamic of health (Hauck and Rice, 2004). We can use transition matrix in NIDS data to detect health mobility in different SES groups and different health statuses.

Transition matrices have been used to study mobility since 1950s (Chen and Cowell, 2017; Woolard and Klasen, 2005; Formby et al., 2004; Trede, 1999; Shorrocks, 1978 and Prais, 1955). The transition matrices

are also used to compare the health mobility between different SES groups (Shorrocks, 1978 and Prais, 1955).

$$M(P) = \frac{n - \sum_1^n trace\ of\ P}{n-1} \qquad (1)$$

M(P) shows mobility in matrix P. Trace of P is the main diagonal cells and n is the number of trace. If $M(P_1) > M(P_2)$, the society "1" has higher health mobility than the society "2". The mobility index shows the likelihood of transiting from one health status to another status for SES group. The transition matrix groups people together and assess their probability of moving between health statuses for the people in that SES group. The mobility index is constraint between zero and one. Mobility index that is equal to one indicates perfect health mobility and index that is equal to zero indicates perfect health immobility. The comparison requires Shorrocks' mobility index as shown by Equation (1) (Shorrocks, 1978). Previously, the index has been used to measure the income mobility and household poverty dynamics in South Africa (Woolard et al., 2012 and Woolard and Klasen, 2005).

Table 4: Health mobility among males between period

	Poor male (0.913)						Non-poor male (0.884)				
	1	2	3	4	5		1	2	3	4	5
1	**0.097**	0.21	0.274	0.242	0.177	1	**0.162**	0.204	0.366	0.162	0.106
2	0.082	**0.23**	0.311	0.222	0.156	2	0.08	**0.221**	0.319	0.193	0.187
3	0.044	0.069	**0.289**	0.298	0.301	3	0.043	0.13	**0.308**	0.297	0.224
4	0.009	0.063	0.227	**0.311**	0.39	4	0.032	0.073	0.263	**0.349**	0.283
5	0.014	0.043	0.207	0.326	**0.41**	5	0.024	0.061	0.266	0.318	**0.333**

**Note: The table shows the transition matrices for both the poor and non-poor male. The matrices are between waves one and five. () shows the mobility index in each SES groups. The figures in bold show the probability of remaining in the same health status.*

The poor males and non-poor males had mobility index of 0.913 and 0.884 respectively. The mobility was calculated using the equation (1). This shows that the poor males had lower probability of reporting same health status initially reported in wave five than non-poor males. In addition, the table shows the probability of reporting same health status at wave five. For example, among the poor males that reported poor health status in wave one, only 9.7% reported poor health status in wave five compared to 16.2 % for the non-poor males. Both the poor males and non-poor males that initially reported poor health status have over 60% probability of reporting either good, very good, or excellent health status. More than 50% of people that initially reported good health status reported either very-good or excellent health status in wave five. The

people that initially reported better health status (very-good and excellent) had higher probability of reporting same health status in wave five.

The transition matrices show that the health inequality between the poor and non-poor males have decreased over the period of the study. The poor males have higher health mobility than the non-poor males, particuraly the males in poor and fair health statuses. The transition matrices also show that, among both the poor and non-poor males, the number of people that reported poor health has declined over the period relative to other health statuses. This shows that the health inequality has decreased; the people that initially reported poor health status have high probability of reporting a different health status in wave five.

Table 4 shows that probability of reporting a health status that is different from the health status reported in wave one follows a positive gradient. The people that initialy reported poor health are less likely to report same health status in wave five than people that initially reported excellent health status. The people initially reporting excellent health status have lowest probability of reporting either poor or fair health status in wave five. The table shows that health mobility is high, and health mobility has decreased health inequality over the period of the study within both poor and non-poor males.

Table 5: Health among females between period

	The poor female (0.908)						The non-poor female (0.896)				
	1	2	3	4	5		1	2	3	4	5
1	**0.162**	0.249	0.319	0.18	0.09	1	**0.152**	0.281	0.3	0.163	0.104
2	0.09	**0.2**	0.329	0.221	0.16	2	0.095	**0.238**	0.334	0.21	0.124
3	0.032	0.095	**0.29**	0.3	0.283	3	0.046	0.128	**0.315**	0.281	0.23
4	0.013	0.055	0.248	**0.313**	0.371	4	0.02	0.079	0.288	**0.317**	0.297
5	0.011	0.035	0.213	0.313	**0.428**	5	0.015	0.051	0.249	0.327	**0.359**

**Note: The table shows the transition matrices for both the poor and non-poor female. The matrices are between wave one and wave five. () shows the mobility index in each SES group. The figures in bold show the probability of remaining in the same health status.*

Poor females has slightly higher health mobility than non-poor females; poor female and non-poor female had mobility index of 0.908 and 0.896, respectivelly. This indicate that the poor females and non-poor females do not have major difference in their probability of changing their health status. This imply that health inequality that existed, in wave one, between the poor and no-poor female has not decreased. The transition matrices further show that health mobility increases as the people move from poor health status to excellent health status. The people that initially reported poor or fair health statuses have high probability of reporting a better health status. The probability of remaining in the initial health status increases as the

initially reported health status moves from poor health status to excellent health status. The female in excellent health status have the highest probability of remaining in their initial health status.

Ataguba (2013) found that the poor people incur more illness than the non-poor. In addition, the poor people have lower medical insurance coverage compared to the non-poor, therefore they have lower demand for healthcare. These results that suggest that health mobility follows a positive gradient which has decreased health inequality are not consistent with the previous literature. The inconsistency may be a result of biased estimation of health mobility from transition matrix.

Contoyannis et al (2004) also caution against the use of transition matrices. The results from transition matrices are dependent on the sample size. Formby et al (2004) report that different inferential approaches and different sampling distributions lead to different results. Other studies have indicated that sampling error can violate the first order Markov properties (Lee et al, 2017). In addition, health is influenced by number of factors. Past health status is among the factors that influence the health because SRHS has a stochastic nature. Therefore, the modelling that does not control for social determinants of health may produce unreliable results.

Conditional Maximum Likelihood Estimation methods

This study uses the Conditional Maximum Likelihood Estimation to analyse the health mobility in South Africa. The methodology addresses the challenges that face transition matrix. Nerlove (1971) modelled the dynamic model for the discrete dependent variable; the lag of the dependent variable is added as explanatory variables. The coefficient on the lagged variable captures the dynamic of health. The simple dynamic model is shown by the equation (2).

Anderson and Hsiao (1982) run Monte Carlo simulation and find that the simple dynamic model is not consistent for the discrete variable. The model will only produce reliable results if the dependent variable obeys the initial conditions. The initial values must be fixed, which requires the initial values to be the beginning of the series. The dependent variable must also have a common mean in different waves and the initial values must not affect the latter health status. In addition, the initial values must be normally distributed. The unobserved individual effect must be independent of the unobserved dynamic process so that the process can converge towards a common mean. Lastly, the unobserved individual effect must be independent of the unobserved dynamic process because initial value are random (Anderson and Hsiao, 1982).

These are strong assumptions, and SRHS fails to meet the requirements (Anderson and Hsiao, 1982). The beginning of health cycle is unknown because the things that happen before a child is born have a bearing

on the adult's health. The SRHS does not converge to a common mean, the health is random, and it is influenced by many factors (Deaton and Paxson, 1998). The initial health influences the latter health statuses which violates initial condition.

Arellano and Bond (1991) confirm that the simple dynamic model cannot be used to study dynamics of health. SRHS is a variable in micro-panel, which are naturally short. In the short panel, N →∞ and T → Fixed number. Arellano and Bond (1991) found that a simple dynamic model on a short panel will produce inconsistent results.

Wooldridge (2005) suggests that Conditional Maximum Likelihood Estimation (CMLE) deals with the error term (ϵ_{it}) of the equation (2). The inclusion of the initial values of the dependent variable as the explanatory variables transform the error term into an Independent and Identically Distributed (IID); this process produces an error term that is comparable to the error term when the variables obeys the initial conditions (Wooldridge, 2005 and Anderson and Hsiao, 1982). The error term contains the unobserved individual heterogeneity and the process that controls for the individual heterogeneity makes the error term, ($\varepsilon_{i1} + v_{it}$), normally distributed and eliminates unobserved heterogeneity (Wooldridge, 2005).

$$SRHS_{it} = \gamma \mathrm{SRHS}_{it-1} + \boldsymbol{\beta} X_{it} + \boldsymbol{\delta} Z_{it} + \epsilon_{it} \qquad (2)$$

$$\epsilon_{it} = \mu_{it} + v_{it} \qquad (3)$$

$$\mu_{it} = \alpha_i + \varphi \mathrm{SRHS}_{i1} + \omega Z_i + \varepsilon_{i1} \qquad (4)$$

$$\mathrm{SRHS}_{it} = \gamma \mathrm{SRHS}_{it-1} + \boldsymbol{\beta} X_{it} + \boldsymbol{\delta} Z_{it} + \varphi \mathrm{SRHS}_{i1} + \omega \overline{X}_i + \varepsilon_{i1} + v_{it} \qquad (5)$$

v_{it} is IID. (σ_{vit} ; 0) and ε_{i1} is IID. ($\sigma_{\varepsilon_{i1}}$; 0)

Where, for any individual *i* at wave *t*: $SRHS_{it}$ represent current health status, SRHS_{it-1} represent previous health status, $SRHS_{i1}$ represent initial health status, X_{it} are the variables of interest such as the livelihood environment; nutrition; lifestyle; access to healthcare and social capital. $\overline{X}_i$ is the average of the explanatory variables such as income. Z_{it} is the control variable such as age and financial standing at age of 15. ϵ_{it} represent the error term, this is the variation in things that are not included in the model μ_{it} in equation (3) is the systematic error term, individual variation that is not controlled. ε_{i1} and v_{it} are the random part of the error term, while α_i is the unobserved part of the systematic error term and it has a constant value.

Therefore, when both initial and lagged variable are added in the model, the unobserved part of the systematic error term falls out because both the current and previous health status contain the same value

with different signs. CMLE controls for the initial condition (Wooldridge, 2005). The model produces consistent results even though both the initial conditions and the asymptotes requirements maybe violated.

In the NIDS data set, SRHS takes the value of one if the person reports excellent health and five if the person reports poor health. This study reverses the code from one for excellent to five and from five for poor to one. This process simplifies the interpretation of the results. A positive coefficient indicates that the people that previously reported excellent, very-good, good and fair health statuses have higher probability of being in the same health statuses in current wave than the people that previously reported poor health status which is the base category. While a negative sign indicates that the people that previously reported excellent, very-good, good and fair health statuses have lower probability of reporting same health statuses than the people that previously reported poor health status.

Gamma, γ, in equation (5) measure the relationship between current health and the previous health status. The value of gamma is constrained between [-1, 1]. The significance and the size of the estimated coefficients on the lagged categories of the dependent variable assess health mobility. Large and highly statistically significant suggest that the current health has a strong relationship with previous health status. Small and highly statistically significant suggests that the current health status has a weak relationship with previous health status. Insignificant Coefficients show that the previous health has no relationship with previous health status and significant coefficient shows that the current health is significantly related to the past health (Contoyannis, et al., 2004).

The coefficient on the initial variable of health, φ, gives insight into the nature of health mobility. If coefficient on initial health is statistically significant and lower than the coefficient on the corresponding lagged health variable, health mobility has decreased health inequality (Contoyannis, et al., 2004). On the contrary, if the coefficient on initial health is statistically significant and higher than the coefficient on the corresponding lagged health variable, health mobility has not decreased health inequality. If coefficient on initial health is not statistically significant and coefficient on the corresponding lagged health variable is positive and significant, health mobility will decrease health inequality (Hauck and Rice, 2004).

This research control for various social factors that are associated with health because the analysis of the dynamics of health that does not control for the social determinants of health is deemed unspecified which causes the coefficients to be biased (Marmot, 2017). The social determinants of health as identified by the literature are access to healthcare, livelihood environment, nutrition intake, social capital and individual lifestyle. Table 6 shows the social determinants of health and how they are measured.

Table 6: Variables

Variables	Description
SRHS	Self-Reported Health Status: 5 if excellent, 4 if very good, 3 if good, 2 if fair and 1 if poor.
Livelihood environmental	
Clean source of light	1 if the person uses electricity from the grid or generator, zero otherwise
Proper sanitation	1 if household has appropriate toilet and access to water.
A good home	1 if the person lives in house made of brick, zero otherwise
Household size	Number of people of the people that live in the household.
Access to healthcare	
Healthcare demand	When respondent last consulted someone about their health. This is ranked from 1 to 5, where the people that reported 5 are people that frequently consult about healthcare.
Nutrition intake	
Food per capita	Amount of money spent on food by household divided by number of people in the household.
Portion of income spent on food	The portion of income spent on food. Amount spent on food divided by income per household.
Social capital	
Trust	If the individual lost a wallet with R200, how likely for it to be returned. Higher rating show that a person has high trust.
Married	1 if the person is married, zero otherwise
Widowed or divorced	1 if the person is widowed or divorced, zero otherwise
Fights	It is on the scale of 1 to 5 which assess the level violence exposure for the household.
Lifestyle	
Unhealthy behaviour	The person engages in gambling, smoking and alcohol consumption. The people with the highest ranking are involved in gambling, smoking and consume alcohol.
Control variables	
Education	It is continuous variable reporting highest education.
Log of mean income	The log of average of income per capita in five waves.
Log of real income	The log of real income per capita
Employed	1 if the person is employed zero otherwise
Unemployed	1 if the person is in labour market but not employed and zero otherwise
Financial standing at 15 years	Household financial standing at age of 15 years old. This is a constant value which is on a scale of 1 to 6. 1 is for the poorest families and 6 is the richest families.
Urban	
Race	Africans is base category other categories are Coloured, Indian and White
Age	The age in the first wave, age square and up to fourth power is included. Age doesn't change within the panel because change would be for everyone this can cause a bias in analysis.

Source: author. Literature that was consulted includes Omotoso and Koch, 2018 and Hauck and Rice, 2004.

Conditional Maximum Likelihood Estimation results

The results for the different SES groups are reported separately in Table 7. The models for men and women are presented separately and further, in each gender group, the results for the poor and non-poor are reported separately throughout. The separation control for systematic heterogeneity which is reported between males and females, and poor and non-poor (Wooldridge, 2005).

Table 7: Health mobility in each SES group

	Poor Male	Poor female	Non-Poor male	Non-poor female
Lagged (t-1) health (good is the base)				
Excellent health	0.086	0.316**	0.437***	0.231***
Very-good health	0.118	0.275**	0.395***	0.22***
Good health	0.073	0.295**	0.308***	0.21***
Fair health	-0.214	0.344**	0.229***	0.124***
Initial condition (wave1) (good is the base)				
Excellent health	0.453***	0.24**	0.356***	0.337***
Very-good health	0.363**	0.329***	0.321***	0.323***
Good health	0.372**	0.178	0.277	0.233***
Fair health	0.111	0.048	0.089	0.089**
Environment				
Clean light	0.171**	0.185***	0.156***	0.167***
Proper sanitation	-0.024	-0.108**	-0.065***	-0.011
A good home	0.045	0.002	0.013	-0.003
Household size	-0.01	0.018*	0.005	0.011***
Access to healthcare				
Healthcare demand	-0.081***	-0.127***	-0.126***	-0.125***
Nutrition intake				
Food per capita	-9.01 E-6	0.001*	-2.35 E-5	3.3 E-4
Portion of income spent on food	0.129*	0.019	-0.002*	-0.006**
Social capital				
Trust	0.037	0.007	0.04***	0.013**
Married	-0.027	0.056	0.136***	0.06***
Widow or divorced	-0.153	0.006	0.061	0.016
Fights	-0.047**	-0.019	-0.004	-2.00E-3
Life style				

Unhealthy index	-0.091**	0.048	-0.083***	-0.057***
Control variables				
Education	0.023**	0.044***	0.027***	0.021***
Log of real income	-0.003	-0.026	0.004	-0.013
Log of mean income	0.093*	0.02	0.075***	0.072***
Employed	0.075	0.08	0.142***	0.114***
Unemployed	0.059	0.254***	0.141***	0.085***
Financial standing at 15 years	0.016	0.018	0.026***	0.02***
Urban	-0.024	-0.124	-0.086***	-0.136***
Coloured	0.023	0.004**	0.032**	0.014
Indian	4.704		-0.177***	0.01
White	-0.377	-0.111	0.004	0.167***
Age	-0.014	0.066	0.006	0.007
Age^2	0.015	-0.23	-0.125	-0.101
Age^3	-0.062	0.217	0.23	0.142
Age^4	0.067	-0.037	-0.135*	-0.064
Rho	0.038	0.054	0.032	0.082
Log Likelihood	-1841.241	-3332.803	-3179.141	-20289.505
N	1 467	2 547	2 561	16 482

Note: The table shows the relationship between current health and the previous health, which indicates health mobility, and the relationship between initial health status and current health status, which indicates individual heterogeneity. Poor health status is the base category. * shows the significance at 1% ** shows the significance at 5% and * shows the significance at 10%.*

Table 7 shows that among poor males, the coefficient on the variables for previous health status is not significant. Wald test show that the results are reliable for intepretation, because variables that are theoretically correlated with health in South Africa are also included in the model. The people that have previouslly reported excellent, very good, good and fair health statuses do not significantly have higher probability of reporting same health statuses than people that have previously reported poor health status. This suggest a high health mobility in the group of poor males.

It is worth noting that coefficients on variables for intitial excellent, very good and good health statuses are statistically significant; each of the coefficients also have a high values which are more than 0.35. Only the coefficient on variable for initial fair health status is not statistically significant ; the probability of reporting fair health status for those initially reported fair health status is not significantly higher than for those initially reporting poor health status. This suggest that, apart from people that initially reporting fair health

status, high health mobility that is observed will not decrease health inequality within poor males group in a long-run.

Among poor females, all coefficiences on the previous health variables are statisticaally significant, and the coefficients follow a limited negative health gradient. Wald test show that the results are reliable for intepretation and the inclusion of the social determinants of health eliminate possibility of biased estimation. Coeffient on variable for people that previously reported excellent health status is 0.316 and it is significant at 5% significance level. The value of coefficient on the variable for people that previously reported very good is lower than for excellent variable at 0.275 and significant at 5% significance level. However, the coefficient on variable for people that previously reported good is higher than coefficient on variablefor very good health at 0.295 and significant at 5% significance level. Coefficent on variable for people that previously reported fair health status is the highest at 0.344 and significant at 5% significance level. The result suggests that health mobility follows a negative health mobility apart from variable for those previously reporting excellent health status.

It is noted that coefficients for the initial variables for health are smaller in magitude than coeffiences on the previous health variables apart from the coefficient on the variable for people that previously reported very good health status. This suggest that health mobility will decrease health inequality among the poor females. However, health mobility will decrease health inequality at a rate that favours the poor females that previously reported better health, which suggests that an aid that would move people from fair and poor health status would accelerate health mobility and the rate at which health inequality decreases.

Among non-poor (both males and females), health gradient that favours the people that previously reported fair health (positive gradient) is observed. The coefficients on the variables for previous health are statistically significant and Wald test show that the results are reliable for intepretation. Since social determinants of health are included, the results are not biased. The results show that the people that previously reported better health are more likelly to report same health compared to people that previously reported worse health status.

In group of non-poor males, the coefficient on variable for people previously reported excellent, very good, good and fair health statuses are 0.437, 0.395, 0.308 and 0.229, respectively. These coefficients are significantly higher than the value of corresponding coeffcients that are on the variables for people initially reported the health status. This suggest that postive health mobility observed in non-poor males will decrease health inequality in long-run.

Among the non-poor females, the coefficient on variables for people previous reported excellent, very good, good and fair health statuses are 0.23, 0.22, 0.21, and 0.124, respectively. These coefficients are significantly lower than corresponding coefficients on the variables for initially reported health status, beside for fair health status. The results show that health mobility in non-poor females has not decreased health inequality.

This research uses the quadrature to test the robustness of the results. When the number of quadrature needed for the model to produce the result are changed, the results for all groups remain stable. Therefore, current results are reliable because it is also noted that Rho statistics are lower than 0.1 for all the groups; unobserved individual heterogeneity has low or no impact on the results. In addition, Wald test, Quadrature test, Likelihood ratio test and attrition test show that these results are reliable.

Discussion of the results and conclusion.

The transition matrix shows that health mobility in all the groups follows a positive gradient constraint pattern; people are likely to report a better health statuses in succeeding wave. The results suggest that health mobility will decrease health inequality. Howoever, transitional methodology encounters a number challenges that couldn't be addressed; the results might not be realiable, but they give us indication on what to expect from conditional maximum likelihood estimation results.

Therefore, conditional maximum likelihood estimation was used to control for social determinants of health; this research has controlled for variables for access to healthcare, livelihood environment, nutrition intake, social capital, and individual lifestyle. The inclusion of social determinants of health produce efficient estimates of coefficient on variable for previous and initial reported health status.

This research finds that, among poor males, health have high mobility, but the mobility has not decreased health inequality over the period. The results do not clearly show whether health mobility follows a gradient constraint or health selection pattern; the coefficients on the variables for previous health are not statistically significant. When ambiguous trend of health mobility prevails, it is difficult to suggest a policy. However, it is clear that the group of poor men have high health mobility in short period; when the experience health shocks or illness, they recover quickly.

This the trend that Professor Sir Michael Marmot observed in many country; Marmot (2017, p. 686) asks: "why treat people and send them back to the conditions that made them sick?" In case of South Africa, it is known that many people live in poor livelihood and work in harzadous environment, and the government have provided free access to healthcare. If this is the explaination for the observed health mobility among

poor males, then this research suggest that policy makers should target the cause of health shocks which is found in poor livelihood environment (Ataguba et al., 2011).

The second explaination of the health mobility that is observed among the poor men is their association or health selection. The poor men might be using curative healthcare and not investing in preventative healthcare which can explain high health mobility. If this is the explaination, then policy makers should emphasise in health compaigns to alter the destructive behaviour.

Ataguba et al. (2011) found that South Africa represents a classic example of the inverse care law. The healthcare usage decreases as the need for healthcare increases. Poor people and people that report poor health status have tendencies to use the curative healthcare while non-poor and people that report excellent health status have tendencies to use the preventative healthcare (Ataguba et al., 2011). This research find that the policy makers will need to intervene for the health inequality to decline. However, this research find that it will require an innovative strategy.

The results for poor females have shown that health mobility follows a limited negative health gradient. Limited negative health gradient suggests that poor females might experience health threshold on their health mobility. The negative gradient is associated with a threshold in health mobility, if people in lower health levels are unable to recover their health in long time (Mutyambizi, et al., 2019). At the first glance, the results suggest that probability of being stuck in bad health status increases as the previous reported health status decrease towards poor health status.

However, further investigation shows that, among poor females, health mobility has decreased health inequality limited to people initially reported very good health status. The coefficient on the variable for people initially reported fair or good health status are not statistically significant which indicate a high health mobility over the period which dismiss the possibility of health threshold. The results show that health selection can reduce health inequality in certain conditions. In South Africa, the use of Practical Approach to Care Kit (PACK) has influenced poor women to use preventative healthcare which can explain the decreasing health inequality that is observed in negative health gradient (Murdoch, et al., 2020). The results also suggest that policy makers can increase health mobility if they increase access to social determinants of health; reversing negative trend of health mobility would increase health mobility and increase rate at which health inequality decreases.

The results for non-poor males show that health mobility follows gradient constraint. Health mobility in this group is an ideal mobility beacause people that have previoyusly reported better health such as excellen

and very good have high probalility of reporting same health status while people that previously reported bad health have high probability of reporting a better health status in current wave. Gradient constraint is a result of access to social determinants of health which provide a protection against health shocks, and when non-poor males get ill, they recover their health as shown by high health mobility among the people previously reported lower health statuses because non-poor males have acess to both preventatitive and curative healthcare (Harris, et al., 2011).

The results suggests that the health mobility has decreased health inequality over the period of the study. The coefficients on the variable for previous health are greater in value than the coefficients on the variables for initial health statuses. Non-poor males have established networks that enhance improvement in their health and they have access to social determinants of health which enhances health gradient constraint.

The results for non-poor females show that health mobility follows a postive health gradient. Health mobility increases as previous reported health status decreases from excellent health status to fair health status. The results show a high health mobility between waves of the panel. The probability of reporting same health status as the previous wave is lower for non-poor females than non-poor males. High health mobility among non-poor females contradicts the expected results because womens are better examiners of their health than men and are expected to use preventative healthcare (Harris, et al., 2011). Therefore, compaigns would decrease the effects of health mobility that follows a health selection pattern.

The results show that health inequality, among non-poor females, has not decreased over the period; the coefficients on the variables for previous health statuses are smaler in size than the coefficient on the variables for initial health beside fair health status. The results show that health has high mobility, but health mobility has not changed distribution of health in a long-run. Therefore, compaigns that encourages people to join network and lifestyle that keep them health would enable health mobility to decrease health inequality in a long-run (Pulsford et al., 2015).

This research finds that, among poor males, health mobility has no particular pattern and health mobility does not decrease health inequality in long-term. Therefore, response from the policy makers need to address the issue of health inequality through both social determinants and campaigns. Among poor females, it is observed that health mobility follows a negative gradient which does not decrease health inequality; the response needs to address health inequality through social determinants. Among non-poor males, it is observed that health mobility follows a positive gradient and health mobility decreases health inequality. Lastly, among non-poor females, health

mobility follows a positive gradient, but health mobility will not decrease health inequality; it is suggested that health campaigns are needed to decrease the impact of health selection mobility.

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