Socioeconomic status and chronic diseases in South Africa

by

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Declaration

By submitting this thesis electronically, I declare that the entirety of the work contained therein is my original work, that I am the authorship owner thereof (unless to the extent explicitly otherwise stated) and that I have not previously in its entirety or part submitted it for obtaining any qualification.

Declaration by the Candidate

With regard to Chapter 2, the nature and scope of my contribution were as follows:

Nature of contribution	**Extent of contribution (%)**
Formulate research question and develop the concept, data analyses and interpretation, and writing of first and final draft	75%

The following co-authors have contributed to Chapter 2:

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Date: 23 September 2021

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The undersigned hereby confirm that:

1. the declaration above accurately reflects the nature and extent of the contributions of the candidate and the co-authors to Chapter 2,
2. no other authors contributed to Chapter 2 besides those specified above, and
3. potential conflicts of interest have been revealed to all interested parties and that the necessary arrangements have been made to use the material in Chapter 2 of this dissertation.

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Abstract

The global burden of non-communicable diseases (NCDs) is on the rise, and is expected to increase. The United Nations, through the 2030 Agenda for Sustainable Development Goals, acknowledged the public health importance of addressing NCDs, and set a goal to reduce premature mortality from NCDs by one-third by 2030. Key to achieving targets for prevention and control of NCDs is a holistic approach to understanding the underlying contextual causes. This thesis examines the role of inequality in socioeconomic status in the development of chronic diseases in South Africa, a highly unequal middle-income country battling communicable diseases and maternal and child mortality. To achieve this, the study had three objectives: (1) To examine how exposure to negative household events and neighbourhood characteristics relates to systolic blood pressure in South Africa; (2) To determine socioeconomic factors that explain depressive symptoms in South Africa; and (3) To ascertain the influence of the COVID-19 pandemic on income-related inequality in depressive symptoms in South Africa. The study is presented in three essays.

In the first essay, I estimate the relationship between systolic blood pressure and exposure to stressful (negative) household events and neighbourhood characteristics. Using the correlated random effects model, I found that systolic blood pressure is significantly higher among respondents from households that had registered the death of a household member and those that reported a reduction in grant income and remittances. The direct effects of neighbourhoods were related to neighbourhood income level, whereby moving from a low-income neighbourhood to a middle-income neighbourhood was negatively associated with systolic blood pressure. With regard to the heterogenous effects of neighbourhoods, I found a negative and significant mean-level "job loss" effect. The implications of the study results are vast in a country like South Africa, which is already burdened with high mortality due to causes such as human immunodeficiency virus/acquired immunodeficiency syndrome (HIV/AIDS) and tuberculosis (TB), injury and homicide, and NCDs such as cardiovascular diseases and diabetes.

In the second essay, I examine the relationship between depressive symptoms and socioeconomic factors using the ordinary least squares model and the fixed effects model. Results from both models suggest significant socioeconomic gradients in depressive symptoms, whereby depressive symptoms are negatively associated with per capita household income, education, and social capital. However, I found a positive and significant association

between depressive symptoms and unemployment only in men. The significant differences in the effects of variables by gender and by residence are a unique contribution to understanding the differences in health in South Africa, and may inform policies. Firstly, there are significant gender- and residence profiles in depression. Secondly, men who self-report good health may overestimate their health, most likely by excluding their state of mental health. Lastly, whilst the goal is to reduce the prevalence of mental disorders by targeting socioeconomic factors, differences by gender and residence underscore the need for mental health policies that promote equity.

As reported in the third essay, I used a recentred influence function regression decomposition method developed by Heckley *et al*. (2016) to ascertain the influence of the COVID-19 pandemic on inequality in depressive symptoms related to income in South Africa. I found that the COVID-19 pandemic negatively and significantly influenced income-related inequality in good mental health in South Africa. This means that the COVID-19 pandemic disproportionately increased mental health problems amongst the affluent. I did not find an education profile in the joint distribution of income and mental health. Self-reported health-, age-, population group-, and gender profiles were present in the covariance between Income and good mental health.

I used publicly available longitudinal data from the South African National Income Dynamics Survey in the study. Overall, the findings of this study suggest that socioeconomic factors contribute to the rising burden of chronic diseases in South Africa. Notwithstanding the study's limitations, this thesis makes a significant contribution to understanding the typical mechanisms and pathways through which poverty and chronic conditions interact and reinforce each other in South Africa, and other low- to middle-income countries. This, in turn, provides useful inputs for policy and programmes to address the burden of chronic conditions in poor societies.

Whilst pharmacological and medical technology advancements are important in extending life expectancy, socioeconomic interventions are equally important in curbing both rising morbidity and mortality from chronic diseases, and in addressing poverty and inequalities in low- to middle-income countries. Unlike physiological causes, socioeconomic determinants of health can be influenced through health- and government policy interventions, which could also be justifiable in terms of efficiency and equity.

Opsomming

Die wêreldwye las van nie-oordraagbare siektes is aan die toeneem, en sal na verwagting vinniger toeneem. Die Verenigde Nasies het deur middel van die 2030 Agenda for Sustainable Development Goals vir volhoubare ontwikkelingsdoelwitte die belangrikheid van openbare gesondheid erken om sulke siektes aan te spreek, en die 'n doelwit gestel om voortydige mortaliteit van nie-oordraagbare siektes teen 2030 met een derde te verminder. Die sleutel tot die bereiking van teikens vir voorkoming en beheer van sulke siektes is 'n holistiese benadering om die onderliggende kontekstuele oorsake te verstaan. Hierdie tesis ondersoek die rol van ongelykheid in sosio-ekonomiese status in die ontwikkeling van chroniese siektes in Suid-Afrika, 'n hoogs ongelyke middelinkomsteland wat sukkel met oordraagbare siektes en moeder- en kindersterftes. Om dit te bereik, het die studie drie doelwitte gehad: (1) Om te ondersoek hoe blootstelling aan negatiewe huishoudelike gebeure en woonbuurt-eienskappe verband hou met sistoliese bloeddruk in Suid-Afrika; (2) Om sosio-ekonomiese faktore te bepaal wat depressiewe simptome in Suid-Afrika verklaar; en (3) om vas te stel wat die invloed van die COVID-19-pandemie op inkomsteverwante ongelykheid in depressiewe simptome in Suid-Afrika is. Die studie word in drie artikels aangebied.

In die eerste artikel skat ek die verband tussen sistoliese bloeddruk en blootstelling aan stresvolle (negatiewe) huishoudelike gebeure en woonbuurt-eienskappe. Deur die gekorreleerde ewekansige effekte-model te gebruik, het ek gevind dat sistoliese bloeddruk aansienlik hoër is onder respondente van huishoudings wat die dood van 'n huishoudinglid geregistreer het en diegene wat 'n vermindering in toelae-inkomste en -oorbetalings gerapporteer het. Die direkte gevolge van woonbuurte was verwant aan buurtinkomstevlak, waardeur die verskuiwing van 'n lae-inkomstebuurt na 'n middelinkomstebuurt negatief geassosieer is met sistoliese bloeddruk. Met betrekking tot die heterogene uitwerking van woonbuurte, het ek 'n negatiewe en beduidende gemiddelde-vlak "werkverlies"-effek gevind. Die implikasies van die studieresultate is groot in 'n land soos Suid-Afrika, wat reeds belas is met hoë mortaliteit as gevolg van oorsake soos menslike immuniteitsgebrekvirus/verworwe immuniteitsgebreksindroom (MIV/VIGS) en tuberkulose (TB), beserings en moord, en nie-oordraagbare siektes soos kardiovaskulêre siektes en diabetes.

In die tweede opstel ondersoek ek die verband tussen depressiewe simptome en sosio-ekonomiese faktore met behulp van die gewone kleinste-kwadrate-model en die vaste-effekte-model. Resultate van beide modelle dui op beduidende sosio-ekonomiese gradiënte in

depressiewe simptome, waardeur depressiewe simptome negatief geassosieer word met per capita huishoudelike inkomste, onderwys, en sosiale kapitaal. Ek het egter slegs by mans 'n positiewe en beduidende verband tussen depressiewe simptome en werkloosheid gevind. Die beduidende verskille in die uitwerking van veranderlikes volgens geslag en woonplek is 'n unieke bydrae om die verskille in gesondheid in Suid-Afrika te verstaan, en kan beleidsrigtings bepaal. Eerstens is daar beduidende geslags- en verblyfprofiele in depressie. Tweedens, mans wat self goeie gesondheid rapporteer, kan hul gesondheid oorskat, heel waarskynlik deur hul toestand van geestesgesondheid uit te sluit. Laastens, hoewel die doelwit is om die voorkoms van geestesversteurings te verminder deur sosio-ekonomiese faktore te teiken, beklemtoon verskille volgens geslag en woonplek die behoefte aan geestesgesondheidsbeleide wat gelykheid bevorder.

Soos gerapporteer in die derde opstel, het ek 'n hersentreerde invloedsfunksie-regressie-ontbindingmetode gebruik wat deur Heckley *et al.* (2016) ontwikkel is om die invloed van die COVID-19-pandemie op ongelykheid in depressiewe simptome wat met inkomste in Suid-Afrika verband hou, vas te stel. Ek het gevind dat die COVID-19-pandemie inkomsteverwante ongelykheid in goeie geestesgesondheid in Suid-Afrika negatief en beduidend beïnvloed het. Dit beteken dat die COVID-19-pandemie geestesgesondheidsprobleme onder die welvarendes buitensporig verhoog het. Ek het nie 'n profiel met betrekking to vlak van onderrig in die gesamentlike verspreiding van inkomste en geestesgesondheid gevind nie. Profiele van selfgerapporteerde gesondheid, ouderdom, bevolkingsgroep en geslags was in die kovariansie tussen inkomste en goeie geestesgesondheid teenwoordig.

Ek het publieke longitudinale data van die Suid-Afrikaanse Nasionale Inkomstedinamika-opname in die studie gebruik. Oor die algemeen dui die bevindinge van hierdie studie daarop dat sosio-ekonomiese faktore bydra tot die toenemende las van chroniese siektes in Suid-Afrika. Nieteenstaande die studie se beperkings, lewer hierdie tesis 'n beduidende bydrae tot die begrip van die tipiese meganismes en weë waardeur armoede en chroniese toestande in wisselwerking tree en mekaar versterk in Suid-Afrika, en ook in ander lae- tot middel-inkomstelande. Dit verskaf, op sy beurt, nuttige insette vir beleid en programme om die las van chroniese toestande in arm samelewings aan te spreek.

Terwyl farmakologiese en mediese tegnologiese vooruitgang belangrik is om lewensverwagting te verleng, is sosio-ekonomiese intervensies ewe belangrik om beide stygende morbiditeit en sterftes weens chroniese siektes te bekamp, en om armoede en ongelykhede in lae- tot middelinkomstelande aan te spreek. Anders as fisiologiese oorsake, kan sosio-ekonomiese determinante van gesondheid beïnvloed word deur gesondheids- en regeringsbeleidsingrypings, wat ook regverdigbaar kan wees in terme van doeltreffendheid en billikheid.

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List of abbreviations and acronyms

AC	absolute concentration index
ARCI	attainment-relative concentration index
BMI	body mass index
EI	Erreygers Index
PHQ-2	Patient Health Questionnaire-2
CES-D10	10-item Centre for Epidemiologic Studies Depression Scale
CFEL	conditional fixed effects logit
CRE	correlated random effects
DBP	diastolic blood pressure
FE	fixed-effects models
IF	influence function
LMINCs	low- to middle-income countries
NCDs	non-communicable diseases
OLS	ordinary least squares
RE	random effects
RIF	recentered influence function
SBP	systolic blood pressure
SES	socioeconomic status
SRCI	shortfall-relative concentration index
WI	Wagstaff Index
ZAR	South African rand

Chapter 1

Introduction and background of the study

1.1 Introduction

The global burden of chronic diseases, also known as non-communicable diseases[1] (NCDs), is on the rise, and is expected to increase. This despite the fact that, in 2016 alone, NCDs contributed 71% of global deaths and 75% of premature deaths (people between the ages of 30 and 60 years) (World Health Organization, 2018). Developing countries are the main contributors to the rising global burden of chronic diseases, due to epidemiological transition in these countries (GBD 2017 Risk Factor Collaborators, 2018; World Health Organization, 2014, 2018). More than three quarters (78%) of global NCD deaths and 85% of global premature deaths are in low- and middle-income countries (LMICs) (World Health Organization, 2018). In sub-Saharan Africa, total disability-adjusted life years (DALYs) due to NCDs increased by 67% between 1990 (90.6 million) and 2017 (151.3 million), translating to a 11.2% increase in the proportion of total DALYs attributable to NCDs over the same period (Gouda *et al.*, 2019). This is worrying, as these countries are still facing a high prevalence of communicable diseases, with very limited fiscal ability to fight these from different fronts.

Due to these alarming statistics, the United Nations, through the 2030 Agenda for Sustainable Development Goals, acknowledged the public health importance of addressing NCDs (United Nations General Assembly, 2015). The UN included a goal to reduce premature mortality from NCDs by one third, and set targets for addressing risk factors by 2030 under Sustainable Development Goal 3 (SDG 3) (United Nations General Assembly, 2015; World Health Organization, 2016). Key to achieving targets for NCDs prevention and control is a holistic approach to understanding the underlying contextual causes.

Over and above biological determinants, health outcomes are a result of micro and macro socioeconomic environments. Socioeconomic factors are increasingly recognised as the fundamental cause of diseases (Cockerham *et al.*, 2017). Over the last few decades, consensus was reached that health is determined by many factors other than medical care. For example,

[1] NCDs are non-transmissible medical conditions, which are often lengthy (Statistics South Africa, 2021). Examples include cardiovascular diseases, chronic respiratory diseases, diabetes, cancer, and mental illnesses. There is increased acknowledgement that mental health should be regarded as a chronic condition/disease, but this is still not widely done (Bernell & Howard, 2016).

McKeown (1979) suggests that factors such as food, housing and sanitary conditions, and work environment are as important as medical care in determining health, and questions the effectiveness of medicine and medical technology in improving health (Cochrane, 1972; DaVanzo & Gertler, 1990; Illich, 1976).

Unemployment, inequality, poverty, and high crime levels are some of the characteristics of developing countries that contribute most to modifiable or avertable behavioural risks such as an unhealthy diet, the abuse of alcohol, and physical inactivity (Jamison *et al*., 2006; Pampel, Krueger & Denney, 2010; Sen, 2002a; Stringhini *et al.*, 2017; Wagstaff, 1986). For example, Jamison *et al.* (2006) noted that hopelessness drives the youths into drug and alcohol abuse which are risks for physical chronic diseases and mental disorders. More so, unemployment and poverty hamper access to healthy diets, good sanitation, clean energy, and health care. Inadequate diet, poor sanitation, and gases from wood and are associated with avoidable poor health while lack of access to adequate health care will deter early diagnosis, timely treatment, and control of diseases. This may result in avoidable burden of disease.

Pampel *et al.* (2010) provide extensive mechanisms through which socioeconomic status (SES) relates to health behaviour. For example, the study suggests that people who are poor and live in poor neighbourhoods are exposed to chronic stress. Poor people, and in poor neighbourhoods, often face challenges in meeting the basic needs; experience more negative events like job loss or chronic illnesses; and deal with marginalisation daily. Stress from these challenges trigger maladaptive behaviours such as alcohol and drug abuse, smoking, overeating and physical inactivity (Pampel *et al.*, 2010). According to Pampel *et al.* (2010), lower earnings and wealth for low-SES people make them focus more on current health and less so on longevity. To this end, low-SES people are likely to spend their surplus income on immediate consumption regardless of the possibility of long-term health costs. Latent traits can also explain the role of SES on health behaviours. In the literature review, Pampel *et al.* (2010) found that crime, attraction to short-term gains, and unhealthy behaviours are influenced by early life family structure and community characteristics. The attraction to short-term gains can result in poor educational performance, limited employment opportunities, and unhealthy behaviour. Less educated people have limited knowledge on the effects of their lifestyle on their own health hence they have less motivation to lead healthy lifestyles.

The distribution of health follows a social gradient where those ranked the lowest in the social hierarchy have a higher risk of illness and a shorter life expectancy (Gallo *et al.*, 2012; Marmot *et al*., 2012; Marmot & Bell, 2016; Pongiglione *et al*., 2015). This socioeconomic gradient in health and longevity exists in all populations and regardless of the measures of socioeconomic status (SES) and health (Bor *et al*., 2017; Grossman, 2004). The socioeconomic status of an individual is a vector of a range of variables that include education, income, employment status, area of residence, housing, neighbourhood characteristics, gender, and ethnicity. These can affect the distribution of health outcomes between and within societies (De Andrade *et al.*, 2015) through their influence on lifestyle choices, health expectations, health-seeking behaviours, and access to healthcare (Brunello *et al*., 2016; Domènech-Abella *et al.*, 2020; Kraft & Kraft, 2021; Marmot, 2017a), resulting in unjust and avoidable health inequities (UCL Institute of Health Equity, 2014).

Neighbourhood characteristics such as deprivation, crime, and limited access to healthcare can aggravate the influence of individual socioeconomic status on health (Boyd *et al*., 2021; Cho *et al*., 2016; Evans *et al*., 2001). Health outcomes for poor people or people from neighbourhoods with high deprivation are poor (O'Donnell *et al*., 2008), while more affluent individuals and societies enjoy better health (Costa-Font & Hernández-Quevedo, 2012). These differences in health can be explained by differences in the quantity and quality of healthcare accessible to each socioeconomic group.

Research across multiple disciplines (including epigenetics, behavioural studies, economics, epidemiology, and demography) concur on the immense role of socioeconomic risks in the development and exacerbation of chronic diseases (Davidson, 2015; Galama & Van Kippersluis, 2018). Socioeconomic status can cause health and be caused by health, and socioeconomic status and health can be jointly determined (Bhattacharya *et al*., 2014). Hence differences in socioeconomic status directly result in disparities in morbidity and mortality (National Academy of Sciences, 2017; Whitehead & Dahlgren, 2007; Willson, 2009).

Epigenetics[2] research supports this notion by demonstrating that socio-environmental factors can bring about a change in a phenotype without a change in a genotype. Socioeconomic disadvantages affect biological functioning of people, exposing them to disease risk (Vineis *et al*., 2020; Wolfe *et al*., 2012). Behavioural science also suggests that health-related behaviours are largely formed by individuals' socioeconomic status, social environments, and the

[2] Epigenetics research attempts to answer questions on why the observable characteristics (phenotype) of the person may differ even if the underlying DNA sequence remains unchanged (Davidson, 2015).

neighbourhood-level characteristics to which they are exposed (Ahnquist *et al*., 2012; Kawachi & Berkman, 2003).

1.2 Economic theories for analysing the interaction between socioeconomic factors and health

Several economic theories have been developed to explain how socioeconomic status determines health, mainly through behaviours. These theories provide researchers with a conceptual framework for analysing the cyclical relationship between health and socioeconomic status and are used in topical policy issues such prevention of diseases and addressing socioeconomic inequalities in health. Below, I summarise models by Grossman (1972), and Wagstaff (1986).

1.2.1 The Grossman Model

Grossman (1972) posited a model that equates health to a capital stock since it depreciates overtime. At birth, an individual is endowed with a health stock, h_0, which deteriorates with age, and at any given time, desired health level can only be increased (replenished) by investing in health-producing goods and services. This desired level of health is achieved when the marginal cost of investing in health equals the marginal benefits derived from that investment.

The importance of socioeconomic status in health within the Grossman Model

Socioeconomic status, as measured by education, employment status, income, housing, and neighbourhood affluency or deprivation, crime, and greenness, among other variables is important in the production and sustaining of health. The "demand for health model" by Grossman illustrates how socioeconomic status is central to an individual's health through determining trade-offs between health and other goods.

The Grossman model can be illustrated through the following simplified intertemporal utility model (adapted from Muurinen (1982)):

$$U = U(\emptyset h_0, \dots, \emptyset h_T; Z_0, \dots, Z_T) \qquad 1$$

In this model, an individual maximises total utility which is a function of health (*h*) and consumption of other goods and services, *Z*, given budget and time constraints[3] – making *h* and *Z* tradable. At any given time period, *t*, an individual's health is a function of the health stock at birth, h_0, the health stock at time *t*, and the service flow per unit of health stock, $\emptyset$ (Grossman, 1972). The total life, *T*, of a person is endogenous to *h*. Health-related decisions such as lifestyle choices and healthcare-care seeking behaviour enter in the total utility function through *h*.

Modelling the total utility function as a series of individual decisions, we can show the intertemporal nature of health-related decisions. Because individuals value both current and future costs and benefits of their decisions, and differently so, their decisions are discounted by a time discount factor, τ, which ranges between zero (0) and one (1) and varies by the value that an individual places on future utility.

$$U = U(h_0, Z_0) + \tau U(h_1, Z_1) + \tau^2 U(h_2, Z_2) + \cdots + \tau^T U(h_T, Z_T) \qquad 2$$

(Muurinen, 1982)

Because health is a capital stock that: individuals can invest in; individuals transfer across time periods; and depreciates over time, with the depreciation rate increasing with age, we can specify an individual's net investment in health as:

$$h_{t+1} - h_t = I_t - \partial_t h_t \qquad 3$$

(Grossman, 1999; Muurinen, 1982)

where I_t is the initial investment in health, ∂_t is the depreciation rate for period *t*, and $\partial_t h_t$ is the depreciation of health. I_t is a function of spending on healthcare (HS_t), time spent in improving health (TH_t), and socioeconomic status (SES_t) (Bhattacharya *et al.*, 2014; Grossman, 1999), that is:

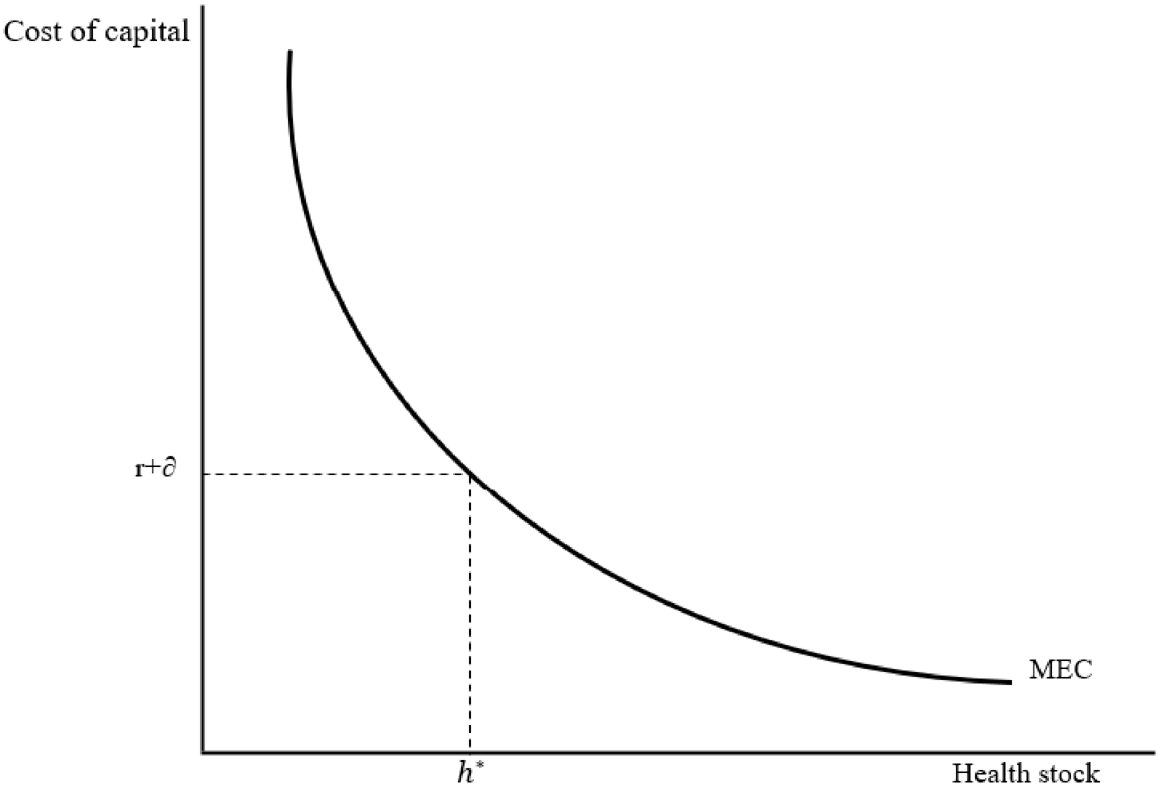
$$I_t = I_t(HS_t, TH_t, SES_t) \qquad 4$$

Given an individual's rate of return and their marginal efficiency of capital (MEC) curve, we can calculate an individual's optimal health stock h^* as shown in Figure 1. There are

[3] The total utility that an individual can achieve depends on their income, and in their time-spending decisions. Time can be spent on income generating or leisure activities; health-promoting activities; or illness due to inadequate spend on healthy activities or on income generating activities that could have enabled them to access healthy foods or to seek high quality healthcare.

diminishing marginal returns to health whereby at low levels of health, a small investment in health results in higher returns in terms of productive time hence the MEC curve is downward sloping. Depreciation of health (∂) and return to other investments other than health (r)[4] are the two costs of investing in health (Bhattacharya *et al.*, 2014). Health must return at least $r + \partial$ in order for the rate of return in health to be at par with rate of return to alternative investments. Hence, $r + \partial$ is the effective price of health stock (Bhattacharya *et al.*, 2014). Just like the demand curve, the MEC shows the optimal health (h^*) associated with the market price ($r + \partial$) of the health stock. At h^*, the marginal cost of investing in health equals the marginal benefit of investing in health.

Figure 1: Optimal health stock



Source: Bhattacharya et al. (2014)

In the Grossman model, the shadow price of health depends on factors other than medical care. The shadow price of health is positively associated with ageing, due to depreciation health stock. To this end, as an individual ages, the price of health will be greater than $r + \partial$, and the optimal health will be below h^*. The model suggests that a decrease in the shadow price can simultaneously increase the quantity of health demanded and reduce the quantity of health care

[4] This is the opportunity cost of investing in health over investing in other goods.

demanded (Grossman, 1972). Changes (increases) in an individual's wage and education will result in the shift of the MEC curve to the right, hence the optimal health will be greater than h^*, for the same cost of capital, $r + \partial$. Increased wage rate does not affect the cost of capital but increases the returns from healthy days. In relation to education, education improves the efficiency of an individual in producing health. For an educated person, less inputs are required to generate a given amount of investment.

However, it is important to note that this holds if we assume a positive relationship between education and health literacy. Education levels do not necessarily translate to health literacy, which is the ability to understand the health benefits of every choice one makes, from food and drinks, shelter, clothing, employment decisions, and spending, among other choices. People who are health literate are more likely to choose options that bring maximum health benefits such as buying food and drinks that have health benefits — guided by nutritional value of the food or drink item; having a gym subscription or spending time exercising — given the documented physical and mental health benefits of exercising; avoiding dangerous or health-threatening jobs; choosing healthy residential areas with good water, with sanitary and hygienic services, and far from pollution; having a medical aid to improve their access to critical but expensive medical care, i.e., good health-seeking behaviour; and health-promoting lifestyle choices in general — given that one cannot be healthier than one's lifestyle allows. Understanding the health benefits at a younger age will most likely increase longevity and reduce old-age-related ailments that are associated with higher shadow prices of health. Education, together with health literacy, is therefore a plausible factor in explaining health disparities between and within countries.

1.2.2 Wagstaff's economics approach to the demand for health

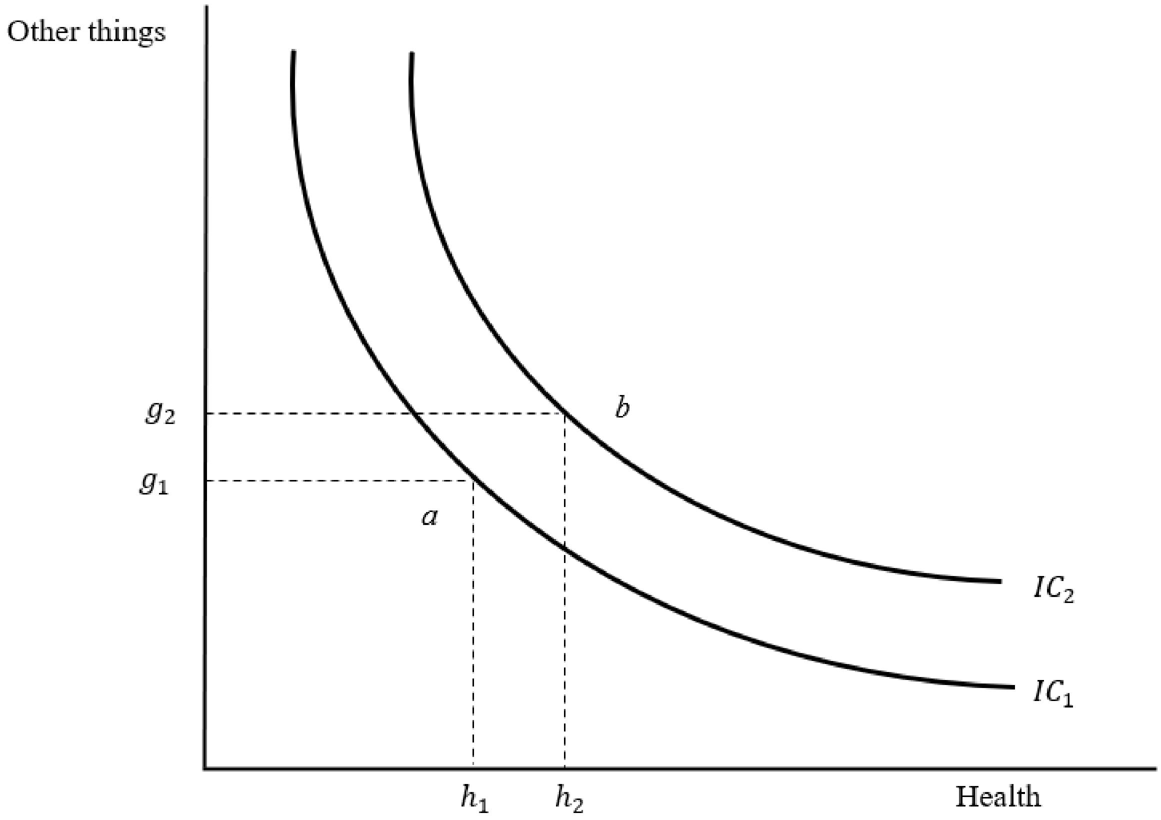
The demand-for-health approach of Wagstaff (1986) explains three concepts through which socioeconomic factors determine one's health[5], emphasizing the importance of non-medical factors on health. The model underscores the importance of targeting socioeconomic factors in the prevention of diseases, and in addressing socioeconomic inequalities in health.

[5] Socioeconomic status influences health through health behaviours or lifestyles such as consumption of health foods, access to healthcare, and health literacy (Wagstaff, 1986).

Concepts of the economics approach

The first is the concept is the indifference map. Under this concept, good health is assumed to be desirable because it feels good to be healthy, and being healthy increases one's productivity, among other reasons (Wagstaff, 1986). However, people and society do not place an overriding value on health over "other things"[6] in life such as education, defence, transport infrastructure, and sports and recreational activities (Wagstaff, 1986). This explains why people lose life from treatable illness due to insufficient resources allocated to saving every life. From the indifference curve concept, we can link an individual's several combinations of health and other things that give them the same level of welfare. To this end, the individual will be indifferent between the combinations on the same curve, say on indifference curve, IC_1 in Figure 2.

Figure 2: Indifference map



Source: Wagstaff (1986)

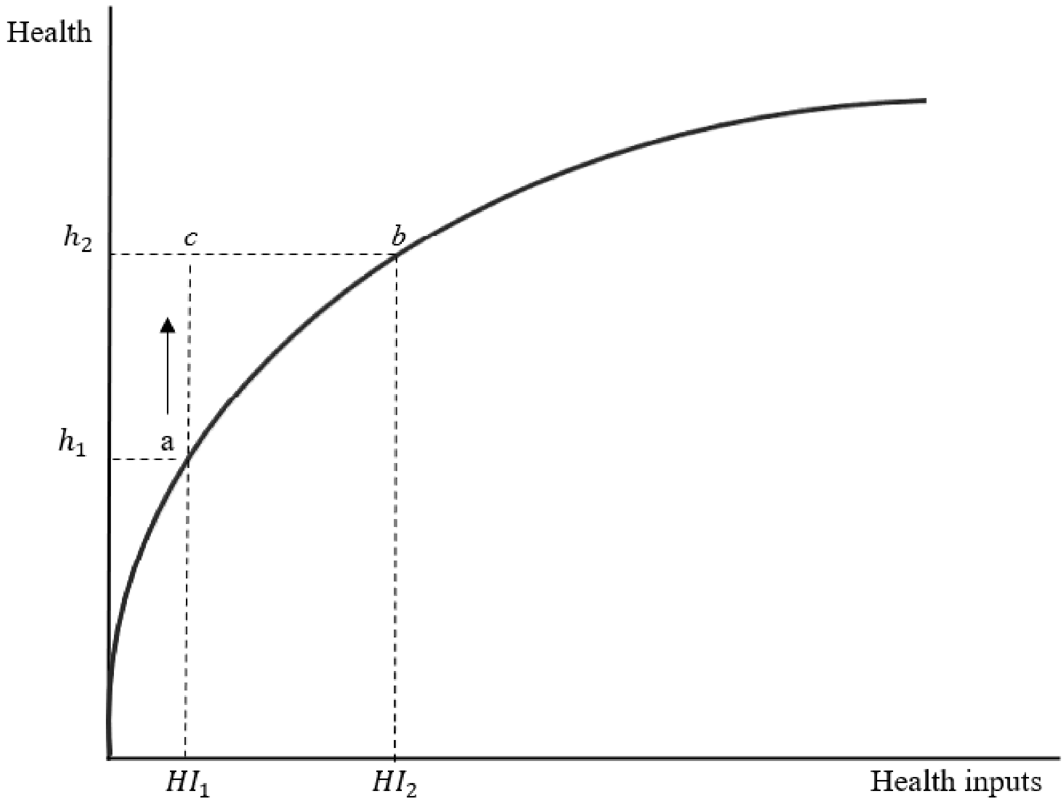
[6] Other things refers to anything else, but health, from which pleasure can be derived (Wagstaff, 1986).

The indifference curve is downward sloping because health is not valued over other things but that for each additional unit of health one gets, they lose units of "other things", and vice versa. Individuals are, however, not indifferent between curves for they always prefer a higher indifference curve which has more of both. For example, using Figure 2, combination b (h_2, g_2) on IC_2 in Figure 2 is preferred to a (h_1, g_1) on IC_1.

Second is the concept of a health production function suggests that people have control over their own since they can control factors such as healthcare utilisation, consumption of healthy foods, and environments, which affect their health. Based on the production function, health is produced from utilising health inputs, such as a balanced diet, exercise, sanitation, and healthcare utilisation (Wagstaff, 1986).

Figure 3 illustrates the health production function, with health inputs on the horizontal axis and health (output) on the vertical axis. For a given technical knowledge, health inputs HI_1 produces health, h_1 (point *a*) and an increase in health inputs from (HI_1 to HI_2) will result in the increase in health from h_1 to h_2 (point *b*). Thus, more, and successive additions to health inputs result in better and successive improvements in health. However, the marginal product of health inputs diminishes as additional health inputs are added. With this principle, the health production function can be used to explain how small increases in health inputs such as health food and sanitation for poor people or societies (who have few health inputs and low health) can result in relatively large changes in health outcomes while large increases in health inputs for the rich may result in relatively small changes in health.

Figure 3: Health production function

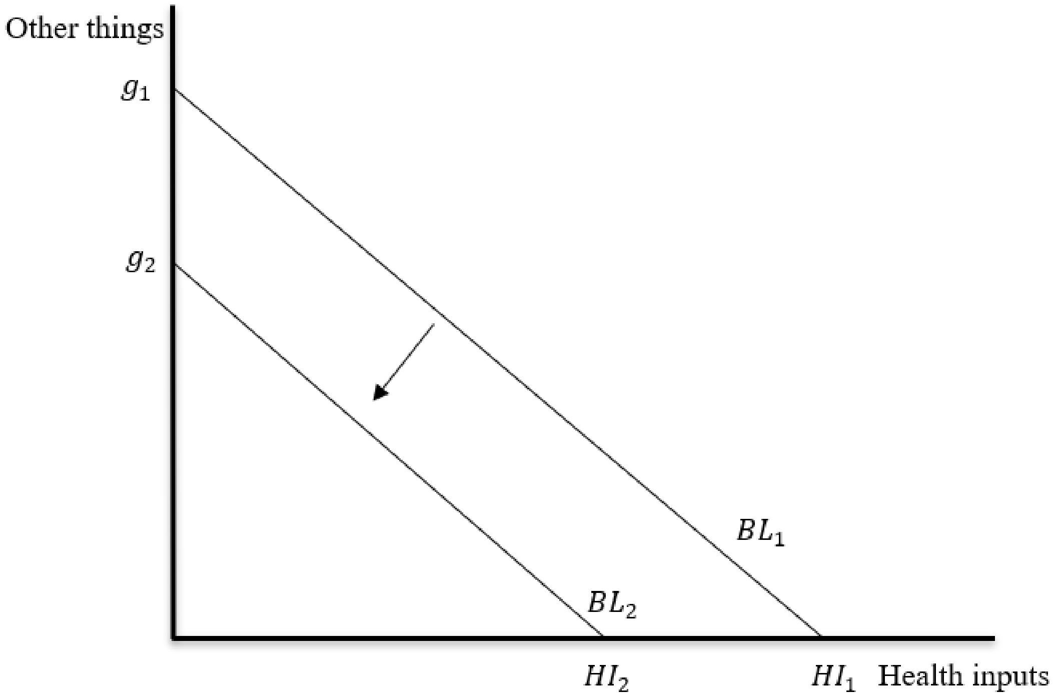


Source: Wagstaff (1986)

Technical knowledge in the production of health, however, changes with changes in medical science like increased understanding of the role of socioeconomic status in the development of chronic diseases. Changes in technical knowledge due to progress in medical sciences makes it possible for people and societies to produce health more efficiently. Improvements in technical knowledge may result in the production of more health with the same inputs. For example, technical efficiency may result in the production health level h_2 from health inputs HI_1, point *c*. Thus, improvements in technical knowledge would shift the production function upwards. Differences in technical knowledge can be use the explain the difference in health due to education. As compared to the less educated, more educated people are more likely to be health literate, making them more likely to understand health hazards of each of their choices, and to create a better diet from available food.

The last concept is the concept of the budget constraint. This concept states that health inputs and other goods are only available at a price. It also states that individuals have limited resources to meet their competing needs, financing health production, and other things. To this end, there will be a trade-off between health inputs and other things, as illustrated the downward sloping budget line BL_1 in Figure 4. If prices of health inputs and other things increase and income remain constant, the budget line will shift downwards to BL_2, which will have combinations of both fewer health inputs and other things. The budget line will also shift downwards if prices remain constant, but income is reduced, for example, through unemployment, reduced working hours, and reduced grant income. If prices of either health inputs or other things increase, with income constant, the budget line will swivel about its intercept on the axis of the good (health inputs or other things) whose price did not change.

Figure 4: Budget constraint



Source: Wagstaff (1986)

Given these concepts, we expect changes in the demand for health after policies such as supplementing the incomes of low-income families, subsidising the price of health inputs, improving the quality education, and creating employment.

Regardless of the differences in explanations in the Grossman (1972) and Wagstaff (1986) models, one can deduce that: socioeconomic factors do affect the initial level and successive improvement of one's health; individuals with a higher socioeconomic status have resources that offer protection against threats to their health; socioeconomic status is strongly associated with preventable health outcomes; and policies aimed at improving socioeconomic status can alleviate the burden of preventable diseases.

While a low socioeconomic status may contribute to the development of chronic diseases, it may also be an outcome of chronic diseases. The upsurge in chronic diseases is likely to counter poverty reduction initiatives in LMICs. This is due to the exorbitant costs associated with treating chronic diseases and related complications, which treatment is often long. Globally, a large share of health expenditure is channelled towards chronic diseases. In low-resource settings, such high healthcare costs quickly drain already shallow household resources and the lean government's purse. Due to less productivity, work-absenteeism, or incapacitation, chronic illnesses also result in loss of income, thereby forcing millions of people into poverty and stifling development (O'Donnell *et al*., 2015). Poverty also limits the ability of people with chronic diseases and their dependants to afford healthcare services and follow a healthy diet. Resultantly, these people remain trapped in poverty and poor health, a phenomenon that can be explained using Galama and Van Kippersluis's (2018) theory of socioeconomic disparities in health over the life cycle[7].

The socioeconomic costs of illness cannot be overemphasised, given that a healthy population directly and indirectly translates into a healthy economy. Sen (2002) underscores the critical role of human health in promoting social justice. Studies suggest that, for socioeconomic-related inequalities in health to be reduced, socioeconomic inequalities have to be reduced (Marmot, 2017b; Marmot *et al.*, 2012; Marmot & Bell, 2016). Therefore, any policy measure that addresses socioeconomic inequalities also addresses health inequalities. Health interventions aimed at socioeconomic determinants of health are both efficiency- and equity-justifiable (World Health Organization, 2013a).

1.3 Study context

South Africa faces a quadruple burden of diseases (Bradshaw *et al*., 2011; National Department of Health, 2020; Statistics South Africa, 2020a). Morbidity and mortality statistics are driven by high incidence of communicable diseases such as the human immunodeficiency

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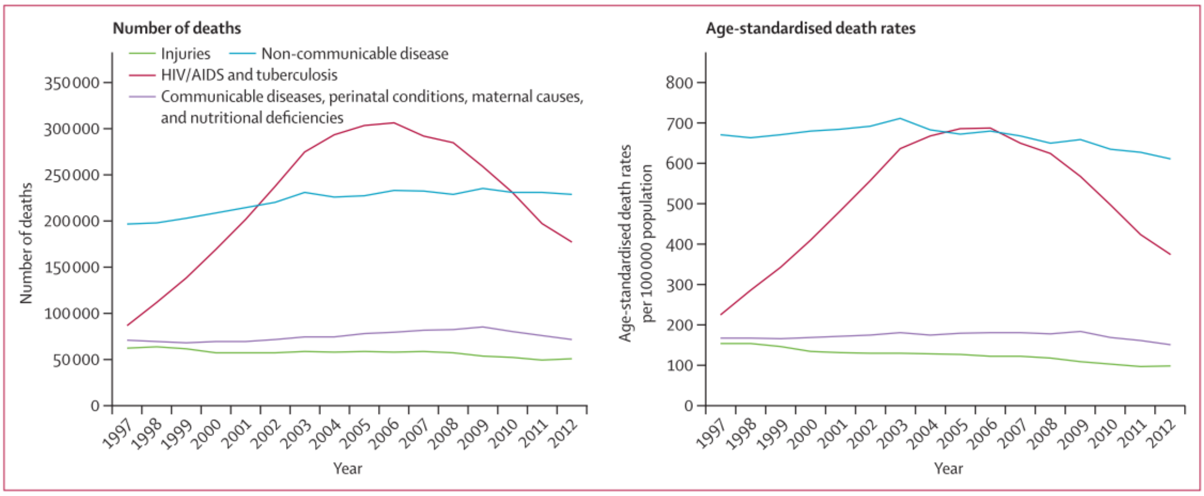
[7] This theory was built based on the observation that medical care explains a relatively small part of observed SES-health gradient across populations over the life cycle (Galama & Van Kippersluis, 2018). The model, therefore, adds behaviours that potentially explain a large part of observed SES-health gradient. The model integrates interactions between SES variables such as education, earnings, and wealth and health behaviours, health, and longevity during adulthoods to the Grossman Model (Demand for health model) (See Galama and Van Kippersluis (2018) for more details about the model. It also explains the disappearance of the SES-health gradient at old ages.

virus/acquired immunodeficiency syndrome (HIV/AIDS) and tuberculosis (TB); maternal and child mortality; NCDs such as hypertension and cardiovascular disease, diabetes, cancer, chronic respiratory diseases, and mental illness; and injury and trauma (Bradshaw *et al.*, 2011; National Department of Health, 2020; Statistics South Africa, 2020a). Figure 5 shows the trends in death statistics from four broad causes of death in South Africa for the period 1997 to 2012. Deaths due to NCDs steadily increased between 1997 and 2012, whilst age-standardised deaths due to NCDs increased until 2003, beyond which they slightly decreased. According to Pillay-van Wyk *et al.* (2016), 43.4% of the 528 956 deaths recorded in South Africa in 2012 were attributable to NCDs. For the same period, HIV/AIDS and TB contributed 33.6%, nutritional causes, maternal conditions, and other communicable diseases contributed 13.5%, and injuries contributed 9.6%.

In 2018, NCDs contributed almost 60% of all deaths in South Africa (Statistics South Africa, 2021). In 2017, six of the top ten leading causes of death in South Africa were non-communicable diseases, with diabetes mellitus the leading cause (Statistics South Africa, 2021). The estimated probability of premature mortality from a chronic disease in South Africa is 27% (National Department of Health, 2019). From 2010 to 2018, the difference in mortality from communicable and non-communicable diseases widened, with the larger share of deaths resulting from non-communicable diseases.

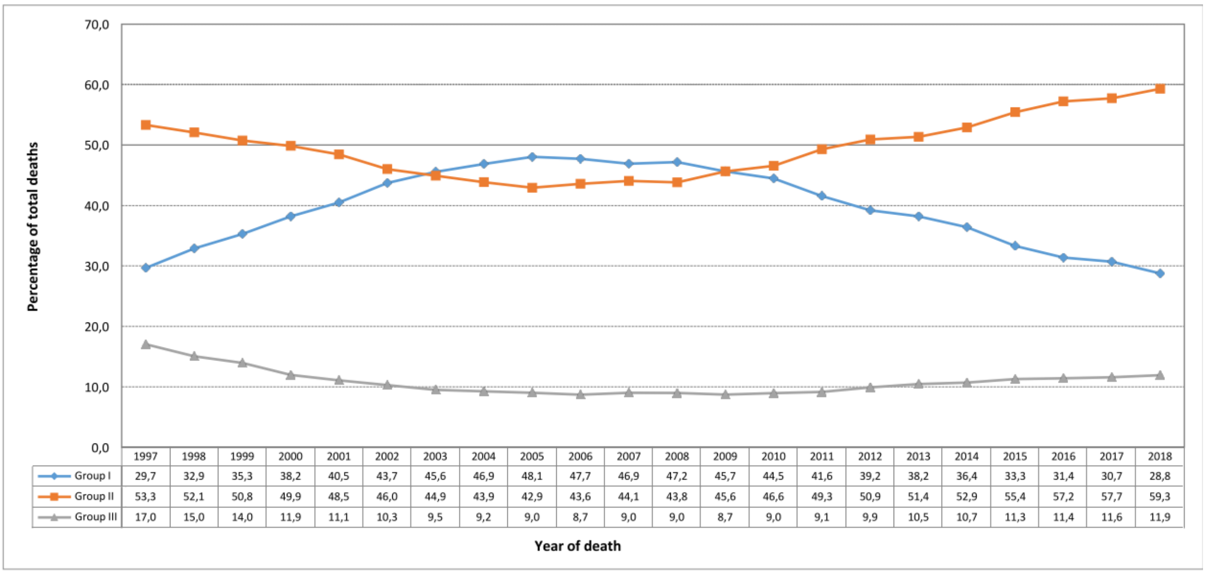
Figure 5: Trends in deaths by four broad causes in South Africa, 1997–2012



Source: Pillay-van Wyk et al. (2016)

Indeed, South Africa, like many other LMICs, has been experiencing epidemiological transition. Figure 6 shows that, from 2005 to 2018, the percentage of deaths due to NCDs steadily increased while deaths due to communicable diseases steadily decreased. The widening gap between the share of deaths from communicable diseases and NCDs from 2010 to 2018 indicates epidemiological shifting of the main causes of deaths in South Africa (Statistics South Africa, 2021). Regardless of gender, the percentage of deaths due to NCDs increases with age between the ages 20 and 74 (Statistics South Africa, 2021), which covers the economically active age group.

Figure 6: Percentage of deaths due to communicable diseases (Group I), NCDs (Group II), and injuries (Group III) by year of death, 1997–2018[8]



Source: Statistics South Africa (2021)

Despite South Africa being economically ranked as an upper-middle income country, there is a high level of persistent unemployment, poverty, inequality (World Bank, 2018), and crime (Statistics South Africa, 2019a). Globally, South Africa is ranked among the five most unequal countries, with a Gini coefficient of per capita household income persistently above 0.6 from 1993 to 2015 (Hundenborn *et al.*, 2018; Statistics South Africa, 2019b; World Bank, 2018). Income inequality results in an array of inequalities, such as inequalities in opportunities, a balanced diet, access to healthcare, and health outcomes. In South Africa, these inequalities are due to the country's legacy of institutionalised racial segregation during apartheid

[8] Group I causes of death include communicable disease, maternal and perinatal causes, and nutrition conditions

(Statistics South Africa, 2019b), and have not decreased since the end of apartheid (Chatterjee *et al*., 2021). More than 50% of South Africans are poverty-stricken, and poverty has been on a rise since 2011 (Francis & Webster, 2019). In terms of aggregate household wealth, 86% belongs to the top 10%, whilst the top 0.1% own close to one-third (Chatterjee *et al.*, 2021).

Inequality in its all dimensions — poverty, unemployment, crime, and other socioeconomic factors — has an impact on health. For example, Bredenkamp *et al.* (2021) report income- and race-related inequalities in life expectancy where longevity favours the relatively affluent and non-Blacks in South Africa. The underlying socioeconomic conditions possibly explain why South Africa is recording poorer health statistics than many countries with a lower income. The health outcomes of a country are associated with both its wealth and how that wealth is distributed (Braveman *et al*., 2018). The increasing burden of chronic diseases cannot be eased by only targeting genetic factors, which are also difficult to address at health policy level. Socioeconomic factors may contribute to both the development of and recovery from ill health. Therefore, attention to socioeconomic factors through governmental policies and increased community awareness is critical in curbing chronic diseases.

South Africa has set a target to reduce the prevalence of NCDs by 28% by 2030, through prevention and treatment, as well as the promotion of mental health (National Department of Health, 2020). For this to be achieved, policies must address the underlying determinants of NCDs that make people more vulnerable. Given the relationship between health and socioeconomic status, understanding the relationship between socioeconomic factors and chronic diseases in South Africa is very important in preventing new cases, as well as in alleviating and controlling existing cases. The cyclical relationship between health and socioeconomic factors means that a reduction in chronic diseases could also potentially have a positive impact on South Africa's extreme inequality, poverty, and the population's health in general.

Inequalities are anti-developmental. For example, high socioeconomic inequalities result in health inequalities, which result in labour market inequalities, which then loops back to socioeconomic inequalities. Thus, the current study aims to examine the relationship between socioeconomic factors and selected chronic conditions in a highly unequal middle-income country characterised by high unemployment and poverty, poor housing, and high crime rates.

1.4 Research questions

The study will examine the role of socioeconomic status in the development of chronic diseases in South Africa. To achieve this, the study has three research questions:

1. What is the relationship of negative household- and neighbourhood characteristics with systolic blood pressure in South Africa?;
2. What are the socioeconomic correlates of mental health in South Africa?; and
3. How did the COVID-19 pandemic affect income-related inequality in depressive symptoms in South Africa?

The three questions will be answered in three essays (in Chapters 2, 3, and 4 of the thesis). In answering the research questions, the following corresponding objectives have been formulated:

1. To examine how exposure to negative household events and neighbourhood events relate to systolic blood pressure in South Africa;
2. To determine the socioeconomic factors that explain depressive symptoms in South Africa; and
3. To ascertain the effect of the COVID-19 pandemic on income-related depressive symptoms, with reference to inequality, in South Africa.

The following sections provide an overview of the thesis.

Chapter 2 (Essay 1): Stressful life events, neighbourhood characteristics, and hypertension in South Africa

This essay examines the relationship of negative household events, including death, serious illness, agricultural shock, job loss, and income reduction, and neighbourhood income level with hypertension in South Africa. To explore this relationship, I analysed large, publicly available panel data from the first three rounds of the South African National Income Dynamics Study (NIDS) (Brophy *et al*., 2018) using a correlated random effects model, adjusted for confounding risk factors such as age, sex, population group, and obesity. I found that systolic blood pressure is significantly higher among respondents from households that had registered the death of a household member and experienced a reduction in grant income and remittances. I also found that the mean-level job loss was associated with lower systolic blood pressure. In relation to neighbourhood income level, I found that people who had moved into middle-income neighbourhoods had a significantly lower systolic blood pressure. I further found that neighbourhood effects on SBP through average education level post-matric was negative. Positive effects of neighbourhood averages of age, widowed, BMI above normal, and alcohol drinking were also found. These results make this study novel and have profound implications for understanding the mechanisms that could explain the significant burden of hypertension in LMICs.

South Africa is a middle-income country with a complex social structure and high levels of inequality, poverty, and burden of disease. These specificities being considered in the current study add value to the results, as most of the literature in this domain is based on research in high-income countries. Furthermore, the roles of grief, and negative financial events in the development and exacerbation of raised blood pressure should not be overlooked. The implications are vast in a country like South Africa which is already burdened with high mortality due to causes such as human immunodeficiency virus/acquired immunodeficiency syndrome (HIV/AIDS) and tuberculosis (TB), and injury and homicide, and NCDs such as cardiovascular diseases and diabetes (Statistics South Africa, 2021). Since these stress-related variables can be modified through policy, the study results reiterate the need for health- and government policy makers to capitalize on the protective effect of neighbourhood income level on raised blood pressure. The results also suggests that reforms on social security grants in South Africa have implications beyond poverty.

In relation to other individual-level covariates, I found a gender profile in SBP whereby being male was associated with higher SBP. Compared to black Africans, Indian and white population groups had significantly lower SBP, whilst the Coloured population group had higher SBP. Being underweight was associated with lower SBP while being overweight and being obese were associated with higher SBP. I also found that those who rarely drink alcohol had higher SBP compared to those who do not drink alcohol. SBP was not found to be associated with place of residence (urbanicity), education level, age, employment status, per capita household income level, marital status, having medical aid, or smoking.

Chapter 3 (Essay 2): Socioeconomic correlates of mental health in South Africa

Globally, mental health disorders are a major contributor to disability, with people with severe disorders dying 10 to 20 years earlier than the general population, mainly due to preventable physical diseases. Behavioural science and epigenetics research acknowledge the role of socioeconomic and social environmental factors in the development of diseases. This essay examines the relationship between depressive symptoms and socioeconomic factors using the five rounds of the NIDS (Brophy *et al.*, 2018). I employed ordinary least squares and two-way fixed effects models to assess the association between the Center for Epidemiological Studies Depression (CES-D10) score and per capita income, education, employment status, place of residence, and neighbourhood attachment. Results from both models suggest significant socioeconomic gradients in depressive symptoms, whereby depressive symptoms are negatively associated with both per capita household income and education. Staying in an urban area is associated with increased depressive symptoms. I also found that people who prefer to continue staying in their current neighbourhoods have significantly lower depressive symptoms scores. However, I found a positive and significant association between depressive symptoms and unemployment only in men.

The direction and significance of the association between depressive symptoms and socioeconomic variables remained, fairly, unchanged when I estimated the models by gender. I also found significant differences in the effects of explanatory variables by gender and by residence. Unemployed men and men with good self-reported health had higher CES-D10 scores than their female counterparts. Over the five time periods covered by the sample, male respondent hand significantly higher CES-D10 scores. In relation to residence, Indians in urban areas had significantly lower CES-D10 scores than Indians in rural areas, whilst whites in urban areas had significantly higher CES-D10 score than whites in rural areas. Being religious and living in an urban area is associated with higher depressive symptoms, compared to being religious and living in a rural area.

The findings suggest the importance of socioeconomic status and social environment, such as income, education, employment, place of residence, and social capital, in both the development and the addressing of mental disorders. The significant differences in the effects of variables by gender and by residence are a unique contribution to understanding the differences in health in South Africa to informing policy. Firstly, there are significant gender and residence differences in depression. Secondly, men who self-report good health may be overreporting their health, most likely by excluding their mental health. Lastly, whilst the goal is to reduce the prevalence of mental disorders by targeting socioeconomic factors, significant differences by gender and residence underscore the need for mental health policies that promote equity. A combination of socioeconomic policy responses will not only improve people's socioeconomic conditions, but also their mental well-being.

Chapter 4 (Essay 3): COVID-19 and income-related mental health inequality in South Africa

Following the outbreak of COVID-19 towards the end of 2019, South Africa, like most countries, was placed in a full national lockdown in March 2020, and economic, physical, and entertainment activities and mobility were severely restrained in an effort to contain the pandemic. Given differences in socioeconomic statuses, individuals' coping abilities in the face of the threat of exposure to the virus and its consequences differ. There is evidence that the pandemic and related public health measures to slow the spread of COVID-19 have worsened existing inequalities (Adams-Prassl *et al*., 2020; Bernardini *et al*., 2021; Bottan, Hoffmann & Vera-Cossio, 2020; Perugini & Vladisavljevic, 2020), with the costs of the pandemic being disproportionately borne by the vulnerable. However, there is also literature that suggests that shocks like pandemics, wars, and civil conflicts narrow inequalities (Milanovic, 2016; Pikkety, 2014; Scheidel, 2017). This essay examines the influence of the COVID-19 pandemic on depressive symptoms as it relates to inequality in South Africa, which is a highly unequal middle-income country (World Bank, 2018).

Data for this essay were drawn from the last three rounds of the NIDS and the fifth round of the NIDS-Coronavirus Rapid Mobile Survey (NIDS-CRAM). The NIDS-CRAM is a nationally representative survey based on adult sample of the fifth round of the NIDS (Ingle *et al*., 2020; Kerr *et al*., 2020). Using the Erreygers index (EI) and the Wagstaff Index (WI), I found that the distribution of good mental health was pro-rich. The index was significant before the pandemic, and insignificant during the pandemic. By means of a relatively new regression-based decomposition method for rank-dependent indices developed by Heckley *et al*. (2016), I found that the COVID-19 pandemic negatively and significantly influenced income-related inequality in good mental health in South Africa. This means that the COVID-19 pandemic disproportionately increased mental health problems amongst the affluent.

I did not find any significant effect of the sample's education level on the joint distribution of income and mental health. Self-reported health negatively influenced all inequality indices. People who all self-report good health are likely to possess similar socioeconomic characteristics including income, and, as such, the income gradient in mental health is likely to be weak. The results also showed that age equal to or above 55 years had a significant negative effect on income-related inequality in good mental health across all the indices. Population group (self-identified), specifically Coloured respondents, showed a positive effect on all four bounded rank-dependent indices' scores, while negative for white respondents over the same indices. Gender profile (negative) in the covariance between income and good mental health was present when inequality was measured using the shortfall-relative concentration index (SRCI). This study is the first in South Africa, a country with pervasive inequalities, to jointly decompose inequality in the covariance between a health outcome (good mental health) and socioeconomic rank (per capita income rank).

Chapter 5: Conclusion

This chapter presents the key findings and policy recommendations of the study. It also discusses the limitations of the study and provides suggestions for future research. Overall, the results of this thesis suggest that socioeconomic factors contribute to the growing burden of chronic diseases in South Africa. Whilst pharmacological and medical technology advancements are important in extending life expectancy, socioeconomic interventions are equally important in efforts to curb both rising morbidity and mortality from chronic diseases in LMICs. Health and government policy interventions that target socioeconomic determinants of health can be justified from both efficiency and equity grounds.

The next chapter contains Essay 1: Stressful life events, neighbourhood characteristics, and systolic blood pressure in South Africa.

Chapter 2

Stressful life events, neighbourhood characteristics, and systolic blood pressure in South Africa

2.1 Introduction

Raised systolic blood pressure (SBP) is the leading risk factor for death and disability-adjusted life years globally (GBD 2019 Risk Factors Collaborators, 2020). It also contributes directly to the global burden of disease, particularly to ischemic heart disease, stroke, and kidney disease (GBD 2019 Risk Factors Collaborators, 2020; Unger *et al.*, 2020). If blood pressure is not controlled and managed, there is a direct increased risk of cardiovascular-related deaths from the mentioned causes. Like other individual health outcomes, blood pressure is associated with, not only individual factors, but also contextual factors, such as neighbourhood characteristics (Leyland & Groenewegen, 2020; Morenoff *et al.*, 2007). Considering the relationships between diseases and individual and contextual factors may improve prevention, diagnosis, treatment, and control of such diseases.

There is an increasing global prevalence of raised blood pressure, particularly in low- and middle-income countries (LMICs) (NCD Risk Factor Collaboration (NCD-RisC), 2017). Literature suggests a positive association between blood pressure and both acute and chronic negative events (Huang *et al.*, 2013; Ohira *et al.*, 2016). Previous studies have reported determinants of hypertension risk to be neighbourhood characteristics such as unemployment, deprivation, perceived safety from crime, food availability, access to healthcare, availability of recreational and leisure services, stress, and family context (Diez Roux *et al.*, 2016; Kaiser *et al.*, 2016; Mujahid *et al.*, 2008). The influence of neighbourhood characteristics on health can also be indirect (Fleischer & Diez Roux, 2008; Leyland & Groenewegen, 2020; Meng, Thompson & Hall, 2013). For example, perceived relative socioeconomic position can affect an individual's feelings and expectations that may, in turn, influence their health status (Meng *et al.*, 2013). The unobserved and indirect effects of neighbourhood characteristics on health disparities may explain how losing a job in a neighbourhood where most people lost their jobs and losing a job in a neighbourhood where most people are employed can have different effects on stress levels.

Ensuing acute stress from 'bad events' and the larger neighbourhood stress dysregulate stress response systems and lower the threshold for reactivity and adaptive responses to subsequent stress (Manyema *et al*., 2018), which can result in the development of hypertension (Malan & Malan, 2017). This could be through maladaptive behavioural responses to stress, such as poor diet, smoking, physical inactivity, and drug abuse (Liu *et al*., 2017; Ohira *et al.*, 2016; Sparrenberger *et al*., 2009), and/or sustained stress-induced stimulation of the hypothalamus–pituitary–adrenal axis and sympathetic activation (Huang *et al*., 2013; Liu *et al.*, 2017).

However, there is, at least to my knowledge, no evidence of a relationship between blood pressure and stressful household events for LMICs like South Africa. In South Africa, the prevalence of raised blood pressure has significantly increased since 1998, from 23% to 44% among men, and from 25% to 46% among women (National Department of Health, 2020). At the same time, the prevalence of causes of negative events such as crime (Statistics South Africa, 2019a) and unemployment is high (Statistics South Africa, 2020b). The level of poverty has become deeper and income inequality more pervasive, and, with a Gini coefficient of 0.63 in 2015, South Africa ranks among the world's most unequal countries (Hundenborn *et al*., 2018; Statistics South Africa, 2019b; World Bank, 2018). South Africa is also confronted with the quadruple burden of non-communicable, communicable, injury, and perinatal and maternal-related health problems (Mayosi *et al*., 2009). These realities make short-term and long-term exposure to household-level stressful or negative events like illness and death more pervasive, unequal, and often persistent in South Africa, relative to other countries on the same income level (Mayosi *et al*., 2012).

Acute events such as, property loss, agriculture shocks, job loss, illness, and death have larger economic burdens on individuals in households and neighbourhoods with higher deprivation, as these individuals lack the safety nets provided by wealth and savings, medical aid, and life- and unemployment insurance (Burger *et al*., 2017). Long-term exposure to challenges like unemployment, living in poverty, and living in high-crime neighbourhoods results in chronic stress, whilst exposure to acute events results in acute stress (Kario, 2012; Ohira *et al.*, 2016). In the present study, I examined the relationship between stressful life events, neighbourhood characteristics, and blood pressure in South Africa, using correlated random effects modelling.

2.2 Methods

2.2.1 Data source

The study used data from the first three rounds of the National Income Dynamics Study (NIDS), conducted in 2008, 2010/2011, and 2012[9]. These first three survey rounds were the only ones that collected information on negative household events, through the household questionnaire. NIDS is a publicly available South African household national panel survey conducted by the Southern Africa Labour and Development Research Unit (SALDRU) at the University of Cape Town's School of Economics (SALDRU, 2020). The survey collects information on household composition, fertility, mortality, education, labour-market participation, poverty, and well-being and health. It also captures data on how households cope with both negative and positive shocks, such as the death of a household member or securing a job (Brophy *et al.*, 2018).

For the first round's sample, a two-stage sampling design was used. This involved selecting 400 primary sampling units (PSUs) from approximately 3 000 PSUs in a national master sample in the first stage (Leibbrandt *et al*., 2009). Dwellings within the 400 PSUs were then identified in the second stage (Leibbrandt *et al*., 2009). All individuals living in households (more than 7 000 households) in these selected PSUs formed the population, referred to as *continuing sample members* (CSMs). Everyone that was a co-resident with a CSM after the first round was also interviewed, and are referred to as *temporary sample members* (TSMs) (Leibbrandt *et al.*, 2009). The individual-level non-response rates for the first round and between the second and third rounds were 6.7% (Leibbrandt *et al.*, 2009) and 16% (De Villiers *et al*., 2013) respectively. Data for TSMs are only available for cross-sectional analyses and not for longitudinal analyses, hence only CSMs aged 15 years and above make up the sample for this study. Based on these restrictions, the eligible sample size survey wave were 15 631 respondents in 2008, 14 443 respondents in 2010/2011, and 14 418 respondents in 2012. Due to missing observations, the sample then reduced to 8 908 respondents in 2008, 9 503 in 2010/11, and to 13 166 in 2012. The largest contributor to samples shrinkage was refusal to have blood pressure measured. The number of respondents who refused to have their blood pressure measured were 1 325 in 2008, 971 in 2010/11, and 160 in 2012.

[9] I used data version 7.0.0 for Wave 1, version 4.0.0 for Wave 2, and version 3.0.0 for Wave 3.

The TSMs are excluded in this chapter because the purpose of this chapter was mainly to determine the relationship between 'negative household events' and systolic blood pressure. Given that the NIDS continues to be repeated with the same household members (CSMs) every two years, and does not track TSMs in the subsequent waves, including TSMs would have the following implications: (1) the relationship between a TSM and a household is not clear, and, as such, it is difficult to determine how a negative household event may affect their health, and (2) there will be a lot of missing observations, since the survey does not follow up on TSMs. Because I restricted the sample to adult CSMs only, I did not use panel weights in the main regression results. The panel weights, better suited for a balanced panel, account for household and individuals characteristics that predicted attrition between Wave 1 and Wave 3, thereby correcting for bias emanating from non-random attrition between Wave 1 and Wave 3 (Brophy *et al.*, 2018). I did not use the balanced panel because I wanted to ensure that the sample size would be as large as possible. To test for the bias that might emanate from non-random attrition, I replicated the fixed effects model with panel weights to check if the coefficients would remain relatively stable.

2.2.2 Measures

Blood pressure screening included SBP and diastolic blood pressure (DBP) readings, performed in duplicate within a period of five minutes. It was measured by trained study personnel in all rounds using factory-calibrated automated oscillometric devices (Omron M7 BP Monitor) validated and recommended for home and professional-use (Coleman *et al.*, 2008). In the regression analysis, the outcome measure (SBP) was an average of two measurements. Where a respondent had one SBP reading, that single reading was the respondent's mean SBP. I used SBP as the dependent variable it has been shown to be a highly accurate measure of cardiovascular risk in all age groups (GBD 2017 Risk Factor Collaborators, 2018; McEniery *et al*., 2016; Unger *et al.*, 2020; Wright *et al*., 2015).

The study's explanatory variables of interest from the household questionnaire on negative events were captured in all three rounds. In the household questionnaire, respondents were asked to report 'any bad events' experienced by their households in the last two years preceding each survey round[10]. The survey contained a predefined list of 11 bad or negative events at household level[11]. Following Burger *et al*. (2017), I aggregated these events into six categories: death of a household member[12]; serious illness or injury in the household; agricultural shock; job loss; grant and remittances reduction; and property loss. Table 1, below, provides the definitions of these negative events.

Table 1: Definitions of negative household events

Negative household event	Definition
Death	Death of any household member who usually lived in the household for at least four nights per week
Serious illness or injury	Serious illness or injury of a household member in the last 24 months
Agriculture shock	Widespread death and/or disease of livestock, or a major crop failure
Job loss	Reduction in work hours or loss of a job of a person on whom the household depended for financial assistance
Reduction in grant income and remittances	Cut-off or decrease of remittances to household, or cut-off or decrease in government grants. Social security grants in South Africa are a tax-financed government initiative aimed at reducing poverty among people who are vulnerable to low income, and at increasing economic growth and development through investment in health, education, and nutrition (Overseas Development Institute, 2006; South African Social Security Agency, 2020a).
Property loss	Theft, fire, or destruction of household property, or any other negative event

[10] The exact question is: "Households sometimes experience bad events. We would like to ask you about any bad events your household may have experienced IN THE LAST 24 MONTHS." The survey also records the month and year the event occurred.

[11] These events were directly captured in the first three waves in the module called "negative events".

[12] Death of a household member is not specifically captured under "negative events" but under the section "mortality history" in the household questionnaire.

I aggregated and used means of individual-level responses on per capita household income at cluster level to control for neighbourhood income level (with three categories namely low-, middle-, and high-income). I only used neighbourhood income because neighbourhood variables like education and crime are all positively correlated with neighbourhood income. Neighbourhood income level determines the goods and services such as food, security, sporting or exercising facilities, and medical facilities, available in the community, which all contribute to health.

In addition, I controlled for observed individual sociodemographic and behavioural characteristics that might be related to blood pressure. These included age, sex, population group, education, marital status, body mass index, per capita household income level, smoking, frequency of alcohol consumption, medical aid, and residence.

2.2.3 Statistical analyses

I used post-stratification sampling weights to adjust for attrition and to make the results generalisable to South Africa (De Villiers *et al.*, 2013). For the descriptive analysis, I used the full sample of adult respondents who had data on negative household events and had a mean DBP and mean SBP that falls within plausible ranges. From literature, a DBP reading is plausible if it is $\geq 30\text{mmHg}$ and $< 180\text{mmHg}$, whilst a plausible SBP reading if it is $\geq 70\text{mmHg}$ and $< 270\text{mmHg}$ (Cois & Ehrlich, 2018). I first analysed the prevalence of negative household events per survey round for all respondents, which amounted to 8 908 observations in 2008, 9 503 observations in 2010/2011, and 13 166 observations in 2012. For the descriptive analysis, I used SBP and DBP values adjusted for age, population group, sex, obesity, smoking, and frequency of alcohol consumption. The analysis of the prevalence of hypertension followed the 2020 International Society of Hypertension Global Hypertension Practice Guidelines, which classifies an individual as hypertensive if $\text{SBP}\frac{and}{or}\text{DBP} \geq 140/90\text{mmHg}$, or if he/she uses blood pressure medication (Unger *et al.*, 2020). I calculated the confidence intervals using robust standard errors.

Health can be determined by both individual level, and group-, neighbourhood- or population level factors (Davidson, 2015; Leyland & Groenewegen, 2020). This means that, over time, differences in neighbourhood characteristics can contribute to disparities in hypertension over and above individual characteristics (Browning *et al.*, 2012; Chaix *et al.*, 2010; Morenoff *et al.*, 2007). To account more accurately for potential effects of differences among individuals and across 400 clusters (neighbourhoods or groups) over time in the sample on blood pressure, I use a correlated random effects (CRE) model (Wooldridge, 2010), one that dates back to Mundlak (1978), for continuous dependent variables.

In panel data, a CRE model allows estimation of the effect of neighbourhood (Level 2) variables while providing unbiased effect estimates of individual-level (Level 1) variables that may be correlated with the Level 2 error, over time (Level 3) (Schunck, 2013). The advantage of using a CRE model is that it combines the advantages of, or unifies, the random- and fixed effects models (Antonakis *et al*., 2021; Schunck, 2013). The CRE model allows us to include time-invariant covariates which cannot be included in a fixed effects model, while giving us the fixed-effects estimates on the time-varying covariates at the same time. These time-invariant variables like gender and population group are important in explaining health disparities in a population. By decomposing and comparing within and between effects in a single model, a CRE model helps in assessing the effect of unobserved heterogeneity in neighbourhoods on the observed relationship between blood pressure and individual-level variables. For example, through a CRE model, one can explain how an individual's blood pressure might be affected differently by having a high income (Level 1) and by residing in a generally affluent neighbourhood (Level 2). For the present study, the CRE model was specified as:

$$SBP_{ijt} = \alpha' x_{ijt} + \pi' \bar{x}_j + \beta' z_{jt} + \delta d_t + u_i + w_j + e_{ijt} \qquad 5$$

where SBP_{ijt} is the systolic blood pressure of individual i in neighbourhood j at time t, x_{ijt} is a vector of negative events that an individual experienced and other individual-level covariates (such as education, age, marital status, body mass index, per capita household income, smoking, frequency of alcohol consumption, medical aid, population group, gender, and residence), and $\bar{x}_j$ is a vector of neighbourhood-level means of all covariates. π is the contextual effects; d_t is the year dummies to capture year-specific effects; and z_{jt} is neighbourhood-level income, while u_i is person-specific fixed effect, $w_j$is neighbourhood fixed effect and e_{ijt} are idiosyncratic errors.

2.3 Results

2.3.1 Descriptive analyses

2.3.1.1 Sociodemographic characteristics of the sample

Table 4 shows the sociodemographic characteristics of the pooled study sample. Black Africans (83.3%) made up the largest share of the study sample, whilst Indians (1.1%) made up the smallest share. Approximately 59% of the sample was female. The share of urban respondents was 45.5%. In terms of education, almost 41.3% of the sample held Grade 8 to 11 as their highest education. Only 6.2% of the sample was classified as underweight, whilst 24.4% was overweight and 24.8% was obese. Only 10% of the sample were members of a medical aid. Of the respondents, 17.3% smoked cigarettes, whilst almost 20% drank alcohol.

2.3.1.2 Negative household events and blood pressure

Approximately 30% of the respondents lived in a household that had experienced one or more negative events over the previous 24 months preceding each survey, as shown in Table 2. The overall prevalence of a single household event was 17.85%, 17.53%, and 18.97%, for 2008, 2010/11, and 2012 respectively (see Table 3). The prevalence of two household events was 8.85% in 2008, 8.63% in 2010/11, and 6.77% in 2012.

Table 2: Prevalence of at least one negative household event in the last 24 months

Year (*n*)	**Prevalence (%) of at least one negative household event [95% CI]**
2008 (8 908)	29.53 [26.54; 32.53]
2010/11 (9 503)	29.86 [26.86; 32.86]
2012 (13 166)	28.65 [26.34; 30.96]

Note: CI is the confidence interval. The analyses used panel weights.

Table 3: Prevalence (%) of household negative events by year, weighted data

Reported negative events	**Year (sample)**		
	2008 (*n* = 8 908)	2010/11 (*n* = 9 503)	2012 (*n* = 13 166)
0	70.47	70.14	71.35
1	17.85	17.53	18.97
2	8.85	8.63	6.77
At least 3	2.83	3.70	2.91

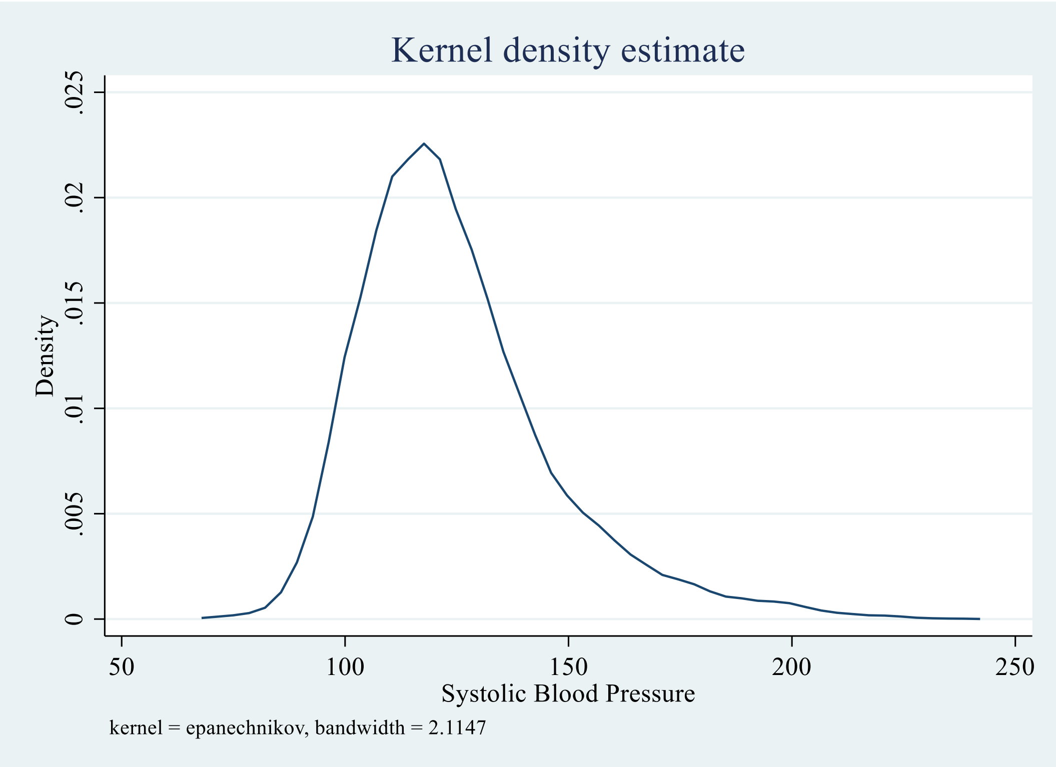
Note: The analysis used panel weights.

Table 4: Characteristics of the pooled sample

Variable	**Total (N = 33 779)**
Per capita household income (ZAR)	
Mean (SD)	1 517.58 (3199.34)
Median (Q1, Q3)	681.8 (367.0, 1419.2)
Systolic Blood Pressure	
Mean (SD)	125.05 (22.23)
Median (Q1, Q3)	121.0 (110.0, 135.5)
Diastolic Blood Pressure	
Mean (SD)	81.15 (13.91)
Median (Q1, Q3)	80.0 (71.5, 89.0)
Age category	
15–24	10 700 (31.7%)
25–39	9 259 (27.4%)
40–54	7 403 (21.9%)
> = 55	6 417 (19.0%)
Population group	
Black African	28 136 (83.3%)
Coloured	4 268 (12.6%)
Indian	366 (1.1%)
White	1 009 (3.0%)
Gender	
Female	19 778 (58.6%)
Male	14 001 (41.4%)
Education category	
No schooling	3 901 (11.5%)
Grade 1–7	7 691 (22.8%)
Grade 8–11	13 936 (41.3%)
Matric	4 592 (13.6%)
Certificate/Degree/Diploma	3 659 (10.8%)
Employment status	
Employed	11 664 (34.5%)
Not economically active	16 600 (49.1%)
Unemployed	5 515 (16.3%)
Marital status	
Never married	19 091 (56.5%)
Married or cohabiting	11 291 (33.4%)
Widowed or divorced	3 397 (10.1%)
Body mass index category	
Normal weight	15 077 (44.6%)
Underweight	2 084 (6.2%)
Overweight	8 256 (24.4%)
Obese	8 362 (24.8%)
Cigarette smoker	
Non-smoker	27 922 (82.7%)
Smoker	5 857 (17.3%)
Frequency of alcohol consumption	
Does not drink	26 961 (79.8%)
Rarely drinks	4 829 (14.3%)
Drinks 1–2 days/week	1 778 (5.3%)
Drinks everyday	211 (0.6%)
Medical aid	
No	30 646 (90.7%)
Yes	3 133 (9.3%)
Residence	
Rural	18 376 (54.4%)
Urban	15 403 (45.6%)

To calculate the prevalence of hypertension (SBP $\frac{and}{or}$ DBP $\geq 140/90$mmHg or if respondents used blood pressure medication), both SBP and DBP were adjusted for confounding factors, which included age, population group, sex, obesity, smoking, and frequency of alcohol consumption in the pooled panel sample. The direct standardisation method was used to adjust for confounding factors. Figure 7 shows the distribution of SBP adjusted of confounding factors. 125.03mmHg overall mean, 126.69mmHG in Wave 1, 124.59mmHg in Wave 2, and 124.14mmHg in Wave 3. Across the three rounds, the adjusted prevalence of hypertension was 19.77%. The prevalence of hypertension was 19.85% in 2008 (95% CI 18.41 – 21.30), 18.59% in 2010/11 (95% CI 17.17 – 20.01), and 20.53% in 2012 (95% CI 19.33 – 21.73).

Figure 7: Distribution of adjusted systolic blood pressure for pooled panel



Source: Author's calculations

Table 5 shows the adjusted hypertension prevalence by number of reported events across the three rounds. Hypertension prevalence was lowest (19.89%) among people who reported at least three events, and highest (23.21%) for a single event. Overall, there was no clear association between number of reported events and hypertension prevalence. However, when using experiencing a household event as a binary variable that takes 1 for event and 0 otherwise, the adjusted hypertension prevalence was higher (22.91%) among those who experienced a negative event as compared to those who did not experience an event (21.72%)

Table 5: Hypertension prevalence by number of reported events across the three waves

Number of events	N	Crude	Adjusted Rate	Confidence Interval
0	23 663	21.93	21.72	[21.28; 22.16]
1	6 295	23.38	23.21	[22.36; 24.07]
2	2 752	21.80	20.62	[19.42; 21.82]
At least 3	992	21.17	19.89	[17.89; 21.89]

Note: The adjusted rate was adjusted for age, population group, sex, obesity, smoking, and frequency of alcohol consumption.

2.3.2 Regression results

Table 6 presents the results of the multivariable-adjusted, ordinary least squares (OLS), random-effects (RE), fixed-effects (FE), and correlated random effects (CRE) models. The focus of this essay was to estimate the effects of stressful life events and direct and indirect neighbourhood characteristics on systolic blood pressure. To this end, the interpretations will be focused on the CRE model (Model 4)[13]. In Model 4, I found that the death of a household member and reductions in grant income and remittances were positively associated with SBP. I also found that moving from a low-income neighbourhood into a middle-income neighbourhood is associated with lower systolic blood pressure. In relation to the unobserved heterogenous effects of neighbourhoods, I found that the mean of neighbourhood-level job loss was associated with lower systolic blood pressure.

In relation to other individual-level covariates, I found a gender profile in SBP whereby being male was associated with higher SBP. Compared to black Africans, Indian and white population groups had significantly lower SBP, whilst the Coloured population group had higher SBP. Being underweight was associated with lower SBP, while being overweight and being obese were associated with higher SBP. I also found that those who rarely drink alcohol

[13] Theoretically, the CRE and the FE models should give similar or directly comparable results on coefficients. Table 6 shows that the coefficients of the negative household events in the CRE (Model 4), and the FE (Model 3) models are closely comparable.

had higher SBP compared to those who do not drink alcohol. SBP was not found to be associated with place of residence (urbanicity), education level, age, employment status, per capita household income level, marital status, having medical aid, or smoking.

Table 6: Multivariable-adjusted OLS, RE, FE, and CRE models with SBP as dependent variable

VARIABLES	(1) POLS	(2) RE	(3) FE	(4) CRE
Negative household events				
Death	0.724**	0.734**	0.900**	0.893**
	(0.328)	(0.307)	(0.371)	(0.372)
Serious illness or injury	-1.117**	-0.880**	-0.445	-0.427
	(0.472)	(0.438)	(0.549)	(0.548)
Agriculture shock	0.045	0.395	0.699	0.678
	(0.776)	(0.741)	(0.891)	(0.891)
Job loss	-1.398***	-0.962**	0.074	0.004
	(0.515)	(0.474)	(0.577)	(0.577)
Grant income and remittances reduction	1.332*	1.678**	2.208**	2.223**
	(0.780)	(0.733)	(0.887)	(0.884)
Property loss	-0.123	-0.283	-0.502	-0.463
	(0.640)	(0.592)	(0.736)	(0.733)
Neighbourhood income level (Low)				
Middle	-0.391	-0.492*	-0.703**	-0.686*
	(0.282)	(0.263)	(0.355)	(0.354)
High	0.148	0.047	-0.161	-0.110
	(0.354)	(0.332)	(0.521)	(0.521)
Socio-demographic variables				
Age (15–24)				
25–39	4.445***	4.402***	0.328	0.322
	(0.298)	(0.280)	(0.530)	(0.529)
40–54	13.518***	13.375***	1.488	1.511
	(0.447)	(0.420)	(0.946)	(0.945)
> = 55	25.003***	24.065***	-0.341	-0.229
	(0.591)	(0.562)	(1.491)	(1.491)
Male	5.739***	5.537***		5.839***
	(0.279)	(0.272)		(0.287)
Population group (black African)				
Coloured	4.337***	4.379***		4.345***
	(0.446)	(0.431)		(0.445)
Indian	-4.862***	-4.907***		-4.697***
	(1.164)	(1.119)		(1.134)
White	-2.341***	-2.059***		-2.236***
	(0.807)	(0.785)		(0.809)
Education (none)				
Grade 1–7	-1.050*	-1.466**	-0.398	-0.460
	(0.591)	(0.575)	(1.900)	(1.894)
Grade 8–11	-2.622***	-3.190***	0.252	0.254
	(0.596)	(0.577)	(2.067)	(2.061)
Matric	-2.809***	-3.311***	1.240	1.289
	(0.643)	(0.623)	(2.169)	(2.163)
Post-matric	-4.085***	-4.244***	1.480	1.534
	(0.679)	(0.660)	(2.187)	(2.182)

Table Continues

Table 6 Continued

VARIABLES	(1) POLS	(2) RE	(3) FE	(4) CRE
Marital status (Never)				
Married/Cohabiting	0.369	0.655**	-0.464	-0.490
	(0.352)	(0.331)	(0.629)	(0.628)
Widowed/Divorced	2.964***	3.018***	-0.651	-0.716
	(0.613)	(0.576)	(1.045)	(1.042)
BMI (Normal)				
Underweight	-3.978***	-3.604***	-1.971***	-2.078***
	(0.470)	(0.429)	(0.583)	(0.579)
Overweight	2.745***	2.354***	0.819**	0.844**
	(0.299)	(0.276)	(0.388)	(0.386)
Obese	6.565***	6.060***	3.624***	3.594***
	(0.357)	(0.335)	(0.542)	(0.542)
Per capita household income level (Low)				
Middle	0.767***	0.594**	-0.017	0.005
	(0.282)	(0.262)	(0.336)	(0.335)
High	1.553***	1.288***	0.573	0.564
	(0.336)	(0.310)	(0.422)	(0.420)
Employment status (Employed)				
Not economically active	0.440	0.178	-0.255	-0.234
	(0.305)	(0.278)	(0.366)	(0.365)
Unemployed	0.066	0.106	0.150	0.133
	(0.329)	(0.302)	(0.377)	(0.375)
Smoker	0.533	0.599*	0.635	0.577
	(0.384)	(0.356)	(0.550)	(0.549)
Frequency of alcohol consumption (None)				
Rarely drinks	1.142***	1.110***	0.891**	0.871**
	(0.339)	(0.308)	(0.382)	(0.381)
Drinks 1–2 days/week	3.592***	2.715***	0.552	0.591
	(0.552)	(0.510)	(0.647)	(0.644)
Drinks every day	-1.310	-1.299	-1.083	-0.965
	(1.543)	(1.486)	(2.038)	(2.037)
Medical insurance	-1.991***	-1.636***	0.338	0.429
	(0.453)	(0.422)	(0.680)	(0.680)
Urban residence	0.235	0.219	0.099	0.199
	(0.292)	(0.277)	(0.660)	(0.657)
Year (2008)				
2010/11	-2.704***	-2.606***	-1.437***	-1.478***
	(0.245)	(0.238)	(0.263)	(0.262)
2012	-3.298***	-3.126***	-1.002***	-1.021***
	(0.233)	(0.227)	(0.287)	(0.287)
Means of all time-variant variables (π)				
Negative household events				
Death				-0.177
				(0.620)
Serious illness or injury				-1.501
				(0.964)
Agriculture shock				-1.131
				(1.708)
Job loss				-2.319**
				(0.991)
Grant income and remittances reduction				-1.840
				(1.539)
Property loss				0.690
				(1.316)

Table Continues

Table 6 Continued

VARIABLES	(1) POLS	(2) RE	(3) FE	(4) CRE
Neighbourhood income level (Low)				
Middle				0.425
				(0.542)
High				0.212
				(0.678)
Socio-demographic variables				
Age (15–24)				
25–39				4.380***
				(0.647)
40–54				12.263***
				(1.080)
> = 55				26.234***
				(1.623)
Education (none)				
Grade 1–7				-0.206
				(1.989)
Grade 8–11				-2.292
				(2.149)
Matric				-3.538
				(2.265)
Post-matric				-5.163**
				(2.297)
Marital status (Never)				
Married/Cohabiting				0.493
				(0.742)
Widowed/Divorced				3.409***
				(1.270)
BMI (Normal)				
Underweight				-2.543***
				(0.838)
Overweight				2.465***
				(0.562)
Obese				3.522***
				(0.684)
Per capita household income level (Low)				
Middle				1.165**
				(0.534)
High				1.315**
				(0.622)
Employment status (Employed)				
Not economically active				0.909
				(0.567)
Unemployed				-0.349
				(0.617)
Smoker				-0.354
				(0.727)
Frequency of alcohol consumption (None)				
Rarely drinks				0.341
				(0.637)
Drinks 1–2 days/week				5.420***
				(1.052)
Drinks every day				-0.811
				(2.877)
Medical insurance				-3.134***
				(0.877)

Table Continues

Table 6 Continued

VARIABLES	(1) POLS	(2) RE	(3) FE	(4) CRE
Urban residence				-0.038
				(0.729)
Year (2008)				
2010/11				-0.989
				(0.718)
2012				-2.667***
				(0.662)
Constant	113.770***	114.787***	124.153***	112.705***
	(0.705)	(0.679)	(1.961)	(0.890)
Observations	33,779	33,779	33,779	33,779
R-squared	0.271	0.355	0.008	0.357
Number of pid	16,334	16,334	16,334	16,334

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Colum (1) presents coefficients from an OLS model; Column (2) presents coefficients from a random-effects model; Column (3) presents results from a fixed-effects model; and Column (4) presents coefficients from a correlated random-effects model. The coefficients in Column 3 are directly comparable to those in Column 4, though column also give coefficients of time-invariant covariates (gender and population group). The mean of variables in Column 4 measures the heterogenous effects of neighbourhoods.

Results are based on an unbalanced panel and unweighted analysis.

Since I did not use the balanced panel because I wanted to retain a large sample, I replicated the fixed-effects model with panel weights, and the coefficients remained relatively stable (see Table 7, Appendix 1.A). Even though there were changes in the size of the coefficients and the significance level, the results that death of a household member and reduction in grant income and remittances still held in a balanced sample estimation for the correlated random model, and fixed effect — its close comparand. Neighbourhood income level, though maintaining the same sign, became insignificant.

I also estimated the CRE model under different specifications (Table 8 in Appendix 1.B) to check for omitted variable biases. The relationships between death of a household member and SBP, and grant income and remittances reduction and SBP, remained stable, controlling for all covariates except neighbourhood income Model 1. In Model 2, I only controlled for neighbourhood-level income and other covariates, except negative household events. I found that moving from a low-income neighbourhood into a middle-income neighbourhood remained negatively associated with SBP.

Another finding (estimated through the CRE model), though not presented in this thesis, was a positive relationship between the count of events and SBP. The mean of *neighbourhood count of negative events* was also positively associated with SBP.

Table 9 in Appendix 1.C presents the results if a binary dependent variable (= 1 if hypertensive, and 0 otherwise[14]) is used. In addition to death of a household member, and reduction in grant income and remittances reduction, job loss in the household increases the odds of being hypertensive.

2.4 Discussion

While several studies have been undertaken to explain the increasing burden of hypertension in developing countries, most of these have paid more attention to traditional behavioural and physiological risk factors. In this study, I used three rounds of a South African longitudinal data set to explore the relationship of negative household events and neighbourhood characteristics with SBP in a large sample (33 779 observations), using a correlated random effects model. Results from the fully adjusted model showed that death of a household member results in significantly higher SBP, compared to people who have not had such an experience. This suggests the effect of uncontrolled grief from bereavement on physical health. This result is similar to that of Buckley *et al.* (2011), who also found a positive association between bereavement and SBP in Australia. Studies have shown that people who have lost a loved one exhibit maladaptive neuroendocrine and immune patterns and poorer health behaviours than prior to the loss, which exposes them to mental and physical health risks (Fagundes & Wu, 2020; Karl *et al*., 2018; Stahl & Schulz, 2014). The implications are vast in a country like South Africa, which is already burdened with high mortality due to causes such as human immunodeficiency virus/acquired immunodeficiency syndrome (HIV/AIDS) and tuberculosis (TB), and injury and homicide, and NCDs such as cardiovascular diseases and diabetes (Statistics South Africa, 2021).

I also found that a reduction in grant income and remittances results in significantly higher SBP, compared to people who have not had this experience. This result is similar to that of Boen and Yang (2016), who found that losses in net worth due to the Great Recession were significantly associated with increases in SBP in America. Social security grants in South Africa are a tax-financed government initiative aimed at reducing poverty (Overseas Development Institute, 2006; South African Social Security Agency, 2020a). This result

[14] For the definition refer to sub-section 2.2.3.

suggests that reforms on social security grants have implications beyond poverty. In South Africa, a reduction in total household grant and remittances income can be due to many reasons. For example the grant recipient becomes ineligible to receive a grant if he or she dies, if the child who was receiving grant turns 18, if one ceases to be a refugee, or if the grant recipient is now above the threshold for which one is eligible to receive grant (South African Social Security Agency, 2020b). In the case of reduced remittances, it could be death or job loss of the person that used to remit. Wealth shocks can affect physiological functioning of people, especially those in low income brackets who lack safety nets, resulting in poor health outcomes (Pool *et al.*, 2018). The relationship between wealth shocks and health outcomes are well-explained (Schwandt, 2018). Chronic stress emanating from food shortages and income reduction is immense, and long-term exposure to basic needs not being met takes a toll on adults' health, as manifests in blood pressure levels.

The results also suggest that average job loss level of the neighbourhood is associated with lower systolic blood pressure. Because a household shock like job loss to a household member is expected to be associated with stress that results in raised SBP, this result maybe be attributed to the unobserved effects of neighbourhood unemployment rate. Some job losses can be driven by local policy or extinction or depletion of resources in sectors where most people were employed. For example, depletion of ores, or policies that ban mining of a certain mineral for health or climate change reasons, in a mine that employed more local people may result in community-wide job losses. When the household is in a neighbourhood with low employment levels, individuals' perceived socioeconomic rank in the neighbourhood may not change if there is a household job loss hence they may lower their expectations which may, in turn, may influence their health status (Meng *et al.*, 2013). I also found that neighbourhood effects on SBP through average education level *post-matric* was negative. Positive effects of neighbourhood averages of age, widowed, BMI above normal, and alcohol drinking were also found.

In relation to neighbourhood income, I found that moving from a low-income neighbourhood is negatively associated with SBP. This result is consistent with literature (for example, Chaix *et al.*, 2010; Morenoff *et al.*, 2007) that suggests that people in more affluent neighbourhoods are at a lower risk of having elevated blood pressure. Neighbourhood income mirrors the quantity and quality of resources available to its residents (Meng *et al.*, 2013). Compared to low-income neighbourhoods, middle-income and affluent neighbourhoods have better healthcare, access to healthy food, healthy lifestyles, less crime, and less stress, which, in turn, are associated with low blood pressure (Kaiser *et al*., 2016). People living in neighbourhoods that are more affluent have better health outcomes relative to those in deprived neighbourhoods, as they can access high-quality healthcare (Augustin *et al*., 2008; Kivimäki *et al*., 2018; Morenoff *et al.*, 2007). For example, Matheson *et al.* (2010) found a significant association between neighbourhood deprivation and hypertension in Canada. This underscores the importance of supportive neighbourhoods in absorbing individual and household shocks and promoting health-seeking behaviours (Leyland & Groenewegen, 2020). It is well documented in literature that neighbourhoods can be stressful (Mayne *et al*., 2018), or neighbourhoods may not offer resources for people with which to cope with stressful events or to support healthy behaviours (Sarkar *et al*., 2018).

This essay is not without limitations. Firstly, in this essay, I did not derive shocks from the panel, and this explains why I did not use the last two survey rounds of the NIDS. The list of negative events in the first three rounds are only the events that were not recorded elsewhere in the questionnaires. For example, if a household member lost their job, this can be directly observed from the adult questionnaire and will not be recorded in the household questionnaire section called "negative events". Thus, the list of negative events only includes impactful job losses of non-resident members. The analysis also excluded TSMs which reduced the sample size. Secondly, the present study used self-reported data based on respondents' recall, except for SBP, which was captured on a two-year basis. Thus, reporting- and recall biases may have affected the accuracy of the results.

The third limitation of this essay emanates from the definition of neighbourhood and the measuring neighbourhood income by aggregating household incomes. Because Cluster IDs are only recorded in the first wave, the analysis included individuals who moved from one neighbourhood to another, but I was not able to track where they actually moved to. More so, given the highly segregated nature of South African neighbourhoods, neighbourhood income level is likely highly correlated with household income. To this end, inaccuracies in the estimations of household income may affect the neighbourhood income level variable. Furthermore, the neighbourhood income level can be influenced by the distribution of rich and poor households in the neighbourhood. In cases where we have single-household neighbourhoods, that household income will be considered as the neighbourhood income.

However, large longitudinal surveys such as this one are uncommon in developing countries; thus, this data set offered me a rare opportunity to explore the association between negative household events, neighbourhood characteristics, and SBP in a heterogeneous population. The few studies that have focused on the role of psychological stress and neighbourhood characteristics in cardiovascular disease have mostly considered symptomatic cardiovascular ailments (Svensson & Theorell, 1983). This is despite the high prevalence of negative events in developing countries because of the quadruple burden of diseases and volatile socioeconomic environments. South Africa is a particularly interesting case, as approximately 30% of all households in the study reported having experienced at least one negative event across the three rounds.

The present study is unique in that correlated random effects models were used to determine the role of both household events and neighbourhood characteristics in hypertension aetiology for South Africa, to account for the intertwined roles of neighbourhood characteristics and negative events in hypertension development. The prevalence of negative events can be neighbourhood-driven; for example, some deaths may result from crime or unavailability of high-quality healthcare in a neighbourhood. The results of this study show that shocks in household income (through reduction of grants and remittances) and the pain of losing a household member contribute to the development of systolic hypertension. I also found a negative association between neighbourhood income level and SBP. These results require a combination of policy interventions by the South African government that, for example, promote healthy lifestyles, health-seeking behaviour, and coping with negative and stressful life events. Given that individuals have little to no control over the quantity and quality of goods and services in their neighbourhoods, the study suggests health and government policies that improve services available in low-income neighbourhoods.

The prevalence of raised blood pressure in many low- and middle-income countries has been increasing over the last few decades (World Health Organization, 2018). The results of the present study suggest that exposure to stress from negative household events and from neighbourhood characteristics are independently associated with blood pressure. An estimated 10% of global healthcare spending directed towards high blood pressure and its related complications (Campbell *et al*., 2014). A systematic review of literature by Zhang *et al.* (2017) showed that educational, screening, and self-monitoring interventions aimed at reducing blood pressure reduce cardiovascular diseases-related morbidity and mortality. However, though cost effectively, it would be expensive to implement interventions. For example, Zhang *et al.* (2017) found that it would cost US$62 for every 1mmHg reduction in systolic blood pressure in the USA and US$0.62 in China and US$29 in Pakistan for the same reduction through educational interventions. The review also found that self-monitoring interventions costed more (US$727 in the USA) for a 1mmHg reduction in SBP. Results of the present study point to the need for cheaper, relevant, non-pharmacological interventions and policy interventions for the prevention, treatment, and control of hypertension in a low-resource setting. Examples of these include emotional support for the bereaved and employment creation and upward review of social grants to improve diet, access to healthcare, and safety nets provided by savings and insurance schemes.

Appendix 1.A

Table 7: Fixed effects regression (unbalanced panel vs balanced panel results)

VARIABLES	(1) Unbalanced panel	(2) Balanced panel
Negative household events		
Death	0.900**	1.174***
	(0.371)	(0.449)
Serious illness or injury	-0.445	0.260
	(0.549)	(0.685)
Agriculture shock	0.699	0.257
	(0.891)	(1.153)
Job loss	0.074	-0.488
	(0.577)	(0.738)
Grant income and remittances reduction	2.208**	1.941*
	(0.887)	(1.077)
Property loss	-0.502	-1.072
	(0.736)	(0.923)
Neighbourhood income level (Low)		
Middle	-0.703**	-0.628
	(0.355)	(0.427)
High	-0.161	-0.315
	(0.521)	(0.629)
Socio-demographic variables		
Age (15–24)		
25–39	0.328	0.363
	(0.530)	(0.640)
40–54	1.488	1.604
	(0.946)	(1.161)
> = 55	-0.341	-0.096
	(1.491)	(1.773)
Education (none)		
Grade 1–7	-0.398	1.318
	(1.900)	(2.635)
Grade 8–11	0.252	2.822
	(2.067)	(2.831)
Matric	1.240	3.010
	(2.169)	(2.939)
Post-matric	1.480	3.778
	(2.187)	(2.947)
Marital status (Never)		
Married/Cohabiting	-0.464	-1.287
	(0.629)	(0.805)
Widowed/Divorced	-0.651	-1.367
	(1.045)	(1.218)
BMI (Normal)		
Underweight	-1.971***	-2.426***
	(0.583)	(0.741)
Overweight	0.819**	0.454
	(0.388)	(0.484)
Obese	3.624***	3.053***
	(0.542)	(0.661)

Table Continues

Table 7 Continued

VARIABLES	(1) Unbalanced panel	(2) Balanced panel
Per capita household income level (Low)		
Middle	-0.017	0.031
	(0.336)	(0.409)
High	0.573	0.561
	(0.422)	(0.523)
Employment status (Employed)		
Not economically active	-0.255	-0.521
	(0.366)	(0.444)
Unemployed	0.150	0.366
	(0.377)	(0.460)
Smoker	0.635	0.594
	(0.550)	(0.714)
Frequency of alcohol consumption (None)		
Rarely drinks	0.891**	1.108**
	(0.382)	(0.472)
Drinks 1–2 days/week	0.552	1.196
	(0.647)	(0.806)
Drinks every day	-1.083	-0.472
	(2.038)	(2.969)
Medical insurance	0.338	0.625
	(0.680)	(0.860)
Urban residence	0.099	-0.213
	(0.660)	(0.856)
Year (2008)		
2010/11	-1.437***	-1.593***
	(0.263)	(0.316)
2012	-1.002***	-1.006***
	(0.287)	(0.351)
Constant	124.153***	124.338***
	(1.961)	(2.639)
Observations	33,779	19,138
R-squared	0.008	0.009
Number of pid	16,334	7,008

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Model 1 is on an unbalanced panel and no weights used. Model 2 is on a balanced panel and panel weights that comes with data were used.

Appendix 1.B

Table 8: Multivariable-adjusted correlated random effects models with SBP as dependent variable

VARIABLES	(1) Neg events	(2) Neighbourhood	(3) All
Negative household events			
Death	0.894**		0.893**
	(0.372)		(0.372)
Serious illness or injury	-0.461		-0.427
	(0.548)		(0.548)
Agriculture shock	0.607		0.678
	(0.890)		(0.891)
Job loss	-0.057		0.004
	(0.577)		(0.577)
Grant income and remittances reduction	2.232**		2.223**
	(0.885)		(0.884)
Property loss	-0.498		-0.463
	(0.733)		(0.733)
Neighbourhood income level (Low)			
Middle		-0.693**	-0.686*
		(0.352)	(0.354)
High		-0.126	-0.110
		(0.520)	(0.521)
Socio-demographic variables			
Age (15–24)			
25–39	0.361	0.307	0.322
	(0.528)	(0.529)	(0.529)
40–54	1.581*	1.546	1.511
	(0.945)	(0.946)	(0.945)
> = 55	-0.166	-0.213	-0.229
	(1.490)	(1.492)	(1.491)
Male	5.839***	5.851***	5.839***
	(0.287)	(0.287)	(0.287)
Population group (Black African)			
Coloured	4.346***	4.394***	4.345***
	(0.445)	(0.444)	(0.445)
Indian	-4.696***	-4.700***	-4.697***
	(1.134)	(1.136)	(1.134)
White	-2.236***	-2.281***	-2.236***
	(0.809)	(0.808)	(0.809)
Education (none)			
Grade 1–7	-0.496	-0.391	-0.460
	(1.891)	(1.895)	(1.894)
Grade 8–11	0.202	0.255	0.254
	(2.058)	(2.063)	(2.061)
Matric	1.277	1.251	1.289
	(2.161)	(2.165)	(2.163)
Post-matric	1.560	1.494	1.534
	(2.179)	(2.183)	(2.182)
Marital status (Never)			
Married/Cohabiting	-0.506	-0.534	-0.490
	(0.628)	(0.628)	(0.628)
Widowed/Divorced	-0.727	-0.611	-0.716
	(1.041)	(1.040)	(1.042)
BMI (Normal)			
Underweight	-2.075***	-2.098***	-2.078***
	(0.579)	(0.579)	(0.579)
Overweight	0.824**	0.836**	0.844**
	(0.386)	(0.387)	(0.386)
Obese	3.584***	3.581***	3.594***
	(0.542)	(0.542)	(0.542)

Table 8 Continues

Table 8 Continued

VARIABLES	(1) Neg events	(2) Neighbourhood	(3) All
Per capita household income level (Low)			
Middle	-0.048	-0.021	0.005
	(0.334)	(0.335)	(0.335)
High	0.510	0.525	0.564
	(0.415)	(0.420)	(0.420)
Employment status (Employed)			
Not economically active	-0.192	-0.270	-0.234
	(0.365)	(0.365)	(0.365)
Unemployed	0.164	0.127	0.133
	(0.375)	(0.375)	(0.375)
Smoker	0.582	0.571	0.577
	(0.549)	(0.549)	(0.549)
Frequency of alcohol consumption (None)			
Rarely drinks	0.862**	0.886**	0.871**
	(0.381)	(0.381)	(0.381)
Drinks 1–2 days/week	0.597	0.600	0.591
	(0.644)	(0.644)	(0.644)
Drinks every day	-0.988	-0.918	-0.965
	(2.038)	(2.033)	(2.037)
Medical insurance	0.453	0.413	0.429
	(0.681)	(0.679)	(0.680)
Urban residence	0.139	0.127	0.199
	(0.657)	(0.657)	(0.657)
Year (2008)			
2010/11	-1.496***	-1.533***	-1.478***
	(0.262)	(0.261)	(0.262)
2012	-1.086***	-1.078***	-1.021***
	(0.279)	(0.285)	(0.287)
Means of all time-variant variables (π)			
Negative household events			
Death	-0.179		-0.177
	(0.620)		(0.620)
Serious illness or injury	-1.468		-1.501
	(0.963)		(0.964)
Agriculture shock	-1.060		-1.131
	(1.706)		(1.708)
Job loss	-2.258**		-2.319**
	(0.991)		(0.991)
Grant income and remittances reduction	-1.846		-1.840
	(1.539)		(1.539)
Property loss	0.725		0.690
	(1.316)		(1.316)
Neighbourhood income level (Low)			
Middle	-0.261	0.350	0.425
	(0.410)	(0.540)	(0.542)
High	0.102	0.145	0.212
	(0.435)	(0.677)	(0.678)
Socio-demographic variables			
Age (15–24)			
25–39	4.341***	4.442***	4.380***
	(0.647)	(0.647)	(0.647)
40–54	12.192***	12.261***	12.263***
	(1.080)	(1.081)	(1.080)
> = 55	26.171***	26.233***	26.234***
	(1.623)	(1.624)	(1.623)
Education (none)			
Grade 1–7	-0.169	-0.301	-0.206
	(1.986)	(1.991)	(1.989)
Grade 8–11	-2.239	-2.336	-2.292
	(2.146)	(2.151)	(2.149)
Matric	-3.526	-3.536	-3.538
	(2.263)	(2.267)	(2.265)
Post-matric	-5.188**	-5.184**	-5.163**
	(2.295)	(2.299)	(2.297)

Table 8 Continued

VARIABLES	(1) Neg events	(2) Neighbourhood	(3) All
Marital status (Never)			
Married/Cohabiting	0.508	0.498	0.493
	(0.742)	(0.742)	(0.742)
Widowed/Divorced	3.420***	3.318***	3.409***
	(1.269)	(1.269)	(1.270)
BMI (Normal)			
Underweight	-2.547***	-2.537***	-2.543***
	(0.838)	(0.838)	(0.838)
Overweight	2.485***	2.481***	2.465***
	(0.561)	(0.562)	(0.562)
Obese	3.532***	3.534***	3.522***
	(0.684)	(0.684)	(0.684)
Per capita household income level (Low)			
Middle	1.218**	1.165**	1.165**
	(0.533)	(0.535)	(0.534)
High	1.369**	1.332**	1.315**
	(0.618)	(0.620)	(0.622)
Employment status (Employed)			
Not economically active	0.867	0.992*	0.909
	(0.567)	(0.567)	(0.567)
Unemployed	-0.379	-0.362	-0.349
	(0.617)	(0.616)	(0.617)
Smoker	-0.359	-0.370	-0.354
	(0.727)	(0.727)	(0.727)
Frequency of alcohol consumption (None)			
Rarely drinks	0.351	0.290	0.341
	(0.637)	(0.637)	(0.637)
Drinks 1–2 days/week	5.415***	5.376***	5.420***
	(1.052)	(1.052)	(1.052)
Drinks every day	-0.786	-0.963	-0.811
	(2.880)	(2.874)	(2.877)
Medical insurance	-3.158***	-3.073***	-3.134***
	(0.877)	(0.877)	(0.877)
Urban residence	0.022	-0.019	-0.038
	(0.729)	(0.728)	(0.729)
Year (2008)			
2010/11	-0.970	-0.955	-0.989
	(0.718)	(0.717)	(0.718)
2012	-2.603***	-2.704***	-2.667***
	(0.659)	(0.660)	(0.662)
Constant	112.704***	112.754***	112.705***
	(0.890)	(0.880)	(0.890)
Observations	33,779	33,779	33,779
R-squared	0.357	0.355	0.357
Number of pid	16,334	16,334	16,334

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Unweighted analysis. Model 1: In addition to negative household events, controlled for individual socio-demographic and behavioural characteristics; Model 2: In addition to neighbourhood income level, controlled for individual socio-demographic and behavioural characteristics; and Model 3 (fully adjusted model): Controlled for all variables (negative household events, neighbourhood income level, and individual socio-demographic and behavioural characteristics).

Appendix 1.C

Table 9: Linear probability model (LPM) and conditional fixed-effects logit (CFEL) model results

VARIABLES	(1) LPM	(2) CFEL Coef	(3) Odds Ratio
Negative household events			
Death	0.006	0.149*	1.161*
	(0.006)	(0.088)	(0.102)
Serious illness or injury	0.001	0.097	1.101
	(0.009)	(0.139)	(0.154)
Agriculture shock	0.029*	0.201	1.222
	(0.016)	(0.206)	(0.252)
Job loss	0.002	0.393**	1.481**
	(0.010)	(0.165)	(0.244)
Grant income and remittances reduction	0.048***	0.489**	1.630**
	(0.015)	(0.213)	(0.347)
Property loss	-0.006	0.096	1.101
	(0.013)	(0.181)	(0.199)
Neighbourhood income level (Low)			
Middle	0.005	-0.013	0.987
	(0.005)	(0.081)	(0.080)
High	0.012*	0.122	1.130
	(0.007)	(0.116)	(0.132)
Socio-demographic variables			
Age (15–24)			
25–39	0.058***	-0.004	0.996
	(0.005)	(0.212)	(0.211)
40–54	0.259***	0.276	1.318
	(0.009)	(0.279)	(0.368)
> = 55	0.464***	0.111	1.117
	(0.011)	(0.334)	(0.373)
Male	-0.001		
	(0.005)		
Population group (Black African)			
Coloured	0.058***		
	(0.009)		
Indian	-0.030		
	(0.027)		
White	-0.073***		
	(0.017)		
Education (none)			
Grade 1–7	0.006	0.031	1.032
	(0.011)	(0.258)	(0.267)
Grade 8–11	-0.025**	0.117	1.124
	(0.011)	(0.414)	(0.465)
Matric	-0.043***	0.093	1.097
	(0.012)	(0.477)	(0.524)
Post-matric	-0.061***	0.359	1.433
	(0.013)	(0.466)	(0.668)
Marital status (Never)			
Married/Cohabiting	0.012*	-0.129	0.879
	(0.007)	(0.141)	(0.124)
Widowed/Divorced	0.046***	0.012	1.012
	(0.012)	(0.165)	(0.167)

Table 9 Continues

Table 9 Continued

VARIABLES	(1) LPM	(2) CFEL Coef	(3) Odds Ratio
BMI (Normal)			
Underweight	-0.016**	0.085	1.089
	(0.008)	(0.168)	(0.183)
Overweight	0.038***	0.078	1.082
	(0.005)	(0.090)	(0.098)
Obese	0.125***	0.380***	1.463***
	(0.007)	(0.111)	(0.162)
Per capita household income level (Low)			
Middle	0.020***	-0.019	0.981
	(0.005)	(0.078)	(0.076)
High	0.026***	0.004	1.004
	(0.006)	(0.096)	(0.097)
Employment status (Employed)			
Not economically active	0.025***	-0.193**	0.825**
	(0.006)	(0.082)	(0.068)
Unemployed	0.006	-0.183*	0.833*
	(0.006)	(0.098)	(0.082)
Smoker	-0.006	0.174	1.190
	(0.007)	(0.113)	(0.134)
Frequency of alcohol consumption (None)			
Rarely drinks	0.007	0.051	1.052
	(0.007)	(0.093)	(0.098)
Drinks 1–2 days/week	0.048***	0.046	1.047
	(0.011)	(0.126)	(0.132)
Drinks every day	-0.001	-0.066	0.936
	(0.033)	(0.298)	(0.278)
Medical insurance	-0.003	0.110	1.117
	(0.009)	(0.166)	(0.185)
Urban residence	0.027***	0.283	1.327
	(0.006)	(0.213)	(0.282)
Year (2008)			
2010/11	-0.047***	-0.326***	0.722***
	(0.005)	(0.058)	(0.042)
2012	-0.022***	0.228***	1.256***
	(0.004)	(0.061)	(0.077)
Constant	0.002		
	(0.013)		
Observations	33,773	6,386	6,386
R-squared	0.269	0.038	0.038

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Unweighted analyses.

The next chapter contains Essay 2: Socioeconomic correlates of mental health in South Africa.

Chapter 3

Socioeconomic correlates of mental health in South Africa

3.1 Introduction

Mental illness and substance use disorders affect millions of individuals globally, imposing an enormous global disease burden on governments, communities, and families attempting to manage the conditions (Batada & Solano, 2019; Marquez, 2018; World Health Organization, 2013b). Mental health is a major contributor to disability globally (Trautmann *et al.*, 2016; World Health Organization, 2013). People with severe mental disorders die 10 to 20 years earlier than the general population, mainly due to preventable physical diseases and higher rates of suicide, homicide, and accidents, as people with mental disorders are at higher risk of contracting communicable diseases, be involved in acts of violence, and sustain accidental injuries (Liu *et al.*, 2017; Westman *et al.*, 2013; World Health Organization, 2019).

In addition to biological risks, the physical and social environments of people in poor or low-income families tend to increase their vulnerability to developing mental health problems. These communities are more likely to experience unemployment, low education, devastating life events, social isolation and exclusion, low social capital, malnutrition, physical illness, exposure to violence, and problems caused by substance abuse (Burger *et al.*, 2017; Burns, 2015; Duke, 2017; Patel *et al.*, 2018; Schneider *et al.*, 2016; World Health Organization, 2017). There is significant evidence of a cyclical relationship between poverty and mental disorders that leads to ever-rising rates of both (Mnookin, 2016; Patel *et al.*, 2015). This makes mental health both a means and an end to socioeconomic development (Lund, 2014). The debilitating nature of mental health problems can, like physical problems, result in sufferers being unable to study or work (Marquez, 2018; Patel *et al.*, 2015). This has a significant direct welfare impact on the individual and a wider impact on family and social stability, and the national economy. Yet, the burden of mental disorders continues to grow globally; around 300 million people (4.4% of the world's population) were affected by depression in 2015, and nearly as many suffered from anxiety (World Health Organization, 2017a).

The burden of mental problems has been growing in South Africa (Williams *et al.*, 2008). This trend is expected to continue with the significant projected population growth and ageing, the growing burden of non-communicable diseases, and co-morbidity between mental health problems, HIV, and other chronic health conditions (Jack *et al.*, 2014; Mayosi *et al.*, 2009;

Williams *et al.*, 2008; Woollett *et al.*, 2017). Literature suggests direct and indirect cross-effects between physical and mental health, whereby past physical health has an effect on mental health, and vice versa (Ohrnberger *et al.*, 2017; Sorsdahl *et al.*, 2018). This may be mediated by employment outcomes like loss of productivity or wages (García-Gómez *et al.*, 2013); impaired decision-making processes (World Health Organization, 2013c), a lack of health-seeking behaviours; lifestyles choices such as a poor diet, smoking, and high alcohol consumption (Sorsdahl *et al.*, 2018), and little social interaction (Steptoe *et al.*, 2013). However, the true burden of mental problems is likely to be underestimated, as co-morbidities make the identification and diagnosis of mental illness challenging (Mensah & Collins, 2015; Prince *et al*., 2007). In addition, patients underreport their conditions, as they fear the stigma and discrimination they may experience as a result of their condition (Bharadwaj *et al.*, 2017; Monteiro, 2015; Qin *et al.*, 2018).

South Africa is a highly unequal upper-middle country whose public mental healthcare services face the challenging resource constraints found in most African countries (Monteiro, 2015). There is no simple solution to South Africa’s specific challenges, and for any future strategy to be successful, it must address the underlying determinants of poor mental health that make people more vulnerable to developing the conditions in the first place. Hence, in this study, I examined the relationship between depressive symptoms and socioeconomic factors in South Africa through a two-way fixed effects regression to control for potential effects that are constant within each individual over the years or are constant across all individuals within each year. Understanding the relationship between socioeconomic factors and mental health could assist policy makers and funders to make evidence-based decisions when allocating South Africa’s limited healthcare resources to reduce the mental health treatment gap. The cyclical relationship between mental health and substance use problems, and both income inequality and physical health, means that a reduction in poor mental health could also potentially have a positive impact on South Africa’s high poverty rate, extreme inequality, and the population’s health in general.

3.2 Background of the study

Mental health is a major contributor to disability globally (Trautmann *et al.*, 2016; World Health Organization, 2013), with depression ranked as the largest contributor to disability in South Africa and globally. In terms of the burden of mental disorders in South Africa, the disability-adjusted life years per every 100 000 population were 3191.01 in South Africa in

2017 (World Health Organization, 2017b). In 2015, depression contributed to 7.2% and 7.5% of all years lived with disability in South Africa and in the world respectively (World Health Organization, 2017a). The South African Stress and Health (SASH) study conducted between 2002 and 2004 reported that, in the year prior to the survey, one out of every seven respondents experienced a common mental health problem, and almost one-third of the adult South African population will experience a mental health problem in their lifetime (Herman *et al.*, 2009; Stein *et al.*, 2009). In 2009, the estimated 12-month prevalence of common mental disorders (anxiety, mood, and substance use disorders) was 16.5% in South Africa (Williams *et al.*, 2009). In 2015, the prevalence of depressive and anxiety disorders in South Africa was 4.6% and 3.4%, and contributed 7.2% and 2.8% respectively to years lived with disability (World Health Organization, 2017a). In South Africa, poor mental health is associated with 24 missed workdays per year (Mall *et al.*, 2015), with adult people suffering severe depression and anxiety problems losing US$4 798 income per year, a loss of approximately US$3.6 billion per year to the economy (Lund *et al.*, 2013).

Despite the high and ever-increasing economic and personal burden of mental health problems and substance abuse, government funding dedicated to mental health services has been constrained (Lund *et al.*, 2013), resulting in a significant treatment gap (Jack *et al.*, 2014; Schneider *et al.*, 2016). The very low mental health workforce rate, limited infrastructure, and constrained supply of mental health medication in South Africa (Docrat *et al.*, 2019) reflects very low expenditure on mental health. The death of 94 mental health patients in 2016 within an average of two months of being transferred from the Life Esidemeni Hospital to 27 unlicenced and underfunded Non-Governmental Organisations (Munshi & Bezuidenhout, 2017) as a cost cutting measure shows how mental health care has been underfunded and not been prioritised. For example in 2017, the World Health Organization (2017b) reported that there were: 1.52 psychiatrist per 100 000 people, and 0.08 child psychiatrist per 100 000, at the same time the Share of total public health expenditure in public mental health was 3%, translating to a total mental health expenditure of ZAR 99.47 per person.

The results from a national survey by Docrat *et al.*, 2019) also found that public expenditure on mental health represented 5% of the total public health expenditure during the 2016/17 financial year. This share of expenditure on mental health ranged from 2.1 to 7.7% across provinces (Docrat *et al.*, 2019). Docrat *et al.* (2019) report that 86% of mental healthcare expenditure is on inpatient care, with approximately 50% of the total expenditure used in psychiatric hospitals, and less than 10% in primary care level. High readmission rates of almost

1 in every 4 inpatients within 3 months of recent discharge cost the national purse of approximately USD112million (Docrat *et al.*, 2019). Given that 84% percent of South Africa's health system is serviced by the public sector (Docrat *et al.*, 2019), mental health preventive measures will help the public sector save resources needed for a stronger mental health system envisaged in the 2002 Mental Health Care Act (National Department of Health, 2002) and in the 2013–2020 National Mental Health Policy Framework and Strategic Plan (National Department of Health, 2013a).

Despite the public mental health care serving the larger share (83%) of the population in 2015, 70% of South Africa's medical practitioners were serving in the private sector (The Rural Mental Health Campaign, 2015). In 2015, 10% of the reported medication stockouts were psychiatric medications (The Rural Mental Health Campaign, 2015). Of the 16.5% of adults who reported that they experienced a mental health condition in the SASH study (Herman *et al.*, 2009), only 25% received treatment for their condition at that time (Seedat *et al.*, 2009). In addition, Suliman *et al.* (2010) found that mental health problems are 10 times less likely to be treated than physical problems, despite causing significantly more disability. The recent crude estimate by Docrat *et al.* (2019) suggest a high mental health treatment gap (92%). The South African Ministry of Health committed to reducing this treatment gap by increasing the number of people screened and treated for mental problems by 30% by 2030 (National Department of Health, 2013b), and reducing per capita alcohol consumption by 20% by 2020. However, there has been no clear progress towards these goals to date.

The socioeconomic conditions prevailing in South Africa expose the most vulnerable groups to mental health risks. South Africa is a middle-income country with a population of 56 million, and is plagued by unemployment, poverty, and inequality (Burns *et al.*, 2017; Cheng *et al.*, 2016; Patel *et al.*, 2018), which are all cyclically related to poor mental health. Burns *et al.* (2017) report a significant association between decreasing household income and depression. Conversely, people with mental health disorders are also more likely to slide into poverty due to exclusion from economic opportunities (as a result of low education, stigma, and discrimination) or the loss of employment because of diminished productivity (Schneider *et al.*, 2016). People struggling with mental illness experience the highest rates of unemployment among all people with disabilities (Chan *et al.*, 2015).

According to the World Bank (2018), at least three million South Africans entered into poverty between 2011 and 2015, increasing the poverty rate from 36% to 40%. With respect to national poverty lines, the poverty headcount ratio is event higher at 55% (World Bank, 2018). The level of poverty has become deeper and more unequal, and with a high Gini coefficient of 63 in 2015, South Africa is the most unequal society in the world (World Bank, 2018). South Africa's unemployment rate remained consistently high between 2008 and 2017, increasing from 22.5% in 2008 to 25.1% in 2015, and to 27.7% in the first half of 2017 (World Bank, 2018).

South Africa is also burdened with a high level of traumatic and stressful events (Burger, Posel *et al.*, 2017), including a much higher incidence of illness and death than other countries with similar economic conditions (Mayosi *et al.*, 2012). South Africa has a high incidence of infectious diseases like the human immunodeficiency virus (HIV) and tuberculosis (TB); high and increasing levels of non-communicable diseases like diabetes and cardiovascular diseases; high child and maternal mortality rates; and a high burden of deaths due to injury (Mayosi *et al.*, 2009). Other sources of social trauma and stress include high rates of sexual assault and violence, frequent changes in households' location and composition, many child- and female-headed households, and exceptionally high levels of chronic unemployment. This trauma is often not matched with sufficient accessible mental health care services for vulnerable groups struggling with poor mental health who are not covered by medical aid schemes (Burger *et al.*, 2017).

3.3 Methods

3.3.1 Data source

In this study, I used the National Income Dynamics Study (NIDS) panel survey data to examine the relationship between socioeconomic status and depressive symptoms in South Africa over the 10-year period from 2008 to 2017[15]. The NIDS is conducted by the Southern Africa Labour and Development Research Unit at the University of Cape Town. The NIDS was designed to follow the same individuals over time and collect data on a range of individual and household indicators. Importantly, the NIDS data include both information on socio-economic status and mental health. For the first round's sample, a two-stage sampling design was used. This involved selecting 400 primary sampling units (PSUs) from approximately 3 000 PSUs in the national sample in the first stage, and identification of dwellings within each PSU in the second

[15] I used data versions 7.0.0 for Wave 1; 4.0.0 for Wave 2; 3.0.0 for Wave 3; 2.0.0 for Wave 4; and 1.0.0 for Wave 5.

stage. All individuals living in households selected from the 400 PSUs formed the population, referred to as *continuing sample members* (CSMs). Everyone that was a co-resident with a CSM after the first round was also interviewed, and are referred to as *temporary sample members* (TSMs) (Leibbrandt *et al.*, 2009).

3.3.2 Measures

I used the score of the 10-item Centre for Epidemiologic Studies Depression Scale (CES-D10) (Radloff, 1977) as the dependent variable. The NIDS questionnaire for adults (individuals aged 15 years and older) includes 10 questions on mental health. The questions specifically captured if the respondent was bothered by things that usually don't bother them; had trouble keeping mind on what they were doing; felt depressed; felt everything they did was an effort; felt hopeless about the future; felt fearful; had restless sleep; not happy; felt lonely; and could not get going, during the prior to the survey. Each of the ten questions had four responses: 0 (*Rarely or none of the time*), 1 (*Some or little of the time*), 2 (*Occasionally or a moderate amount of time*), and 3 (*All the time*). These scores from the ten questions, which make up the CES-D10, can be aggregated to create a depressive symptom scale ranging from 0 (*Best*) to 30. Survey-based measures of mental health have been validated as good measures of depression and other psychiatric disorders (Andresen *et al.*, 1994; Das *et al.*, 2008). The CES-D10 scale has also been validated in South Africa using local languages (Baron *et al.*, 2017)[16]. It is used frequently in South African studies, and is considered a reliable depression screening tool (Tomita & Burns, 2013). The CES-D10 scale does not determine the absence or presence of recognised mental disorders, but is used to measure a continuity of psychological problems (Steffick, 2000), with the likelihood of being depressed increasing with an increasing score. In the regression analyses in the present study, the CES-D10 score was used as the continuous variable, as it accurately reflects the different mental health needs of individuals (Patel *et al.*, 2018).

The correlates included a number of economic and demographic indicators (Ardington & Case, 2010; Burger, *et al.*, 2017; Hamad *et al.*, 2008; Tomita & Burns, 2013). These are: per capita real household income level, education level, employment status, marital status, residence, age category, gender, population group, social capital (religiousness and neighbourhood

[16] Validity and reliability of the CES-D10 as a depression-screening instrument were tested in Zulu, Xhosa, and coloured Afrikaans populations.

attachment), self-reported health status, and respondent's depression score in the previous round.

3.3.3 Statistical analyses

To adjust for attrition and to make the results generalisable to South Africa, I used post-stratification sampling weights for data analyses (De Villiers *et al.*, 2013). For descriptive analysis, I present a pooled summary of all variables. I also analysed the prevalence of the possibility of a major depressive episode using a threshold of a CES-D10 score of at least 10, suggested by Andresen *et al.* (1994), also used by Burger *et al.* (2017).

For regression analysis, I used the full sample of adult respondents who were successfully interviewed in any of the rounds. This amounted to 15 576 observations in 2008, 17 624 observations in 2010/11, 18 686 observations in 2012, 22 740 observations in 2014/15, and 23 891 observations in 2017. To explore the relationship between socioeconomic indicators and depressive symptom scores, I first used ordinary least squares (OLS). The socioeconomic variables of interest were: years of education, per capita real household income (real household income divided by household size), employment status (employed or unemployed), and location of residence (rural or urban). I also included marital status (never married, married/cohabiting, or widowed/divorced, with *Never married* as the reference group); population group (black African, Coloured, Indian, or white, with black African as the reference group); religiousness (religious or not); respondent's self-reported health (poor/fair or good); and age. To capture social capital, I also included the respondent's preference to stay in the current neighbourhood (unsure, stay or leave, with *Unsure* as the reference group). I also controlled for the respondent's history of depression by including the respondent's depressive symptom score from the previous round.

I then used a fixed effects model to obtain the relationship between socioeconomic correlates and depressive symptoms, adjusted for several invariant and latent individual characteristics (like genetic factors) that can increase the risk for depression (Angrist & Pischke, 2009). The fixed effects model was specified as:

$$y_{it} = \beta x_{it} + \delta d_t + u_i + e_{it} \qquad 6,$$

where y_{it} was the dependent variable (CES-D10 score), and $u_i (i = 1, \ldots, n)$ were fixed effects to be estimated. In addition to individual and time fixed effects, the regressions included changes in the observed individual characteristics as independent variables (x_{it}). These includes the logarithm of per capita household income, employment status, location of residence, marital status, years of education, religiousness, and preference to stay in the current neighbourhood. Time-invariant unobserved heterogeneity, u_i, was removed by subtracting averages of each individual across time in Equation 6, expressed as:

$$y_{it} - \bar{y}_i = \beta(x_{it} - \bar{x}_i) + \delta(d_t - \bar{d}_t) + (u_i - \bar{u}_i) + (e_{it} - \bar{e}_i) \qquad 7 \text{ (within-transformation),}$$

which is written as:

$$\ddot{y}_{it} = \beta\ddot{x}_{it} + \delta\ddot{d}_{it} + \ddot{e}_{it} \qquad 8,$$

a time-demeaned equation.

3.4 Results

3.4.1 Descriptive analyses

The results of the analysis reported in this section are based on unbalanced pooled sample of adult respondents who completed all 10 questions on depressive symptoms in each round. Table 10 shows the sociodemographic characteristics of the pooled study sample. The mean CES-D10 score was 6.93. The share of male respondents in the sample was 42.2%. black Africans (82.1%) made up the largest share of the study sample, whilst Indians (1%) made up the smallest share. The share of urban respondents was 48.3%. In terms of education, almost 42.9% of the sample held Grade 8 to 11 as their highest education. Only 11.1% of the sample would prefer to leave their current neighbourhood, whilst 12% were unsure on whether to leave or stay and 70% would want to continue in their current neighbourhood. Age group 15–24 made up the largest share (32.8%) of the sample followed by age group 25–29 (30.6%). In terms of employment status, 36.2% were employed and 15.3% were unemployed, while 48.5 were not economically active. A large share (87.6%) reported good self-assessed health. Only 9.2% of the sample were members of a medical aid. The sample was mostly religious, with 90.9% reporting to have a religious affiliation.

Figure 8, below, shows the distribution of the CES-D10 scores across the five rounds. In 2008, 32.14% (95% CI 29.89 – 34.39) of respondents in the sample had scores of at least 10. This share decreased to 21.29% (95% CI 18.83 – 23.73) in 2010/2011, beyond which it increased to 23.18% (95% CI 20.85 – 25.51) in 2012, and to 23.56% (95% CI 21.47 – 26.65) in 2014/2015.

This later decreased to 22.70% (95% CI 21.10 – 24.3) in 2017. Overall, 24.39% (95% CI 23.38 – 25.40) of respondents had CES-D10 scores of 10 and above across the five rounds.

Figure 8: Distribution of depressive symptom score

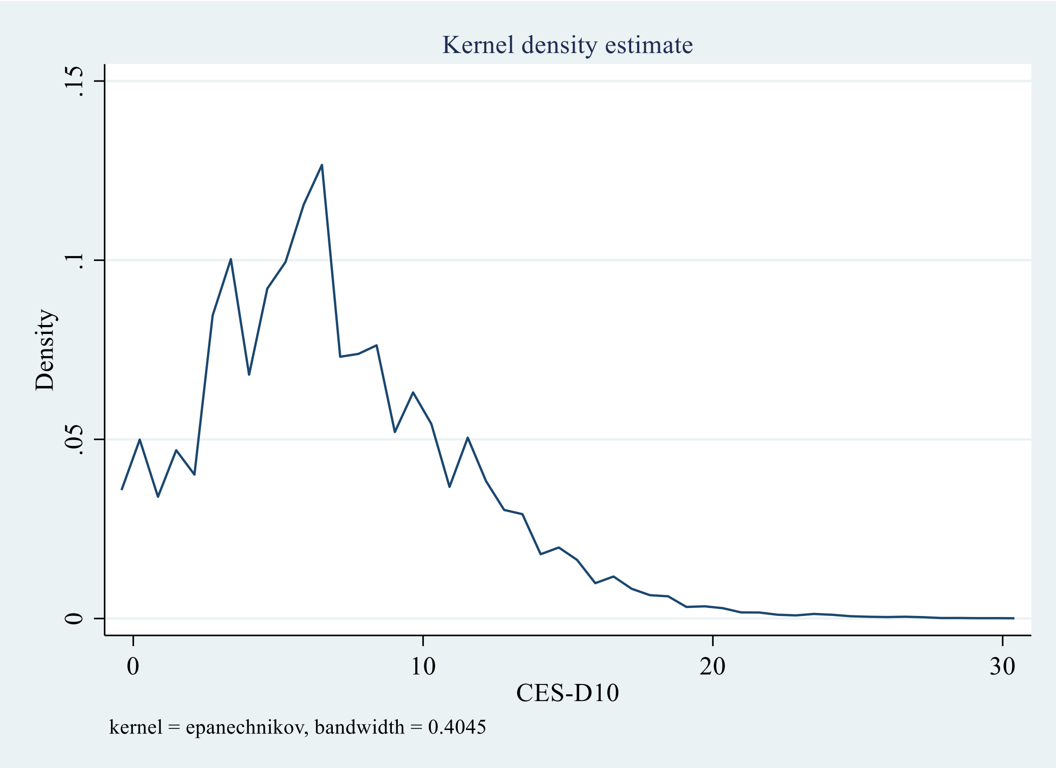


Table 10: Characteristics of the pooled sample

Variable	**Total (*N* = 88 198)**
CES-D10 score	
Mean (SD)	6.93 (4.38)
Median (Q1, Q3)	6.0 (4.0, 10.0)
Per capita household income level	
Poor	25 471 (28.9%)
Middle-income	28 679 (32.5%)
Rich	34 048 (38.6%)
Age category	
15–24	28 926 (32.8%)
25–39	26 973 (30.6%)
40–54	17 784 (20.2%)
> = 55	14 515 (16.5%)
Population group	
African	72 396 (82.1%)
Coloured	12 279 (13.9%)
Indian	909 (1.0%)
White	2 614 (3.0%)
Gender	
Female	51 012 (57.8%)
Male	37 186 (42.2%)
Education category	
No schooling	8 116 (9.2%)
Grade 1–7	17 664 (20.0%)
Grade 8–11	37 826 (42.9%)
Matric	13 094 (14.8%)
Certificate/Degree/Diploma	11 498 (13.0%)
Employment status	
Employed	31 920 (36.2%)
Not economically active	42 749 (48.5%)
Unemployed	13 529 (15.3%)
Marital status	
Never married	56 543 (64.1%)
Married or cohabiting	24 532 (27.8%)
Widowed or divorced	7 123 (8.1%)
Medical aid	
No	80 043 (90.8%)
Yes	8 155 (9.2%)
Residence	
Rural	45 568 (51.7%)
Urban	42 630 (48.3%)
Religious affiliation	
No	8 142 (9.2%)
Yes	80 056 (90.8%)
Preference to stay in the current neighbourhood	
Unsure	10 542 (12.0%)
Stay	67 882 (77.0%)
Leave	9 774 (11.1%)
Self-assessed health	
Poor	10 932 (12.4%)
Good	77 266 (87.6%)

3.4.2 Regression results

The regression results in Table 11 are from the unweighted OLS (Models 1 and 5), the random effects model (Model 2), and the fixed effects estimations (Models 3 and 4). OLS Model 1 is on the full pooled sample and does not control for the lagged depression score. Although Model 1 fails to account for unobserved heterogeneity, it was estimated to create sample consistent used for the FE models. In OLS Model 5, I included the lagged CES-D10 score, because current mental health depends on past mental condition. The conclusions of this thesis are based on fixed effects regressions. For the fixed effects regression, I had two models: Model 3 controlled for socioeconomic variables and adjusted for time and individual fixed effects, and Model 4 contained the socio-economic variables, time and individual fixed effects, and other covariates. The fixed effects regression coefficients in Model 4 largely confirmed the OLS Model 5 results. The difference between results of Models 4 and 5 was related to education and age, which are less time-variant.

In Model 4, I found that people who were employed and became economically inactive had higher depressive symptoms scores. I also found that, acquiring *matric* certificate as level of education is positively associated with CES-D10 score. Shifts in income level, from low per capita household income to middle rank and from low per capita household income to high rank, were both significantly associated with low CES-D10 scores. I also found that people who got married (from being single), and those who became religious (from having no religious affiliation) had lower CES-D10 scores. An improvement in self-reported health (from poor to good) was associated with a lower CES-D 10 score. I found no significant associations between getting a medical aid and CES-D10, or between shifts in age categories and CES-D10 scores. Moving into an urban area was found to be negatively associated with CES-D10 score. Changes in preference to stay in the current neighbourhood were also significant in explaining CES-D10 scores, with preferring to *stay* having a negative coefficient, and preferring to *leave* showing a positive coefficient. Preferring to stay in the current neighbourhood and good self-reported health had larger coefficients. I also found that switching from being non-religious to being religious was modestly associated with lower depressive symptoms scores.

The OLS models and random effects results were similar on all variables. There was an education-level gradient whereby higher levels, as compared to no education, were significantly associated with lower depressive symptoms scores. Compared to with *low per capita household income*, people in *middle* and *higher* ranks had significantly low CES-D10 scores. I found that being employed is protective of depressive symptoms, as shown by positive coefficients for *economically inactive* and *unemployed*. Across the five models, location of residence was significantly associated with the depression scores, with respondents in urban areas having higher depressive symptom scores compared to their counterparts in rural areas. Respondents who preferred to continue staying in their current neighbourhoods had significantly lower depression scores, while those who preferred to leave had higher depression scores. The average depression scores were significantly lower for people with good self-reported health. There were also gender-, age-, and population group profiles in CES-D10 scores. I also found that having a medical aid and being religious offer protection against depressive symptoms. To test the effect the possible effect of attrition on regression results in Table 11, I replicated these regression models using a balanced panel and panel weights. The coefficients remained relatively stable, suggesting that attrition (non-random attrition that is correlated with mental health) had no influence on the results (see Table 13 in Appendix 2.A).

Though the purpose of this study was to examine the effect of socioeconomic factors on the CES-D10 score (depressive symptoms), I also estimated conditional fixed-effects logit (CFEL) regression models (and linear probability models) for the full sample, and by gender, and by residence sub-samples (Table 14 in Appendix 2.B) for sensitivity analysis. The CFEL models estimated the effects of variables on the likelihood of one being screened positive for depression (CES-D10 score >= 10), whilst the OLS, random effects, and fixed-effects models (used in the main analysis) estimated the effect of variables on the depression score. In the CFEL, I report the odds ratio and not marginal effects, as these cannot be estimated with the current Stata programs, and also because the interpretation can be difficult (Norton, 2012; Norton & Dowd, 2018). The signs of coefficients and significance of variables confirm the results from linear models presented in Table 11.

Because explanatory variables for health can differ by gender and by place of residence, Table 12 presents the fixed effects and the conditional fixed-effects logit (CFEL) regression results by gender and residence[17]. I also tested to see if the difference between *male* and *female*, and between *rural* and *urban* are statistically significant by interacting the gender and residence dummies variables with all other covariates. The coefficients of population group,

[17] Table 15 in Appendix 2.C presents the full results by gender and by residence. Regressions are both on a continuous dependent variable (CES-D10) score and binary dependent variables (=1 if CES-D10>=10 and 0, otherwise).

neighbourhood attachment, medical aid, and year, interacted with residence, were significant, suggesting that the differences in coefficients in the sub-samples were statistically significant under the fixed-effects model (Model 2). For CFEL, residence interactions with 'being religious', neighbourhood attachment, and year were significant in Model 4, suggesting that the coefficients of variables between rural and urban sub-sample were different.

In relation to gender differences, the coefficients of *unemployed*, *good self-reported health*, and *year* interacted with *gender*, and were significant under the fixed-effects model (Model 1). This suggested that the coefficients of these variables were significantly different between gender sub-samples. In Model 3, the coefficients of *neighbourhood attachment* and *being religious*, interacted with residence, were significant, suggesting that the differences by gender were statistically significant.

Table 11: Regression results with CES-D10 score as the dependent variable

	OLS	Random effects	Fixed – effects models		OLS lagged *dep var*
VARIABLES	(1)	(2)	(3)	(4)	(5)
Depressive symptom score in the previous wave					0.034***
					(0.005)
Education (none)					
Grade 1–7	-0.216***	-0.224***		-0.166	-0.127
	(0.063)	(0.063)		(0.233)	(0.079)
Grade 8–11	-0.545***	-0.552***		0.103	-0.509***
	(0.065)	(0.065)		(0.248)	(0.081)
Matric	-0.576***	-0.573***		0.461*	-0.565***
	(0.073)	(0.073)		(0.262)	(0.092)
Post-matric	-0.805***	-0.808***		0.164	-0.793***
	(0.076)	(0.076)		(0.266)	(0.093)
Per capita household income level (Low)					
Middle	-0.344***	-0.343***	-0.279***	-0.286***	-0.388***
	(0.037)	(0.037)	(0.051)	(0.051)	(0.050)
High	-0.533***	-0.527***	-0.304***	-0.316***	-0.573***
	(0.043)	(0.043)	(0.065)	(0.065)	(0.054)
Employment status (Employed)					
Not economically active	0.353***	0.352***	0.381***	0.405***	0.446***
	(0.038)	(0.038)	(0.055)	(0.055)	(0.048)
Unemployed	0.096**	0.095**	-0.010	-0.009	-0.092
	(0.046)	(0.045)	(0.062)	(0.062)	(0.058)
Urban residence	0.315***	0.315***	0.402***	0.357***	0.382***
	(0.032)	(0.032)	(0.095)	(0.095)	(0.041)
Age (15–24)					
25–39	1.006***	0.995***		0.121	0.780***
	(0.040)	(0.040)		(0.082)	(0.052)
40–54	1.374***	1.366***		0.028	1.168***
	(0.053)	(0.053)		(0.142)	(0.068)
> = 55	1.265***	1.268***		-0.057	1.047***
	(0.062)	(0.062)		(0.202)	(0.080)
Male	-0.298***	-0.299***			-0.231***
	(0.030)	(0.030)			(0.039)
Marital status (Never)					
Married/Cohabiting	-0.544***	-0.535***		-0.186**	-0.591***
Table Continues to next page	(0.041)	(0.041)		(0.091)	(0.051)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Widowed/Divorced	0.379***	0.378***		0.182	0.231***
	(0.068)	(0.067)		(0.134)	(0.082)
Population group (black African)					
Coloured	-1.478***	-1.474***			-1.494***
	(0.047)	(0.047)			(0.059)
Indian	-1.297***	-1.304***			-1.025***
	(0.146)	(0.146)			(0.182)
White	-1.547***	-1.560***			-1.117***
	(0.100)	(0.099)			(0.137)
Religious	-0.312***	-0.305***		-0.109*	-0.332***
	(0.048)	(0.048)		(0.066)	(0.065)
Preference to stay in the current neighbourhood (Unsure)					
Stay	-0.757***	-0.757***	-0.725***	-0.736***	-0.753***
	(0.044)	(0.044)	(0.058)	(0.058)	(0.059)
Leave	0.357***	0.357***	0.376***	0.343***	0.402***
	(0.062)	(0.062)	(0.078)	(0.078)	(0.083)
Self-reported health status (Poor/Fair)					
Good health	-1.721***	-1.705***		-1.217***	-1.544***
	(0.053)	(0.053)		(0.068)	(0.069)
Medical insurance	-0.568***	-0.564***		-0.140	-0.496***
	(0.056)	(0.056)		(0.102)	(0.073)
Year (2008)					
2010/11	-0.887***	-0.889***	-0.961***	-0.875***	
	(0.049)	(0.049)	(0.055)	(0.056)	
2012	-1.040***	-1.039***	-0.925***	-0.865***	
	(0.048)	(0.048)	(0.055)	(0.057)	
2014/15	-1.123***	-1.121***	-0.860***	-0.848***	
	(0.049)	(0.049)	(0.058)	(0.066)	
2017	-1.213***	-1.209***	-0.795***	-0.810***	
	(0.050)	(0.050)	(0.061)	(0.073)	
Constant	10.378***	10.359***	8.009***	9.093***	9.061***
	(0.110)	(0.110)	(0.090)	(0.260)	(0.147)
Observations	88,198	88,198	88,198	88,198	49,950
R-squared	0.100	0.167	0.020	0.027	0.082
Number of pid	35,288	35,288	35,288	35,288	22,248

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Notes: Unweighted analysis. Model 1: OLS regression; Model 2: Random effects model; Model 3: Fixed effects model which controlled for socioeconomic variables and adjusted for time and individual fixed effects; Model 5: Fixed effects model that controlled for socioeconomic, time and individual fixed effects, and other covariates; and Model 1: OLS regression with a lagged CES-D10 score.

Table 12: Comparisons by gender and residence – fixed effects and conditional fixed effects logit results

VARIABLES	Fixed effects (FE) Female vs Male	Fixed effects (FE) Rural vs Urban	Conditional FE Logit (Odds Ratio) Female vs Male	Conditional FE Logit (Odds Ratio) Rural vs Urban
	(1)	(2)	(3)	(4)
Education (none)				
Grade 1–7	-0.359	-0.160	0.959	1.051
	(0.311)	(0.266)	(0.151)	(0.150)
Grade 8–11	-0.158	0.158	1.107	1.244
	(0.345)	(0.282)	(0.195)	(0.193)
Matric	0.179	0.476	1.307	1.420**
	(0.366)	(0.302)	(0.246)	(0.240)
Post-matric	0.036	0.184	1.166	1.252
	(0.374)	(0.312)	(0.225)	(0.220)
Per capita household income level (Low)				
Middle	-0.263***	-0.207***	0.852***	0.895***
	(0.066)	(0.064)	(0.031)	(0.034)
High	-0.317***	-0.254***	0.856***	0.892**
	(0.087)	(0.088)	(0.041)	(0.046)
Employment status (Employed)				
Not economically active	0.399***	0.437***	1.181***	1.242***
	(0.073)	(0.076)	(0.048)	(0.054)
Unemployed	-0.100	-0.010	0.960	1.013
	(0.081)	(0.085)	(0.045)	(0.052)
Urban residence	0.332**	0.353	1.215***	1.270
	(0.131)	(0.487)	(0.090)	(0.326)
Age (15–24)				
25–39	0.089	0.208*	1.038	1.092
	(0.111)	(0.106)	(0.065)	(0.070)
40–54	-0.123	0.061	0.993	1.119
	(0.187)	(0.182)	(0.103)	(0.118)
> = 55	-0.118	-0.030	0.996	1.017
	(0.265)	(0.252)	(0.143)	(0.147)
Marital status				
Married/Cohabiting	-0.184	-0.249**	0.918	0.912
	(0.121)	(0.120)	(0.062)	(0.065)
Widowed/Divorced	0.233	0.346*	1.166*	1.220**
	(0.164)	(0.185)	(0.099)	(0.118)
Religious	-0.032	-0.050	1.086	1.105**
	(0.117)	(0.083)	(0.068)	(0.054)
Preference to stay in the current neighbourhood (Unsure)				
Stay	-0.718***	-0.630***	0.779***	0.812***
	(0.077)	(0.079)	(0.033)	(0.037)
Leave	0.369***	0.376***	1.325***	1.346***
	(0.105)	(0.110)	(0.073)	(0.083)
Self-reported health status (Poor/Fair)				
Good health	-1.294***	-1.274***	0.614***	0.612***
	(0.085)	(0.092)	(0.025)	(0.028)
Medical insurance	-0.035	0.108	1.019	1.087
	(0.144)	(0.170)	(0.087)	(0.123)
Year (2008)				
2010/11	-0.998***	-0.959***	0.604***	0.578***
	(0.074)	(0.075)	(0.024)	(0.024)
2012	-1.040***	-1.022***	0.682***	0.681***
	(0.075)	(0.078)	(0.027)	(0.029)

Table 12 Continues

Table 12 Continued

VARIABLES	Fixed effects (FE) Female vs Male (1)	Fixed effects (FE) Rural vs Urban (2)	Conditional FE Logit (Odds Ratio) Female vs Male (3)	Conditional FE Logit (Odds Ratio) Rural vs Urban (4)
2014/15	-1.035***	-1.343***	0.651***	0.543***
	(0.088)	(0.089)	(0.031)	(0.027)
2017	-0.958***	-0.994***	0.707***	0.647***
	(0.098)	(0.098)	(0.037)	(0.036)
Interactions for comparison of variables				
Variable#Gender				
Education level #Male	Y		Y	
Per capita household income level (Low)#Male	Y		Y	
Employment status (Employed)				
Not economically active#Male	0.017		1.051	
	(0.112)		(0.068)	
Unemployed#Male	0.213*		1.071	
	(0.125)		(0.079)	
Urban#Male	Y		Y	
Age category#Male	Y		Y	
Marital status#Male	Y		Y	
Religious#Male	Y		Y	
Preference to stay in the current neighbourhood #Male	Y		Y	
Good self-reported health status#Male	0.240*		1.027	
	(0.140)		(0.073)	
Medical insurance#Male	Y		Y	
Year (2008)				
2010/11#Male	0.323***		1.085	
	(0.112)		(0.070)	
2012#Male	0.454***		1.150**	
	(0.116)		(0.075)	
2014/15#Male	0.468***		1.164**	
	(0.132)		(0.088)	
2017#Male	0.380***		1.101	
	(0.146)		(0.094)	
Variable#Residence				
Education #Urban		Y		Y
Per capita household income level#Urban		Y		Y
Employment status #Urban		Y		Y
Age #Urban		Y		Y
Male#Urban		Y		Y
Marital status #Urban		Y		Y
Population group (Black African)				
Coloured#Urban		-0.333		0.774
		(0.308)		(0.174)
Indian#Urban		-2.488**		0.474
		(1.220)		(0.282)
White#Urban		2.087**		1.559
		(0.873)		(1.930)
Religious#Urban		-0.126		0.873*
		(0.134)		(0.067)
Preference to stay in the current neighbourhood (Unsure)				
Stay#Urban residence		-0.222*		0.880*
		(0.115)		(0.058)
Leave#Urban residence		-0.090		0.918
		(0.155)		(0.078)
Good health self-reported health #Urban		Y		Y

Table Continues

Table 12 Continued

VARIABLES	Fixed effects (FE) Female vs Male (1)	Fixed effects (FE) Rural vs Urban (2)	Conditional FE Logit (Odds Ratio) Female vs Male (3)	Conditional FE Logit (Odds Ratio) Rural vs Urban (4)
Medical insurance#Urban		-0.346*		0.808
		(0.203)		(0.109)
Year (2008)				
2010/11#Urban		0.165		1.175***
		(0.111)		(0.073)
2012#Urban		0.323***		1.120*
		(0.113)		(0.070)
2014/15#Urban		0.988***		1.631***
		(0.125)		(0.115)
2017#Urban		0.374***		1.300***
		(0.134)		(0.099)
Constant	9.366***	9.071***		
	(0.447)	(0.307)		
Observations	88,198	88,198	44,667	44,667
R-squared	0.028	0.030	0.029	0.031
Number of pid	35,288	35,288		

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Fixed Effects – CES-D10 is the dependent variable, and Conditional fixed effects logit used a binary dependent variable (=1 if CES-D10>=10; 0, otherwise. Gender is binary: = 1 if male and 0 otherwise. Residence is binary: = 1 if urban, and 0 otherwise. Coefficients of variable before interactions are: for females in Models 1 and 3, and for Rural in models 2 and 4. Coefficients of interaction terms are the differences in the coefficients of variables for males and females in Models 1 and 2, and for urban and rural. ***Y*** means the variable has been controlled for but is not statistically significant and for space purposes, I deleted the coefficients and standard errors.

3.5 Discussion

Most studies on the depressive symptoms correlates in developing countries were cross-sectional. In this study, I used five rounds of a South African longitudinal data set to examine the socioeconomic correlates in a large national sample (at least 20 000 observations). Results are based on both the OLS and fixed effects models, as they captured different relationship dimensions between depressive symptoms and socioeconomic variables. The OLS model captured associations between recent depressive symptoms and recent socioeconomic variables, whereas the fixed effects model captured corelations between changes in depressive symptoms and changes in socioeconomic variables. The regression results suggest significant socioeconomic gradients in depressive symptoms, whereby income, education, location of residence, and neighbourhood attachment play significant roles in influencing depressive symptoms in adults. This study highlighted gender and residential differences in the factors explaining the development of depressive symptoms.

In the fixed-effects model, respondents who had an increase in per capita income had significant decrease in depressive symptoms. This result is similar to that of Assari *et al*. (2018) and Golberstein (2015), who also found that income significantly improves mental health. In the present study, respondents who had moved to urban areas reported a significant increase in depressive symptoms. This in line with the literature on urbanicity and mental health, which suggests that the urban social, economic, and physical environments can contribute to mental health problems (Krabbendam *et al*., 2020; Penkalla & Kohler, 2014). In addition, respondents who became sure of their preference to continue residing in their current neighbourhoods experienced a significant lowering of their depressive symptoms. This reiterates the important role of social capital like neighbourhood attachment and social trust in the control of depression (Tomita & Burns, 2013). Similar to Braam and Koenig (2019), I also found that switching from being non-religious to being religious was modestly associated with lower depressive symptoms scores. Religious groups offer support to their members during distress which may prevent the onset of depression or they may help fasten resolving depression episodes should they develop (Braam & Koenig, 2019). I also found that adults who had reported an improvement in self-reported health from *'poor'* to *'good'* had a significant decrease in depressive symptoms. This is in line with other studies (Jack *et al.*, 2014; Mayosi *et al.*, 2009; Sorsdahl *et al.*, 2018; Williams *et al.*, 2008; Woollett *et al.*, 2017) that found comorbidities between mental health and physical illness. The present study's results therefore confirm the need for integral care for people with mental health problems to include screening for physical ailments, and vice versa, for there is no health without mental health (Prince *et al.*, 2007).

Most of the OLS regression results were in line with the fixed effects results, and were consistent with existing evidence based on the NIDS cross-sectional data (Ardington & Case, 2010; Tomita & Burns, 2013) and the first three rounds (Burger *et al.*, 2017) in South Africa. For example, this study shows that neighbourhood social capital, as measured through neighbourhood attachment, is associated with the depressive symptom score, consistent with the views of (Tomita & Burns, 2013). This study differs from previous studies in that it used more data points (five waves) than previous studies. For example, the studies of Ardington and Case (2010) and Tomita and Burns (2013) were cross-sectional, and Burger *et al.* (2017) used the first three waves. The relationship of variables in a cross-sectional study is not guaranteed to be stable and representative. For example, there were issues with the earlier versions of Wave 2 data, such as: (1) people were interviewed in more than one household and incorrectly presented as two separate records; (2) some people were incorrectly recorded as deceased in Wave 2, when they were still alive (Siljeur, 2016). Thus, results from an analysis of a single wave or a limited number of waves, especially before the newer versions, may mirror the weaknesses of data used. In the current study, I used the updated versions of the data (versions 7.0.0 for Wave 1; 4.0.0 for Wave 2; 3.0.0 for Wave 3; 2.0.0 for Wave 4; and 1.0.0 for Wave 5).

I also found significant differences in the effects of explanatory variables by gender and by residence. Unemployed men and men with good self-reported health had higher CES-D10 scores than their female counterparts. Over the five time periods covered by the sample, male respondents had significantly higher CES-D10 scores. In relation to residence, Indians in urban areas had significantly lower CES-D10 scores than Indians in rural areas, whilst whites in urban areas had significantly higher CES-D10 scores than whites in rural areas. Being religious and living in an urban area is associated with higher depressive symptoms than being religious and living a in rural area. The significant differences in the effects of variables by gender and by residence are a unique contribution to understanding the differences in health in South Africa, and may inform policy. Firstly, there are significant gender and residence differences in depression. Secondly, men who self-report good health may be overrating their health, most likely by excluding their state of mental health. Lastly, whilst the goal is to reduce the prevalence of mental disorders by targeting socioeconomic factors, significant differences by gender and residence underscore the need for mental health policies that promote equity. Interventions that create employment for men or offer support to unemployed men, and provide mental health education for men, would result in an improvement of men's mental health. There is also need for provision of affordable medical aid schemes for people in urban areas as medical aids are associated with lower scores of depressive symptoms.

While the present study may not have the granularity and sensitivity of previous psychological studies, its strength lies in the detection of broad patterns in a large sample of South Africans, with at least 15 000 observations in each round. Additionally, because it was a panel, I was able to employ fixed effects estimation, which eliminated confounding time-invariant individual heterogeneity such as genetic endowments and personality traits to a large extent. This strengthens the credibility and the robustness of the results.

The main limitation of this study is that it could have been susceptible to reporting- and recall biases, as the depression index was based on one-week's recall of depressive symptoms. Reporting- and recall biases, together with fear of stigma and discrimination associated with mental health problems, may have resulted in underreporting of depressive symptoms. Under-reporting may have caused bias in the results to the degree or pattern of under-reporting of depressive symptoms. For example, if the poor underreport their mental health, we are likely to underestimate the income gradient in depressive symptoms. If results are biased, policies based on the results of this study will be ill-informed and ineffective. However, this is a limitation shared by all survey-based studies. This study contributes to the existing research in mental health through the utilisation of longitudinal data to examine the temporal association between socioeconomic indicators and depression in South Africa, a research gap highlighted by Tomita and Burns (2013).

In a country faced with a high poverty rate, high income inequality, and a high unemployment rate (World Bank, 2018), the strong correlation between depressive symptoms and per capita household income illustrates that mental health interventions should be viewed as an integral part of antipoverty policies and programmes. These results indicate the need for depression prevention and treatment in South Africa through the expansion of affordable primary mental healthcare and improvement of socioeconomic living conditions, mainly through pro-poor policies and programmes. Due to the stigma associated with mental health and mental health services in LMICs (Semrau *et al*., 2015), it is likely that the uptake, cost effectiveness, and efficacy of counselling is very low in these countries, South Africa included. However, the use of trained lay health workers in primary healthcare has been found to be a sustainable, effective, and affordable solution to narrow the mental health treatment gap in LMICs like India (Patel *et al.*, 2010), Zimbabwe (Chibanda *et al.*, 2016), and Nepal (Jordans *et al.*, 2019). In Zimbabwe, the randomised control trial is done through the Friendship Bench intervention, which offers primary mental healthcare using trained elderly women (Chibanda, 2017).

Public policy proposals that raise per capita income may have important effects on mental health outcomes. Such policy proposals include employment creation, constant review of minimum wages, broadening and upward review of social security grants, and family planning. Education on mental health disorders and substance abuse is vital to reduce the stigma associated with mental health. This will help people with mental disorders to accurately report their mental health problems, adhere to treatment, and access income-generating opportunities.

Appendix 2.A

Table 13: Regression results with CES-D10 score as the dependent variable, weighted using panel weights (balanced panel)

	OLS	Random effects	Fixed – effects models		OLS lagged *dep var*
VARIABLES	(1)	(2)	(3)	(4)	(5)
Depressive symptom score in the previous wave					0.039***
					(0.012)
Education (none)					
Grade 1–7	-0.037	-0.049		-0.211	-0.077
	(0.121)	(0.096)		(0.454)	(0.133)
Grade 8–11	-0.430***	-0.438***		-0.026	-0.419***
	(0.129)	(0.101)		(0.570)	(0.150)
Matric	-0.723***	-0.616***		-0.066	-0.582***
	(0.164)	(0.118)		(0.608)	(0.183)
Post-matric	-0.961***	-0.750***		-0.322	-0.823***
	(0.154)	(0.120)		(0.586)	(0.173)
Per capita household income level (Low)					
Middle	-0.149	-0.260***	-0.229**	-0.222**	-0.199
	(0.103)	(0.063)	(0.113)	(0.112)	(0.123)
High	-0.312**	-0.424***	-0.172	-0.192	-0.203
	(0.121)	(0.075)	(0.141)	(0.140)	(0.136)
Employment status (Employed)					
Not economically active	0.491***	0.382***	0.437***	0.456***	0.549***
	(0.102)	(0.064)	(0.118)	(0.121)	(0.109)
Unemployed	0.156	0.019	0.066	0.091	-0.057
	(0.125)	(0.075)	(0.140)	(0.140)	(0.129)
Urban residence	0.461***	0.218***	0.408	0.404	0.500***
	(0.112)	(0.055)	(0.261)	(0.262)	(0.130)
Age (15–24)					
25–39	0.754***	0.730***		0.169	0.563***
	(0.110)	(0.077)		(0.171)	(0.138)
40–54	1.006***	1.098***		0.096	0.850***
Table 13 Continues	(0.157)	(0.093)		(0.294)	(0.178)

Table 13 Continued

	OLS	Random effects	Fixed – effects models		OLS lagged *dep var*
VARIABLES	(1)	(2)	(3)	(4)	(5)
> = 55	0.853***	0.965***		0.255	0.724***
	(0.177)	(0.110)		(0.422)	(0.216)
Male	-0.382***	-0.346***			-0.321***
	(0.082)	(0.055)			(0.097)
Marital status (Never)					
Married/Cohabiting	-0.593***	-0.551***		-0.275	-0.700***
	(0.101)	(0.065)		(0.173)	(0.105)
Widowed/Divorced	0.162	0.233**		-0.195	0.058
	(0.153)	(0.101)		(0.286)	(0.156)
Population group (Black African)					
Coloured	-1.042***	-1.715***			-0.861***
	(0.206)	(0.082)			(0.228)
Indian	-1.407**	-1.361***			-1.381**
	(0.593)	(0.276)			(0.572)
White	-1.276***	-1.574***			-0.976***
	(0.290)	(0.232)			(0.354)
Religious	-0.242*	-0.115		-0.090	-0.307*
	(0.145)	(0.089)		(0.152)	(0.167)
Preference to stay in the current neighbourhood (Unsure)					
Stay	-0.886***	-0.730***	-0.786***	-0.779***	-0.890***
	(0.123)	(0.079)	(0.135)	(0.135)	(0.147)
Leave	0.132	0.381***	0.215	0.200	0.322
	(0.205)	(0.111)	(0.187)	(0.186)	(0.238)
Self-reported health status (Poor/Fair)					
Good health	-1.637***	-1.557***		-1.146***	-1.632***
	(0.156)	(0.081)		(0.148)	(0.159)
Medical insurance	-0.551***	-0.486***		0.335	-0.533***
	(0.163)	(0.100)		(0.212)	(0.180)
Year (2008)					
2010/11	-1.070***	-0.998***	-1.184***	-1.104***	
	(0.212)	(0.076)	(0.116)	(0.119)	
2012	-1.142***	-0.966***	-1.190***	-1.140***	
Table 13 Continues	(0.167)	(0.076)	(0.111)	(0.119)	

Table 13 Continued

	OLS	Random effects	Fixed – effects models		OLS lagged *dep var*
VARIABLES	(1)	(2)	(3)	(4)	(5)
2014/15	-0.863***	-1.108***	-0.783***	-0.772***	
	(0.201)	(0.083)	(0.127)	(0.143)	
2017	-0.948***	-1.079***	-0.843***	-0.820***	
	(0.170)	(0.085)	(0.128)	(0.157)	
Constant	10.313***	10.178***	8.217***	9.330***	9.099***
	(0.318)	(0.181)	(0.226)	(0.617)	(0.388)
Observations	30,408	30,408	30,408	30,408	23,297
R-squared	0.086		0.025	0.033	0.073
Number of pid		6,834	6,834	6,834	

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The coefficients remained relatively stable (comparable to those in Table 11 in Section 3.4.2), suggesting that attrition (non-random attrition that is correlated with mental health) had no influence on the results.

Appendix 2.B

Table 14: Linear probability models and conditional fixed effects model (Binary dependent variable (Depressed = 1 if CES-D10>=10, and Depressed = 0 if CES-D10<10)

	Linear probability model (LPM)		Conditional fixed – effects logistic regression (CFEL) – Odds Ratio (OR)				
	All	All	All	Female	Male	Rural	Urban
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Depression status in the previous wave		0.017***					
		(0.005)					
Education (none)							
Grade 1–7	-0.016**	-0.013	1.076	0.959	1.303	1.063	1.084
	(0.007)	(0.008)	(0.134)	(0.151)	(0.266)	(0.163)	(0.242)
Grade 8–11	-0.037***	-0.038***	1.259*	1.107	1.538**	1.229	1.343
	(0.007)	(0.009)	(0.171)	(0.195)	(0.334)	(0.208)	(0.321)
Matric	-0.039***	-0.041***	1.496***	1.307	1.845***	1.464**	1.556*
	(0.007)	(0.010)	(0.217)	(0.246)	(0.427)	(0.275)	(0.388)
Post-matric	-0.059***	-0.062***	1.300*	1.166	1.542*	1.293	1.338
	(0.008)	(0.010)	(0.192)	(0.225)	(0.361)	(0.253)	(0.336)
Per capita household income level (Low)							
Middle	-0.035***	-0.033***	0.852***	0.852***	0.859***	0.890***	0.830***
	(0.004)	(0.005)	(0.025)	(0.031)	(0.042)	(0.035)	(0.040)
High	-0.045***	-0.045***	0.860***	0.856***	0.868**	0.886**	0.837***
	(0.004)	(0.006)	(0.032)	(0.041)	(0.052)	(0.048)	(0.047)
Employment status (Employed)							
Not economically active	0.026***	0.031***	1.201***	1.181***	1.241***	1.242***	1.178***
	(0.004)	(0.005)	(0.038)	(0.048)	(0.064)	(0.056)	(0.056)
Unemployed	0.002	-0.016***	0.987	0.960	1.028	1.005	1.002
	(0.005)	(0.006)	(0.036)	(0.045)	(0.059)	(0.053)	(0.053)
Marital status (Never)							
Married/Cohabiting	-0.045***	-0.055***	0.931	0.918	0.950	0.912	0.890
	(0.004)	(0.005)	(0.049)	(0.062)	(0.082)	(0.071)	(0.070)
Widowed/Divorced	0.027***	0.013	1.129*	1.166*	1.032	1.204*	0.949
	(0.007)	(0.009)	(0.080)	(0.099)	(0.138)	(0.123)	(0.100)
Urban residence	0.027***	0.034***	1.266***	1.215***	1.335***		
	(0.003)	(0.004)	(0.071)	(0.090)	(0.113)		
Age (15–24)							
25–39	0.077***	0.064***	1.058	1.038	1.081	1.080	1.020
	(0.004)	(0.005)	(0.051)	(0.065)	(0.080)	(0.077)	(0.073)
40–54	0.109***	0.096***	1.060	0.993	1.202	1.142	0.980
Table Continues to next page	(0.005)	(0.007)	(0.087)	(0.103)	(0.163)	(0.137)	(0.118)

VARIABLES	All (LPM) (1)	All (LPM) (2)	All (CFEL – OR) (3)	Female (CFEL – OR) (4)	Male (CFEL – OR) (5)	Rural (CFEL – OR) (6)	Urban (CFEL – OR) (7)
> = 55	0.097***	0.086***	0.991	0.996	1.002	1.067	0.919
	(0.006)	(0.008)	(0.113)	(0.143)	(0.190)	(0.176)	(0.154)
Religious	-0.008	-0.006	1.043	1.086	1.023	1.090*	0.986
	(0.005)	(0.007)	(0.039)	(0.068)	(0.049)	(0.055)	(0.062)
Preference to stay in the current neighbourhood (Unsure)							
Stay	-0.049***	-0.051***	0.763***	0.779***	0.739***	0.801***	0.714***
	(0.005)	(0.006)	(0.025)	(0.033)	(0.038)	(0.038)	(0.035)
Leave	0.048***	0.054***	1.294***	1.325***	1.252***	1.350***	1.230***
	(0.006)	(0.008)	(0.055)	(0.073)	(0.082)	(0.086)	(0.076)
Self-reported health status (Poor/Fair)							
Good health	-0.135***	-0.129***	0.618***	0.614***	0.630***	0.607***	0.629***
	(0.005)	(0.007)	(0.021)	(0.025)	(0.037)	(0.028)	(0.032)
Medical insurance	-0.037***	-0.031***	0.935	1.019	0.831*	1.076	0.911
	(0.005)	(0.007)	(0.061)	(0.087)	(0.083)	(0.129)	(0.074)
Male	-0.022***	-0.017***					
	(0.003)	(0.004)					
Population group (Black African)							
Coloured	-0.086***	-0.091***					
	(0.004)	(0.005)					
Indian	-0.090***	-0.075***					
	(0.013)	(0.016)					
White	-0.096***	-0.066***					
	(0.008)	(0.011)					
Year (2008)							
2010/11	-0.085***		0.622***	0.604***	0.656***	0.585***	0.685***
	(0.005)		(0.019)	(0.024)	(0.034)	(0.025)	(0.033)
2012	-0.071***		0.717***	0.682***	0.784***	0.683***	0.768***
	(0.005)		(0.023)	(0.027)	(0.041)	(0.030)	(0.037)
2014/15	-0.088***		0.690***	0.651***	0.758***	0.547***	0.900*
	(0.005)		(0.025)	(0.031)	(0.045)	(0.029)	(0.049)
2017	-0.084***		0.733***	0.707***	0.779***	0.655***	0.860**
	(0.005)		(0.030)	(0.037)	(0.052)	(0.039)	(0.053)
Constant	0.489***	0.407***					
	(0.011)	(0.015)					
Observations	88,198	49,989	44,667	27,455	17,212	22,378	19,786
R-squared	0.056	0.045	0.028	0.031	0.026	0.034	0.026

Note: Models 1, 2, and 3 confirm the results of Models 1, 5, and 4, respectively, in Table 14. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix 2.C

Table 15: Comparisons by gender and residence – OLS, fixed effects, and conditional fixed effects logit results

	Gender (Female vs Male)			Residence (Rural vs Urban)		
VARIABLES	OLS	FE	CFEL	OLS	FE	CFEL
	(1)	(2)	(3)	(4)	(5)	(6)
Education (none)						
Grade 1–7	-0.164**	-0.359	0.959	-0.124	-0.160	1.051
	(0.082)	(0.311)	(0.151)	(0.075)	(0.266)	(0.150)
Grade 8–11	-0.590***	-0.158	1.107	-0.515***	0.158	1.244
	(0.085)	(0.345)	(0.195)	(0.080)	(0.282)	(0.193)
Matric	-0.647***	0.179	1.307	-0.480***	0.476	1.420**
	(0.097)	(0.366)	(0.246)	(0.093)	(0.302)	(0.240)
Post-matric	-0.792***	0.036	1.166	-0.797***	0.184	1.252
	(0.101)	(0.374)	(0.225)	(0.100)	(0.312)	(0.220)
Per capita household income level (Low)						
Middle	-0.330***	-0.263***	0.852***	-0.245***	-0.207***	0.895***
	(0.049)	(0.066)	(0.031)	(0.046)	(0.064)	(0.034)
High	-0.530***	-0.317***	0.856***	-0.453***	-0.254***	0.892**
	(0.058)	(0.087)	(0.041)	(0.058)	(0.088)	(0.046)
Employment status (Employed)						
Not economically active	0.303***	0.399***	1.181***	0.389***	0.437***	1.242***
	(0.051)	(0.073)	(0.048)	(0.053)	(0.076)	(0.054)
Unemployed	-0.044	-0.100	0.960	0.064	-0.010	1.013
	(0.060)	(0.081)	(0.045)	(0.063)	(0.085)	(0.052)
Urban residence	0.312***	0.332**	1.215***	0.852***	0.353	1.270
	(0.043)	(0.131)	(0.090)	(0.232)	(0.487)	(0.326)
Age (15–24)						
25–39	0.960***	0.089	1.038	1.098***	0.208*	1.092
	(0.053)	(0.111)	(0.065)	(0.054)	(0.106)	(0.070)
40–54	1.303***	-0.123	0.993	1.484***	0.061	1.119
	(0.069)	(0.187)	(0.103)	(0.072)	(0.182)	(0.118)
> = 55	1.192***	-0.118	0.996	1.381***	-0.030	1.017
	(0.083)	(0.265)	(0.143)	(0.085)	(0.252)	(0.147)
Male	-0.794***			-0.259***		
	(0.221)			(0.041)		
Marital status (Never)						
Married/Cohabiting	-0.483***	-0.184	0.918	-0.598***	-0.249**	0.912
	(0.053)	(0.121)	(0.062)	(0.057)	(0.120)	(0.065)
Widowed/Divorced	0.345***	0.233	1.166*	0.329***	0.346*	1.220**
	(0.079)	(0.164)	(0.099)	(0.093)	(0.185)	(0.118)
Population group (Black African)						
Coloured	-1.405***			-1.269***		
	(0.063)			(0.093)		
Indian	-1.386***			-0.685***		
	(0.196)			(0.241)		

Table 15 Continues

Table 15 Continued

	Gender (Female vs Male)			Residence (Rural vs Urban)		
VARIABLES	OLS	FE	CFEL	OLS	FE	CFEL
	(1)	(2)	(3)	(4)	(5)	(6)
White	-1.628***			-1.366***		
	(0.144)			(0.290)		
Religious	-0.207**	-0.032	1.086	-0.202***	-0.050	1.105**
	(0.086)	(0.117)	(0.068)	(0.061)	(0.083)	(0.054)
Preference to stay in the current neighbourhood (Unsure)						
Stay	-0.758***	-0.718***	0.779***	-0.595***	-0.630***	0.812***
	(0.059)	(0.077)	(0.033)	(0.060)	(0.079)	(0.037)
Leave	0.388***	0.369***	1.325***	0.526***	0.376***	1.346***
	(0.084)	(0.105)	(0.073)	(0.086)	(0.110)	(0.083)
Self-reported health status (Poor/Fair)						
Good health	-1.789***	-1.294***	0.614***	-1.719***	-1.274***	0.612***
	(0.068)	(0.085)	(0.025)	(0.073)	(0.092)	(0.028)
Medical insurance	-0.496***	-0.035	1.019	-0.355***	0.108	1.087
	(0.080)	(0.144)	(0.087)	(0.103)	(0.170)	(0.123)
Year (2008)						
2010/11	-1.019***	-0.998***	0.604***	-0.991***	-0.959***	0.578***
	(0.066)	(0.074)	(0.024)	(0.067)	(0.075)	(0.024)
2012	-1.217***	-1.040***	0.682***	-1.237***	-1.022***	0.681***
	(0.064)	(0.075)	(0.027)	(0.067)	(0.078)	(0.029)
2014/15	-1.310***	-1.035***	0.651***	-1.633***	-1.343***	0.543***
	(0.067)	(0.088)	(0.031)	(0.067)	(0.089)	(0.027)
2017	-1.357***	-0.958***	0.707***	-1.396***	-0.994***	0.647***
	(0.068)	(0.098)	(0.037)	(0.069)	(0.098)	(0.036)
Interactions for comparison of coefficients						
Grade 1–7#Male	-0.143	0.502	1.359			
	(0.128)	(0.464)	(0.350)			
Grade 8–11#Male	0.082	0.601	1.390			
	(0.131)	(0.494)	(0.388)			
Matric#Male	0.145	0.645	1.412			
	(0.147)	(0.522)	(0.421)			
Post-matric#Male	-0.063	0.292	1.322			
	(0.154)	(0.530)	(0.401)			
Per capita household income level (Low)						
Middle#Male	-0.042	-0.050	1.008			
	(0.076)	(0.104)	(0.062)			
High#Male	-0.030	-0.007	1.013			
	(0.088)	(0.132)	(0.078)			
Employment status (Employed)						
Not economically active#Male	0.098	0.017	1.051			
	(0.077)	(0.112)	(0.068)			
Unemployed#Male	0.311***	0.213*	1.071			
	(0.093)	(0.125)	(0.079)			
Urban residence#Male	0.007	0.050	1.099			
Table 15 Continues	(0.064)	(0.191)	(0.124)			

Table 15 Continued

VARIABLES	Gender (Female vs Male) OLS (1)	FE (2)	CFEL (3)	Residence (Rural vs Urban) OLS (4)	FE (5)	CFEL (6)
Age (15–24)						
25–39#Male	0.112	0.060	1.042			
	(0.080)	(0.163)	(0.101)			
40–54#Male	0.165	0.410	1.210			
	(0.108)	(0.288)	(0.207)			
> = 55#Male	0.190	0.203	1.006			
	(0.127)	(0.410)	(0.239)			
Marital status (Never)						
Married/Cohabiting#Male	-0.136	-0.017	1.034			
	(0.086)	(0.183)	(0.114)			
Widowed/Divorced#Male	0.120	-0.173	0.885			
	(0.157)	(0.284)	(0.140)			
Population group (Black African)						
Coloured#Male	-0.173*					
	(0.094)					
Indian#Male	0.205					
	(0.293)					
White#Male	0.196					
	(0.197)					
Religious#Male	-0.145	-0.115	0.942			
	(0.104)	(0.141)	(0.074)			
Preference to stay in the current neighbourhood (Unsure)						
Stay#Male	0.001	-0.037	0.949			
	(0.089)	(0.116)	(0.063)			
Leave#Male	-0.072	-0.055	0.945			
	(0.124)	(0.156)	(0.081)			
Self-reported health status (Poor/Fair)						
Good health#Male	0.206*	0.240*	1.027			
	(0.110)	(0.140)	(0.073)			
Medical insurance#Male	-0.156	-0.220	0.816			
	(0.112)	(0.203)	(0.107)			
Year (2008)						
2010/11#Male	0.321***	0.323***	1.085			
	(0.098)	(0.112)	(0.070)			
2012#Male	0.437***	0.454***	1.150**			
	(0.097)	(0.116)	(0.075)			
2014/15#Male	0.450***	0.468***	1.164**			
	(0.098)	(0.132)	(0.088)			
2017#Male	0.356***	0.380***	1.101			
	(0.099)	(0.146)	(0.094)			
Education (none)						
Grade 1–7#Urban residence				-0.199	0.018	1.084
				(0.144)	(0.425)	(0.230)

Table 15 Continue

Table 15 Continued

	Gender (Female vs Male)			Residence (Rural vs Urban)		
VARIABLES	OLS	FE	CFEL	OLS	FE	CFEL
	(1)	(2)	(3)	(4)	(5)	(6)
Grade 8–11#Urban residence				-0.023	-0.037	1.092
				(0.144)	(0.427)	(0.236)
Matric#Urban residence				-0.132	0.029	1.166
				(0.159)	(0.444)	(0.267)
Post-matric#Urban residence				0.001	-0.009	1.112
				(0.165)	(0.450)	(0.259)
Per capita household income level (Low)						
Middle#Urban residence				-0.238***	-0.136	0.917
				(0.080)	(0.107)	(0.055)
High#Urban residence				-0.225**	-0.137	0.921
				(0.089)	(0.132)	(0.069)
Employment status (Employed)						
Not economically active#Urban residence				-0.039	-0.040	0.949
				(0.076)	(0.108)	(0.059)
Unemployed#Urban residence				0.095	0.050	0.980
				(0.092)	(0.123)	(0.071)
Age (15–24)						
25–39#Urban residence				-0.200**	-0.160	0.935
				(0.080)	(0.140)	(0.078)
40–54#Urban residence				-0.214**	-0.066	0.895
				(0.105)	(0.221)	(0.115)
> = 55#Urban residence				-0.228*	-0.085	0.930
				(0.124)	(0.309)	(0.164)
Male#Urban residence				-0.077	0.089	1.090
				(0.060)	(0.186)	(0.121)
Marital status (Never)						
Married/Cohabiting#Urban residence				0.108	0.099	1.021
				(0.082)	(0.162)	(0.098)
Widowed/Divorced#Urban residence				0.093	-0.368	0.836
				(0.135)	(0.255)	(0.111)
Population group (Black African)						
Coloured#Urban residence				-0.256**	-0.333	0.774
				(0.107)	(0.308)	(0.174)
Indian#Urban residence				-0.989***	-2.488**	0.474
				(0.302)	(1.220)	(0.282)
White#Urban residence				-0.150	2.087**	1.559
				(0.310)	(0.873)	(1.930)
Religious#Urban residence				-0.271***	-0.126	0.873*
				(0.100)	(0.134)	(0.067)
Preference to stay in the current neighbourhood (Unsure)						
Stay#Urban residence				-0.332***	-0.222*	0.880*
				(0.088)	(0.115)	(0.058)
Leave#Urban residence				-0.366***	-0.090	0.918
Table 15 Continues				(0.123)	(0.155)	(0.078)

Table 15 Continued

	Gender (Female vs Male)			Rural vs Urban		
VARIABLES	OLS	FE	CFEL	OLS	FE	CFEL
	(1)	(2)	(3)	(4)	(5)	(6)
Self-reported health status (Poor/Fair)						
Good health#Urban residence				0.013	0.138	1.026
				(0.107)	(0.135)	(0.069)
Medical insurance#Urban residence				-0.246**	-0.346*	0.808
				(0.122)	(0.203)	(0.109)
Year (2008)						
2010/11#Urban residence				0.185*	0.165	1.175***
				(0.098)	(0.111)	(0.073)
2012#Urban residence				0.394***	0.323***	1.120*
				(0.097)	(0.113)	(0.070)
2014/15#Urban residence				1.011***	0.988***	1.631***
				(0.098)	(0.125)	(0.115)
2017#Urban residence				0.357***	0.374***	1.300***
				(0.100)	(0.134)	(0.099)
Constant	10.545***	9.366***		10.136***	9.071***	
	(0.152)	(0.447)		(0.143)	(0.307)	
Observations	88,198	88,198	44,667	88,198	88,198	44,667
R-squared	0.101	0.028	0.029	0.102	0.030	0.031
Number of pid		35,288			35,288	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: This table is the full version of results in Table 12.

Model 1, Model 2, Model 4, and Model 5 – CES-D10 is the dependent variable. Model 3 and Model 6 used a binary dependent variable (=1 if CES-D10>=10; 0, otherwise. Gender is binary: = 1 if male and 0 otherwise. Residence is binary: = 1 if urban, and 0 otherwise.

Interpretation: Coefficients of variable before interactions are: for females in Models 1, 2, and 3, and for Rural in models 4, 5, and 6. Coefficients of interaction terms are the differences in the coefficients of variables for males and females in Models 1 and 2, and for urban and rural. ***Y*** means the variable has been controlled for but is not statistically significant and for space purposes, I deleted the coefficients and standard errors.

The next chapter presents Essay 3: COVID-19 and income-related mental health inequality in South Africa.

Chapter 4

COVID-19 and income-related mental health inequality in South Africa

4.1 Introduction

The COVID-19 pandemic has caused significant social and economic disruptions across the globe, resulting in the world's most severe recession since World War II, and is the first pandemic-only-triggered recession since 1870 (World Bank, 2020). People's ability to cope with the pandemic and its consequences differ. Current evidence suggests that the pandemic and related public health measures instituted to slow down the spread of COVID-19 have worsened existing inequalities (Adams-Prassl *et al.*, 2020; Bernardini *et al.*, 2021; Bottan *et al.*, 2020; Perugini & Vladisavljevic, 2020), with the burden of the pandemic being disproportionately borne by the vulnerable. However, there is literature that suggest that shocks like pandemics, wars, and civil conflicts narrow inequalities (Milanovic, 2016; Pikkety, 2014; Scheidel, 2017). Be that as it may, the economic impacts of COVID-19 containment measures will affect the incidence, prevalence, and distribution of mental ill health, now and for years to come. Therefore, the present study was aimed at ascertaining the impact of the COVID-19 pandemic on income-related mental health inequality.

Globally, it is known that people with a higher socioeconomic status enjoy healthier and longer lives than those ranked lower (Bor *et al.*, 2017; Gallo *et al.*, 2012; Marmot & Bell, 2016). Such inequality, which is widespread and persistent, presents a challenge to researchers and policy makers (Coveney *et al.*, 2018). Disparities in health outcomes exist both across and within countries. Health inequalities emanate from differences in determinants that impact health production (Costa-Fonta & Hernández-Quevedo, 2015). These determinants include gender, social status, income, neighbourhood characteristics, employment status, lifestyle, and ethnicity, among others.

Efforts aimed at reducing health inequalities and to improve health outcomes are paramount in health and healthcare policy-making globally, and are a development goal in low- and middle-income countries (O'Donnell *et al.*, 2008). In this essay, I look at the changes in inequalities in a specific neglected and under-researched dimension of health — mental health. There is increased acknowledgement that mental health should be regarded as a chronic condition or disease, but this still not widely done (Bernell & Howard, 2016). Besides mental health being an important dimension of health on its own, it has also been suggested to have strong links to physical health (Lotfaliany *et al*., 2018; Ohrnberger *et al*., 2017). The present study documented trends in income-related inequality in depressive symptoms in South Africa between 2012 and 2021, which covers a period both before and during the COVID-19 pandemic. By means of the regression-based decomposition, I examine the most important correlates of the observed patterns for income-related inequality in depressive symptoms in South Africa before and during the COVID-19 pandemic. Given that I identify the COVID-19 effect through a time dummy, and that there could be a lot of micro and macro factors (not included) that could have influenced mental health between 2017 and 2021, this study does not claim a causal effect of the pandemic on mental health, but assesses how mental health prevalence and distribution changed between a relatively "normal period" (pre-pandemic) and an "abnormal period" (reflected at 2021). Based on the assessment, the study presents context-specific measures that can be implemented to improve mental health in South Africa.

4.2 Background of the study

COVID-19 and its related containment measures are associated with substantial socio-economic readjustment, which plays a pivotal role in the development and distribution of mental disorders. Event studies suggest that occurrence of a negative life event results in illness through causal sequencing (Monroe, 1982). In this case, the outbreak, magnitude, and severity of the COVID-19 pandemic may have serious and enduring effects on people's psychological, behavioural, and social spheres, which may result in mental disorders. To curb the pandemic, the South African government implemented different measures, such as closing of non-essential activities, social distancing, and travel restrictions. This discouraged important human interactions that both improve social capital and sustain the economy, such as enjoying entertainment and sporting activities, tourism, and sharing enclosed working areas.

COVID-19-related measures were guided mainly by *"…the level of infections and rate of transmission, the capacity of health facilities, the extent of the implementation of public health interventions and the economic and social impact of continued restrictions"* (Government of South Africa, 2022). These measures helped to contain COVID-19 through restrictions on lifestyle. Table 16 summarizes the measures that were implemented in South Africa.

Table 16: The COVID-19 Timeline in South Africa

Date	COVID-19 alert level
26 Mar – 30 Apr 2020	**Alert level 5 (high COVID-19 spread with a low health system readiness)** Restriction on the movement of persons and goods; prohibition of public transport; prohibition of evictions; contact tracing; mining sector capacity reduced to 50%; borders and tourism closed; penalty for failure to comply; sale of liquor and cigarettes prohibited; hospitality and travels banned
1 – 31 May 2020	**Alert level 4 high (COVID-19 spread with a low to moderate health system readiness)** Curfew and mandatory protocols; restrictions on movements; funeral attendances capped at 50 mourners; gyms and fitness centres, night clubs, and casinos closed
1 Jun – 17 Aug 2020	**Alert level 3 (moderate COVID-19 spread with a moderate health system readiness)** Curfews and mandatory protocols when in public; leisure and tourism partially open; domestic travels allowed; Exercising allowed (6am-6pm); liquor sales for offsite consumption (Mon to Thurs -9am – 5pm)
18 Aug – 20 Sep 2020	**Alert level 2 (moderate COVID-19 spread with a high health system readiness)** Curfews and mandatory protocols when in public; gatherings with a cap on attendance; less restrictions on movement of people and goods
21 Sep – 28 Dec 2020	**Alert level 1 (low COVID-19 spread with a high health system readiness)** Curfews and mandatory protocols when in public; all international travels open subject to health protocols; universities and school open for in-person teaching
29 Dec 2020 – 28 Feb 2021	**Adjusted alert level 3 (moderate COVID-19 spread with a moderate health system readiness)** new COVID-19 variant discovered, curfew (9 pm – 5 am curfew) and mandatory protocols when in public; schools reopened on 15 February; public events open to maximum of 50 attendees; vaccine phase 1 – healthcare workers
1 Mar – 30 May 2021	**Adjusted alert level 1 (low COVID-19 spread with a high health system readiness)** Vaccine phase 2 – healthcare workers; curfews and mandatory protocols when in public; schools reopen; most facilities open to the public
31 May – 15 Jun 2021	**Adjusted alert level 2 (moderate COVID-19 spread with a high health system readiness)** Curfew (11pm-4am) and mandatory protocols when in public; leisure facilities open; funerals and gatherings restricted to less than 250 people
16 Jun – 27 Jun 2021	**Adjusted alert level 3 (moderate COVID-19 spread with a moderate health system readiness)** Curfew (10pm-4am) and mandatory protocols when in public; gatherings allowed to 50 for indoors and 100 for outdoors; schools close earlier; vaccine phase 2 – for essential workers; visits to old age homes and care facilities restricted; interprovincial travel to and from Gauteng is prohibited with limited exceptions
28 Jun – 25 Jul 2021	**Adjusted alert level 4 (COVID-19 spread with a low to moderate health system readiness)** Vaccine phase 2 – for over 60yrs; partial reopening of borders; transportation of cargo allowed from other countries; capacity restrictions for domestic public transport; interprovincial and leisure travels allowed; sale of liquor prohibited
26 Jul – 12 Sep 2021	**Adjusted alert level 3 (moderate COVID-19 spread with a moderate health system readiness)** Schools reopen on 26 July and mask breaks for students every two hours; mandatory protocols when in public (masks and social distance); funeral attendance capped at 50; initiation practices are allowed; partial reopening of borders; vaccine phase 3- below 50yrs; sale of liquor for offsite consumption allowed (10am-6pm)
13 – 30 Sep 2021	**Adjusted alert level 2 (moderate COVID-19 spread with a high health system readiness)** Curfew (11pm to 4am); leisure and fitness centres open to the public; mandatory protocols when in public; gatherings restricted to 250 people if indoors or 500 people if outdoors 11pm-4am
1 Oct 2021 – 4 Apr 2022	**Adjusted alert level 1 (low COVID-19 spread with a high health system readiness)** Most restrictions relaxed; travels allowed; mandatory public protocol
5 Apr 2022	**The National State of Disaster is lifted**

Source: Government of South Africa (2022)

Changes in lifestyles due to "Alert levels" resulted in increases in the incidence of depression, loneliness, substance abuse and violent crimes in South Africa (Oyenubi & Kollamparambil, 2020). Between July and December 2020, mental health in South Africa significantly deteriorated, with the share of the population screening positive for depression increasing from 24% to 29% between July and December 2020 (Spaull *et al.*, 2021). The risk of screening positive increased for black Africans, but not for other population groups over the same period. Those in formal employment were found to have greater protection against depressive symptoms than those who were unemployed (Oyenubi & Kollamparambil, 2020).

Given that South Africa is a middle-income country with a complex social structure, high poverty rate, significant income inequality, a high unemployment rate (World Bank, 2018), and a high disease burden, significant differences in the way that people experience and cope with the COVID-19 containment measures is to be expected (Oyenubi & Kollamparambil, 2020). Literature shows that income inequality is positively associated with the risk of depression (Patel *et al.*, 2018). Current evidence shows that the pandemic weighed heavier on the most vulnerable in South Africa (Burger & Mchenga, 2021; Nwosu & Oyenubi, 2021; Oyenubi & Kollamparambil, 2020; Spaull *et al.*, 2020), which might spell unequal mental health outcomes. For the upper class in urban areas, lockdown-induced restriction of movements, suspension of nonessential businesses, as well as changes in behaviour may be depressing. However, for the lower-income classes in townships and rural areas, lockdown meant a loss of income due to forced disengagement from the labour market and informal income-generating activities, which led to poverty (Oyenubi & Kollamparambil, 2020). This asymmetrical burden of the pandemic will likely deepen income-related inequality in depressive symptoms in a country that already ranks among the most unequal in the world. This is despite efforts by the government to minimise the financial impact of the pandemic for the poor by topping up existing government grants and introducing a COVID-19 relief grant for unemployed people who do not qualify for the existing social grants.

The reinforcing circular relationship between poverty and mental illness is widely documented (Mnookin, 2016; Patel *et al*., 2015). The social causation theory posits that poverty increases the risk of mental illness through chronic stress, social and economic exclusion, lowered social capital, malnutrition and exposure to violent crimes (Lund *et al*., 2011). The COVID-19 pandemic created conducive environments for the social causation pathway that links poverty and mental health in South Africa. People, mostly those in vulnerable or non-essential sectors, lost their jobs, adding to their financial stress, exacerbated malnutrition and social exclusion, lowered social capital, and heightened exposure to crime (Oyenubi & Kollamparambil, 2020). Poverty-induced stress predisposes people to mental disorders, while mental disorders, in turn, increase the risk of falling into, and/or remaining in, poverty (Lund *et al.*, 2011; Stoop, Leibbrandt & Zizzamia, 2019), leading to ever-rising rates of both (Mnookin, 2016; Patel *et al.*, 2015).

That negative life events are associated with vulnerability to depression is well documented globally, but mostly so in developed countries (Burger *et al.*, 2017). Few studies have been conducted in developing countries, and little is known about the contribution of large exogenous events like the COVID-19 pandemic on socioeconomic-related inequalities in mental health. In this study, I explored the role of the COVID-19 pandemic on income-related inequality depressive symptoms inequality in South Africa. To achieve this, I utilised a regression-based decomposition method for bivariate rank-dependent indices, developed by Heckley *et al*. (2016), to ascertain the impact of the COVID-19 pandemic and socioeconomic factors on income-related mental health inequality. This method directly decomposes the weighted covariance of the health- and socioeconomic ranking variable (Heckley *et al*., 2016).

4.3 Methods

4.3.1 Data source

I used data from the fifth round of the National Income Dynamic Study (NIDS) and the fifth round of the NIDS-Coronavirus Rapid Mobile (NIDS-CRAM) survey. NIDS is a publicly available nationally representative data; the data are collected every two years, which commenced in 2008. The fifth round of the NIDS survey was carried out in 2017. Two-stage stratified cluster sampling design was used in collecting NIDS data (Leibbrandt *et al*., 2009). In the first stage, 400 primary sampling units (PSUs) were selected from 3 000 PSUs, contained in the national master sample (Brophy *et al.*, 2018; Leibbrandt *et al*., 2009). Individuals from the randomly sampled households from the 400 PSUs were thereafter interviewed in the second stage.

NIDS-CRAM is a nationally representative survey that was drawn from the fifth-round adult sample of the NIDS (Ingle *et al*., 2020; Kerr *et al.*, 2020). The data from the fifth round of the NIDS-CRAM were collected between 6 April and 11 May 2021 (Spaull *et al.*, 2021). The choice for the NIDS's last round and the fifth round of the NIDS-CRAM was motivated by unavailability of items referring to emotional wellbeing in the NIDS-CRAM's first round, and the need to increase the sample size of the balanced panel data. Though information on emotional wellbeing was collected in the subsequent NIDS-CRAM rounds, the NIDS-CRAM sample was largest in the fifth round.

4.3.2 Measures

The study measured socioeconomic rank through real per capita household income. The *health* variable was binary, with *1* representing good mental health and zero (*0*) representing having screened positive for depressive symptoms. Dichotomisation of depressive symptoms was based on two non-directly comparable screening tools. Screening of depression in the NIDS is based on the 10-item Centre for Epidemiological Studies Depression Scale (CES-D10) (Radloff, 1977), which ranges from *0* (*Good*) to *30* (*Worst*)[18]. To dichotomise the CES-D10 scores, any score equal to or greater than 10 was classified as 'bad mental health' (screened positive for depressive symptoms). The cut-off of CES-D10 >= 10 was recommended by Andresen *et al.* (1994), and has also been used in other studies (Oyenubi & Kollamparambil, 2020). Screening for depressive symptoms in the NIDS-CRAM (a telephonic interview) survey made use of the two-question version of the Patient Health Questionnaire (PHQ-2) (Kroenke, Spitzer & Williams, 2003). The PHQ-2 collected information on whether the respondent: (1) had little interest or pleasure in doing things; and (2) felt down, depressed or hopeless, over the two weeks preceding the survey. The two questions had four predefined responses: *0* (*Not at all*), *1* (*Several days*), *2* (*More than half the days*), and *3* (*Nearly every day*). After adding individual responses from the two questions, the total scores ranged from *0* (*Good*) to *6* (*Worst*). The recommended cut-off for bad mental health is PHQ-2 >= 3 (Kroenke *et al.*, 2003). Though different, both the CES-D10 and PHQ-2 instruments have been validated for screening of depressive symptoms (Baron *et al.*, 2017; Levis *et al.*, 2020). Whilst there could be translation-related problems with the PHQ-2, the CES-D10 has been validated in South African languages (Baron *et al.*, 2017).

Household income, which I used to compute per capita household income, was measured differently in the two datasets. The NIDS provides aggregate numerical households income values (Argent, 2009), whilst in the NIDS-CRAM income is a one-shot response to the household income question (Ardington, 2020). Information on household income in NIDS-CRAM does not allow for full imputations of income as in NIDS (Köhler & Bhorat, 2020). Therefore, I adjusted household income values in the NIDS-CRAM 5 to estimate numeric

[18] More explanation on the CES-D10 scores is provided in Chapter 2, under Section 2.2.2

household incomes that would be comparable to the NIDS 2017 household numeric values using an aggregation technique proposed by Köhler and Bhorat (2020).

This essay provides a new dimension to the degree of income-related inequality in good mental health in South Africa. I measured the impact of the COVID-19 pandemic on income-related inequality in self-reported mental health. The study captured the impact of the pandemic through the time dummy. Time and region are some of the contextual features that affect socioeconomic-related inequality in depression (Lorant *et al*., 2003). The other correlates in models are age, years of education, employment status, place of residence, gender, marital status, and population group.

4.3.3 Statistical analyses

4.3.3.1 Measuring socioeconomic inequality in good mental health

Analysis of the extent of socioeconomic inequality in mental health was done in two stages. First, I measured socioeconomic inequality in good mental health using the Erreygers Index (EI) and the Wagstaff Index (WI). The EI and WI are suitable for health variables that are binary (Erreygers, 2009a,b; O'Donnell *et al.*, 2016); in this case, good mental health was either *0* (minimum or lower bound) or *1* (maximum or upper bound).

The rank dependent indices (*I*) normalise the absolute concentration (AC) through multiplying the AC with weighting function. The EI is an absolute concentration (AC) index, adjusted for a bounded variable, derived from a normalised binary variable, whereas the value judgement underlying the WI is complex (Heckley *et al*., 2016; O'Donnell *et al*., 2016). The AC was expressed as follows:

$$AC = 2Cov(h_i, r_i) \qquad 9,$$

where r_i was the rank of an individual in the income (per capita real household income) distribution, with the poorest rank equal to *1* (minimum) and the richest rank equal to the maximum (for quintiles the rank would be 5); h_i was the health variable (*Good mental health*) with mean μ_h, and *Cov* was the covariance. Thus, the AC was defined as twice the covariance of the good mental health and the fractional rank of the individual in the income distribution.

Adjusting the AC (in Equation 5) using the weighting function,

$$W^{EI}(F_h) = \frac{4}{b_h - a_h} \qquad 10,$$

where a_h and b_h are minimum (*0*) and maximum (*1*) values of good mental health, respectively, the EI was then defined as:

$$EI = \frac{4}{b_h - a_h} AC \tag{11}$$

After substitutions, this will reduce to:

$$EI = 8Cov(h_i, r_i) \tag{12}$$

The weighting function for the WI is:

$$W^{WI}(F_h) = \frac{b_h - a_h}{(b_h - \mu_h)(\mu_h - a_h)} \tag{13}$$

and after substitutions, the WI will be given by:

$$WI = \frac{2Cov(h_i, r_i)}{(\mu_h)(1 - \mu_h)} \tag{14}$$

The EI and WI are summary statistics ranging from -1 to +1, and measures the degree of inequality in the population. The EI or WI value of zero (*0*) reflects equal distribution of good mental health, and the corresponding concentration curve coincides with the line of equality (45° line). A positive EI or WI means that good mental health is concentrated among the rich, while a negative EI or WI means that the poor have a greater than proportional share of good mental health.

For decomposition analysis, I also used two more indices: the attainment-relative concentration index (ARCI), and the shortfall-relative concentration index (SRCI)[19]. The ARCI is an index that is invariant to the proportional change in attainment of bounded health variable (Erreygers & Van Ourti, 2011). The ARCI is given by:

$$ARCI = \frac{2Cov(h_i, r_i)}{\mu_h} \tag{15}$$

The SRCI an index applied the ARCI but to ill-health or shortfalls in health (Heckley *et al.*, 2016). The SRCI is given by:

[19] The four indices presented above are all for bounded health variables. The differences in the indices emanate from the weighting function used when normalizing the AC, and as such comparing the indices is not a robustness test (O'Donnell *et al.*, 2016). The four indices perform the same task, to measure inequality when faced with a finite health variable and as such the choice of an index is a value judgement – whether relative invariance or the mirror condition (Heckley *et al.*, 2016; O'Donnell *et al.*, 2016).

$$SRCI = \frac{2Cov(h_i, r_i)}{1-\mu_h} \qquad 16$$

Second, I used concentration curves to graphically illustrate per capita real household income inequality in good mental health. The concentration curve mapped the cumulative proportion of good mental health along the y-axis against the cumulative proportion of the sample, ranked by increasing per capita real household income, along the x-axis. The further away from the line of equality the concentration curves were situated the greater the inequality was. A concentration curve below the line of equality meant that good mental health was concentrated among the richest people in the sample. I make use of the *conindex* Stata command by O'Donnell *et al.* (2016) to calculate the concentration indices and plot concentration curves.

4.3.3.2 The RIF decomposition of a rank-dependent index (I)

To assess the pandemic-associated changes in the income-related inequality of good mental health, I used the recentered influence function (RIF) decomposition method of rank-dependent indices developed by Heckley *et al.* (2016). This descriptive decomposition method was developed from the work by Firpo *et al.* (2009), on the RIF decompositions of univariate income inequality measures of such as the percentile differences and ratios, variance, the Gini index, and the unconditional quantile. The RIF was derived from the influence function (IF) (Heckley *et al.*, 2016).

In a RIF decomposition method, decomposition of a particular rank-dependent index involves computing the corresponding vector of RIF values using the formulas developed by Heckley *et al.* (2016) first. RIF values express the influence of each observation of health and socioeconomic status on the inequality indicator. This means that RIF values for individuals tell us how the index changes if those individuals were to be removed from the sample (Heckley *et al.*, 2016; Kessels & Erreygers, 2019). The RIF values served as the dependent variables in linear regressions. The RIF regression yields the marginal effects of the variables on the influence they exert on the index, which is the weighted covariance between health and socioeconomic rank (Heckley *et al.*, 2016; Kessels & Erreygers, 2019). This RIF regression decomposition approach was also used by Cai *et al.* (2017) in China to examine health inequality related to income.

Below, I present the reduced versions of the IF and the RIF formulas for the rank-dependent index by Heckley *et al.* (2016) that I adapted from the work of Kessels and Erreygers (2019). The IF of rank-dependent index (*I*) is defined as:

$$IF_i^I = \mu_h - h_i - 2I + \tilde{f}_i h_i - 2glp_i \qquad 17,$$

where μ_h is the mean of health, h_i; $\tilde{f_i}$ is the relative fractional rank, which is the fractional rank (f_i) divided by its average (μ_f), where f_i is defined as:

$$f_i \equiv \frac{1}{n}\left(r_i - \frac{1}{2}\right) \text{ and } \mu_f = \frac{1}{2}$$

Hence, $\tilde{f_i} = 2f_i$, which varies between $\frac{1}{n}$ and $2 - \frac{1}{n}$

The glp_i is the generalised Lorenz point of individual *i*, that is, the absolute concentration curve co-ordinate of the individual defined as:

$$glp_i = \frac{h_i + 2\sum_{j=0}^{i-1} h_j}{2n} \qquad 18$$

The RIF for the rank-dependent index (RIF_i^I) is the sum of the influence function of the rank-dependent index and the value of the rank-dependent index (*I*); that is,

$$RIF_i^I = IF_i^I + I. \qquad 19,$$

where *I* is any of the four rank-dependent indices (*I*) for bounded health variables. These are the EI, the ARCI, the SRCI, and the WI. I decomposed four indices because there is a lack of consensus as to which index to use when measuring inequality in health (Heckley *et al.*, 2016).

The regression equation for the RIF^I was expressed as:

$$RIF_i^I = \phi_0 + \phi_1 x_{1,i} + \phi_2 x_{2,i} + \cdots + \phi_q x_{q,i} + \psi_i, \qquad 20,$$

Where ϕ_0 was the intercept, ϕ_1, ϕ_2,…, ϕ_q represented the explanatory variables' marginal degrees of influence on *I*, and ψ_i was the error term, where $E(\psi_i|x_{1,i}, \dots, x_{q,i}) = 0$.

Under the following identifying assumptions:

Assumption I: The I is a continuously differentiable,

Assumption II: The RIF of the I is additively linear in independent variables and error term, and

Assumption III: Exogeneity – zero conditional mean of error terms,

I could optimally estimate marginal effects of variables on the rank-dependent index (*I*) (Equation 11), using OLS (hence the name RIF-I-OLS) (Heckley *et al.*, 2016).

4.3.3.3 Linear probability and conditional fixed effects logit

Because the study captured the impact of the pandemic through the time dummy, I estimated linear probability and conditional fixed effects logit models of the binary dependent variable on the time dummy and the interaction between the time dummy and income level. The purpose of this exercise was to see if the gap in mental health problems widened after the pandemic. I specified the model as follows:

$$h_{it} = \alpha + \beta_1 NonPoor_{it} + \beta_2 PostCOVID_t + \beta_3 (NonPoor \times PostCOVID)_{it} + \gamma' X_{it} + u_i + \varepsilon_{it} \qquad 21$$

Where h_{it} is the binary measure of mental health (which takes 1 if respondent has bad mental health and 0 otherwise), $NonPoor_{it}$ takes 1 if the individual's per capita household income is above the lower-bound poverty datum line and 0 if below the lower-bound poverty datum line. $PostCOVID_t$ takes 1 if year is 2021 and 0 if year is 2017. X_{it} was a set of time varying controls, and u_i indicated individual fixed effects.

4.4 Results

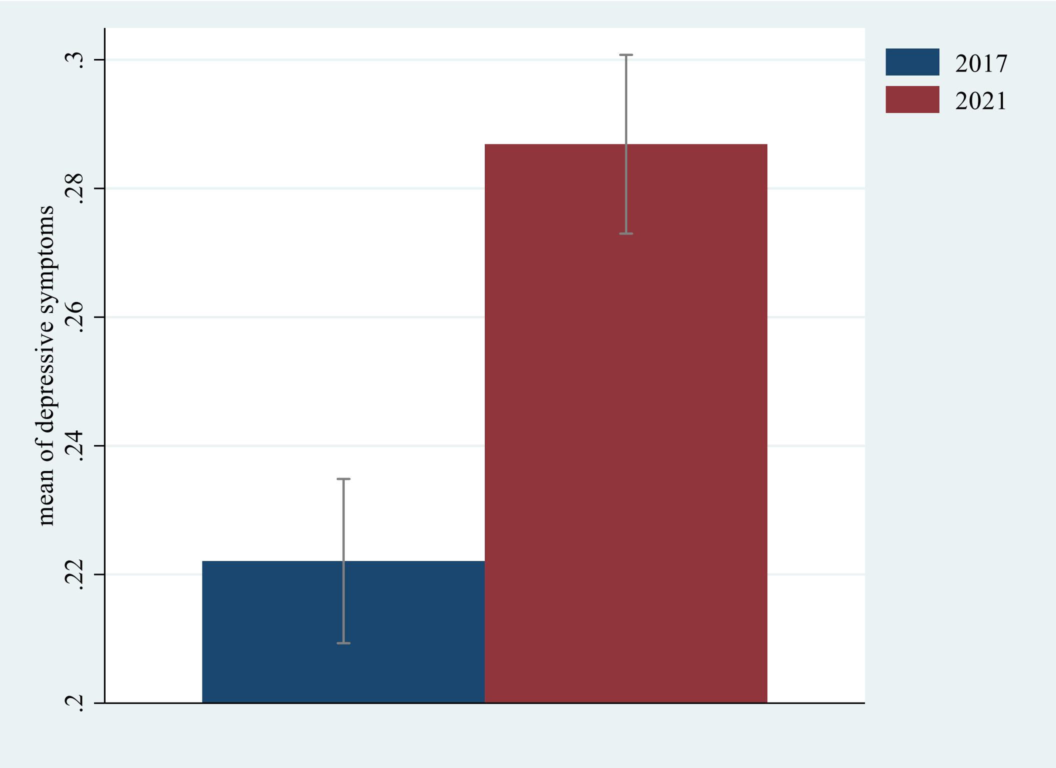
4.4.1 Descriptive analyses

Table 17, below, shows a summary of the sample. The sample was made up of 8 150 observations. One in every four adults in the sample screened positive for depressive symptoms at least once during the period under study. In Figure 9, the share of people who screened positive for depressive symptoms increased between 2017 (pre-pandemic period) and 2021 (during the pandemic). This share increased from 22.21% in 2017 to 28.69% in 2021. In relation to the trends in the distribution of depressive symptoms by income quintiles, Figure 10 shows a negative gradient prior to the pandemic. The share of people who screened positive for depressive symptoms was highest among the poorest (Quintile 1), and lowest among the richest (Quintile 5). The income gradient in depressive symptoms disappeared during the pandemic. The prevalence of depressive symptoms decreased for the poorest, but increased for other income ranks. The share of people screening positive for depressive symptoms was highest in the middle class (Quintile 3). The prevalence of depressive symptoms was lowest among the richest (Quintile 5) and the second poorest (Quintile 2).

Table 17: Characteristics of the pooled sample

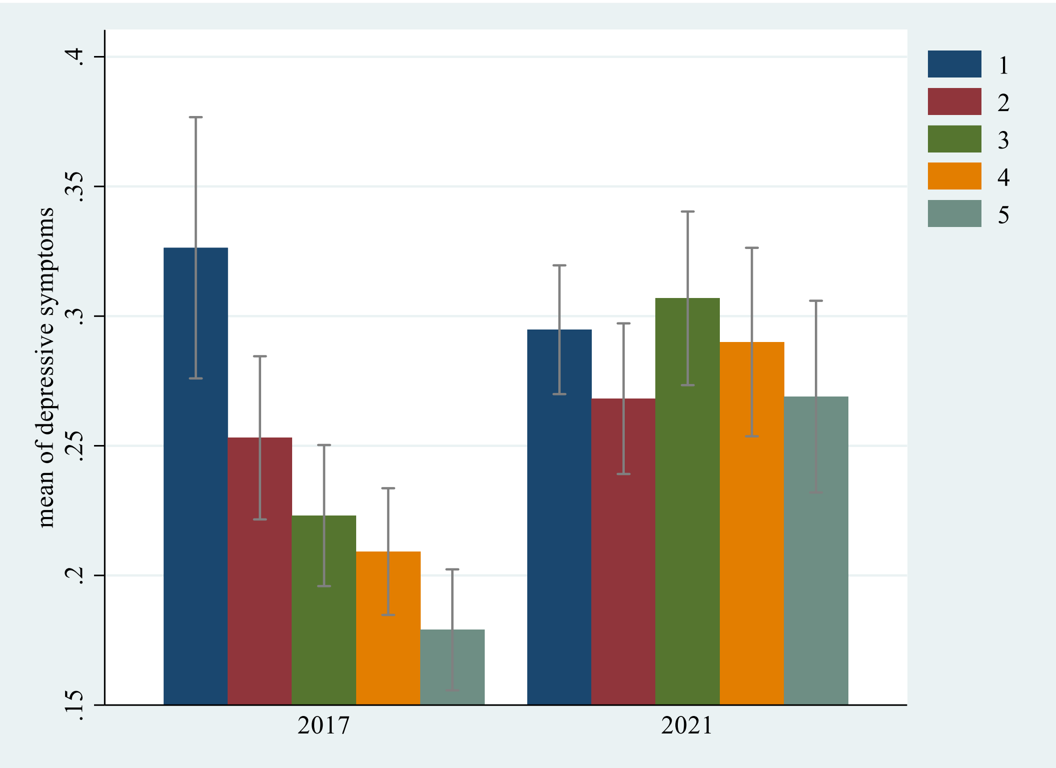
Variable	Total (N = 8 150)
Per capita household income (ZAR)	
Mean (SD)	2 049.23 (10541.23)
Median (Q1, Q3)	911.4 (455.3, 1967.1)
Screened positive for depressive symptoms	
No	6 076 (74.6%)
Yes	2 074 (25.4%)
Education level	
No schooling	173 (2.1%)
Grade 1–7	963 (11.8%)
Grade 8–11	3 367 (41.3%)
Matric	2 628 (32.2%)
Certificate/Degree/Diploma	1 019 (12.5%)
Employment status	
Employed	3 717 (45.8%)
Not economically active	2 550 (31.4%)
Unemployed	1 852 (22.8%)
Residence	
Rural	3 313 (40.7%)
Urban	4 837 (59.3%)
Age categories	
15–24	1 681 (20.6%)
25–39	3 433 (42.1%)
40–54	2 025 (24.8%)
>=55	1 011 (12.4%)
Gender	
Male	3 092 (37.9%)
Female	5 058 (62.1%)
Marital status	
never married	2 864 (35.1%)
married or cohabiting	5 053 (62.0%)
widowed or divorced	233 (2.9%)
Population group	
African	7 206 (88.4%)
Coloured	780 (9.6%)
Indian	40 (0.5%)
White	124 (1.5%)
Self-assessed health	
Poor	1 486 (18.2%)
Good	6 664 (81.8%)

Figure 9: Trends in the proportion of people who screened positive for depressive symptoms



Source: Author's calculations

Figure 10: Proportion of people who screened positive for depressive symptoms by income quintiles between 2017 and 2021



Source: Author's calculations

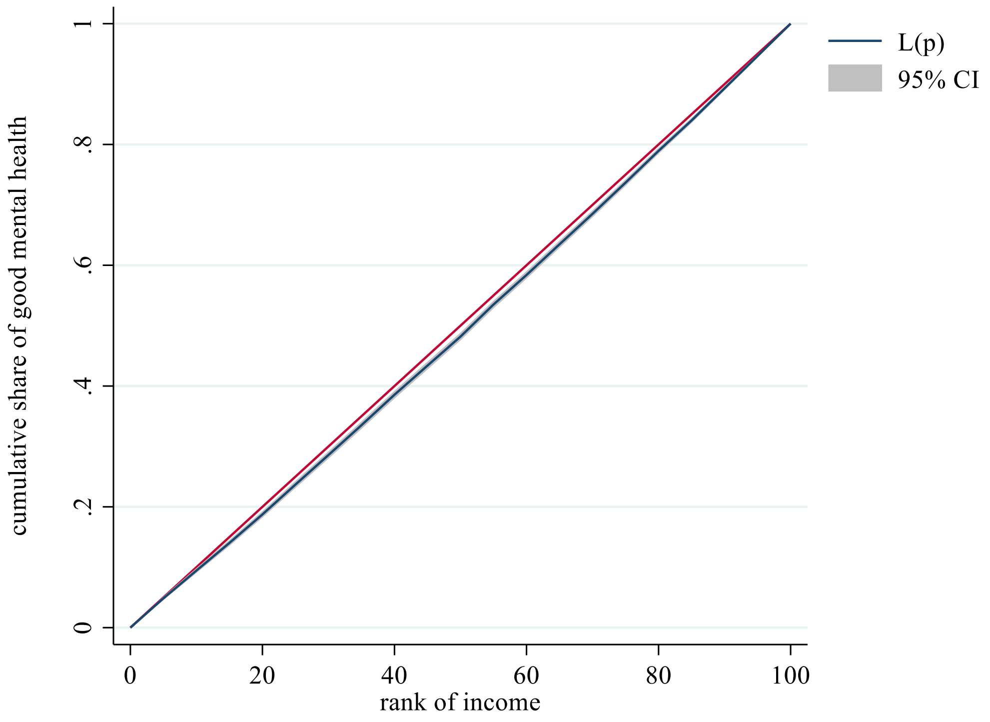
4.4.2 Socioeconomic inequality in good mental health

The EI estimate for good mental health was 0.062 for the pooled sample, from 2017 to 2021. For the same period, the Wagstaff Index (WI) was 0.083. This indicated that good mental health was disproportionately concentrated among the rich, identified by a higher position in the per capita household income distribution in the sample. The point estimates in Table 18 suggest that the EI and WI were not significant in 2021. The results of the *F*-tests (EI: F-stat = 13.067; *p*-value = 0.000; and WI: F-stat = 63.058; *p*-value = 0.000) do not support the null hypothesis that the index is the same across the time points.

Table 18: Trend in inequality of good mental health

Year	Observations	EI value (robust std. error)	*p*-value	WI value (robust std. error)	*p*-value
2017	4 075	0.067 (0.024)	0.006	0.098 (0.035)	0.006
2021	4 075	0.013 (0.030)	0.301	0.016 (0.037)	0.678

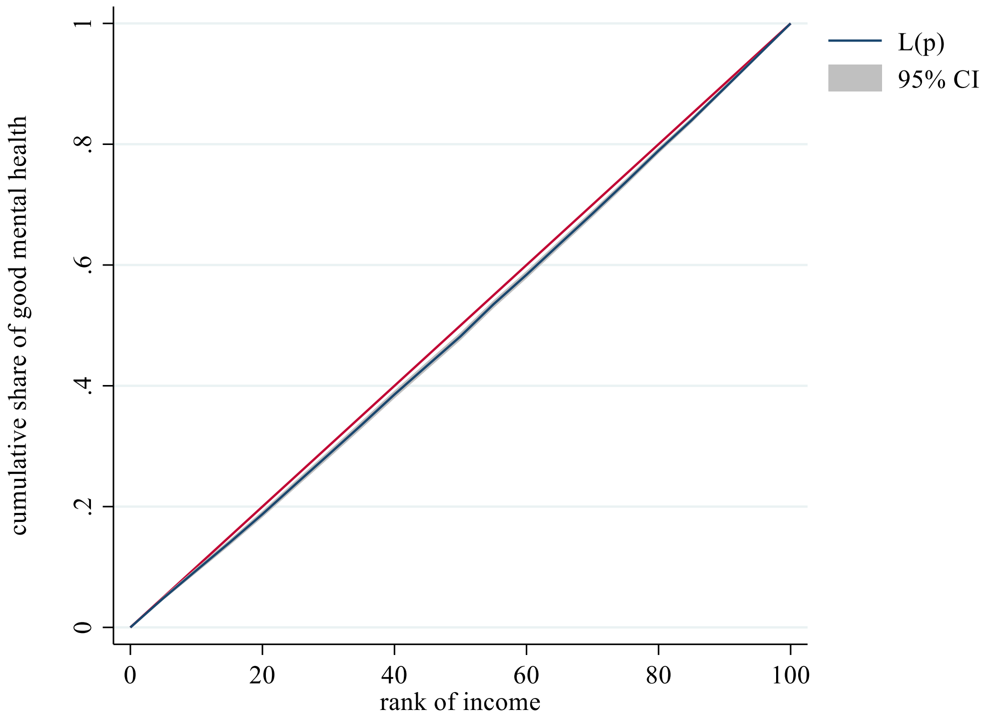
Figure 11: The EI concentration curve for prevalence of good mental health against per capita household income rank



Source: Author's calculations

Figure 11 (EI) (above) and Figure 12 (WI) (below) show the distribution of good mental health in the pooled sample. The concentration curves lay below the line of equality, an indication that good mental health was disproportionately concentrated or higher among those ranked rich according to per capita household income.

Figure 12: The WI concentration curve for prevalence of good mental health against per capita household income rank



Source: Author's calculations

4.4.3 RIF regression results

To estimate the influence of the COVID-19 pandemic on inequality in good mental health, I used the RIF regression method. Table 19 presents the results for RIF-I-OLS for bounded and rank-dependent indices, namely the EI, ARCI, SRCI, and WI. The results in Table 19 suggest that the COVID-19 pandemic did affect the relationship between good mental health and per capita household income as reflected in the RIF of EI, ARCI, SRCI and WI. That is, the COVID-19 pandemic negatively influenced the inequality index (covariance between per capita household income and good mental health) when measured using the EI, ARCI, SRCI and WI. I found that the sample's education did not significantly influence the four inequality indices' scores, whilst self-reported health negatively influenced all inequality indices. The results also showed that age equal or above 55 years had a significant negative effect on income-related inequality in good mental health across all the indices. This meant that the covariance between per capita household income and good mental health was lower in the group older >=55 years, compared to those aged 15–24 years. Population group (self-identified), specifically Coloured respondents, showed a positive effect on all four bounded rank-dependent indices' scores while negative for white respondents over the same indices. Gender profile in the covariance between income and good mental health was present when inequality was measured using the SRCI where a negative was present.

Because education determines labour market outcomes, I did not include employment status in the models presented in Table 19. This was to avoid the 'bad control problem', which would have complicated the interpretation of both education and employment status (Angrist & Pischke, 2009; Heckley *et al.*, 2016). Though employment status can influence income-related inequality in mental health, it is also an outcome of education, meaning that it is also driven by inequalities in education. Interpreting the influence of education on inequality would be difficult. For sensitivity analysis, I controlled for employment status and excluded education in Table 21, Appendix 3.A. The results in relation to the COVID-19 dummy and other covariates remained stable and consistent in meaning. Being economically inactive negatively influenced the correlation between income and mental depressive symptoms. As shown in Table 22, in Appendix 3.B, I controlled for both employment status and education. Again, the results in relation to the COVID-19 dummy and other covariates remained stable and consistent in meaning. Education remained statistically insignificant, whilst not economically active remained significant.

In all models in the RIF-I-OLS regression tables, bootstrap (1 000 repetitions) standard errors are in parenthesis.

4.4.4 Linear probability and conditional fixed effects logit regression results

Model 3 in Table 20 suggests that being non-poor is associated with reduced odds of being depressed. I found no significant association between the post-COVID-19 dummy and depressive symptoms. However, interacting the post-COVID-19 dummy and being non-poor increased the odds of being depressed. This confirmed the distribution of mental health in Table 18 and RIF-I-OLS regression results in Table 19, that the COVID-19 pandemic is associated with distortions in the distributions of good mental health by income.

Table 19: RIF-I-OLS decomposition estimates of COVID-19 pandemic and socioeconomic variables (excluding employment status) on income-related good mental health inequality

Variables	EI	ARCI	SRCI	WI
	(1)	(2)	(3)	(4)
Education (none)				
Grade 1–7	0.031	0.010	0.033	0.043
	(0.074)	(0.025)	(0.071)	(0.096)
Grade 8–11	-0.010	-0.004	-0.004	-0.008
	(0.072)	(0.024)	(0.070)	(0.094)
Matric	-0.013	-0.005	-0.011	-0.016
	(0.073)	(0.025)	(0.071)	(0.095)
Post-matric	0.048	0.014	0.066	0.080
	(0.075)	(0.025)	(0.074)	(0.099)
Rural	0.004	0.001	0.009	0.010
	(0.023)	(0.008)	(0.023)	(0.031)
Age (15–24)				
25–39	0.025	0.010	0.011	0.021
	(0.029)	(0.010)	(0.028)	(0.037)
40–54	0.013	0.006	-0.006	0.000
	(0.036)	(0.012)	(0.035)	(0.046)
> = 55	-0.086*	-0.028*	-0.090**	-0.118*
	(0.046)	(0.016)	(0.045)	(0.061)
Female	-0.032	-0.010	-0.039*	-0.049
	(0.023)	(0.008)	(0.023)	(0.030)
Marital status (Never)				
Married/cohabiting	0.028	0.008	0.040	0.048
	(0.038)	(0.013)	(0.039)	(0.052)
Widowed/divorced	-0.026	-0.007	-0.039	-0.046
	(0.074)	(0.025)	(0.076)	(0.100)
Self-reported health	-0.109***	-0.041***	-0.072**	-0.113***
	(0.033)	(0.011)	(0.032)	(0.043)
Population group (African)				
Coloured	0.082**	0.029**	0.071*	0.099*
	(0.040)	(0.013)	(0.040)	(0.053)
Indian	-0.095	-0.032	-0.096	-0.128
	(0.208)	(0.068)	(0.221)	(0.288)
White	-0.339**	-0.110**	-0.366**	-0.476**
	(0.142)	(0.047)	(0.149)	(0.196)
Year (2017)				
2021 (Post-COVID-19 pandemic)	**-0.117*** **	**-0.038*** **	**-0.130*** **	**-0.167*** **
	(0.039)	**(0.013)**	**(0.039)**	**(0.052)**
Constant	0.212***	0.073***	0.188**	0.261**
	(0.082)	(0.028)	(0.079)	(0.107)
Observations	8,150	8,150	8,150	8,150

Bootstrap standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Balanced sample. EI = Erreygers index; ARCI = attainment-relative concentration index; SRCI = shortfall-relative concentration index; WI = Wagstaff index RIF decomposition

Table 20: Linear probability and conditional fixed effects logit regression results

VARIABLES	LPM (1)	Fixed-Effects (Conditional) Logit: Logit coefficients (2)	Odds ratio (3)
Non-poor	-0.086***	-0.498***	0.607***
	(0.015)	(0.118)	(0.072)
Post-COVID-19 (2021)	-0.013	0.005	1.005
	(0.021)	(0.153)	(0.154)
Non-poor#Post-(COVID-19 (2021)	**0.083*** **	**0.688*** **	**1.989*** **
	(0.021)	**(0.148)**	**(0.294)**
Education (None)			
Grade 1–7	-0.008	-0.460	0.631
	(0.035)	(0.348)	(0.220)
Grade 8–11	-0.020	-0.592*	0.553*
	(0.034)	(0.336)	(0.186)
Matric	0.000	-0.236	0.789
	(0.035)	(0.343)	(0.271)
Post-matric	-0.054	-0.529*	0.589*
	(0.035)	(0.318)	(0.188)
Rural	-0.030***	0.136	1.146
	(0.010)	(0.106)	(0.122)
Age (15–24)			
25–39	0.056***	0.021	1.022
	(0.013)	(0.179)	(0.183)
40–54	0.073***	-0.099	0.906
	(0.016)	(0.268)	(0.243)
> = 55	0.030	-0.347	0.707
	(0.021)	(0.421)	(0.297)
Female	0.024**		
	(0.010)		
Marital status (Never)			
Married/cohabiting	-0.039**	-0.242*	0.785*
	(0.017)	(0.132)	(0.104)
Widowed/divorced	0.054*	0.450**	1.569**
	(0.031)	(0.224)	(0.352)
Self-reported health	-0.134***	-0.574***	0.563***
	(0.014)	(0.103)	(0.058)
Population group (African)			
Coloured	0.042***		
	(0.016)		
Indian	0.018		
	(0.063)		
White	0.131***		
	(0.048)		
Constant	0.385***		
	(0.039)		
Observations	8,150	3,180	3,180
R-squared	0.031	0.059	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: For this table, mental ill-health is the dependent variable which takes 1 if the respondent has bad mental health and 0 otherwise.

4.5 Discussion

The COVID-19 pandemic has affected lives the world over, and its effects on employment and education are expected to be enduring. Event studies have shown that such dramatic negative life events have a substantial impact on both physical and mental health. Recent literature has shown that such negative life events weigh differently on people, based on their ability to cope, which is also determined by the differential protection of safety nets. Understanding the effect of large events such as the COVID-19 pandemic on health is a very important step in dealing with the pandemic and post-pandemic rebuilding. In this study, I show trends in the distribution of depressive symptoms from the pre-COVID-19 period to the first year of the pandemic. I also used the EI and the WI to show how inequality in the distribution of good mental health has evolved. I then used a relatively new and innovative decomposition method, developed by Heckley *et al.* (2016), to decompose income-related inequality in good mental health in South Africa, a highly unequal middle-income country. To examine if the gap in mental health problems widened after the pandemic, I estimated linear probability and conditional fixed effects logit models of the binary dependent variable on the COVID-19 dummy and the interaction between the COVID-19 dummy and income level.

I found that the share of respondents who screened positive for depressive symptoms increased between 2017 and 2021, the COVID-19 pandemic period. Using the EI and the WI, I also found that the distribution of good mental health was pro-rich for the pooled sample (both pre-COVID-19 and during the pandemic). However, the magnitude of inequality in the distribution of good mental health became statistically insignificant in 2021. This means that the income gradient in mental health that existed before the pandemic disappeared. The prevalence of depressive symptoms increased for all income groups, but disproportionally so for the middle class up to the richest. The conditional fixed effects logit model results also confirmed the effect of the pandemic, through income level, on the likelihood of being depressed. This scenario is not unique to the COVID-19 pandemic or to South Africa; studies have shown that shocks such as pandemics and wars have equalising effects (Milanovic, 2016; Pikkety, 2014; Scheidel, 2017). Literature (for example Jamison *et al.* (2006); Marmot *et al.* (2012); Marmot & Bell (2016); Pampel *et al.* (2010); Pongiglione *et al.* (2015)) suggests positive correlation between health and socioeconomic variables like education, income, and employment status. On the other hand, the pandemic and measures implemented to curb the pandemic has affected household productivity and incomes. This might have also affected access to health stimulating/producing goods and services, like healthy food, gymnasiums, vacationing, and socialising, that are accessible through a high income. Adjustment to these changes could have taken a toll on their mental well-being.

However, these results should not be interpreted as a reduction in depressive symptoms among the poor. The poor were also at high risk of COVID-19 and were exposed to high income shocks since most of the poor are in sectors regarded as non-essential. The possible explanation of the narrowing inequality in mental health could reflect stress inoculation amongst the poor. Because of historical inequalities in South Africa, the poor are likely to have had experienced more hardships than the rich, and may therefore have become more resilient (Höltge *et al*., 2018), which would explain the absence of a significant increase in the number of poor people screening positive for depressive symptoms. This means that incidence of mental disorders will be disproportionately higher among the affluent than it will be among the poor there by narrowing or reducing the income-related disparities in mental health.

The results could also be explained by different health expectation of different incomes groups. Because the study used self-reported depressive symptoms, it is possible that the rich tend to overestimate their ill-health whilst the poor tend to underestimate their ill-health. In this regard, Burger *et al.* (2020) found a higher COVID-19 risk perception among the rich. If the poor underreported their mental health, then we are likely underestimating the income gradient in depressive symptoms. Another explanation could be that social support reforms such as the COVID-19 relief grant, as well as increasing the Child Support Grant and all other social grants, provided the poor with a cushion against the COVID-19-related income shocks (South African Social Security Agency, 2020a). The study results are similar to those of Oyenubi and Kollamparambil (2020) and Posel *et al.* (2021), who also found a higher prevalence of depressive symptoms among the rich during the COVID-19 pandemic in South Africa.

The RIF-I-OLS decomposition results suggest that the COVID-19 pandemic negatively and significantly influenced the income-related inequality in good mental health in South Africa. This means that the COVID-19 pandemic disproportionately increased mental health problems amongst the affluent. I did not find any significant effect of the sample’s education level on the joint distribution of income and mental health. Given inequality in education in South Africa (De Clercq, 2020), it is most likely that education, in absolute terms, cannot have an effect on the correlation between income and mental health. Addressing inequalities in education may play a role in addressing income-related inequality. Self-reported health negatively influenced all inequality indices. People who all self-report good health are likely to possess similar socioeconomic characteristics including income, as such the correlation between income-gradient in mental health is likely to be weak.

The results also showed that age equal to or above 55 years had a significant negative effect on income-related inequality in good mental health across all the indices. This meant that the covariance between per capita household income and good mental health was lower in the group older >=55 years, compared to those aged 15–24 years. The "Gradient over the Life Cycle" theory suggest that inequalities in health are widest in mid-life and narrow later in life (Galama & Van Kippersluis, 2018). Early-life health inequalities grow with increasing economic and health advantages of higher SES in mid-life. This will narrow in later life, due to mortality selection, whereby lower SES people are more likely to die earlier than the healthier, higher-SES people (Galama & Van Kippersluis, 2018). Another explanation is that deterioration of health in later life is largely associated with age, rather than with other predictors like SES (Galama & Van Kippersluis, 2018; Grossman, 1972).

Population group (self-identified), specifically Coloured respondents, showed a positive effect on all four bounded rank-dependent indices' scores, while negative for white respondents over the same indices. This suggests that there is an income gradient for the Coloured population group, whereby the richer enjoy good mental health. Hence, policies that improve the income of the poor could improve their mental health, thereby promoting equality in health. Gende*r* profile in the covariance between income and good mental health was present when inequality was measured using the SRCI; it was found that *female* negatively influenced the SRCI. This implies that for women, the covariation between income and depressive symptoms was low. To improve equality in mental health for women, we would need to look at other factors. The differences in the size and signs of the coefficients of the COVID-19 pandemic and other variables across the four indices may be a reflection of the underlying weighting functions for each index (Heckley *et al.*, 2016).

This study is not without limitations. The study used self-reported depressive symptoms as an indicator of mental ill health. Whilst self-rated depressive symptoms can give a good understanding of the mental health problems in South Africa, I cannot rule out biased results emanating from unobserved heterogeneity. The probability of screening positive also entails issues such as stigmatisation and poor mental health reporting attitudes. This may have resulted in underreporting of mental health problems amongst the poor and overreporting amongst the rich. Furthermore, inequalities in mental health largely depend on how one screens for mental disorders. For example, through self-reported health, pharmaceuticals, diagnoses in primary care, and inpatient or outpatient diagnoses, one finds different distributions of mental ill health.

However, analyses of survey data that measure inequality using self-assessed health can rarely be spared such criticism. The strengths of the present study emanate from the size and type of data, and decomposition technique used. I used more than 8 000 observations, drawn from a longitudinal data set, which provided a unique opportunity to carry out the study in a low- to medium-income country marred by historical inequalities. Unlike one-sided regression, which could yield biased results due to using only the health variable, I used the relatively new and more reliable RIF decomposition approach, which jointly considers the health and socioeconomic variables (Heckley *et al.*, 2016; Kessels & Erreygers, 2019). The method also requires fewer identifying assumptions to yield valid estimates, which are easier to interpret, compared to other decomposition approaches (Heckley *et al.*, 2016).

The developing mental health effects of the COVID-19 pandemic can be offset by tractable social welfare and other policy measures to reduce historical inequalities, for example, in income, education, health and healthcare, and access to resources that fulfil basic needs. Results suggest that, under normal circumstances, the rich enjoy better mental health, and also that, during large exogenous economic shocks, the income gradient disappears. The prevalence of depressive symptoms was highest among the middle class, but significantly decreased for the poorest. These two findings suggest the need to reform social security, especially in times of significant shocks. There is need to continuously review grants and add new grants. Relief grants and increases in other grants might have offered protection against depression. Most members of the middle class were affected financially, but they did not meet the threshold for social grants available, and there is a need to adjust the threshold for grant eligibility, adjust the way "middle class" is defined (Burger *et al.*, 2017), or create new grants to cater for the middle class during significant shocks.

Given the relationship of health with poverty and inequality, polices that seek to address material inequality are key in addressing inequalities in physical and mental health. During the rebuilding period, there is need for employment creation, especially for the marginalised and vulnerable. There is also need for urgent review of existing mental healthcare, in order to match it with the new mental health statistics. To this end, there is need to scale up mental health services during tough periods like the COVID-19 pandemic. There is evidence of the efficacy of psychological therapies delivered by non-specialists (Kohrt *et al*., 2018; Singla *et* *al*., 2017). Given that resilience is a possible explanation to low prevalence of depressive symptoms, there is need for interventions that will help build resilience. For example, there is need for mental health promotion at very young ages, in order to foster awareness and transparency, to combat stigma and build resilience. There is need for promoting social capital, which will offer support in time of distress.

Appendix 3.A

Table 21: RIF-I-OLS decomposition estimates of COVID-19 pandemic and socioeconomic variables (including employment status but excluding education) on income-related good mental health inequality

	RIF-I-OLS decomposition			
Statistic	EI	ARCI	SRCI	WI
	1	2	3	4
Employment status (Employed)				
Not economically active	-0.056**	-0.018*	-0.066**	-0.084**
	(0.028)	(0.010)	(0.028)	(0.037)
Unemployed	-0.000	0.001	-0.009	-0.008
	(0.029)	(0.010)	(0.028)	(0.038)
Rural	0.007	0.002	0.013	0.014
	(0.024)	(0.008)	(0.023)	(0.031)
Age (15–24)				
25–39	0.013	0.006	-0.002	0.004
	(0.031)	(0.010)	(0.030)	(0.040)
40–54	0.008	0.005	-0.014	-0.009
	(0.037)	(0.013)	(0.035)	(0.048)
> = 55	-0.050	-0.016	-0.054	-0.070
	(0.043)	(0.014)	(0.042)	(0.056)
Female	-0.027	-0.008	-0.033	-0.041
	(0.023)	(0.008)	(0.023)	(0.030)
Marital status (Never)				
Married/cohabiting	0.026	0.007	0.038	0.046
	(0.038)	(0.013)	(0.039)	(0.052)
Widowed/divorced	-0.031	-0.009	-0.044	-0.053
	(0.072)	(0.024)	(0.074)	(0.097)
Good self-reported health	-0.111***	-0.041***	-0.074**	-0.115***
	(0.034)	(0.012)	(0.033)	(0.044)
Population group (African)				
Coloured	0.078*	0.027**	0.066	0.093*
	(0.040)	(0.013)	(0.041)	(0.054)
Indian	-0.104	-0.034	-0.107	-0.141
	(0.205)	(0.067)	(0.218)	(0.285)
White	-0.343**	-0.111**	-0.368**	-0.480**
	(0.138)	(0.045)	(0.145)	(0.191)
Year (2017)				
2021 (Post-COVID-19 pandemic)	**-0.142*** **	**-0.045*** **	**-0.158*** **	**-0.203*** **
	(0.038)	**(0.013)**	**(0.038)**	**(0.051)**
Constant	0.243***	0.082***	0.233***	0.315***
	(0.049)	(0.017)	(0.048)	(0.064)
Observations	8,150	8,150	8,150	8,150

Bootstrap standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: EI = Erreygers index; ARCI = attainment-relative concentration index; SRCI = shortfall-relative concentration index; WI = Wagstaff index RIF decomposition.

Appendix 3.B

Table 22: RIF-I-OLS decomposition estimates including both education and employment status as covariates

Statistic	EI	ARCI	SRCI	WI
Education (none)				
Grade 1–7	0.034	0.011	0.036	0.047
	(0.070)	(0.024)	(0.067)	(0.091)
Grade 8–11	-0.010	-0.004	-0.004	-0.008
	(0.069)	(0.023)	(0.067)	(0.090)
Matric	-0.017	-0.006	-0.016	-0.022
	(0.072)	(0.024)	(0.070)	(0.094)
Post-matric	0.042	0.012	0.058	0.070
	(0.072)	(0.024)	(0.071)	(0.095)
Employment status (Employed)				
Not economically active	-0.054*	-0.017*	-0.063**	-0.080**
	(0.029)	(0.010)	(0.029)	(0.039)
Unemployed	-0.000	0.001	-0.008	-0.007
	(0.030)	(0.010)	(0.029)	(0.039)
Rural	0.007	0.001	0.013	0.014
	(0.024)	(0.008)	(0.024)	(0.032)
Age (15–24)				
25–39	0.007	0.004	-0.010	-0.006
	(0.031)	(0.011)	(0.030)	(0.040)
40–54	-0.006	0.001	-0.028	-0.027
	(0.039)	(0.013)	(0.037)	(0.050)
> = 55	-0.076	-0.025	-0.081*	-0.106
	(0.049)	(0.016)	(0.048)	(0.064)
Female	-0.027	-0.008	-0.033	-0.041
	(0.024)	(0.008)	(0.024)	(0.032)
Marital status (Never)				
Married/cohabiting	0.026	0.007	0.037	0.044
	(0.037)	(0.012)	(0.038)	(0.050)
Widowed/divorced	-0.029	-0.008	-0.042	-0.051
	(0.072)	(0.024)	(0.073)	(0.097)
Good self-reported health	-0.110***	-0.041***	-0.073**	-0.114**
	(0.035)	(0.012)	(0.033)	(0.045)
Population group (African)				
Coloured	0.079**	0.028**	0.067*	0.095*
	(0.040)	(0.013)	(0.040)	(0.053)
Indian	-0.102	-0.034	-0.104	-0.138
	(0.198)	(0.065)	(0.211)	(0.276)
White	-0.337**	-0.109**	-0.364**	-0.474**
	(0.137)	(0.045)	(0.144)	(0.188)
Year (2017)				
2021 (Post-COVID-19 pandemic)	**-0.127*** **	**-0.041*** **	**-0.140*** **	**-0.180*** **
	(0.037)	**(0.012)**	**(0.038)**	**(0.050)**
Constant	0.245***	0.083***	0.228***	0.312***
	(0.085)	(0.029)	(0.082)	(0.110)
Observations	8,150	8,150	8,150	8,150

Note: Bootstrap standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; EI = Erreygers index; ARCI = attainment-relative concentration index; SRCI = shortfall-relative concentration index; WI = Wagstaff index RIF decomposition.

The next chapter concludes the thesis.

Chapter 5

Summary and conclusion

5.1 Introduction

The aim of this study was to determine the relationship between socioeconomic factors and chronic diseases in South Africa. In this chapter, I first present a summary of the main findings reported in the three essays in this thesis and their contributions to literature. Second, I present an analysis of the results and what these mean for policy aimed at addressing socioeconomic challenges and the rising burden of chronic diseases in South Africa and other low- to middle-income countries (LMICs). This chapter also highlights the limitations of this study, followed by suggestions of areas for further research and concluding remarks.

5.2 Summary of findings

The prevalence of chronic diseases is on the rise globally, with this trend largely attributed to epidemiological shifts in LMICs. In South Africa, chronic diseases make up six of the top ten diseases. The rise in chronic disease came at a time when South Africa was still burdened by communicable diseases, the maternal and child mortality of developing countries, and injury and trauma. This translates into increased competition for very limited resources. Given that chronic illnesses, and their related complications, are often lengthy and very expensive to treat, the burden of such diseases is unbearable for most households. More than 50% of South African households are poverty-stricken, and their financial burden and income losses due to chronic illness will worsen their already dire situation. South Africa targets to reduce NCDs-related premature deaths by one-third by 2030 (National Department of Health, 2020). As some of the causes (socioeconomic factors) of chronic diseases are avoidable or preventable, this study sought to determine which of those determinants explain prevalent chronic diseases in South Africa.

To this end, this study had three main objectives:

1. To examine how exposure to negative household events and neighbourhood events relate to systolic blood pressure in South Africa;
2. To determine socioeconomic factors that explain depressive symptoms in South Africa; and

3. To ascertain the influence of the COVID-19 pandemic on income-related inequality in depressive symptoms in South Africa.

The objectives were addressed in Chapters 2, 3, and 4 respectively.

In Chapter 2, I estimated the relationship between systolic blood pressure and exposure to stressful (negative) household events and neighbourhood characteristics. Using the correlated random effects model on the data from the first three rounds of the NIDS, I found that people from households that reported death and a reduction in grant and remittances income in one of the periods had significantly higher systolic blood pressure. I also found that people who moved into higher-income neighbourhoods had higher systolic blood pressure. These results have implications for our understanding of how factors other than individual characteristics and genetic make-up can explain the development of raised blood pressure in LMICs. For South Africa and other LMICs to achieve a significant reduction in premature mortality, it will require preventive and supportive interventions at household and community levels. Grief and negative financial shocks, if not addressed, can lead to raised blood pressure. Pharmacological treatment of non-communicable diseases can extend life expectancy, but preventive interventions can improve both the quality and length of life. Community support during grief, coupled with the provision of facilities that improve lifestyle and health seeking-behaviours is important. Social support grants should be viewed as a way to jointly improve the livelihood of the poor and provide protection against ill health.

In relation to neighbourhood effects, the results also suggest that individuals of a household that reported job loss in a neighbourhood where more people lost jobs had lower systolic blood pressure. In relation to neighbourhood income level, I found that people who had moved into middle-income neighbourhoods had a significantly lower systolic blood pressure. Because a household shock like a household member losing his/her job is expected to be associated with stress that results in raised SBP, this result maybe be attributable to the unobserved effects of neighbourhood unemployment rate. When the household is in a neighbourhood with low employment levels, individuals' perceived rank in the neighbourhood may not change if there is a household job loss; hence, they may lower their expectations, which may, in turn, may influence their health status (Meng *et al.*, 2013). I also found that neighbourhood effects on SBP through average education level post-matric were negative. Positive effects of neighbourhood averages of age, widowed, BMI above normal, and alcohol drinking were also found.

In relation to other individual-level covariates, I found a gender profile in SBP whereby being male was associated with higher SBP. Compared to black Africans, Indian and white population groups had significantly lower SBP, whilst the Coloured population group had higher SBP. Being underweight was associated with lower SBP, while being overweight and being obese were associated with higher SBP. I also found that those who rarely drink alcohol had higher SBP compared to those who do not drink alcohol. SBP was not found to be associated with place of residence (urbanicity), education level, age, employment status, per capita household income level, marital status, having medical aid, or smoking.

Chapter 3 examined the relationship between depressive symptoms and socioeconomic factors using the ordinary least squares and the fixed effects models. Data from the available five NIDS (a period of 10 years) rounds were collected. Regression results showed significant socioeconomic gradients in depressive symptoms, whereby income, education, location of residence, neighbourhood attachment, and religiousness were shown to play significant roles in depressive symptoms in adults. These significant relationships remained fairly similar even when I estimated logit models where the dependent variable, depressed, equals one (1) if the CES-D10 score is greater or equal to 10, and zero (0) otherwise.

I also found significant differences in the effects of explanatory variables by gender and by residence. Unemployed men and men with good self-reported health had higher CES-D10 scores than their female counterparts. Over the five time periods covered by the sample, male respondents had significantly higher CES-D10 scores. In relation to residence, Indians in urban areas had significantly lower CES-D10 scores than Indians in rural areas, whilst whites in urban areas had significantly higher CES-D10 score than whites in rural areas. Being religious and living in an urban area is associated with higher depressive symptoms than being religious and living in a rural area. Given that there is a cyclical relationship between mental and physical health and poverty (Mnookin, 2016; Patel *et al.*, 2015), this study responds to the global call to improve health and quality of life for everyone. Addressing socioeconomic correlates would have ripple effects on mental wellbeing and physical health, and on addressing poverty and inequalities in developing countries.

In Chapter 4, I reported how the COVID-19 pandemic influences income-related inequality in good mental health. I used a relatively new RIF regression decomposition method developed by Heckley *et al.* (2016). Like any other shock, the COVID-19 pandemic and the related containment measures have effects on both income and mental health. This study adds to the body of literature by estimating the influence of COVID-19 pandemic on the joint distribution of per capita household income and depressive symptoms. The narrowing gap in income-related inequality in depressive symptoms may be explained by social grant reforms during the pandemic and stress inoculation. This calls for programmes to help build resilience at a young age. There is also need for government to continue with reforms in social grants, as these have protective effects on health. I did not find a profile for education level in the joint distribution of income and mental health. Self-reported health-, age-, population group-, and gender profiles were present in the covariance between income and good mental health.

This thesis makes an important contribution to the literature on socioeconomic status and health, particularly in LMICs through the identification of factors that explain the rising burden of non-communicable diseases in a complex society.

5.3 Implications for policy

In this thesis, I identified socioeconomic factors that explain the burden of two of South Africa's most prevalent chronic illnesses. However, several studies suggest that socioeconomic status is also determined by health. Income- and wealth inequality have both been on the increase since the official end of apartheid (Chatterjee *et al.*, 2021; Statistics South Africa, 2019b), while at the same time, the share of total deaths due to non-communicable diseases has soared. Given that poverty and unemployment, among other socioeconomic problems, in South Africa, are also growing, I suggest the formulation of appropriate policies to help curb the socioeconomic-related burden of non-communicable diseases.

Setting the context of chronic diseases, from prevalence, causes or risks, to inequalities, in South Africa is important in coming up with context-specific policies and prioritisations of already-stretched and limited budget and resources. Results from this study have shown that the prevalence of raised blood pressure and mental health problems is high, and have been increasing. Socioeconomic factors such as education, employment, and income were found to be positively associated with these chronic conditions. This means that policies and interventions to prevent chronic diseases interventions should address these variables.

Results from the first essay suggest that reforms in social security grants have implications beyond poverty. According to South African Social Security Agency (2020b), a grant recipient becomes ineligible to receive a grant if he/she dies and if he or she turns 18 for reasons such as death and the child who receiving grant turning 18, among other reasons. Turning 18 does not translate into financial stability, especially in a country with high youth unemployment. If a grant recipient dies, the household has two problems: the grief due to losing a household member, and a reduction in household income. For the vulnerable, a reduction in total household grant and remittances degrades their socioeconomic status. This reduces their access to basic needs and services, which increases stress, which will manifest in raised systolic blood pressure. I, therefore, suggest extended financial support and public psychosocial support to the household that lost a member.

The positive association between death of a household member and SBP suggests the need for public psychosocial support for grieving family members. Grieving people often exhibit maladaptive neuroendocrine and immune patterns and poorer health behaviours than prior to the loss, which expose them to mental and physical health risks (Fagundes & Wu, 2020; Karl *et al*., 2018; Stahl & Schulz, 2014). The implications are vast in a country like South Africa, which is already burdened with high mortality due to causes such as human immunodeficiency virus/acquired immunodeficiency syndrome (HIV/AIDS) and tuberculosis (TB), injury and homicide, and NCDs such as cardiovascular diseases and diabetes (Statistics South Africa, 2021).

In relation to direct and indirect effects of neighbourhood characteristics on individual blood pressure, I suggest people- and health-driven policies in any community. Given that individuals have little to no control over the quantity and quality of goods and services available in their neighbourhoods, the study suggests health- and government policies that improve services available in low-income neighbourhoods. Based on the effect of social capital (neighbourhood attachment and religiousness) on depressive symptoms, improved policing, service delivery, and infrastructure will also improve mental health. People are attached to safe environments with high quality services, and the results from *Essay 2* suggests that individuals who prefer to stay in their current neighbourhoods had significantly lower depressive symptoms.

The significant differences in the effects of explanatory variables by gender and by residence on depressive symptoms, presented in *Essay 2*, are a unique contribution to understanding the differences in health in South Africa, and to informing policy. Whilst the goal is to reduce the prevalence of mental disorders by targeting socioeconomic factors, significant differences by gender and residence underscore the need for mental health policies that promote equity. For example, men who self-report good health may be overrating their health, most likely by excluding their mental health. This means that, in addition to country-wide mental health awareness campaigns, interventions that provide men with safe spaces to talk without being judged are important. Affordable medical aid schemes are needed in urbans areas, as these provide protection against depression. The effects of poverty in urban areas are more dire than the effects of poverty in rural areas, since everything consumed in an urban household is purchased. To this end, poor people are less likely to prioritise purchasing medical aid cover and less likely to utilise mental health services, which are often expensive.

The results in *Essay 3* suggest that, under normal circumstances, the rich enjoyed better mental health and, also, that, during large exogenous economic shocks, the income gradient disappeared. The prevalence of depressive symptoms was highest among the middle class, but significantly decreased for the poorest. These two findings suggest the need to reform social security, especially in times of large shocks. There is a need to continuously add new grants and review the amounts paid to grants recipients. Relief grants and increases in other grants might have offered protection against depression. The middle class also suffer financial shocks during large exogenous shocks, but members of this class are less likely meet the threshold for social grants, which indicates need to adjust the threshold for grant eligibility and/or adjust the definitions of class (Burger *et al.*, 2017), or create new grants to cater for the middle class during large shocks.

Health and equity justification for proposed socioeconomic policies

Socioeconomic status influences health outcomes through various behavioural, environmental, and clinical mechanisms (Benzeval *et al.*, 2014; Wolfe *et al.*, 2012). Poverty and poor health are inseparable worldwide. In a case study in the book *Voices of the poor, Volume 1: Can anyone hear us?* by Narayan *et al*. (1999, p. 87), one respondent from Moldova reported that they were ill because of poverty, and that poverty is synonymous with illness. Globally, the determinants of poor health emanate from social, economic, and political injustices. These injustices can also be a consequence of poor health, as poor health traps societies in poverty. Chronic illnesses, caregiving, and lives lost reduce economic productivity, trapping millions in poverty, a scenario Bor *et al.* (2017) refer to as the 'health-poverty trap'. Poor people lack social, economic, and political freedom, and are often powerless because they cannot access resources and opportunities that would make them independent (Sen, 2000). Living in fear of what tomorrow holds for them makes them vulnerable to depression and related physical chronic diseases.

Marginalised and vulnerable people are often the worst affected by chronic illnesses, yet they have limited information and access to health services that could help them prevent, manage, and treat such illnesses. Unavailability of health services, transport costs to reach a healthcare centre, high consultation fees, and the high cost of medication can be distressing for both the sick and their families. In worst cases, families make tough decisions like selling possessions, such as property and livestock, and taking children out of school to cover the financial costs associated with chronic illnesses. The consequences of losing property and school dropouts have long-lasting ripple effects on financial means and health at both micro- and macro levels. Zhou *et al.* (2020) found that illness of household members is one of the main causes of poverty in rural China. Poor health impedes educational performance, reduces economic opportunities, hampers productivity (Benzeval *et al.*, 2014), and can lead to debt due to costs of medication, thereby increasing people's vulnerability to future shocks. Because of poverty and inequality, the poor engage in heavy and risky jobs, and neglect selfcare and basic healthcare in order to be able to afford minimum basic needs. Good health contributes to a country's development through educational attainment, increases labour productivity, and reduces healthcare expenditure. Reducing socioeconomic deficiencies, making sure people have equitable servicing of basic needs, and strengthening national health systems and social security are vital in improving health and quality of life.

The relationship between socioeconomic status and health means that socioeconomic policy must be viewed as health policy, and vice versa, and that pro-poor approaches should be taken in both. As important as it is to tackle specific diseases, it is equally crucial to address the causes, as this will reduce the chances of recurrences and the development of new diseases. The political, social, and economic structures that create and sustain discrimination, poverty, and inequality need to be reformed in order break the link between poverty and poor health. Literature suggests that the increase in life expectancy in wealthy countries is not sorely based on advancements in medical science, but more on improvement of living conditions (Spence & Lewis, 2009). In LMICs, breaking the cyclical relationship of poverty with poor health is a vital pre-condition for economic development (Organisation for Economic Co-operation and Development, 2003).

Reducing obstacles to health, such as poverty, unemployment, a lack of proper housing, poor education, discrimination, and limited access to healthcare is key for South Africa to achieve its health goals. Inequalities in health are a consequence of inequalities in resources and opportunities available to different socioeconomic and political groups. Negative economic shocks and poverty expose people, especially the poor, to chronic stress, and can cause mental illness. When faced with negative economic shocks like job loss or unexpected and exorbitant healthcare costs, poor families have no wealth from which to draw. Chronic stress, regardless of its magnitude, can lead to chronic diseases such as diabetes, raised blood pressure, and heart disease through dysregulation of the immune system (McEwen, 2012; Wilkinson & Marmot, 2003). It can also lead to reduced functional status, depressive symptoms, and poor self-rated health, and can inhibit parents' ability to give optimal care to their children. Household adversities expose children to the risks of poor physical and mental health (Simon, 2016).

Breaking the poverty–poor health cycle through anti-poverty programmes and cash transfers is therefore important. More income and wealth can cushion the poor against stress related to financial problems and neighbourhood crime and violence and improve access to health-producing goods and services. Studies have shown that multi-faceted anti-poverty programmes and unconditional cash transfers improve mental health around world (Ridley *et al*., 2020); for example, in Malawi (Angeles *et al*., 2019) and South Africa (Ohrnberger *et al*., 2020), and that they reduce intergenerational transmission of depression in South Africa (Eyal & Burns, 2019). To this end, broadening social protection to protect the poor, the jobless, and the vulnerable from the impoverishing costs of healthcare can go a long way towards dealing with the burden of chronic diseases in South Africa. Resources to subsidise health-producing commodities for the poor, the marginalised, and the vulnerable could be mobilised through wealth taxes.

Income inequality in South Africa has increased significantly since the official end of apartheid, with the country's Gini coefficient consistently above 0.6 (Hundenborn *et al.*, 2018; Statistics South Africa, 2019b; World Bank, 2018). Since the population health of a country depends on both its wealth level and how that wealth is distributed (Braveman *et al.*, 2018), this high inequality may explain the worsening burden due to non-communicable diseases and disparities in the distribution of such diseases. Disparities in health begin at birth (Wolfe, 2011), and can become intergenerational. With the growing recognition of the influence of nonclinical factors on health outcomes, health reforms should target socioeconomic determinants of health. Polices that seek to address socioeconomic inequalities are key in addressing inequalities in physical and mental health. Because poor people cannot afford medical aid, they face barriers to accessing high-quality healthcare services. Thus, there is need for the reform of health systems to address socioeconomic biases in health service delivery, in order to improve access for marginalized and vulnerable groups. Furthermore. there is need to make available resources to promote awareness of chronic physical diseases and mental ill health, and to curb the associated stigma and discrimination. In addition, people need to be encouraged to seek healthcare early. There is evidence that high government expenditure on public services is associated with longevity (Health Affairs, 2018).

The cost of treating non-communicable diseases is higher than the cost of preventing them (World Health Organization, 2013d). A person cannot be healthier than his or her living, working, learning, and playing environments. To achieve population health targets and reduce the risks of ill health requires improving of socioeconomic factors such as poverty, nutrition, education, gender equality, and environmental risks from before birth to older ages (Magnuson, 2013). Policy decisions that improve socioeconomic status and neighbourhoods have important downstream effects on health. A pro-poor approach in the health sector is required, whereby high-quality affordable health services reach vulnerable groups and remote communities. Policy initiatives that improve socioeconomic status can improve health for least- to middle-ranked people in terms of socioeconomic status. South Africa should prioritise a good start to life for every child by providing adequate social and health protection for women, young families, and communities with high deprivation. There is also a need to encourage creation and reassertion of social cohesion or capital and responsibility in communities in order to achieve greater health equity at a societal level (Marmot *et al.*, 2012).

There are direct and indirect cross-effects between physical and mental health, whereby past physical health has an effect on mental health, and vice versa (Ohrnberger *et al.*, 2017; Sorsdahl *et al.*, 2018). Literature suggests that depression stimulates risks of other chronic conditions such as heart problems and stroke (Kok *et al*., 2012; Lotfaliany *et al.*, 2018). I suggest scaling up integrated healthcare, whereby mental healthcare is offered to people with physical health problems.

5.4 Limitations of the thesis

While this thesis identifies socioeconomic factors that can be targeted to reduce the burden of chronic diseases in South Africa, it is not without limitations. This study used only secondary data drawn from surveys. The main limitation of this data is that most variables were self-reported and based on respondents' two-year recall. For example, in Chapter 2, while blood pressure was objectively measured during the interviews, reporting of negative household events depended on household representatives' recall of events that happened over a period of 24 months. Pertaining specifically to stressful life events, Hepp *et al.* (2006) investigated consistency in reporting of potentially traumatic events in Zurich in 1993 and 1999, and found a high level (63.9%) of reporting inconsistency for traumatic events that happened between 1993 and 1999. This calls for a cautious approach when using self-reported stressful life events for research, as this method can affect the accuracy of the results, due to overreporting or under-reporting.

As reported in Chapters 3 and 4, the screening index (CES-D10 score) for depressive symptoms was generated from ten response items, all based on a respondent's one-week recall of emotional health. Another limitation worth pointing out is that, as reported in Chapter 4, screening for depressive symptoms was based on two (CES-D10 and PHQ-2) non-directly comparable screening tools. The PHQ-2 uses a respondent's two-week recall of two major indicators of mental health. Recall bias may make screening for depressive symptoms susceptible to overestimation or underestimation. Results from the two chapters may also have been affected by unobserved reporting heterogeneity. Given that mental health is associated with stigma and discrimination, underreporting of depressive symptoms is also inevitable. Furthermore, there is the possibility of overreporting and underreporting of emotional health due to the emotional condition of the respondent at the time of the survey. Self-reported health may also reflect individuals' expectations of ideal health based on socioeconomic status, or they may benchmark their health against that of their peers. For example, literature suggests that the rich or educated and older people tend to overreport their ill-health, whilst the poor or less educated underreport (Bago d'Uva *et al*., 2008; Maheswaran *et al*., 2015; Rossouw *et al*., 2018).

Adaptation and mental conditioning can also limit a respondent's self-assessment of emotional health. For example, people who grew up in a disease-plagued community where access to healthcare is limited may accept treatable conditions as normal (Sen, 2002b). Through adaptation, they gain an acceptable level of well-being even when faced with events and situations that can seriously affect their health (Heyink, 1993). Thus, chronically ill respondents may report higher-than-expected levels of health. Equally, people who have experienced numerous negative events for the greater part of their lives are less likely to report these stressful events and associated stress. This bias in reporting depressive symptoms may distort the degree of socioeconomic-related inequality in mental health.

The other limitation related to Chapter 4 is the measure for socioeconomic status (per capita household income) used in this study. Income as a measure of socioeconomic status represents market-based channels only, excluding free public services and political and social freedoms (Burger, McAravey & Van der Berg, 2017). Given the pervasiveness of inequality and poverty in South Africa, ranking people based on income ignores the political and social dimensions of class. Following the outbreak of COVID-19 in 2019, most countries entered a full national lockdown during which people were isolated in their homes, and mobility was limited to acquiring basic goods and services. For people who did not have access to information, electricity, water, and sanitation, who were unemployed or had lost their jobs — which are important capabilities (Burger *et al.*, 2017) — life became much harder. This may have had a major impact on their mental health.

However, these limitations are shared by all survey-based studies. True health is unobservable, and can only be ascertained by objective measures like anthropometric measures and biomarkers, which are expensive to collect through national surveys, hence the use of self-reports (Shmueli, 2003). The use of self-reported health has been backed by literature as a reliable predictor of health outcomes from morbidity to mortality when used in nationally representative health surveys (Bago d'Uva *et al.*, 2008; Doiron *et al*., 2015; Maheswaran *et al.*, 2015) like the NIDS. The CES-D10 and the PHQ-2 tools are validated for screening for depressive symptoms in large surveys (Baron *et al*., 2017; Levis *et al.*, 2020; Manea *et al.*, 2016). Large longitudinal surveys like the NIDS are scarce in developing countries, hence the dearth of longitudinal studies to address challenges facing LMICs. The NIDS data set offered me a rare opportunity to explore the association between chronic diseases and socioeconomic factors in a heterogeneous population and contribute to related literature. South Africa is particularly interesting due to its high prevalence of negative events, crime, high levels of unemployment, poverty, and inequality, and a quadruple burden of diseases. These all make exposure to chronic stress and illnesses inevitable.

5.5 Suggestions for future research

Though the study has limitations, it makes a significant contribution to understanding the typical mechanisms and pathways through which poverty and chronic conditions interact and reinforce each other in South Africa and other low- to middle-income countries. The results may also provide useful inputs for policies and programmes to address the chronic condition burden in poor neighbourhoods. Suggestions for further research emanate from the negative attributes of the data used in this study.

Inequalities and socioeconomic gradients in health largely depend on how we screen for ill health. For example, we may find different distributions of ill health when using self-reported health, pharmaceuticals, diagnoses in primary care, and inpatient or outpatient diagnoses. Because self-reported data based on respondents' recall were used in this study, except for systolic blood pressure, future studies could use objective measures of health, like clinical screening. I would suggest field work where participants would have 24-hour blood pressure measuring devices, complemented with diaries, to track blood pressure and life events in real time. This would aid capturing of negative events, emotional wellbeing, and blood pressure in a high-frequency panel. I had initially planned this fieldwork, but, due to limited funding and time, I had to abandon the idea.

Future studies could also investigate reporting heterogeneity in emotional well-being across various dimensions, such as socioeconomic status, sex, age, and population group in South Africa, using vignettes and hierarchical ordered probit modelling (HOPIT) (King *et al.*, 2004). I could not do this in the present study, because there were no questions with which to compare responses in the NIDS. The only data set that would have helped me carry out this study, the World Health Organization's Study on Global AGEing and Adult Health Wave 2, had not yet released into the public domain.

In relation to Chapter 4, I used income as a measure of socioeconomic status. I propose that future studies use multi-dimensional measures of socioeconomic status to adequately capture socioeconomic rank. For example, creating a socioeconomic index using the capabilities approach (Burger *et al.*, 2017) using multiple correspondence analysis would broadly measure socioeconomic class. Socioeconomic status reflects complex interactions in the social, economic, and political environments in which people live and function. Future studies in South Africa could also measure socioeconomic status using wealth. Wealth offers material and psychosocial advantages that could improve intergenerational health and explain intergenerational disparities in health (Braveman *et al.*, 2018).

5.6 Concluding remarks

This thesis contributes to existing literature on the relationship between socioeconomic factors and health outcomes in South Africa and LMICs in several ways. I have shown that exposure to stressful life events and neighbourhood characteristics have effects on blood pressure (Essay 1). Specifically, I found that losing a household member and reduction in household grand income through grants and remittances reduction is associated higher blood pressure. I have also identified direct and indirect neighbourhood effects on an individual's health. In Essay 2, I identified which socioeconomic factors contribute to South Africa's growing burden of mental ill health. I also found significant differences in the factors explaining depressive symptoms in men and women, and in rural and urban areas. I showed the trend in income-related inequality in good mental health in Essay 3. Using a relatively new decomposition method, I also ascertained the impact of a large exogenous shock on socioeconomic-related inequality in mental health in South Africa. Large longitudinal data sets were used in the study, which enabled the capturing of dynamic changes in dependent and independent variables. In addition, the decomposition of bivariate indices allowed me to examine how good mental health and per capita household income jointly affect inequality indicators. The results may aid identification of population groups to be targeted in order to significantly improve health outcomes through socioeconomic policy.

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