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Dimensions of Health and Well-being in South Africa

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I declare that the research contained in this thesis is my own work.

A handwritten signature in dark ink, appearing to read 'R. Dobрева', is positioned above the printed name.

Ralitza Dobрева

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Abstract

Recent welfare research has widened its focus, incorporating dimensions of satisfaction and health, while relative status, inequality, and perception-based indicators have come to the fore in the array of material well-being measures. This thesis focuses on the relationship between health and material well-being. It has two aims: first, to investigate the reliability of self-rated health (SRH) as an overall health measure in the South African context; and second, to examine the relationships between SRH and socioeconomic status and inequality, taking into account the role of perceptions. Further, the innate gender disparities in these relationships are explicitly recognised throughout.

Chapters 2 and 3 approach the first aim from opposing angles. Chapter 2 addresses the reporting heterogeneity in SRH, which is its main disadvantage. The heterogeneous reporting patterns found are similar for men and women, with notable differences in the role of household material resources and location type. Nevertheless, the analysis corroborates international evidence that SRH is an internally consistent measure when employed in panel data analysis. Chapter 3 tests the validity of SRH in the South African context, based on its main advantage as a predictor of the most reliable health indicator: death.

Chapter 4 examines the relationships of health with absolute income, rank, and inequality, using both measured and perceived indicators of rank and inequality. The findings show that perceived measures of rank and inequality have a greater impact on SRH than measured indicators, and these effects are stronger for women.

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Acronyms

ARV	Anti-retroviral therapy
CSM	Continuing sample member (of a panel survey)
EQ5-D	EQ-5D is a standardized survey instrument developed by the EuroQol Group. It measures health-related quality of life in five dimensions: mobility, self-care, usual activities, pain/discomfort, and anxiety/depression. The EQ-5D consists of a descriptive system and a visual analogue scale (VAS).
FEOP	Fixed effects ordered probit
HOPIT	Hierarchical ordered probit model
NIDS	National Income Dynamics Study
POP	Pooled ordered probit
REGOPROB	Random effects generalised ordered probit
REOP	Random effects ordered probit
SES	Socioeconomic status
SRH	Self-rated health, usually assessed using a single survey question asking respondents to rate their current health on a five-point scale: “excellent”, “very good”, “good”, “fair”, or “poor”.
TSM	Temporary sample member (of a panel survey)
UN	United Nations
VAS	Visual analogue scale, usually vertical, which serves as the visual equivalent of SRH in surveys
WHO	World Health Organization

Chapter 1

Introduction

The aftermath of the Global Financial Crisis of 2007/8 spurred ongoing efforts to gain insight into the different dimensions of well-being (Stiglitz *et al.*, 2009); and the relevance of these lines of enquiry re-emerged in the context of the Covid-19 pandemic (Fitoussi *et al.*, 2021). As a result, the multifaceted nature of well-being has gained substantial acceptance, in both the research and policy dialogues, with well-being and satisfaction as essential elements of development. By incorporating social and sustainability aspects, well-being measures, which incorporate a broader range of indicators, offer richer perspectives than the established production-based and individualistic approaches to measuring progress (Deaton, 2001; Frank, 2005; Sen, 1999). Much has been learned, yet much remains unclear, about the credible measurement of the different well-being dimensions and the nature of the relationships among them.

Health is an important component of broader welfare concepts: this is echoed by the World Health Organization's definition of health as "a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity" (WHO, 1948:1). Other important dimensions are relative standing and inequality, which have reignited broader and deeper dialogues about their causes and consequences (Deaton, 2013a; Marmot, 2015; Piketty, 2014; Rajan, 2011). The role of perceived indicators of socioeconomic status (SES) has also received increasing attention because of their complementarity to measured indicators and their ability to aggregate social and economic factors, both present and anticipated (Singh-Manoux *et al.*, 2005).

Material well-being (measured as income or wealth) is only one among many sources of inequality and it is important to examine its interactions with other sources, such as gender, race, or social stratum more closely (Sen & Östlin, 2008). Specifically, the literature on gender inequalities in health recognises three groups of drivers: biological, statistical, and social (Denton & Walters, 1999; Wizeman, 2012). The fundamental differences in the ways these forces shape both the health and the material well-being of men and women are recognised, but still not well understood.

These discussions are especially relevant for South Africa, which has remained among the most unequal societies in the world since its democratic transition in 1994. The most recent World Bank

report identifies South Africa as the most unequal country in the world (out of 164 countries, for which data is available), with a Gini of 0.67, based per capita consumption in 2018 (Sulla *et al.*, 2022). South Africa's Gini coefficient has stayed stubbornly above 0.6, despite a wide social safety net, including housing, healthcare, and social grants (Hundenborn *et al.*, 2018; Leibbrandt *et al.*, 2010; Stats SA, 2019; Sulla *et al.*, 2022). According to the World Wealth and Income Database¹, the share of South Africa's wealth owned by the top 1% of earners has doubled since the late 1970s (Izmirliloglu, 2015).

This level of material disparity is partly a consequence of the legacy of the apartheid system, whose institutions were designed to segregate and marginalise according to race and gender. More recently, inequality in South Africa's has been underpinned in large degree by long-standing disparities in labour market incomes (Hundenborn *et al.*, 2018), as limited progress has been made in addressing the country's "Triple Threat" of unemployment, inequality and poverty under democratic rule (Gumede, 2014; Leibbrandt *et al.*, 2010). Under apartheid, the institutionalised economic marginalisation of the African majority worked through at least three channels (Seekings & Nattrass, 2016). First, land dispossession destroyed the self-sufficient African peasantry. Second, unemployment became widespread: oppressed groups were directly prevented from accessing lucrative parts of the labour market; in addition, these groups lacked the necessary skills, credentials, and networks, not least because of the dual education system, in which the oppressed majority received limited and poor quality offerings (Fedderke *et al.*, 2000; Seekings & Nattrass, 2016). Third, social welfare support was not available to non-White households (Seekings & Nattrass, 2016). In addition, apartheid's growth trajectory shaped patterns of poverty and affluence through import-substituting industrialisation and state support for capital-intensive, resource-based industries, such as mining, minerals processing, and heavy industries (e.g. basic chemicals and steel) (Fine & Rustonjee, 1996; Roberts, 2014).

The macroeconomic strategies implemented in the early years of the country's democratic transition have been described as neo-liberal in their essence, with a greater focus on improving the country's growth trajectory, than on broadening the base of capital ownership and on creating more, and more diverse, employment opportunities (Seekings & Nattrass, 2016). For example, the

¹ The World Wealth Database was first created in 2011 and then expanded in 2015 by Facundo Alvaredo, Anthony B. Atkinson, Thomas Piketty, Emmanuel Saez, and Gabriel Zucman. The database provides data on income and wealth distributions around the world and their historical developments.

manufacturing sector (which contributes a large share of value added) has experienced slow growth and even slower diversification, while remaining under the dominance of capital-intensive producers, thus enforcing the limited labour-absorption capacity of the economy (Roberts, 2014). In addition, rapid trade reform after democratisation has led to a rise in imports, yet it has struggled to boost exports, especially in low-skilled, labour-intensive industries (Edwards, 2014). These factors have shaped the disparate labour market outcomes, which drive the stubbornly high inequality in the country (Hundenborn *et al.*, 2018).

In an effort to address the Triple Threat, successive democratic governments have established strong social safety nets (Hall & Woolard, 2014). Hence, poverty reduction efforts have made some advances, though the absolute level of poverty remains high; however, unemployment and inequality have proved more complex and difficult to combat (Finn & Leibbrandt, 2018).

Health disparities, which also have historical underpinnings, have proven to be persistent, driven by demographic, socioeconomic, infrastructural, policy-related, as well as behavioural factors (Alaba & Chola, 2013; Ataguba *et al.*, 2015; Burger & Christian, 2020; Mukong *et al.*, 2017). The demographic and socioeconomic factors that drive health inequality in South Africa include age, gender, race, income, and geographical location, among others, which have a bearing on the country's health system, leading to poor outcomes (Obuaku-Igwe, 2015). After the demise of apartheid, healthcare access has improved through the implementation of free primary healthcare, the provision of essential medicines, the choice of termination of pregnancy, anti-smoking laws, and extended community service of newly qualified medical professionals (Burger *et al.*, 2012; Burger & Christian, 2020; Hall & Woolard, 2014). Nevertheless, access to basic social services, including healthcare, remains widely unequal along racial, provincial, and rural-urban dimensions (Ataguba *et al.*, 2011; Harris *et al.*, 2011).

Notably, gender remains an important stratifier with regard to both material and health disparities in the South African context (Casale *et al.*, 2021; Herman *et al.*, 2009; Mayosi *et al.*, 2012; Stats SA, 2019). Gender disparities are discussed in more detail in the context of each of the chapters to follow.

This thesis aims to fill only a part of the bigger research gap in understanding how broader measurements of welfare relate to current mainstream proxies in South Africa's diverse context.

Specifically, the overall aim is to study the nature of the relationships between health and aspects of material well-being, including absolute income, relative income (rank), and income inequality, paying attention to their gender-distinct features. In addition, the thesis aims to investigate whether measured and perceived indicators of rank and inequality differ in their associations with health.

In order to accomplish these aims, it is necessary to establish a credible and reliable indicator of overall health, suitable for this enquiry. The first two empirical studies (Chapter 2 and Chapter 3) examine the nature and reliability of self-rated health (SRH) as a descriptor of general health. A single survey question elicits the subjective and instantaneous judgement behind SRH: “How would you describe your health at present? Would you say it is excellent, very good, good, fair, or poor?” In reporting her health status, a respondent chooses which social, economic and biological factors to consider relevant, based on her knowledge and experience. The choices behind the rating involve the social features of the individual’s environment – they influence the choice of reference group (for example, comprising individuals of similar age, social standing, and geographic proximity) and play a role in forming the individual’s understanding of the continuum between excellent and poor health. These choices result in an indicator, which is suitable for the study of how socioeconomic factors affect health. Inasmuch as it is a reliable assessment of overall health at an individual level, SRH is an indicator that is substantially shaped by social forces.

Paradoxically, SRH is the most controversial and purely subjective health indicator; yet, a body of international evidence points to its reliability when studying individuals over time (Bailis *et al.*, 2003; Zajacova & Dowd, 2011; Ziebarth, 2010). However, since there is no universal benchmark for comparison, SRH is subject to differential patterns of reporting (known as reporting heterogeneity) according to the individual’s demographic and socioeconomic characteristics. This drawback challenges the comparability of SRH across individuals or groups (Jürges, 2007; Kerkhofs & Lindeboom, 1995; Lindeboom & van Doorslaer, 2004; Schneider *et al.*, 2012). The gender-distinct patterns of reporting heterogeneity in SRH in South Africa are investigated in Chapter 2. The chapter adds to the international literature by analysing nationally-representative data from a diverse developing country, by employing a panel data method, and by examining whether the drivers of reporting heterogeneity differ between men and women.

Despite its subjective nature, a strong argument in favour of SRH as a useful and credible measure is its ability to predict mortality. This independent predictive power applies over relatively long

time horizons, and after other health indicators (which are often seen as more objective), as well as a range of individual characteristics, are taken into account (Benyamini & Idler, 1999; DeSalvo *et al.*, 2006; Idler & Benyamini, 1997; Jylhä, 2009). The objective of the second empirical study (Chapter 3) is to shed more light on the nature of SRH and the different aspects that men and women take into account in their ratings. The chapter expands Ardington and Gasealahwe's (2014) research about the predictive capacity of SRH for mortality in South Africa by studying two time horizons (two years and six years) and untangling the differences in this predictive capacity by gender.

Chapter 4 tests three hypotheses regarding the relationships of health with absolute and relative material well-being: the absolute income hypothesis, relative income hypothesis, and the income inequality hypothesis. Regarding the latter two, the analysis also examines the different roles of measured and perceived rank and inequality. In order to understand how these relationships differ by gender, they are analysed separately for men and women.

The third empirical study builds on the understanding of SRH as a health measure, its advantages and drawbacks, as well as its link to context and resources available to the individual. Research to date has investigated some of the aspects of the health-socioeconomic status (SES) relationship in South Africa, but this fledgling literature has not compared the roles of measured or perceived relative income (rank), and income inequality, or focussed on the gender differences in these relationships. In addition, the use of panel data allows for individual characteristics, such as personal affect and genetic predispositions, that are difficult to measure and do not change over time (unobserved individual heterogeneity), to be taken into account using empirical methods.

The data for this thesis comes from the first four waves of the National Income Dynamics Study (NIDS), a large-sample nationally representative panel survey of South Africa (SALDRU, 2008; 2010; 2012; 2014). The original sample selected to participate comprised 28 266 individuals living in 7 296 households. At present, data from the five waves collected in 2008, 2010/11, 2012, 2014/15 and 2017 is available in the public domain. The data from Wave 5 was not included in the thesis, as the bulk of the analysis was conducted before its release. A breakdown of the samples for each wave is presented in Table 1.1.

It is worth noting that NIDS is a panel survey, which tracks the individual. Households are not tracked, as they dissolve and/or new households form around selected participants. Hence, the term Continuing Sample Members (CSMs) is used to refer to all individuals (adults and children), who were resident in the households selected for Wave 1, as well as any children born to female CSMs in subsequent waves. In order to collect detailed household information, individuals who resided with CSMs (but were not CSMs themselves) were also interviewed for each wave – they are referred to as Temporary Sample Members (TSMs).

NIDS offers the possibility to explore in depth the relationship between health, on the one hand, and socioeconomic status and inequality on the other, as it is the first South African survey that includes a range of questions about income and expenditure, about perceived relative standing, and about various aspects of health. In addition, the panel nature of NIDS offers the possibility to employ methods with accuracy and other estimation advantages, which are discussed in each chapter.

Table 1.1 CSMs and TSMs successfully interviewed by wave

Wave	Individuals	Households	CSMs	TSMs
Wave 1 (2008)	26 776	7 305	26 776	0
Wave 2 (2010/11)	28 538	6 787	22 970	5 568
Wave 3 (2012)	32 597	8 040	24 334	8 263
Wave 4 (2014/15)	37 396	9 620	25 268	12 128

Source: Own calculations from Table 1.2 in Chinhema et al. (2016). The table includes respondents of all ages and those interviewed by proxy.

The structure of the thesis is as follows. Chapter 2 is an empirical study of the patterns of reporting heterogeneity in SRH. In Chapter 3, the predictive capacity of SRH for mortality is tested. The relationships between health, and economic indicators (absolute income, relative income (rank), and income inequality, including the role of perceptions about rank and inequality), are investigated in Chapter 4. The analyses are stratified by gender throughout. Finally, Chapter 5 concludes by providing an overview of the findings and points to avenues for future research.

Chapter 2

“Your health at present”: South African patterns of reporting heterogeneity in self-rated health

2.1. Introduction

Health is an important aspect of well-being and an increasingly relevant development indicator. Goal Three of UN’s Sustainable Development Goals for 2030 is to “[e]nsure healthy lives and promote well-being for all at all ages” (UN, 2015: 14). Moreover, one of the specific targets related to this goal is to “strengthen the capacity of all countries, in particular developing countries, for early warning, risk reduction and management of national and global health risks” (UN, 2015: 17). Achieving such goals depends on the measurement and tracking of population health, and on developing reliable indicators for prevention and early warning – a challenging and complex task.

At the individual level, if an attribute such as “true health” exists, it is unobservable, difficult to define conceptually, and even more challenging to measure. The simplest measure of an individual’s overall health is their own (typically one-word) assessment. A commonly used way of making this assessment, often referred to as self-rated health (SRH), is to ask respondents to describe their current health using a five-point scale (usually, “excellent”, “very good”, “good”, “fair”, or “poor”). SRH is a widely used measure, which has strong practical and conceptual advantages over other measures. It is an important all-round health indicator because it draws on information which is privy to each individual, and which is difficult for health professionals to access in its entirety (Jylhä, 2009). However, the purely subjective nature of SRH that is the source of its main advantage, is also its main disadvantage. Health reporting is influenced by an array of individual characteristics and factors related to context and experience – thus, the reliability and comparability of SRH across individuals is in question.

In assessing their health, individuals will make a comparison with a reference group they consider most relevant. Their subjective evaluation will also take into account a selection of physical and mental conditions, considering aspects of their personal history and evaluating their health through the lenses of cultural conditioning and language peculiarities (Etilé & Milcent, 2006; Groot, 2000; Lindeboom & van Doorslaer, 2004; Shmueli, 2003; van Doorslaer & Jones, 2003). Hence, SRH is

likely to reflect some health aspects better than others, and it captures an element of an individual's long-term view of herself (i.e. it is part of her enduring self-concept), her health, and her health-related behaviours (Bailis *et al.*, 2003). Hence, SRH is a reflection of “true health”, but with a degree of distortion due to reporting behaviour, which depends on individual-specific characteristics. This distortion, often referred to as reporting heterogeneity or reporting bias, presents challenges for comparisons between individuals and for generating aggregate measures, but it may make it a useful indicator when tracking individuals over time.

The measurement of health and identifying sub-populations at risk is a key input into policy-making, action and progress assessment in addressing the substantial challenges that socially, culturally, and economically diverse countries, such as South Africa, confront. Specifically, South Africa is said to be weighed down by a quadruple burden of disease (National Department of Health, 2015). First, it is still the home of the greatest number of people living with HIV/AIDS, with a linked high burden of tuberculosis (TB). Second, South Africa's maternal and child mortality rates are high, even in comparison to its lower-income developing country peers. Third, the country faces alarming levels of violence and injuries; and fourth, its burden of non-communicable diseases (NCDs) is growing rapidly (Bradshaw *et al.*, 2007; National Department of Health, 2015).

The aim of this chapter is to investigate the reliability of SRH as a measure of an individual's overall health in South Africa and clarify its limitations, thus extending research concerning the reliability of health perceptions in a developing country context. Despite its extensive use internationally, there are few rigorous studies on the reporting heterogeneity in SRH for developing countries (some examples include Wu *et al.* (2013) and Zhang *et al.* (2015) for China; Molina (2016) for China and Indonesia; Bago d'Uva *et al.* (2008) for China, India and Indonesia; Paul and Valtonen (2016) for Russia; and Rossouw *et al.* (2018) for South Africa).

Further, in the South African context, heterogeneity in reporting may be a particularly important problem, given the large socio-economic disparities, the diversity of cultural and language groups, the relative isolation of people living in many rural areas of the country, and South Africa's economic geography, shaped by a lengthy history of segregation policies. South Africans' experiences in interacting with the country's dual healthcare system are also likely to shape their health perceptions: those who are poorer and uninsured turn to public healthcare, which provides

mainly primary services, and is known for shortages and long queues; while the richer and insured citizens benefit from the higher-quality private care (Charasse-Pouélé & Fournier, 2006; Coovadia *et al.*, 2009; Harris *et al.*, 2011).

Thus far, there have been few studies on the measurement of health and its reliability in South Africa, partly due to data constraints. Two of these studies (Boyce & Harris, 2011; Charasse-Pouélé & Fournier, 2006) focus specifically on differences in reporting behaviour along racial lines, while Jelsma and Ferguson (2004) consider differences by socioeconomic status (proxied by income and education). A more recent study by Rossouw *et al.* (2018) focuses on wealth-driven as well as race-related reporting heterogeneity in SRH, using data for respondents aged 50 and over. In order to answer the question of whether SRH is a credible measure in the diverse South African context, this chapter investigates the extent to which the differences in self-reporting behaviour are driven by a range of demographic and socioeconomic characteristics, whose impacts are likely to differ between men and women. The study contributes to the literature from developing countries by incorporating a broader range of characteristics, which may drive differential health reporting behaviour, by considering gender-specific reporting patterns explicitly, and by applying a panel data method on nationally representative data, which includes adults of all ages.

The data used is from the first four waves of the South African National Income Dynamics Study (NIDS), a nationally representative panel dataset. A general overview of NIDS and summary statistics have been provided in Chapter 1. NIDS makes available data on a range of health indicators, as well as demographic and socioeconomic variables. It also tracks individuals over time, which allows for rigorous panel data methods to be applied in answering the research questions of this chapter. In contrast, other data sources on health in South Africa (such as the Demographic Health Surveys, or the Study on Global Ageing and Adult Health (SAGE) conducted by the WHO) allow only for cross-sectional analysis, or analysis of repeated cross-sections.

The analysis is conducted separately by gender. A large array of biological, psychological, behavioural, historical, and social influences, points to substantial differences in health, in its related behaviours, and in health perceptions between men and women (Benyamini *et al.*, 2003; Denton *et al.*, 2004; Denton & Walters, 1999). In South Africa, the role of historical and social factors in shaping health is central, increasing gender disparities further (Alaba & Chola, 2013;

Harris & Vermaak, 2015). Many such disparities have persisted in the post-Apartheid era: for instance, despite a dramatic rise in labour force participation among women, the progress in reducing poverty has been uneven between the genders, as a consequence of higher unemployment rates, lower earnings, and differences in household structure between men and women (Casale *et al.*, 2021; Posel & Hall, 2021; Posel & Rogan, 2009).

Regarding gender differences in SRH in particular, in previous studies, mostly on elderly subpopulations from developed countries, this measure has been shown to be a better overall health assessment for women, incorporating many aspects, but a more accurate indicator of physical health for men (Benyamini *et al.*, 2003; Benyamini *et al.*, 2000). In contrast to women who reflect on a wide range of factors when rating their health, studies suggest that men base their evaluations mostly on physical health and on diagnoses of life-threatening conditions (Benyamini *et al.*, 2003). Social and economic factors such as income, employment and social support have a stronger link with the health of women, while behaviours such as smoking, alcohol consumption are more important drivers for men (Denton *et al.*, 2004; Denton & Walters, 1999). However, it is not clear whether the same factors drive the gender differences in health reporting in the South African context.

This chapter adds to previous knowledge on reporting heterogeneity in SRH by using a panel data methodology on a nationally-representative dataset from a diverse developing country; it also sheds new light on whether reporting patterns are distinct by gender. The chapter is organised as follows. The next section reviews the literature on the reliability of self-rated health and on reporting biases, including the South African and international empirical evidence. Section 2.3 outlines the data and methodology used. The results are discussed in Section 2.4. Section 2.5 concludes with a summary of findings, the limitations of the study, and remarks on directions for future research.

2.2. Literature review

An individual's own opinion about his or her overall health is subjective, yet widely used in research because of its all-encompassing nature. This review of the theoretical perspectives and empirical evidence begins with a discussion of the challenges associated with health measurement,

then zooms in on the advantages and drawbacks of using SRH in research. Next, the factors that give rise to differences in self-reporting (e.g. personal, cultural, and socioeconomic characteristics) are illustrated with international empirical studies on reporting heterogeneity. A more detailed discussion of the gender aspects (both theoretical and empirical) of reporting heterogeneity in SRH follows. The section concludes with an overview of previous South Africa studies on SRH and final remarks.

The measurement of health

The assessment of health presents a number of practical and conceptual difficulties, as “...“health” is a multiattribute concept, and not all of its attributes can be easily determined” (Cutler *et al.*, 1997: 218). Health measures can be classified into the following four types (Ziebarth, 2010):

- a) Subjective measures, such as self-rated health (also referred to as self-assessed health, or health satisfaction), are based on the respondent’s view, often using a five-point scale (e.g. excellent, very good, good, fair, or poor).
- b) “Quazi-objective” health measures (Ziebarth, 2010: 116) are also self-reported, but are assumed to have more factual underpinnings. They are derived from lists of symptoms, experiences with chronic diseases, or difficulties with performing day-to-day tasks (e.g. SF-12, SF-36, the McMaster Health Utility Index, or the limitations to Activities of Daily Living (ADL)).
- c) Vignette-based measures require the respondent to rate their own health as well as the health of fictitious individuals described in a series of examples, which are termed vignettes. This approach estimates individuals’ “true health” by using a common benchmark and allows for comparisons between individuals.
- d) Objective measures entail external assessments, often made by a physician or a nurse. Some examples are height, weight, body mass index (BMI), blood pressure, blood tests, or physician records.

Assuming that there exists an underlying “true health” attribute, which is unobservable, each type of measure reflects various aspects of this attribute, but with a degree of measurement error (Jylhä, 2009). Since the main health measure to be used in this thesis is SRH, the next sub-section reviews its main pros and cons.

Advantages and drawbacks of SRH

SRH offers a strong practical advantage over other more objective measures (e.g. lists of self-reported symptoms, or physician-assessed health) because it is easy, cheap, and fast to collect in surveys by using a single question, and hence it is widely available. It also offers several conceptual advantages. First, it is an all-encompassing measure: SRH is seen as “a global self-evaluation of health” (Bailis *et al.*, 2003:203) and “while researchers are measuring the parts, respondents have access to the whole” (Idler & Benyamini, 1997:28). Second, SRH is likely to be a dynamic appraisal, including improvements, deteriorations, and elements of the respondent’s enduring self-concept (Bailis *et al.*, 2003; Huisman & Deeg, 2010; Idler & Benyamini, 1997). Third, SRH may encapsulate the availability of physical, emotional or social resources that can either moderate a health decline, or aid a recovery after illness (Idler & Benyamini, 1997).

Further, substantial evidence in favour of SRH as an effective measure reflecting a global self-evaluation of health, is its independent ability to predict mortality, even when used *in addition to* a range of more objective health indicators and health-related behaviours – e.g. measures of chronic conditions, physical functioning, medication use, healthcare utilisation, smoking, and alcohol consumption.

In South Africa, based on data from the first two waves of NIDS, Ardington and Gasealahwe (2014) show that SRH is a significant predictor of two-year mortality, even after controlling for socioeconomic status and other subjective and objective health indicators. In Chapter 3, this relationship, including its gender-specific aspects, is investigated in more depth over two-year, four-year, and six-year horizons.

The subjective nature of SRH, which provides its advantages, is also its main weakness: it is affected by the mechanisms behind perception forming, and by measurement error (Crossley & Kennedy, 2002; Sen, 2002). The respondents’ opinions are shaped by their experiences and context. For example, individuals who are educated and those who have access to better healthcare are likely to be better informed about their illnesses; also, people in poorer settings may perceive a certain burden of symptoms as not out of the ordinary (Sen, 2002). Hence, SRH may not be comparable between countries or even between rich and poor regions in the same country (Jürges, 2007; Lindeboom & van Doorslaer, 2004; Sen, 2002). The variations in individuals’ perceptions,

reflected in different reporting styles, lead to reporting heterogeneity, which will be explored further in the following sub-section. It is worth noting, however, that such heterogeneity has a bearing not only on SRH, but also on all other self-reported measures – the most common measures in large surveys.

Another difficulty is that SRH may be endogenous to an important range of factors, making causal links difficult to identify. For example, educated individuals are likely to be in better health because they are more informed, and less likely to adopt harmful behaviours; but the reverse also applies: healthier individuals are in a better position to obtain higher levels of education (Cutler & Lleras-Muney, 2010). Similarly, SRH has two-way links with other socio-economic status measures, with decisions regarding labour market participation, and hence with receipts of social benefits, and with personality disposition, among others (Currie & Madrian, 1999; Disney *et al.*, 2006). This endogeneity complicates its use, the study of its determinants, and the interpretation of its effects on decision-making. These difficulties, however, arise with the use of all health measures.

A third reason for questioning the reliability of SRH (related to endogeneity) lies in the “justification hypothesis”, which states that some respondents who have retired early or who are not economically active may skew their self-assessments of health in a socially acceptable manner, in order to justify their lack of involvement in the labour market (Baker *et al.*, 2004; Myers, 1982). Fourth, self-assessments are likely to reflect certain aspects of health better than others. For example, using data from Norfolk, UK, Mavaddat *et al.* (2011) find that SRH is significantly associated with all aspects of health (physical, mental and social), but it has the strongest link with physical well-being.

Lastly, further reasons that cast doubt on the reliability of SRH are psychological factors and personality dispositions that may influence self-assessments, as well as information asymmetries in the awareness of conditions or illnesses that have mild or no symptoms (for example, hypertension or the early stages of HIV). Using US data, Goodwin and Engstrom (2002) observed that among respondents with no self-reported physical health problems, positive health perceptions were associated with the traits of agreeableness, openness to experience, extraversion and conscientiousness; while neuroticism was linked to negative health perceptions. Further, an individual’s mood, goals, and other psychological filters may colour the factors that receive

attention in her current assessment (Huisman & Deeg, 2010). While psychological factors do play a role, they appear to be largely related to cross-sectional differences in health assessments, while the main factors driving SRH variation over time relate to changes in physical health and physical limitations (Mavaddat *et al.*, 2011; Mora *et al.*, 2008). Information asymmetries, especially in settings with unequal access to healthcare or substantial variability in its quality, may be reflected in overestimation of health status for disadvantaged groups (Ardington & Case, 2009; Sen, 2002).

Reporting heterogeneity

The disadvantages of SRH discussed above raise questions about its usefulness in empirical research. The calls for caution regarding SRH have centred around two problems. First, it is not a cardinal measure of health, and second, it suffers from biases such as state-dependant reporting bias, scale of reference bias, and response category cut-point shift, which cast doubt on its comparability between individuals or groups.

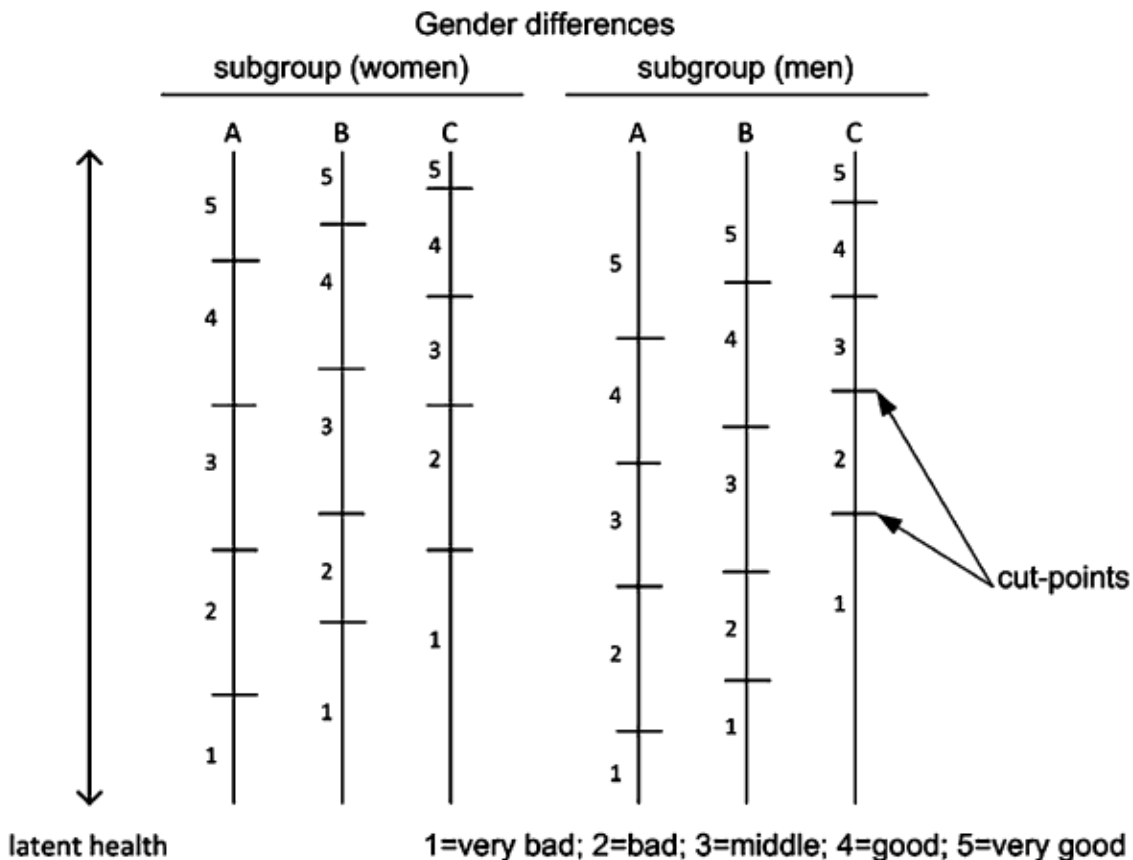
An important strand of the literature is concerned with the comparability of SRH between groups – specifically, with distinguishing between differences due to “true health” and those due to reporting styles, and any systematic patterns of measurement error (Crossley & Kennedy, 2002; Jürges, 2007; Kerkhofs & Lindeboom, 1995; Lindeboom & van Doorslaer, 2004; Pfarr *et al.*, 2012). Assuming that the underlying “true health” variable is unobservable (latent) and continuous, respondents to the general health question project their perceptions into a reporting category, from “excellent” to “poor” (Jürges, 2007; Lindeboom & van Doorslaer, 2004). The categories are “verbal representations of different health states” (Jürges, 2007:164). The interpretations of the category labels may differ between groups – for example, older people are likely to view health deficiencies less harshly than younger respondents with the same conditions (Groot, 2000). This kind of discrepancy causes a parallel shift in all the categories (the entire distribution) of SRH and is referred to as an “index shift” (Lindeboom & van Doorslaer, 2004).

Further, the threshold points between categories may also differ due to variation in reporting behaviour between groups – this makes one or more of the categories wider or narrower, and is often labelled a “cut-point shift” (Lindeboom & van Doorslaer, 2004). For example, cultural norms for a certain group that favour an upbeat attitude may induce respondents to avoid the worst category (Crossley & Kennedy, 2002). For this group, the categories indicating good health are

expected to be wider than the category for poor health, when benchmarked against “true health” (a latent health index). In other words, for individuals in this cultural group, it will take a significantly greater deterioration to report their health as ‘poor’, than for individuals in other groups. Shades of meaning in different languages can also result in cut point shifts. For example, Jürges (2007) notes that when translated into a particular language, a category can be appear as an overstatement – e.g. “*ausgezeichnet*” in German may be perceived as an exaggeration, akin to “outstanding”, versus “excellent” in English, thus prompting respondents to opt for more reasonable-sounding categories.

The concepts of cut-point shift and index shift are illustrated in Figure 2.1 and explained further in section 2.3.1, which presents an empirical model for their measurement. In Figure 2.1 the latent “true health” is represented by the vertical line on the left, next to which the cut-points for three individual women (or subgroups of women) and three individual men (or subgroups of men) are shown. It is apparent that there are differences within the subgroups of men and women, since the cut-points describe each person’s reporting style. The commonly observed between-gender differences are also illustrated, with women displaying, on average, narrower top categories (for excellent health) and wider bottom categories (for poor health), compared to the men.

Figure 2.1 Cut-point shift in the distribution of self-rated health



Source: Figure 2 in Schneider et al. (2012) with reference to Murray et al. (2003)

Moreover, the reference groups or standards used in self-assessments are often unclear. Respondents may compare their health with people of same age group and/or same gender; or with a wider group they interact with (co-workers, friends, and neighbours), with the general population; or with themselves in the past. Baron-Epel and Kaplan (2001) show that the wording of the SRH question (in their study, whether or not it includes the clause “compared to people your age”) matters, but the variation in the responses depends on age, education, and the number of reported diseases (a more objective health measure).

Despite various degrees of reservation among researchers, with some turning away from using SRH as a measure of health completely (Myers, 1982), it is likely to be no worse a measure than other self-reported indicators. Quasi-objective self-assessments of chronic conditions, pain, and limitations to ADL also suffer from measurement error and reporting heterogeneity that are far

from negligible (Baker *et al.*, 2004). Further, using data from France, Tubeuf *et al.* (2008) find that the self-reported chronic conditions indicator is affected by reporting bias to a greater degree than SRH, and hence SRH is a more accurate reflection of the latent variable “true health”. In order to increase the usefulness of SRH as a health measure, methods of analysing it need to be sensitive to heterogeneous responses.

Factors driving reporting heterogeneity

Reporting heterogeneity stems from observable and unobservable individual characteristics. The most common observable characteristics are gender, age, race, education, access to resources (usually measured by household income or expenditure), marital status, and location (country of residence or geo-type, such as an urban or rural area). Unobservable (or difficult to measure) characteristics also play a role. These include, for example, genetic characteristics and personality traits, such as neuroticism (Stephan *et al.*, 2020), or motivation to engage in healthy behaviours (Bailis *et al.*, 2003). The probability of developing illnesses, chronic conditions, or (the lack of) adherence to positive behaviours or medical treatments are often associated with unobserved traits. Such traits give rise to unmeasurable differences between individuals, which are referred to as unobserved individual heterogeneity. While this kind of heterogeneity has a bearing on reporting behaviour, the characteristics behind it are likely to be time invariant, since they form part of an individual’s biological make-up, or enduring self-concept (Bailis *et al.*, 2003; Jylhä, 2009; Stephan *et al.*, 2020; Svedberg *et al.*, 2001). Empirical methods for assessing reporting heterogeneity should take into account both observable and unobservable traits. The treatment of unobserved heterogeneity is possible when the same individuals are observed over time, i.e. with the use of panel data – further discussion of the empirical treatment relevant for this analysis is presented in section 2.3.1. The rationales behind the choice of observed characteristics included as drivers reporting behaviour in this study are discussed next.

Gender aspects

In considering gender differences in health, a common starting point is the paradox that men give more positive ratings to their health, and appear to be affected less by morbidity and disability, yet women have lower mortality rates at every age (Case & Paxson, 2005; Denton & Walters, 1999; Idler, 2003; Kiecolt-Glaser & Newton, 2001). The complex nature of gender health disparities, the

historically prevalent limitations and biases in the design of health studies (e.g. insufficient inclusion of women in clinical trials), as well as lack of emphasis on testing gender differences and on sex-specific reporting, mean that these disparities are far from being well-documented or understood (Wizeman, 2012). Particularly with regard to health research in the social sciences, Denton and Walters (1999: 1222) note that “... at best, studies have tended to control for sex rather than analysing the importance of gender”.

The recent literature focusing on gender inequalities in health recognises three groups of drivers: biological, statistical, and social (Zhang *et al.*, 2015). Biological differences work through genetic, hormonal and evolutionary influences, which also have a bearing on behaviour. Gender is known to moderate or amplify the severity of, and to cause variability in, the symptoms of specific conditions, but further research is ongoing to uncover the precise mechanisms at work (Wizeman, 2012). Statistical differences relate to data from large surveys, which elicit higher response rates and more complete information from women than from men in most countries; hence, the analysis for women tends to benefit from higher accuracy and statistical power (Idler, 2003).

For the purposes of social research, Denton *et al.* (2004) provide a useful framework, which identifies three groups of social determinants (structural, behavioural, and psychosocial), and proposes two hypotheses about the differential health impacts of these determinants on men's and women's health and health perceptions. The structural group consists of factors, which have to do with the respondent's demographic characteristics and environment, such as age, household size, income, education, occupation, and social support. The second group comprises behavioural factors, including lifestyle and habits, such as smoking, exercise, and healthcare-seeking behaviour. In the third group are psychosocial factors, specific to the individual's experience, which are purely subjective. These can be divided into the following three sub-categories. Critical life events encompass experiences such as early-life trauma, abuse, family-related and financial shocks. Chronic stressors are long-term strains – for example, occupational or child-related problems. Psychological resources include self-esteem (the degree of positive feeling about oneself), mastery (which relates to the sense that the individual has control over his or her life chances and life course), and coherence (which is the degree to which the individual perceives him/herself as able to understand, cope with, and find meaning in life events) (Denton *et al.*, 2004).

The two hypotheses proposed by Denton *et al.* (2004) concern the gender variability in the impact of the above social determinants on self-rated health. The differential exposure hypothesis proposes that women's higher self-reported morbidity is explained by their more limited access to resources necessary for health, poorer work and living conditions, and more stressful circumstances, often to do with female gender roles. The differential vulnerability hypothesis suggests that women have dissimilar responses to the structural, behavioural and psychosocial determinants to men, and this is reflected in their worse self-reported health. There is evidence in support of both the differential exposure and differential vulnerability hypotheses, but the degrees of gender disparity depend on the type of determinant, the life-cycle stage, and some features of the respondent's context (Case & Paxson, 2005; Denton *et al.*, 2004; Macintyre *et al.*, 1996). These issues and some of the mechanisms of influence are discussed further in Chapter 4.

Other aspects related to reporting heterogeneity

In addition to gender, a range of individual and household characteristics are also typically correlated with differences in the patterns of health status reporting. Age plays a role in the value of health capital and in reporting behaviour. Inherited health capital depreciates with age, but the process is ameliorated by education, or slowed by other investments in health (Grossman, 1972). Age appears to drive reporting heterogeneity for two reasons. First, the tendency for individuals to be more tolerant of health conditions, or to manage them better, increases with age (Jylhä, 2009). This phenomenon is known as “response shift” (Schwartz *et al.*, 2004). Second, age is important in the choice of a reference group. For example, the explicit inclusion of the phrase “compared to people your age” in the question eliciting self-rating, may alter the pattern of responses received. Specifically, respondents with no chronic diseases, those aged 65 to 75, and those with less than twelve years of education give a better rating to their health when prompted to compare with the people of the same age, implying that they use broader reference groups when replying to the less specific SRH question (Baron-Epel & Kaplan, 2001).

Race is often included as a control for genetic, cultural, or language factors. In the South African context, it is also still strongly tied to a wide range of socioeconomic factors such as wealth, employment status, and membership of a medical aid scheme (Alaba & Chola, 2013; Boyce & Harris, 2011; Charasse-Pouélé & Fournier, 2006). Disparities along racial lines persist in the

access to healthcare of varying quality, as well as in the factors driving demand for healthcare (Burger & Christian, 2020; Gilson & McIntyre, 2007; McIntyre & Gilson, 2002).

Education plays an important role in shaping health-reporting behaviour. The “education gradient” in health is the empirical observation that additional years of education are conducive to better health (Cutler & Lleras-Muney, 2006). Education may influence health via income or occupation, but this effect explains the education gradient only partially. Importantly, education modifies information processing and decision making, hence it can be a driver of reporting heterogeneity. The latter can also be related to the two-way link between education and health (a selection effect), or the link may be via other characteristics (such as conscientiousness), which are difficult to measure (Cutler & Lleras-Muney, 2006). However, evidence from international studies shows that the positive effect of education on health becomes weaker with age (Cutler & Lleras-Muney, 2010; Cutler *et al.*, 2008).

Access to resources (usually measured by household income or expenditure) is an important factor for investments in health capital (Grossman, 1972). However, it is important to keep in mind that the positive association between material resources and health, known as “the gradient (in health)”, is mediated by other factors (Deaton, 2013a). Higher household income is related to better living conditions, a lifestyle conducive to illness prevention, improved access to healthcare, and to higher quality of care an individual can receive (Charasse-Pouélé & Fournier, 2006; Deaton, 2013a). Together with material resources, family size has a bearing on the individual’s capability to withstand health shocks. Though larger households may facilitate learning about self-medication, for example (Ellis & Mwabu, 1991), there is some evidence they may pose a disadvantage because of heightened financial and sanitary risks (Charasse-Pouélé & Fournier, 2006).

Marital status is related to physical and emotional health. It has been consistently found that married people are in better physical health than those who are unmarried, but the extent of the benefits differs by gender and depends on the quality of the relationship (Guner *et al.*, 2014; Kiecolt-Glaser & Newton, 2001). The health gap between married and single individuals widens with age (Guner *et al.*, 2014). Further, the physical health benefits of marriage accrue to a greater degree to men (Guner *et al.*, 2014), while women are more vulnerable to marriage-related stress, but they also enjoy a steeper increase in subjective well-being from a better-quality relationship (Kiecolt-Glaser & Newton, 2001). The positive effect of a well-functioning marriage is likely to

stem both from its link to the physical and emotional aspects of “true health”, and from its bearing on health perceptions; hence, marital status is likely to influence health reporting.

Regarding emotional health, marital distress is strongly linked to depression for both men and women (Kiecolt-Glaser & Newton, 2001), while a supportive relationship facilitates a positive outlook and speeds up recovery after a wide range of health shocks (Guner *et al.*, 2014). The protective effect of marriage works directly through the influence of marital interactions on physiological mechanisms, and also indirectly through behaviour modification: married men and women participate in more health-promoting activities, and have fewer harmful habits or maladaptive coping strategies (Kiecolt-Glaser & Newton, 2001).

Location may refer to a country of residence, or a geographical type of area (such as urban or rural area), or the type of settlement (formal or informal), or neighbourhood. As location is a proxy for living and working conditions, as well as access to services and as economic and social resources, its influence has to do with quantity and quality of healthcare, social support, as well as exposure to different types of risks (Brownson *et al.*, 2009; Kawachi & Berkman, 2003). Context, experiences, and relative isolation may all be reflected in differential health reporting by type of location.

Gender health gaps in South Africa

Life expectancy for women has exceeded that for men in all countries since 2006 (Barford *et al.*, 2006; Crimmins *et al.*, 2019; Goldin & Lleras-Muney, 2018). The gender gap has narrowed, but it remains significant in South Africa where in 2014 (when data for wave 4 of NIDS was collected), women had a life expectancy of 65.8 years, compared to 60 years for men (Stats SA, 2013). The burden of many diseases and disabilities is unevenly distributed between the genders, in a pattern that is common in most countries: while women are more likely to suffer from chronic diseases or disabilities, which are not life-threatening, men are more likely to suffer from conditions with a higher risk of death. For example, women are more likely to self-report having been diagnosed with hypertension, while men have are more likely to be diagnosed with TB, which can be fatal if not treated timeously (Stats SA, 2013). In line with international patterns, a greater proportion of South African women than men experience low-level mental health problems (Herman *et al.*, 2009). Uneven gender patterns are associated with all four of the so-called “colliding epidemics”,

which describe South Africa's greatest current health challenges: HIV and tuberculosis; chronic illness and mental health; injury and violence; and maternal, neonatal, and child health (Mayosi *et al.*, 2012).

Specifically, issues around maternal health are the largest contributors to gender health disparities in South Africa. Despite significant progress in this area, the maternal mortality rate remains high at 141 per 100,000 live births, compared to the average rates of 16/100,000 in developed countries and 230/100,000 in developing countries in 2013 (Statistics South Africa, 2015). Further, the limited data available points to much higher prevalence of maternal and perinatal mental disorders in South Africa than in developed countries, as well as in many developing countries (Bennett *et al.*, 2004; Cooper *et al.*, 1999; Rochat *et al.*, 2006). In sum, the South African gender differentials in health outcomes are evident in both communicable and non-communicable diseases, in mental and physical health (Statistics South Africa, 2013), as well as in experiences of injury and violence (CSVR, 2009; Harris & Vermaak, 2015).

Reporting heterogeneity in SRH in South Africa

To date, four studies have investigated the extent of reporting bias in self-rated health measures in South Africa (Boyce & Harris, 2011; Charasse-Pouélé & Fournier, 2006; Jelsma & Ferguson, 2004; Rossouw *et al.*, 2018). These studies differ in their aims, data sources and samples, and in the methods used (Table 2.1). Boyce & Harris (2011) and Charasse-Pouélé and Fournier (2006) focus on race as a proxy for socioeconomic status in South Africa, but also as a driver of differences in reporting behaviour. Jelsma and Ferguson (2004) investigate heterogeneity in self-ratings of health between respondents of different material means, proxied by household income or wealth, while Rossouw *et al.* (2018) consider both race and wealth, but only for elderly adults.

Boyce & Harris (2011) explore reporting styles by considering the racial patterns reflected in a number of health indicators using data from South African Social Attitudes Survey (SASAS) 2008 – an individual-level survey (not a household survey) with a very small sample size, relative to the nationally representative micro-datasets. They find that the disparities are much more pronounced when considering SRH alone, than when considering other (self-reported) health domains, including mobility, vision, hearing, and mental health. The study employs descriptive statistical methods and hence it does not control for socioeconomic and demographic factors other than race.

Charasse-Pouélé and Fournier (2006) use a modified Oaxaca-Blinder decomposition to disentangle the contributions to the racial health gap due to socioeconomic disparities (indirect racial effect) and those due to discrimination or to other more intrinsic characteristics (direct racial effect). In their results, while the indirect effect shows the expected large disparity in favour of Whites, the direct effect, which assesses the differences in health between Whites and Africans with similar observable characteristics, indicates that Africans would be in worse health if presented with the Whites' health model. Charasse-Pouélé and Fournier (2006) understand the causes to be linked to potential racial differences in the health production functions, which are in turn related to divergences in health concepts, in addition to historical inequalities in living conditions, and in the provision and quality of healthcare.

Boyce and Harris (2011) also acknowledge these entrenched socioeconomic disparities, and attempt to shed direct light on the differences in the resulting health concepts between the races by comparing the reference groups against which respondents benchmark their health assessments, as well as by testing their attitudes to several aspects of health, expressed as statements. On average, the reference groups for Whites and Indians consist of a closer circle of family and friends, while Africans are more likely to compare their health to a broader group, including neighbours or co-workers, or those of similar age, gender, or income. Regarding health attitudes, the only statistically significant difference relates to the statement, "Richer people are healthier people", which was met with agreement from a substantially larger proportion of Africans than from other groups.

In a study localised to Cape Town's Woodstock suburb, Jelsma and Ferguson (2004) set out to investigate health disparities by socioeconomic status (SES) using a standard questionnaire, EQ-5D, which includes a visual analogue scale (VAS – this is the visual equivalent of SRH), as well as self-reports on a number of specific health domains. SES is proxied by the household's monthly income bracket, and by the individual's employment status and years of education. Using descriptive and multiple regression methods, they find that the distribution of VAS scores represents a wider health disparity by SES, than is accounted for by the scores on the other indicators. The authors conclude that SES is a qualifier in the reliability of the overall health rating (VAS), but they do not offer explanations, nor do they attribute this result specifically to reporting heterogeneity.

Table 2.1 South African studies on reporting heterogeneity in self-reported indicators

Study	Data and coverage	Method and key health indicator(s)	Focus	Findings	Gender-specific?
Boyce and Harris (2011)	SASAS (South African Social Attitudes Survey) 2008; nationally representative survey (sample size = 2,904)	Descriptive statistics; SRH, self-assessments in five physical functioning domains, retrospective SRH	Socioeconomic and reporting differences in SRH by race	Racial health disparities are closely tied to the association between race and socioeconomic status, but race also has an independent impact. Racial differences are reduced when measured by less subjective health indicators, compared to SRH.	No
Charasse-Pouélé and Fournier (2006)	October Household Survey (OHS) 1999; large nationally representative household survey (sample size = 92,471; study includes Africans and Whites only)	Oaxaca-Blinder decomposition; SRH	Racial health disparities due to observed socioeconomic factors (indirect effect) and unobserved factors (direct effect)	As expected, the indirect effect shows Africans (who are materially worse off and are less educated) to be in worse health than Whites; however, the direct effect reveals a more complex relationship, linked to past discrimination, as well as disparities in healthcare access and quality.	Gender is used as a control variable
Jelsma and Ferguson (2004)	Survey of Woodstock (diverse neighbourhood of Cape Town) residents (sample size = 1,159)	Multiple regression; visual-analogue scale (VAS), health-related quality of life (HRQoL), assessed using EQ-5D index measure) ²	Disparities in perceived health (VAS) by socioeconomic status (household income, employment status and education)	Lower income is found to be associated with worse perceived health (VAS) than more objective indicators would suggest.	No
Rossouw <i>et al.</i> (2018)	Study on Global Ageing and Adult Health (SAGE) 2008; nationally representative sample of people aged 50 and older (sample size is approx. 3,400)	Anchoring vignettes / HOPIT approach ³ ; self-assessments in 16 domains of physical and emotional functioning, anchoring vignettes	Reporting heterogeneity by wealth quintile and race	The poor self-report their health more optimistically than the rich, i.e. they underestimate their health needs.	Gender is used as a control variable

² EQ-5D is a standardized survey instrument developed by the EuroQol Group. It measures health-related quality of life in five dimensions: mobility, self-care, usual activities, pain/discomfort, and anxiety/depression. The EQ-5D consists of a descriptive system and a visual analogue scale (VAS).

³ Hierarchical ordered probit model

In contrast, using sixteen self-reported health domains as measures, the evidence presented by Rossouw *et al.* (2018) points to the poor taking a milder view of their health than the wealthier respondents. The health domains include aspects of physical functioning, mental health, and social well-being (related to relationships and conflict, for example). Wealth is measured in terms of an index composed of the household's durable assets, characteristics of the dwelling, and whether the household had access to basic services, such as sanitation and water. Among the South African studies conducted to date, Rossouw *et al.* (2018) employ the most rigorous methodology, the anchoring vignettes approach, which allows for the most direct benchmarking of reporting styles. This approach compares the way respondents with different characteristics assess fictitious individuals' health (anchoring vignettes), relative to ratings of their own health in the sixteen domains they examined, using data from the Study on Global Ageing and Adult Health (SAGE), conducted by the World Health Organization (WHO) on South Africans aged 50 and above. Rossouw *et al.* (2018) find evidence in favour of heterogeneous reporting between the poor (wealth quintile 1) and non-poor (wealth quintile 5) for ten out of the sixteen health domains, indicating that the poor in the 50 and over age group underestimate their health needs compared to the non-poor. Further, "... within race groups, reporting is heterogeneous and health gaps by wealth are severely underestimated when using observed, uncorrected reports" (Rossouw *et al.*, 2018:1951).

The South African studies conducted to date have focussed on specific characteristics, such as race and/or socioeconomic status, but a wider array of factors likely shape heterogeneous reporting styles. Importantly, few international studies, and none of the South African studies, investigate the issue of gender differences in reporting heterogeneity patterns. This chapter provides new insights in three other ways. First, the analysis is not restricted to a single time point, as it is based on recent panel data in four waves collected between 2008 and 2014. Second, the study is not limited to the older age group – rather, it covers a nationally representative sample. Third, the analysis employs a technique, which utilises the advantages of repeated observations of the same individuals. Regarding the international literature, the study contributes to the relative dearth of studies on health-reporting styles in developing countries, and it applies the method developed by Pfarr *et al.* (2010) to study within-country, rather than between-country, differences.

2.3. Methods

This chapter analyses data from the first four waves of the longitudinal National Income Dynamics Study (NIDS) (see Chapter 1) (SALDRU, 2008; 2010; 2012; 2014). The estimation methods used are discussed next, after which the results are presented in section 2.4.

2.3.1 Model of reporting heterogeneity: cut-point shifts vs index shifts

Differences in reporting styles (reporting heterogeneity) between demographic and economic groups are investigated by utilising the model developed by Kerkhofs and Lindeboom (1995). The model assumes that “true health” (H^*) is a continuous but unobservable (latent) variable. The individual’s assessment of “true health” is reflected in their response to the survey question (on SRH), represented by H^S . Since, by definition, “true health” is unobservable, more objective health measures are used as benchmarks against which to identify differences in reporting styles (Kerkhofs & Lindeboom, 1995; Lindeboom & van Doorslaer, 2004). These measures are discussed in section 2.3.4 below.

SRH (H^S) can be viewed as determined by “true health” (H^*), reporting behaviour (X_I), and a random error component (ε_1). The effects of reporting behaviour on SRH are captured by the β_1 ’s.

$$H^S = f_1(H^*, X_I, \varepsilon_1; \beta_1) \quad (2.1a)$$

“True health” can be assumed to be composed of a proxy (the more objective measure H^0), a vector of factors that affect true heterogeneity in health (X_2), and a random error (ε_2).

$$H^* = f_2(H^0, X_2, \varepsilon_2; \beta_2) \quad (2.1b)$$

H^S is an ordered categorical variable, and divergence in reporting styles may influence the group means of the index function and also change the cut-off points between the categories, $j = 1, \dots, n$.

$$H^S = j \leftrightarrow c_{j-1} < H^* \leq c_j, \quad j = 1, \dots, n \quad (2.2a)$$

The possible dependence of the cut-off points on X_I is given by the function $g_j(\cdot)$.

$$c_j = g_j(X_I; \beta_{1j}), \quad j = 1, \dots, n-1, c_0 = -\infty, c_n = \infty \quad (2.2b)$$

Assuming a simple form for the approximation (2.1a), the following equation can be thought of as reflecting true health as a measured component, which depends on H_0 , and a further component,

which depends on the “true” impacts of personal characteristics (e.g. age as one of the elements in X_2) on health, which is not captured by the more objective measure, H_0 .

$$H^* = f(H^0; \alpha) + X_2' \beta_2 + \varepsilon_2 \quad (2.1b')$$

Combining the above relationships results in the empirical equivalent of (2.2a).

$$H^S = j \leftrightarrow g_{j-1}(X_1; \beta_{1j-1}) - X_2' \beta_2 < f(H^0; \alpha) + \varepsilon_2 \leq g_j(X_1; \beta_{1j}) - X_2' \beta_2 \quad (2.3a)$$

Separate ordered response models will be estimated by gender, hence the above equation becomes:

$$H^S = j \leftrightarrow \delta_{j-1}^k < f(H^0; \alpha^k) + \varepsilon_2^k \leq \delta_j^k \quad (2.3b)$$

This estimation equation takes into account differences in both index shifts, (represented by α), and cut-points (represented by δ_j) between the subgroups, k (men and women, in the case of this chapter).

In order to distinguish index shifts from cut-point shifts, the hypothesis that the β_{1j} 's are identical for all categories (that is, for all values of j) can be imposed. This is the null hypothesis, which implies that group-specific characteristics (such as gender and age, for example) do not influence perceptions about the location of cut-points between the categories of SRH. Hence, the rejection of the null hypothesis leads to the conclusion that the thresholds between SRH categories are affected by different reporting styles, in other words, reporting heterogeneity leads to cut-point shifts.

2.3.2 Implementation: the random effects generalised ordered probit (REGOPROB)

The estimation method utilised in this chapter, the random effects generalised ordered probit, offers insights into self-reporting behaviour by taking advantage of the unbalanced panel structure of the data. This method is the best available alternative for understanding patterns of reporting heterogeneity, in the absence of anchoring vignettes in the NIDS questionnaire. The REGOPROB is an extension of the conventional probit method. Instead of starting from “the parallel lines assumption” (explained below), the model tests the assumption's validity by employing an iterative procedure and a Wald test for each of the explanatory variables, as well as for the overall final model. This section explains how the REGOPROB builds on the simpler approaches,

specifically the ordered probit and the random effects ordered probit (REOP), to provide a method that distinguishes between the two kinds of reporting heterogeneity: index shifts and cut-point shifts.

The equation for the ordered probit estimation is given by:

$$\begin{aligned}
 Y_{it}^* &= X_{it}\beta + \varepsilon_{it} \\
 i &= 1, \dots, N \\
 t &= 1, \dots, T
 \end{aligned} \tag{2.4}$$

where Y_{it}^* is an unobserved (latent) dependent variable, which is assumed to be continuous (here, it represents true health); X_{it} is a vector of explanatory variables (here, more objective health measures and demographic variables); β is a vector of unknown parameters; ε_{it} is the error term; i is an index of individuals; and t is a time index.

Y_{it}^* is unobserved, but instead, surveyed individuals provide a proxy, Y_{it} (here, the categorical variable SRH), such that:

$$\begin{aligned}
 Y_{it} &= 0 \quad \text{if} \quad Y_{it}^* \leq 0 \\
 Y_{it} &= 1 \quad \text{if} \quad 0 < Y_{it}^* \leq \tau_1 \\
 Y_{it} &= 2 \quad \text{if} \quad \tau_1 < Y_{it}^* \leq \tau_2 \\
 &\dots \\
 Y_{it} &= J \quad \text{if} \quad \tau_{J-1} \leq Y_{it}^*
 \end{aligned} \tag{2.5}$$

where Y_{it} is the categorical variable SRH, which has J ordered response options, and τ is a vector of unknown cut-point parameters, to be estimated using the elements of the vector β .

The probit model generates a single index reflecting the underlying latent variable Y^* and it assumes that a change in one of the explanatory variables shifts this index uniformly, but that the slope coefficient β remains unchanged across individuals, or groups of individuals. This is referred to as the “parallel lines assumption”. In other words, with regard to reporting heterogeneity, the ordered probit model is constrained to reflect only index shifts. In contrast, the generalised ordered

probit relaxes this assumption and allows for the cut-points between SRH categories to vary between individuals or groups of individuals. That is, it allows for variation in the slope coefficients β , in addition to index shifts.

The random effects ordered probit (REOP) takes the panel structure of the data into account by allowing for unobserved heterogeneity between individuals (Pfarr *et al.*, 2010). The REOP assumes that individual-specific heterogeneity is distributed randomly across the population and it provides cluster-specific coefficients (Wooldridge, 2010). It can be expressed as follows:

$$Y_{it} = \mu + X_{it}\beta + \alpha_i + u_{it} \quad (2.6)$$

where α_i is the individual-specific heterogeneity and u_{it} is an idiosyncratic error term.

This chapter implements Kerkhofs and Lindeboom's (1995) model by estimating random effects generalised ordered probit (REGOPROB) regressions. The REGOPROB utilises panel data to estimate two kinds of heterogeneity: unobserved individual heterogeneity, which is assumed to be distributed randomly across the population, and observed heterogeneity, which is reflected in differences in the cut points and hence in the slope coefficients (Pfarr *et al.*, 2010; Pfarr *et al.*, 2012). The REGOPROB applies the iterative procedure designed by Pfarr *et al.* (2010), which conducts a Wald test to test the parallel lines hypothesis for each explanatory variable. If this hypothesis is rejected, then different cut-points are estimated. As a final step, the REGOPROB procedure tests the hypothesis that the final model differs significantly from the REOP (in which the parallel lines assumption is taken to be valid) using a global Wald test (Pfarr *et al.*, 2010).

In the Wald tests (as applied to individual variables or the overall model), when the null hypothesis of no cut-point shifts is not rejected, then index shifts remain to be investigated. If there are differences in reported health between groups, this may be due to certain groups truly being healthier, or a result of reporting behaviour that displaces all categories of SRH in parallel, i.e. index shifts⁴. The distinction between (quasi-) objective and reporting differences in health can be made with the use of the more objective health measures as benchmarks (as in equation (2.3a) above).

⁴ Another possible explanation is that the concept of health has changed for a particular group (Ziebarth, 2010).

The assessment of reporting heterogeneity using other self-reported health measures as benchmarks has the obvious disadvantage that all self-reported indicators contain measurement error and are likely to be affected by heterogeneous reporting (Bago d'Uva *et al.*, 2008; Rossouw *et al.*, 2018; Tubeuf, 2009). Hence, it is an arbitrary decision to deem quasi-objective measures as more accurate reflections of “true health”. However, given data constraints, using several quasi-objective measures to benchmark SRH against is the next-best solution to having data on objective indicators or vignette data, which are costly to collect and also contain a degree of measurement error.

In order to accommodate data constraints, the approach taken in this chapter deviates somewhat from the reporting heterogeneity estimation models used by Kerkhofs and Lindeboom (1995), van Doorslaer and Jones (2003), and Pfarr *et al.* (2012), among others. The common approach is to construct one or more benchmarks (usually, a “true health” index, or physical and mental health indices), which aggregate the effects of a number of conditions on health into one, with the guidance of a specific instrument, such as the Hopkins Symptom Checklist (HSCL) (Kerkhofs & Lindeboom, 1995; Lindeboom & Kerkhofs, 2009), the McMaster Health Utility Index Mark 3 (HUI3) (Lindeboom & van Doorslaer, 2004), or by first estimating disability weights for individual conditions by regressing against an overarching variable that reflects long-term conditions or disabilities (Pfarr *et al.*, 2012). The health section in the NIDS questionnaire does not utilise a standard battery of questions (e.g. those for the HSCL, or the McMaster Health Utility Index Mark 3), and does not contain an overarching binary variable that can be used for estimating disability weights using a logit model. Hence, there is no credible way to aggregate the indicators into a single benchmark. (The battery of questions on the limitations in the activities of daily living (ADL) was only included in Waves 1 and 2.) Instead, in the following analysis, the quasi-objective (self-reported) and objective (measured) health indicators are used directly as controls in the reporting heterogeneity regressions – these indicators, taken together, constitute a benchmark against which reporting heterogeneity is measured. (The benchmark is described in more detail in section 2.3.4 below.)

2.3.3 Sample

The sub-sample used in this chapter is restricted to adults (here defined as aged 18 and over) and continuing sample members (CSMs) only⁵ (Brown *et al.*, 2012). The REGOPROB regression technique, described above, requires longitudinal data, such as the NIDS dataset. An unbalanced panel of the first four waves of NIDS is employed. The mechanisms behind reporting behaviour are likely to be distinct by gender, given the conceptual and contextual factors discussed above in Section 2.2. Hence, separate regressions are estimated by gender.

2.3.4 Health measures

The main variables of interest are sourced from the health section of the adult questionnaire, which includes a number of self-reported indicators, as well as measured indicators – these are described below. In addition, there is a range of questions about demographic and socioeconomic characteristics of the individual and household, which makes NIDS suitable for exploring patterns of reporting heterogeneity. The self-reported and measured health indicators are described next, followed by the individual and household demographic and socioeconomic characteristics. Brief descriptions of these variables, including the base categories for the categorical variables, are included together with the descriptive statistics in Table 2.2.

General health

Self-rates health (SRH) is a comprehensive reflection of health. The NIDS question eliciting the individual's subjective rating is J1: "How would you describe your health at present? Would you say it is excellent, very good, good, fair, or poor?". The two categories, which reflect less-than-good health – that is "fair" and "poor" – are combined to produce a four-level SRH measure because relatively few respondents throughout the panel chose the lowest category.

The quasi-objective health indicators, used as benchmarks for assessing reporting behaviour, are described next. These benchmarks reflect three health aspects: health conditions, health behaviours, and healthcare utilisation (Pfarr *et al.*, 2012). Chronic conditions, other conditions, symptoms experienced in the last 30 days, and the depression scale reflect physical and mental

⁵ CSMs are the resident members of all original households selected to participate in Wave 1 households. CSMs include children who were living in these households and any children born to or adopted by female CSMs in the following waves. In contrast, temporary sample members (TSMs) are household members who are co-resident with CSMs from wave 2 onwards (Brown *et al.*, 2012). The latter are excluded from the analysis in this chapter.

health conditions; health behaviours are captured by alcohol consumption, smoking, and physical activity; while the time elapsed since the last medical consultation is a proxy for healthcare utilisation.

Chronic conditions

The question related to chronic conditions in the battery of health questions asked: “Have you ever been told by a doctor, nurse, or healthcare professional that you have [...]” (J13). Respondents were presented with a list of seven conditions, namely: tuberculosis (TB), high blood pressure, diabetes, stroke, asthma, heart problems, and/or cancer. The variable used here divides individuals into three categories: those with no known chronic conditions, those with exactly one, and those with two or more.

Other condition or disability

A follow-up question probed whether the respondent had another major illness or disability (J17), after which a spontaneous response question requested more details. The expected responses included any form of disability (e.g. sight, hearing, or speech), psychological or psychiatric disorders, HIV/AIDS, epilepsy, Alzheimer’s disease, etc. For the purpose of the analysis below, a binary indicator is generated; it equals one if the respondent had one or more other condition or disability, and zero otherwise.

Regular drinker

Regarding alcohol consumption, the NIDS respondents were asked two questions. The first was, “How often do you drink alcohol?” (J31). The follow-up question was, “On a day that you have an alcoholic drink, how many standard drinks do you usually have? *A standard drink is a small glass of wine; a 330 ml can of regular beer, a tot of spirits, or a mixed drink.*” (J32). The majority of respondents answered the first question; however, the variable corresponding to the second question contains a large number of missing values. Therefore, the variable for a regular drinker employed here is based only on the first question; it is a binary indicator of whether the individual consumed alcohol three or more times per week. South Africa does not have precise guidelines regarding alcohol consumption, rather, there is a food-based dietary guideline⁶, worded as: “If you

⁶ “Food-based dietary guidelines (FBDGs) are brief, positive dietary recommendation messages that are used to inform consumers how to choose food and beverage combinations that will lead to a diet that is adequate, that meets

drink alcohol, drink sensibly” (Jacobs & Steyn, 2013). Given this, the indicator for alcohol consumption in the analysis is based roughly on the “hazardous drinking score”, a screening tool developed by the United States’ Substance Abuse and Mental Health Services Administration (SAMHSA, nd)⁷.

Smoker

This binary variable reflects whether the individual smokes cigarettes currently. Although the NIDS questionnaire also contains a question on whether the respondent had smoked previously, the benefits of ceasing to smoke are known and well documented (US Department of Health and Human Services, 2014) – hence, current behaviour is assumed to be most important to current health. Joining international efforts to reduce tobacco use, South Africa introduced legislation to limit smoking in public places in 1993, which was amended with tighter regulations in 2008. The legislation, together with increased taxes on tobacco, a ban on advertising, and a partial ban on smoking in public, may have aided progress towards this goal, but a large proportion of adult South Africans continue to use tobacco products (Reddy *et al.*, 2015). According to WHO estimates using 2018 data, the tobacco smoking prevalence rates in South Africa were 34.3% for men and 7.1% for women, slightly higher than the corresponding global rates of 32.4% and 5.5% (WHO, 2019), keeping in mind that smoking behaviour is likely to be increasingly underreported in more recent years, as a result of rising stigmatisation (Liber & Warner, 2018).

Exercise

In NIDS, physical exercise is gauged via a single question, “How regularly do you exercise?” (J25). The WHO recommends that adults should do at least 150 minutes of moderate aerobic physical activity throughout the course of a week (WHO, 2010). Since only 27% of men and 12% of women from the sample used in this chapter met this criterion, a less stringent one was applied for the purposes of the analysis, namely, a binary indicator of whether the individual exercises at least once a week.

nutrient need and that is, at the same time, prudent, for example, which lowers the risk of noncommunicable diseases (NCDs)” (Vorster *et al.*, 2013: S3).

⁷ However, the “hazardous drinking score” scale does not assume that drinking three or more times per week is necessarily hazardous – this depends on the quantities consumed (SAMHSA, nd). Similarly, this assumption is not imposed for the analysis in this chapter.

Depressed

The NIDS questionnaire allows for the assessment of mild depression, as it includes a ten-item scale, developed by the Centre for Epidemiological Studies (CES-D10) (Radloff, 1977). An individual can be said to suffer from mild depression if she scores 10 or higher, out of the possible maximum 30, on the ten-question scale (Radloff, 1977). The scale has been validated for use with Zulu, Xhosa, and Afrikaans-speaking individuals in South Africa (Baron *et al.*, 2017). Hence, the binary indicator used in the analysis is equal to one if the CES-D10 score was 10 or higher, and zero otherwise.

Symptoms

The health section of the NIDS questionnaire also provides a gauge of short-term health through the list of 24 symptoms the respondent may have experienced in the last 30 days, ranging from a headache to serious injury (as a result of an accident or act of violence). For the purposes of the analysis, this list is combined into a single variable, showing whether the individual experienced at least one of the symptoms.

Last medical consultation

The health-care seeking behaviour measure is based on a question about the time elapsed since the respondent's last medical consultation. Since some of the eight possible time intervals in the NIDS questionnaire (from "never" to "in the last 30 days") were rarely chosen, the indicator employed here was reduced to three categories, namely: "five or more years ago or never", "one to four years ago", and "in the last year".

In addition to the above self-reported health indicators, the NIDS questionnaire includes measured indicators. The NIDS field workers were instructed to measure each respondent's weight, height, waist circumference, and blood pressure twice (Ardington & Case, 2009; Ardington & Gasealahwe, 2012). The assessment of reporting heterogeneity in this chapter is conducted first excluding and then including two measured indicators (namely, body mass index (BMI) category and hypertension) as part of the set of health benchmarks, for the reasons discussed below.

Body mass index (BMI) category

The body mass index is a widely used measure of nutritional status. It is calculated as the individual's weight (in kilograms) divided by the square of her height (in metres). This chapter

follows the common practice of bracketing this measure into four categories, according to the WHO classification, namely: underweight (BMI below 18.5), normal (BMI between 18.5 and 24.9), overweight (BMI between 25 and 29.9), and obese (BMI above 30). These categories are defined only for ages 20 and older (WHO2000). For respondents with two non-missing measurements, the average weight and height are used for the BMI calculation. Observations with a BMI below 10 or above 50 in both assessments are omitted from the analysis, as these are likely the result of measurement errors. It is worth noting that the use of the BMI indicator warrants caution because it is subject to non-random patterns of missing data. For example, in wave 1, White women were three times more likely to have missing weight and height data, compared to African women, while the proportion of missing values for white men was twice that for African men (Ardington & Case, 2009). In the pooled sample of waves 1 to 4 used in the estimation, the share of White women for whom BMI cannot not be calculated (mostly because of missing values) is 17%, compared to 12% of African women; the corresponding proportions for men are approximately the same.

Hypertension

To generate the indicator employed here, where available, the two blood pressure measurements were averaged, and the result was transformed into a binary indicator for hypertension. A respondent was deemed to be hypertensive if her average systolic reading was above 179 or her average diastolic reading was above 109. Similarly to the BMI indicator, the pattern of missing blood pressure measurements is non-random. In the pooled sample of waves 1 to 4 used in the estimation, the proportion of White women with missing blood pressure readings is 20%, compared to 9% of Black women; for men, the corresponding proportions are 19% and 8%. Hence, two versions of the reporting heterogeneity regression are estimated: the first one excludes, while the second one includes, the BMI categories and hypertension indicators.

2.3.5 Demographic and socioeconomic characteristics

In order to verify whether reporting heterogeneity exists between individuals with different demographic and socioeconomic characteristics, the following key individual-level and household-level variables are included in the regression model. The individual's age (in completed years) enters in a quadratic fashion, as the path of individuals' health perceptions over time is assumed to be non-linear. The four population groups commonly delineated in official South

African surveys are African, Coloured, Asian/Indian, and White. The analysis in this chapter excludes Asian/Indian respondents because of the small sub-sample sizes in each wave of NIDS.

In the NIDS data, there are five categories available for marital status. For the purposes of this chapter, marital status is reduced to three categories: ‘single’ (never married), ‘married or cohabiting’, and ‘divorced, separated, or widowed’. Education is included as a four-level variable with categories based on years of schooling, namely: no schooling or incomplete primary (up to 6 years of education), primary or incomplete secondary (between 7 and 11 years), secondary or incomplete tertiary (between 12 and 14 years), and some level of tertiary education (15 years or more). Given the historical geographic segregation in South Africa, another important control variable is geographical type (geo-type) – in line with the new official classification introduced in the 2011 Census, the geo-type can be urban, traditional, or farms. Urban areas are defined as built-up cities and towns, including formal and informal settlements; traditional areas are villages on community-owned land, which is under traditional leaders’ authority (these areas were part of the former “homelands” or “Bantustans”); and farms are commercial farming areas (Chinhema *et al.*, 2016).

The proxy for household expenditure used in the analysis is real monthly household expenditure per capita. This proxy is based on the derived total household expenditure variable from NIDS, which was imputed to cover all surveyed households (Argent, 2009) and it is adjusted for household size and for inflation. All values are inflated to the price level prevailing in November 2014, the last month of interviews for wave 4.

2.4. Descriptive statistics

The descriptive statistics for the variables used in the analysis are presented separately for men and women aged 18 and older in Tables 2.2 and 2.3. The self-reported health indicators show, as expected, higher morbidity among women: they are more likely than men to have been diagnosed with at least one chronic condition, to have a disability, to have experienced symptoms of illness recently, or to suffer from mild depression. The substantial gender differences in lifestyle behaviours are reflected both in the higher rates of smoking and alcohol consumption among men, but also in men’s better exercise habits. Health-care seeking behaviour has the expected gender pattern, where women are more likely than men to have consulted a health practitioner within the last four years.

With regard to demographic and socioeconomic characteristics, as is common in large surveys, there are more female respondents with complete information on all the questions of interest and women, on average, are older than men. Gender differences in educational attainment have narrowed in the post-Apartheid period (Spaull & Makaluza, 2019). However, a gender gap remains among the least educated (who tend to be older than the rest of the sample), as 20% of women have no education or an incomplete primary education, versus 18% of men, but the same share of men and women (about 4%) have tertiary education. The race composition of the sample is similar for men and women. From the expenditure quintiles, it is evident that there are more women in the bottom three quintiles of households, and more men in the top quintile. Men are more likely to be never married and to live in an urban area, while women are more likely to be previously married and live in traditional areas (formerly known as ‘homelands’). Differences in the residential location of women and men reflect historical, and continuing, patterns of predominantly male labour migration from rural to urban areas in South Africa (Posel, 2010; Posel & Casale, 2003). Differences in marital status arise partly from a longer life expectancy among women and also because women tend to marry men who are older than they are.

Table 2.2 Health indicators: descriptions and summary statistics

Variable	Definition		Men	Women
Self-rated health (4-level)	Self-rated health			
	1 if fair or poor	Fair or poor	0.104	0.160***
	2 if good		(0.004)	(0.005)
	3 if very good	Good	0.234	0.262***
	4 if excellent		(0.006)	(0.005)
		Very good	0.292	0.277**
			(0.007)	(0.006)
		Excellent	0.371	0.301***
			(0.008)	(0.007)
Other self-reported indicators				
Chronic conditions	Number of diagnosed chronic conditions			
		None [#]	0.854	0.761***
			(0.007)	(0.007)
		One	0.047	0.059***
			(0.003)	(0.003)
		Two or more	0.099	0.180***
			(0.005)	(0.006)
Other condition	Other major illnesses or disability			
		No [#]	0.949	0.934***
			(0.003)	(0.003)
		Yes	0.051	0.066***
			(0.003)	(0.003)
Regular drinker	Drinks alcohol at least 3 times/week			
		No [#]	0.938	0.987***
			(0.003)	(0.002)
		Yes	0.062	0.013***
			(0.003)	(0.002)
Smoker	Smokes currently			
		No [#]	0.635	0.912***
			(0.010)	(0.009)
		Yes	0.365	0.088***
			(0.010)	(0.009)
Exercise	Frequency of physical exercise			
		Never or infrequently [#]	0.659	0.832***
			(0.008)	(0.009)
		At least once/week	0.341	0.168***
			(0.008)	(0.009)

Table 2.2 (continued)

Variable	Definition		Men	Women
Depressed	Mildly depressed (score of 10 or more on the CES-D10 scale)	No [#]	0.763 (0.007)	0.715*** (0.008)
		Yes	0.237 (0.007)	0.285*** (0.008)
Last medical consultation	Time elapsed since the last medical consultation	5 or more yrs ago or never [#]	0.217 (0.010)	0.135*** (0.006)
		1 to 4 yrs ago	0.424 (0.010)	0.342*** (0.008)
		Within the last year	0.360 (0.009)	0.523*** (0.008)
Symptoms	Number of symptoms experiences in the last 30 days	None [#]	0.494 (0.007)	0.388*** (0.007)
		1 or more	0.506 (0.007)	0.612*** (0.007)
Measured health indicators				
BMI category	Body mass index category (for ages 20 and above only) Underweight: 10.00 - 18.49 Normal: 18.50 - 24.99 Overweight: 25.00 - 29.99 Obese: 30.00 and above	Underweight	0.079 (0.005)	0.029*** (0.002)
		Normal [#]	0.535 (0.013)	0.288*** (0.007)
		Overweight	0.242 (0.010)	0.272*** (0.006)
		Obese	0.143 (0.008)	0.410*** (0.010)
Hypertension	Hypertension (systolic blood pressure above 160; diastolic blood pressure above 100)	No [#]	0.992 (0.001)	0.988*** (0.001)
		Yes	0.008 (0.001)	0.012*** (0.001)
N			20489	30583

Source: Own calculations based on Wave 1 to 4 of NIDS

Notes: *** Mean or proportion difference between men and women is statistically significant at the 1% level ($p < 0.01$), ** 5% level ($p < 0.05$); or * 10% level ($p < 0.1$). # denotes the omitted (base) category for categorical variables. Robust standard errors are shown in parentheses. Estimates are weighted using the post-stratified weights.

Table 2.3 Demographic and socioeconomic variables

Variable	Definition		Men	Women
Age	Age at last birthday		37.996 (0.434)	39.906*** (0.314)
Race	Population group classification, based on commonly-used categories in national surveys	African [#]	0.807 (0.024)	0.792* (0.024)
		Coloured	0.088 (0.018)	0.095* (0.018)
		White	0.105 (0.017)	0.112 (0.018)
Marital status		Never married [#]	0.541 (0.016)	0.459*** (0.012)
		Married/cohabiting	0.399 (0.014)	0.390 (0.011)
		Divorced/separated/ widowed	0.059 (0.007)	0.151*** (0.005)
Education	Based on years of schooling: None or incomplete primary (0-6 yrs) Primary or incomplete secondary (7-11 yrs) Secondary or incomplete tertiary (12-14 yrs) Tertiary (15 years or more)	None [#]	0.183 (0.010)	0.204** (0.010)
		Primary	0.475 (0.012)	0.463 (0.010)
		Secondary	0.303 (0.013)	0.292 (0.010)
		Tertiary	0.039 (0.009)	0.040 (0.007)
Expenditure	Real household expenditure per capita quintiles	Quintile 1 [#]	0.097 (0.007)	0.145*** (0.008)
		Quintile 2	0.105 (0.007)	0.152*** (0.007)
		Quintile 3	0.132 (0.006)	0.168*** (0.006)
		Quintile 4	0.217 (0.009)	0.211 (0.008)
		Quintile 5	0.448 (0.019)	0.324*** (0.019)
Geo-type	Type of geographical area, as per the definition adopted in Census 2011	Urban [#]	0.672 (0.027)	0.633*** (0.028)
		Traditional	0.279 (0.026)	0.331*** (0.028)
		Farms	0.049 (0.008)	0.036*** (0.006)
N			20489	30583

Source: Own calculations based on Wave 1 to 4 of NIDS

Notes: *** Mean or proportion difference between men and women is statistically significant at the 1% level ($p < 0.01$), ** 5% level ($p < 0.05$), or * 10% level ($p < 0.1$). # denotes the omitted (base) category for categorical variables. Robust standard errors are shown in parentheses. Estimates are weighted using the post-stratified weights.

2.5. Results

Tables 2.4 and 2.5 present the results from a random effects generalised ordered probit (REGOPROB) regressions for men and women, using the Stata routine developed by Pfarr *et al.* (2010). As discussed in the methodology, the estimations do not utilise a single benchmark or index for “true health”, but rather use the quazi-objective health indicators, as well as variables reflecting lifestyle and health-care seeking behaviour, as the more objective health benchmarks, against which the reporting styles, driven by individual characteristics and socioeconomic factors, can be assessed. An alternative specification of the REGOPROB results, which includes the two measured indicators, is reported in Appendix 2.A.

For each gender, three equations representing binary choices are estimated. The first equation, shown in the first column of each table, represents the comparison of the highest health category (“excellent”) with the three lower ones (“very good”, “good”, “fair or poor”); the second equation relates to the choice between the top two categories (“excellent” and “very good”) and the bottom two (“good” and “fair or poor”); while the last equation juxtaposes the lowest category (“fair or poor”) against the others (“excellent”, “very good”, “good”,). The results can be interpreted as follows: a positive and statistically significant coefficient means individuals with the corresponding characteristic will tend to provide a better health evaluation. For example, a positive coefficient in the first column means that, on average, individuals are more likely to report being in “excellent” health. A negative and statistically significant coefficient implies the opposite tendency.

Cut-point shifts are identified when a demographic or socioeconomic characteristic has different and statistically significant coefficients in one or more of the REGOPROB equations (columns). Such a finding implies that the cut points between the SRH categories are not equally spaced for individuals with the corresponding characteristic, compared to the reference category (or for a marginal change if the characteristic is a continuous variable) (Schneider *et al.*, 2012). For example, the same degree of deterioration, say, in the underlying “true health” index will lead an individual from one group to switch to a lower SRH category, while an individual from another group will leave their health rating unchanged. An index shift occurs where a characteristic leads to statistically significant coefficients that are the same in all three of the equations (Schneider *et al.*, 2012). In addition, as mentioned in section 2.3.2, the Wald test for each overall model tests the

null hypothesis that the model does not differ significantly from the REOP; in other words, it tests the validity of the parallel lines assumption for all variables in the model (Pfarr *et al.*, 2010).

Men

In the model for men, education, expenditure quintiles, and marital status cause index shifts. Education appears to have a positive effect on health: more educated respondents are increasingly more likely to report better health, compared to individuals with no education. More household resources also appear to have a favourable effect on health, which is reflected in the positive index shifts for the second to fifth expenditure quintiles of household expenditure, compared to the bottom quintile; however, the distinction between the bottom two quintiles is statistically significant only at the 10% level. Married men rate their health more positively than their unattached counterparts, while there is no significant difference between the perceptions of never married and formerly married men.

Variables with coefficients for which the parallel lines assumption does not hold drive the reporting heterogeneity in SRH. For men, apart from age and age squared, there are cut-point shifts with regard to race and location (or geographic type). As expected, the coefficients on the two age variables reflect a negative effect. The relationship is stronger and linear in the first equation (as older men are less likely to rate their health as excellent), but it weakens and accelerates slightly with age when the lower SRH categories are considered together (in the second and third equations). The positive and strongly statistically significant coefficients on the race dummy variables across the first two equations imply that Coloured and White men tend to report being in better health than the reference category, African men, with larger differences for White men. This finding is consistent with the descriptive results reported by Boyce and Harris (2011).

Table 2.4 Reporting heterogeneity in self-rated health: Men

		Dependent variable: Four-level self-rated health					
		1 vs. 2-4		1-2 vs. 3-4		1-3 vs. 4	
		Coefficient	SE	Coefficient	SE	Coefficient	SE
Age		-0.029***	(0.005)	-0.010***	(0.004)	-0.008**	(0.004)
Age squared		0.007	(0.005)	-0.009**	(0.004)	-0.010**	(0.004)
Race							
	Coloured	0.107***	(0.042)	0.080**	(0.032)	-0.029	(0.032)
	White	0.369***	(0.072)	0.138**	(0.055)	-0.075	(0.056)
Education							
	Primary	0.196***	(0.025)	0.196***	(0.025)	0.196***	(0.025)
	Secondary	0.309***	(0.030)	0.309***	(0.030)	0.309***	(0.030)
	Tertiary	0.448***	(0.066)	0.448***	(0.066)	0.448***	(0.066)
Expenditure quintiles							
	Quintile 2	0.059*	(0.030)	0.059*	(0.030)	0.059*	(0.030)
	Quintile 3	0.140***	(0.030)	0.140***	(0.030)	0.140***	(0.030)
	Quintile 4	0.118***	(0.029)	0.118***	(0.029)	0.118***	(0.029)
	Quintile 5	0.180***	(0.030)	0.180***	(0.030)	0.180***	(0.030)
Marital status							
	Married/cohabiting	0.114***	(0.025)	0.114***	(0.025)	0.114***	(0.025)
	Divorced/Separated/Widowed	0.052	(0.045)	0.052	(0.045)	0.052	(0.045)
Geo-type							
	Traditional	0.127***	(0.033)	0.027	(0.025)	-0.080***	(0.025)
	Farms	0.051	(0.032)	0.051	(0.032)	0.051	(0.032)
Chronic conditions							
	1 condition	-0.282***	(0.037)	-0.282***	(0.037)	-0.282***	(0.037)
	2 or more conditions	-0.460***	(0.030)	-0.460***	(0.030)	-0.460***	(0.030)
Other condition or disability		-0.733***	(0.043)	-0.679***	(0.045)	-0.538***	(0.057)
Regular drinker		-0.065*	(0.035)	-0.065*	(0.035)	-0.065*	(0.035)
Smoker		-0.092***	(0.019)	-0.092***	(0.019)	-0.092***	(0.019)
Exercise		0.102***	(0.019)	0.102***	(0.019)	0.102***	(0.019)
Depressed		-0.281***	(0.030)	-0.247***	(0.023)	-0.157***	(0.024)
Symptoms		-0.628***	(0.032)	-0.394***	(0.021)	-0.368***	(0.021)
Last medical consultation							
	1-4 years ago	-0.090*	(0.047)	-0.081***	(0.027)	-0.199***	(0.025)
	Within last yr	-0.670***	(0.045)	-0.472***	(0.030)	-0.405***	(0.029)
Wave							
	Wave 2	0.288***	(0.039)	0.211***	(0.030)	0.138***	(0.029)
	Wave 3	0.341***	(0.038)	0.026	(0.028)	-0.017	(0.029)
	Wave 4	0.366***	(0.037)	0.031	(0.027)	-0.020	(0.028)
Constant		2.706***	(0.119)	1.042***	(0.085)	0.193**	(0.085)
N		20489					
Rho		0.079***	(0.010)				

Source: Own calculations based on Wave 1 to 4 of NIDS

Notes: The sample consists of men aged 18 and older. Standard errors are in parentheses. *** Coefficient is statistically significant at the 1% level ($p < 0.01$), ** 5% level ($p < 0.05$), or * 10% level ($p < 0.1$).

Table 2.5 Reporting heterogeneity in self-rated health: Women

		Dependent variable: Four-level self-rated health					
		1 vs. 2-4		1-2 vs. 3-4		1-3 vs. 4	
		Coefficient	SE	Coefficient	SE	Coefficient	SE
Age		-0.030***	(0.003)	-0.013***	(0.003)	-0.015***	(0.003)
Age squared		0.009***	(0.003)	-0.006**	(0.003)	-0.002	(0.003)
Race							
	Coloured	0.154***	(0.033)	0.168***	(0.027)	0.025	(0.029)
	White	0.454***	(0.062)	0.327***	(0.049)	0.063	(0.050)
Education							
	Primary	0.200***	(0.020)	0.200***	(0.020)	0.200***	(0.020)
	Secondary	0.360***	(0.025)	0.360***	(0.025)	0.360***	(0.025)
	Tertiary	0.448***	(0.053)	0.448***	(0.053)	0.448***	(0.053)
Expenditure quintiles							
	Quintile 2	0.027	(0.022)	0.027	(0.022)	0.027	(0.022)
	Quintile 3	-0.017	(0.030)	-0.000	(0.025)	0.086***	(0.027)
	Quintile 4	0.008	(0.030)	-0.002	(0.026)	0.100***	(0.027)
	Quintile 5	0.029	(0.034)	0.059**	(0.029)	0.195***	(0.029)
Marital status							
	Married/cohabiting	0.064***	(0.018)	0.064***	(0.018)	0.064***	(0.018)
	Divorced/Separated/Widowed	0.035	(0.024)	0.035	(0.024)	0.035	(0.024)
Geo-type							
	Traditional	0.097***	(0.024)	0.082***	(0.020)	-0.029	(0.021)
	Farms	0.000	(0.043)	0.069**	(0.035)	-0.065*	(0.038)
Chronic conditions							
	1 condition	-0.253***	(0.028)	-0.253***	(0.028)	-0.253***	(0.028)
	2 or more conditions	-0.399***	(0.020)	-0.399***	(0.020)	-0.399***	(0.020)
Other condition or disability		-0.696***	(0.032)	-0.502***	(0.034)	-0.373***	(0.042)
Regular drinker		-0.128**	(0.059)	-0.128**	(0.059)	-0.128**	(0.059)
Smoker		-0.081***	(0.027)	-0.081***	(0.027)	-0.081***	(0.027)
Exercise		0.059***	(0.020)	0.059***	(0.020)	0.059***	(0.020)
Depressed		-0.300***	(0.021)	-0.221***	(0.018)	-0.131***	(0.020)
Symptoms		-0.613***	(0.025)	-0.416***	(0.017)	-0.440***	(0.018)
Last medical consultation							
	1-4 years ago	0.042	(0.040)	-0.084***	(0.026)	-0.161***	(0.026)
	Within last yr	-0.509***	(0.037)	-0.442***	(0.026)	-0.363***	(0.026)
Wave							
	Wave 2	0.234***	(0.028)	0.270***	(0.023)	0.191***	(0.025)
	Wave 3	0.365***	(0.027)	0.133***	(0.023)	0.035	(0.024)
	Wave 4	0.498***	(0.027)	0.207***	(0.022)	0.063***	(0.024)
Constant		2.638***	(0.090)	1.036***	(0.068)	0.197***	(0.070)
N		30583					
Rho		0.058***	(0.007)				

Source: Own calculations based on wave 1 to 4 of NIDS

Notes: The sample consists of women ages 18 and older. Standard errors are in parentheses. *** Coefficient is statistically significant at the 1% level ($p < 0.01$), ** 5% level ($p < 0.05$), or * 10% level ($p < 0.1$).

The cut-point shift is largest in the first equation, which means that for Coloured and White men, *ceteris paribus*, it would take a larger health deterioration for Coloured men to choose a less-than-good rating, compared to African men, and this pattern is amplified for White men. However, the differences by race are insignificant in the third equation, which juxtaposes the lowest SRH category (“fair or poor”) against those reflecting good health. Men’s reporting styles also differ with respect to location. In comparison with urban dwellers (the base category), respondents living in traditional areas (formerly termed “homelands”) tend to choose in favour of the moderate categories “good” or “very good” and avoid extremes.

Women

For women, the constrained variables (representing parallel shifts for all SRH categories) are the same as for men, with the exception of the expenditure quintile dummy variables. The health benefits of education are similar in magnitude for both genders, while marriage has a much smaller, but still significant, positive effect for women.

Reporting heterogeneity for women is driven by age, race, household expenditure, and geo type. In contrast to men, a non-linear pattern in age is evident in the first equation, which shows that women are more likely to perceive their health as “fair or poor” with age, but this effect slows over time – in other words, milder health perceptions become more pronounced with time. This is consistent with findings for South Africa that women’s healthcare costs are lower than men’s from about age 40 onwards (McLeod, 2012). McLeod offers no explanation, but a possible mechanism has to do with the likelihood of maternal healthcare costs to be incurred at younger ages, as well as the higher probability of life-threatening conditions for men, while women tend to suffer from disabling, but non-life-threatening conditions. However, when considering the top two against the bottom two SRH categories, the likelihood of women reporting worse health shows a slight acceleration with passing years. The coefficients on the race dummy variables describe a similar pattern for women as for men, although the significant associations are stronger for women. Once again, these differences are not statistically significant in the third equation.

The most notable contrast in reporting behaviours between the genders has to do with the effect of household expenditure. While being in a household that can afford greater levels of expenditure implies uniform shifts into better health categories for men, it has a weaker and heterogeneous

effect for women. This type of reporting heterogeneity for women is reflected in mostly statistically insignificant coefficients in the first two equations, but highly significant coefficients in the third equation. Hence, women who live in households with more material resources (in expenditure quintiles 2 to 5) are significantly more likely to describe their health as “excellent” than those in the poorest 20% of households (the reference category).

Compared to women living in urban areas, those living in traditional areas are more optimistic about their health, but the relationship is weaker in the second equation and not significant in the last equation. Rural women appear to avoid extremes – this is reflected in a higher probability that they choose the top two SRH categories rather than the bottom two; however, they also avoid reporting their health as “excellent”.

Considering the overall models (which include all three estimated equations or columns), for both men and women, the Wald tests fail to reject the null hypothesis that the parallel lines assumption is valid, at the 1% and 5% significance levels, but not at the 10% level. The p-value for men is 0.059 and for women it is 0.077. On the whole, the results show that the drivers of reporting bias are similar for both genders, with key distinctions regarding age, household expenditure, and location type, but the results are dominated by index shifts, rather than the more distorting cut-point shifts.

The results from the specification which includes the measured indicators for BMI and hypertension show similar patterns of reporting heterogeneity (Appendix 2.A). Regarding the overall models (incorporating all three equations or columns), the Wald test fails to reject the null hypothesis that the parallel lines assumption is valid at the 1% and 5% significance levels for women (with a p-value of 0.06) and at all conventional significance levels for men (with a p-value of 0.19). Hence, women’s reporting behaviour reflects more variability and heterogeneity, which is consistent with the international literature (Idler, 2003). The inclusion of the objective indicators reduces the goodness of fit of the overall model somewhat (with lower values for rho), which may be a reflection of the prevalence of inconsistencies in health reporting over time and the discrepancies between self-reported and measured indicators. For example, using data from Wave 1 of NIDS, Ardington and Case (2009) show that for those individuals whose blood pressure measurements were in the range indicating mild hypertension, only 49% of women and 26% of men reported ever being diagnosed with the condition by a health professional.

It is informative to note how the quasi-objective and measured indicators affect men's and women's health differently. These indicators are mainly used as controls, and so it is not appropriate to interpret them in the light of reporting heterogeneity, but there are some interesting differences between the genders in their effect on SRH. Regarding the self-reported benchmark indicators, the impacts on men and women are of similar magnitude, with the exception of chronic conditions, which appear to take a greater toll on men's health, but regular exercise benefits men more. When measured indicators are included, underweight men and women are in worse health, while being overweight has a small but significant positive effect on SRH. For women only, a BMI in the 'obese' range appears to be protective of poor health. This result is in line with the positive association between socioeconomic indicators and obesity reported by Ardington and Gasealahwe (2012), and it may stem partly from the cultural perception for Africans that a more curvaceous figure is reflective of being materially and physically better-off (Wittenberg, 2013).

2.6. Discussion

There are a number of similarities in the results for men and women. Specifically, being married leads to a positive index shift, which is smaller for women. There is also a positive index shift, with a graded effect, for higher levels of education, compared to none. The education coefficients are of similar size for men and women.

Nonetheless, the analysis confirms the importance of examining reporting heterogeneity patterns separately by gender. The results presented in Section 2.5 show that household expenditure is linked to distortionary reporting of SRH (in the form of cut-point shifts) only for women. The reporting heterogeneity related to household expenditure may reflect not only direct financial, but also physical and psychological coping mechanisms related to the availability of resources, and access to formal or informal risk-mitigating strategies (Gertler & Gruber, 2002; Havemann & Van der Berg, 2003; Jylhä, 2010). The similarities in reporting patterns by gender are in line with findings from other countries (see, for example, Zhang *et al.* (2015)), and distortionary health reporting appears to be linked to the entrenched gender and racial differentials in South African economic conditions (Posel & Rogan, 2009).

With regard to race, this study shows that differences in reporting styles – which are also identified in the studies by Boyce and Harris (2011) and Jelsma and Ferguson (2004) – are dominated by heterogeneity among women. Overall, the results in this chapter are in line with international

literature, confirming that more factors are associated with cut-point shifts in women's reporting behaviour, than in men's, as the perceptions of each gender are shaped by the differential exposure and vulnerability to a range of influences (Denton and Walters, 1999). However, the overall reporting heterogeneity results for both genders are not strongly at odds with the parallel lines assumption.

2.7. Tests for attrition bias

The test designed by Beckett, Gould, Lillard, and Welch (known as the BGLW test for attrition bias) was employed to verify the effects of attrition on the reporting heterogeneity models in Tables 2.4 and 2.5 (Beckett *et al.*, 1988). This test investigates the effects of attrition in the next period on the outcome variable in the present period. The BGLW test involves including a binary indicator for whether the respondent attrited in the subsequent wave (that is, a binary variable which equals one if the individual was not interviewed successfully for any reason, and equals zero otherwise), as well as interaction terms of this binary variable with all the regressors, into the regression results for the baseline wave (Baulch & Quisumbing, 2011). The null hypothesis of no attrition bias is equivalent to testing whether the binary attrition variable and its interaction terms with the regressors are not jointly statistically significant.

The BGLW test was conducted for each pair of consecutive waves (Wave 1 to Wave 4), as non-random patterns of (positive) attrition were recorded between Waves 1 and 2, and also between Waves 3 and 4 (Brown *et al.*, 2012; Chinhema *et al.*, 2016). In addition, the test was applied in the conventional way and in reverse for Waves 2 and 3 because of the negative attrition recorded between Wave 2 and Wave 3 of NIDS (De Villiers *et al.*, 2013). The 'reverse' test for the effect of the negative attrition between Wave 2 and Wave 3 was conducted by setting Wave 3 as the 'baseline wave' and including a binary variable for individuals who were interviewed in Wave 3 but not in Wave 2, as well as interactions of this variable with the other explanatory variables, into the regression results for Wave 3.

The BGLW test results are presented in Table 2.6. They suggest that attrition had a limited effect on the regression results. The evidence supports the null hypothesis of no attrition bias (i.e. joint insignificance of the attrition dummy variable and its interaction terms with the explanatory variables in the models) for the most part. The only exceptions are Wave 1 to Wave 2 attrition for men (at all conventional significance levels) and Wave 2 to Wave 3 attrition for women (at the 5%

and 10% significance levels, but not at the 1% level). The complete results of the BGLW test are included in Appendix 2.B.

Table 2.6 BGLW test for attrition in regression models

	Men			Women		
	Chi2	df	p-value	Chi2	df	p-value
Wave 1-2	40.840	22.000	0.009	28.329	22.000	0.165
Wave 2-3	21.117	22.000	0.514	35.155	22.000	0.037
Wave 3-2	27.107	22.000	0.207	27.029	22.000	0.210
Wave 3-4	21.937	22.000	0.464	26.068	22.000	0.249

Source: Own calculations using NIDS Waves 1 to 4 (2008; 2010-12; 2012; 2014-15).

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in are shown in parentheses.

2.8. Conclusion

Self-rated health (SRH) is “perhaps the most frequently used measure of health in the social sciences” (Denton et al, 2004: 2597). From the common health measures available in survey data, it may be conceptually and practically the closest to the broad definition of health used by the WHO (1948). However, the subjective nature of this measure puts its accuracy and reliability into question. The aim of this chapter was to establish the reliability of SRH by investigating the differences in reporting styles in a culturally and socioeconomically diverse setting such as South Africa. In contrast to previous studies for South Africa, the analysis employed the random effects generalised ordered probit (REGOPROB) iterative estimation procedure, developed by Pfarr *et al.* (2012), to identify differences in reporting behaviour in the form of index shifts and cut-point shifts when SRH is benchmarked against a set of quazi-objective (self-reported) and measured health indicators. The unbalanced panel data used was from the first four waves of the National Income Dynamics Study (NIDS), a South African nationally representative survey.

The research presented in this chapter adds to the South African literature by offering a broader view on reporting heterogeneity in SRH: it uses data with wider coverage of the population, and it considers a greater number of factors, which can contribute to differences in reporting behaviour, compared to earlier studies. In addition, by estimating separate SRH functions for men and women, it takes the intrinsic gender differences in health and in self-reporting regarding general health into account. In contrast, previous South African studies and many international studies only include gender as a control variable. From an international perspective, the study adds to the small but

growing body of evidence from developing countries on this issue, and it is one of the few that tests reporting differences using panel data.

The main findings from this chapter's empirical analysis are that some within-gender differences in reporting styles exist, but the majority are in the form of index shifts, rather than the more distorting cut-point shifts. The factors that lead to heterogeneous reporting behaviour are mostly similar for men and women. The largest differences by gender are in the role of material resources available in the household (in the form of household expenditure adjusted for household size) and in location type. Men in living in households with higher expenditure per capita quintiles exhibit large upward index shifts in health reporting. In contrast, for women, variation in household expenditure per capita is associated with cut-point shifts. In addition, location type leads to gender-distinct cut-point shifts for people living in traditional areas (formerly known as "homelands").

The gender and racial differences in reporting styles are likely to be linked, in part, to differences in knowledge and awareness about health conditions (Olgati *et al.*, 2012). Differences in rates of diagnosed conditions, rooted in historical disparities along these stratifiers, persist not least because of the dual healthcare system in South Africa (Ataguba & McIntyre, 2012). While Rossouw *et al.* (2018) find that at similar wealth levels, no significant differences in health by race remain, the results in this chapter show a cut-point shift for White and Coloured women and men, compared to Africans. This reporting distortion by race occurs in addition to considering household expenditure, which exhibits a graded index shift for men and cut-point shifts for women. The reporting heterogeneity by race possibly reflects that there are broad, cross-cultural reference groups for both women and men (Von Fintel, 2015). The larger coefficients for women may point to more importance and variability in the choices of reference groups for this group. This is broadly consistent with the gender-distinct psychosocial mechanisms linking socioeconomic conditions and health, described by Denton *et al.* (2004) and Finkel *et al.* (2016), among others.

Caution still needs to be exercised in using SRH for making cross-sectional comparisons between individuals and between groups without demographic and socioeconomic qualifiers. This also applies to seeking highly calibrated measures of the strength of the relationships between health and other factors. Nonetheless, the analysis conducted in this chapter does corroborate the reliability of SRH, especially in research based on panel data. Panel data analysis methods allow

for unobserved individual heterogeneity and reporting styles to be taken into account, provided these are time-invariant.

The analysis presented here is subject to a number of methodological and data limitations. The accuracy of the estimates distinguishing index shifts from cut-point shifts depends on the reliability of the more objective health measures used as benchmarks. All self-reported indicators may also be subject to some degree of reporting heterogeneity; nevertheless, the use of panel data may partly ameliorate this problem. Another limitation is that the reference groups that individuals have in mind when rating their health are difficult to delineate (Boyce & Harris, 2011; Von Fintel, 2015), and the REGOPROB methodology does not take the relevant reference groups into account explicitly.

Apart from measurement problems with health indicators, further data limitations apply in particular to the medical consultation variable, which does not reflect the nature or quality of care received. With regard to the measured indicators (height and weight, used in the BMI calculation, as well as blood pressure), selection bias related to missing values is a concern, since response rates were lower than those for the self-reported indicators; in addition, response rates were higher among African and Coloured respondents than among Whites.

To sum up, and as expressed by Jylhä (2009:313), “... the absence of a direct objective measure of “true health” means that there is no gold standard, no clear criterion, for the validity of self-rated health”. This applies to all self-reported measures of health used in practice. The results from this chapter’s analysis show that even in the diverse South African context, SRH is a credible measure of overall current health in longitudinal studies, but they are a reminder that separate analyses by gender should be considered and controls for socioeconomic disparities along racial, marital, material, and geographical lines should be included. The main drawback of SRH is that the relative emphasis on various health aspects differs from individual to individual. However, SRH has distinct advantages over other health indicators, both self-reported and measured, as it incorporates health aspects that the individual is aware of but that evade other measures. This property enables SRH to predict mortality even after a range of other health indicators, as well as demographic and socioeconomic characteristics are taken into account. This is explored in Chapter 3.

Appendix 2.A

Table 2.7 Reporting heterogeneity in SRH: Men (incl. measured indicators)

		Dependent variable: Four-level self-rated health					
		1 vs. 2-4		1-2 vs. 3-4		1-3 vs. 4	
		Coeff.	SE	Coeff.	SE	Coeff.	SE
Age		-0.032***	(0.006)	-0.013***	(0.004)	-0.012**	(0.005)
Age squared		0.010*	(0.006)	-0.005	(0.005)	-0.005	(0.005)
Race							
	Coloured	0.108**	(0.046)	0.079**	(0.035)	-0.011	(0.036)
	White	0.350***	(0.083)	0.109*	(0.062)	-0.124*	(0.064)
Education							
	Primary	0.165***	(0.027)	0.165***	(0.027)	0.165***	(0.027)
	Secondary	0.287***	(0.033)	0.287***	(0.033)	0.287***	(0.033)
	Tertiary	0.365***	(0.072)	0.365***	(0.072)	0.365***	(0.072)
Expenditure quintiles							
	Quintile 2	0.094***	(0.034)	0.094***	(0.034)	0.094***	(0.034)
	Quintile 3	0.182***	(0.034)	0.182***	(0.034)	0.182***	(0.034)
	Quintile 4	0.166***	(0.033)	0.166***	(0.033)	0.166***	(0.033)
	Quintile 5	0.212***	(0.034)	0.212***	(0.034)	0.212***	(0.034)
Marital status							
	Married/cohabiting	0.094***	(0.026)	0.094***	(0.026)	0.094***	(0.026)
	Divorced/Separated/Widowed	0.028	(0.049)	0.028	(0.049)	0.028	(0.049)
Geo-type							
	Traditional	0.130***	(0.036)	0.026	(0.027)	-0.064**	(0.027)
	Farms	0.059*	(0.035)	0.059*	(0.035)	0.059*	(0.035)
Chronic conditions							
	1 condition	-0.278***	(0.041)	-0.278***	(0.041)	-0.278***	(0.041)
	2 or more conditions	-0.475***	(0.034)	-0.475***	(0.034)	-0.475***	(0.034)
Other condition or disability		-0.702***	(0.049)	-0.632***	(0.050)	-0.499***	(0.063)
Regular drinker		-0.075**	(0.038)	-0.075**	(0.038)	-0.075**	(0.038)
Smoker		-0.076***	(0.021)	-0.076***	(0.021)	-0.076***	(0.021)
Exercise		0.097***	(0.021)	0.097***	(0.021)	0.097***	(0.021)
Depressed		-0.262***	(0.033)	-0.234***	(0.026)	-0.149***	(0.027)
Symptoms		-0.592***	(0.036)	-0.390***	(0.023)	-0.370***	(0.023)

Table 2.7 (continued)

		Dependent variable: Four-level self-rated health					
		1 vs. 2-4		1-2 vs. 3-4		1-3 vs. 4	
Last medical consultation							
	1-4 years ago	-0.088*	(0.053)	-0.089***	(0.031)	-0.210***	(0.028)
	Within last yr	-0.673***	(0.050)	-0.467***	(0.033)	-0.428***	(0.032)
BMI category							
	Underweight	-0.199***	(0.033)	-0.199***	(0.033)	-0.199***	(0.033)
	Overweight	0.132***	(0.039)	0.051*	(0.029)	-0.007	(0.029)
	Obese	-0.012	(0.032)	-0.012	(0.032)	-0.012	(0.032)
Hypertension		0.011	(0.088)	0.011	(0.088)	0.011	(0.088)
Wave							
	Wave 2	0.272***	(0.045)	0.206***	(0.034)	0.106***	(0.034)
	Wave 3	0.327***	(0.042)	0.043	(0.032)	-0.017	(0.032)
	Wave 4	0.362***	(0.040)	0.048	(0.031)	-0.015	(0.031)
Constant		2.758***	(0.144)	1.095***	(0.104)	0.272***	(0.105)
N		16290					
Rho		0.072***	(0.011)				

Source: Own calculations based on wave 1 to 4 of NIDS

Notes: The sample consists of men aged 20 and older. Standard errors are in parentheses. *** Coefficient is statistically significant at the 1% level ($p < 0.01$), ** 5% level ($p < 0.05$), or * 10% level ($p < 0.1$). The p-value from the Wald test of the parallel lines assumption for the final model is 0.191, hence the null hypothesis that the final model does not violate the parallel lines assumption cannot be rejected at all conventional significance levels.

Table 2.8 Reporting heterogeneity in SRH: Women (incl. measured indicators)

		Dependent variable: Four-level self-rated health					
		1 vs. 2-4		1-2 vs. 3-4		1-3 vs. 4	
		Coeff.	SE	Coeff.	SE	Coeff.	SE
Age		-0.038***	(0.004)	-0.016***	(0.003)	-0.013***	(0.004)
Age squared		0.016***	(0.004)	-0.004	(0.003)	-0.004	(0.004)
Race							
	Coloured	0.170***	(0.037)	0.144***	(0.031)	0.023	(0.032)
	White	0.432***	(0.072)	0.322***	(0.056)	0.076	(0.058)
Educ							
	Primary	0.174***	(0.021)	0.174***	(0.021)	0.174***	(0.021)
	Secondary	0.325***	(0.027)	0.325***	(0.027)	0.325***	(0.027)
	Tertiary	0.396***	(0.058)	0.396***	(0.058)	0.396***	(0.058)
Expenditure quintiles							
	Quintile 2	0.041*	(0.024)	0.041*	(0.024)	0.041*	(0.024)
	Quintile 3	-0.028	(0.033)	0.008	(0.028)	0.101***	(0.030)
	Quintile 4	0.009	(0.034)	0.006	(0.029)	0.129***	(0.030)
	Quintile 5	0.007	(0.038)	0.079**	(0.032)	0.229***	(0.033)
Marital status							
	Married/cohabiting	0.046**	(0.019)	0.046**	(0.019)	0.046**	(0.019)
	Divorced/Separated/Widowed	0.029	(0.026)	0.029	(0.026)	0.029	(0.026)
Geo-type							
	Traditional	0.066**	(0.027)	0.055**	(0.022)	-0.024	(0.023)
	Farms	-0.025	(0.047)	0.066*	(0.038)	-0.058	(0.042)
Chronic conditions							
	1 condition	-0.258***	(0.031)	-0.258***	(0.031)	-0.258***	(0.031)
	2 or more conditions	-0.403***	(0.022)	-0.403***	(0.022)	-0.403***	(0.022)
Other condition or disability		-0.685***	(0.035)	-0.506***	(0.037)	-0.401***	(0.046)
Regular drinker		-0.113*	(0.065)	-0.113*	(0.065)	-0.113*	(0.065)
Smoker		-0.076**	(0.030)	-0.076**	(0.030)	-0.076**	(0.030)
Exercise		0.045*	(0.023)	0.045*	(0.023)	0.045*	(0.023)
Depressed		-0.295***	(0.023)	-0.231***	(0.020)	-0.141***	(0.022)
Symptoms		-0.626***	(0.028)	-0.410***	(0.019)	-0.431***	(0.020)
Last medical consultation							
	1-4 years ago	-0.009	(0.045)	-0.102***	(0.030)	-0.184***	(0.029)
	Within last yr	-0.564***	(0.042)	-0.451***	(0.029)	-0.388***	(0.029)

Table 2.8 (continued)

		Dependent variable: Four-level self-rated health					
		1 vs. 2-4		1-2 vs. 3-4		1-3 vs. 4	
BMI category							
	Underweight	-0.161***	(0.041)	-0.161***	(0.041)	-0.161***	(0.041)
	Overweight	0.140***	(0.030)	0.019	(0.024)	-0.036	(0.025)
	Obese	0.123***	(0.028)	0.019	(0.023)	-0.010	(0.024)
Hypertension		-0.123**	(0.059)	-0.123**	(0.059)	-0.123**	(0.059)
Wave							
	Wave 2	0.254***	(0.032)	0.290***	(0.027)	0.192***	(0.028)
	Wave 3	0.390***	(0.030)	0.159***	(0.025)	0.055**	(0.027)
	Wave 4	0.528***	(0.030)	0.226***	(0.025)	0.089***	(0.027)
Constant		2.833***	(0.109)	1.141***	(0.083)	0.224***	(0.087)
N		24759					
Rho		0.053***	(0.008)				

Source: Own calculations based on wave 1 to 4 of NIDS

Notes: The sample consists of women aged 20 and older. Standard errors are in parentheses. *** Coefficient is statistically significant at the 1% level ($p < 0.01$), ** 5% level ($p < 0.05$), or * 10% level ($p < 0.1$). The p-value from the Wald test of parallel lines assumption for the final model is 0.061, hence the null hypothesis that the parallel lines assumption cannot be rejected at the 1% and 5% significance levels.

Appendix 2.B

Test for attrition bias

Table 2.9 BGLW test for attrition bias

Dependent variable		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Four-level SRH		W1-2 Men	W1-2 Women	W2-3 Men	W2-3 Women	W3-2 Men	W3-2 Women	W3-4 Men	W3-4 Women
Age		-0.031*** (0.008)	-0.016*** (0.005)	-0.004 (0.007)	-0.025*** (0.005)	-0.005 (0.006)	-0.013*** (0.004)	-0.007 (0.006)	-0.015*** (0.004)
Age squared		0.012 (0.008)	-0.004 (0.005)	-0.015** (0.007)	0.008 (0.005)	-0.016** (0.006)	-0.006 (0.004)	-0.014** (0.007)	-0.004 (0.005)
Race									
	Coloured	0.085 (0.068)	0.177*** (0.057)	0.058 (0.067)	0.162** (0.064)	0.038 (0.053)	0.023 (0.047)	0.007 (0.052)	0.020 (0.045)
	White	0.038 (0.098)	0.259*** (0.099)	0.248** (0.120)	0.440*** (0.108)	-0.091 (0.108)	0.092 (0.095)	-0.095 (0.101)	0.001 (0.090)
Education									
	Primary	0.149*** (0.054)	0.249*** (0.042)	0.152*** (0.055)	0.169*** (0.040)	0.161*** (0.050)	0.133*** (0.038)	0.149*** (0.050)	0.149*** (0.038)
	Secondary	0.322*** (0.066)	0.490*** (0.055)	0.224*** (0.067)	0.312*** (0.055)	0.332*** (0.061)	0.288*** (0.048)	0.340*** (0.060)	0.301*** (0.048)
	Tertiary	0.727*** (0.175)	0.724*** (0.151)	0.125 (0.146)	0.369*** (0.110)	0.539*** (0.132)	0.247** (0.109)	0.412*** (0.132)	0.313*** (0.107)
Expenditure quintiles									
	Quintile 2	-0.037 (0.069)	0.021 (0.048)	0.136* (0.077)	0.075 (0.051)	0.139** (0.059)	0.077* (0.042)	0.153** (0.060)	0.061 (0.043)
	Quintile 3	0.027 (0.067)	-0.050 (0.052)	0.202*** (0.072)	0.134*** (0.050)	0.236*** (0.057)	0.078* (0.042)	0.241*** (0.059)	0.062 (0.043)
	Quintile 4	0.030 (0.070)	0.002 (0.054)	0.144* (0.074)	0.093* (0.056)	0.173*** (0.056)	0.042 (0.043)	0.189*** (0.057)	0.033 (0.044)
	Quintile 5	0.120 (0.076)	0.062 (0.064)	0.249*** (0.074)	0.174*** (0.060)	0.241*** (0.057)	0.143*** (0.048)	0.255*** (0.058)	0.130*** (0.049)

Table 2.9 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Four-level SRH	W1-2 Men	W1-2 Women	W2-3 Men	W2-3 Women	W3-2 Men	W3-2 Women	W3-4 Men	W3-4 Women
Marital status								
Married/cohabiting	0.157*** (0.056)	0.077** (0.038)	0.120** (0.058)	0.095** (0.041)	0.158*** (0.051)	0.106*** (0.035)	0.131*** (0.049)	0.117*** (0.034)
Divorced/Separated/Widowed	0.088 (0.108)	0.022 (0.055)	0.052 (0.117)	0.045 (0.051)	0.107 (0.093)	0.090* (0.047)	0.108 (0.094)	0.090* (0.047)
Geo-type								
Traditional	0.000 (0.060)	0.068 (0.053)	-0.035 (0.062)	0.015 (0.051)	-0.041 (0.041)	-0.048 (0.032)	-0.041 (0.041)	-0.068** (0.032)
Farms	0.106 (0.076)	0.072 (0.068)	-0.176** (0.078)	-0.242*** (0.076)	0.127* (0.068)	0.015 (0.060)	0.190*** (0.067)	0.023 (0.059)
Chronic conditions								
1 condition	-0.315*** (0.089)	-0.317*** (0.062)	-0.452*** (0.098)	-0.379*** (0.080)	-0.277*** (0.068)	-0.180*** (0.051)	-0.288*** (0.069)	-0.160*** (0.050)
2 or more conditions	-0.598*** (0.078)	-0.477*** (0.046)	-0.537*** (0.076)	-0.546*** (0.047)	-0.426*** (0.060)	-0.362*** (0.038)	-0.405*** (0.061)	-0.335*** (0.039)
Other condition or disability	-0.757*** (0.082)	-0.716*** (0.065)	-0.871*** (0.115)	-0.867*** (0.102)	-0.516*** (0.082)	-0.473*** (0.058)	-0.552*** (0.082)	-0.492*** (0.057)
Regular drinker	-0.180** (0.074)	-0.250* (0.133)	-0.078 (0.078)	-0.153 (0.138)	-0.069 (0.070)	-0.113 (0.120)	-0.063 (0.069)	-0.066 (0.119)
Smoker	-0.027 (0.044)	-0.099* (0.055)	-0.070* (0.042)	0.029 (0.057)	-0.146*** (0.038)	-0.182*** (0.057)	-0.134*** (0.038)	-0.208*** (0.055)
Exercise	0.115*** (0.044)	0.053 (0.043)	0.134** (0.054)	0.026 (0.061)	0.066* (0.039)	0.103** (0.044)	0.078** (0.037)	0.092** (0.043)
Depressed	-0.138*** (0.047)	-0.208*** (0.034)	-0.339*** (0.053)	-0.220*** (0.041)	-0.128*** (0.040)	-0.107*** (0.030)	-0.119*** (0.040)	-0.089*** (0.030)
Symptoms	-0.611*** (0.046)	-0.590*** (0.039)	-0.355*** (0.041)	-0.417*** (0.037)	-0.345*** (0.036)	-0.443*** (0.029)	-0.369*** (0.035)	-0.444*** (0.029)
Last medical consultation								
1-4 years ago	-0.255*** (0.065)	-0.162*** (0.060)	-0.045 (0.060)	-0.022 (0.058)	-0.111** (0.045)	-0.110** (0.044)	-0.112** (0.044)	-0.056 (0.044)
Within last yr	-0.590*** (0.063)	-0.503*** (0.061)	-0.612*** (0.067)	-0.506*** (0.063)	-0.443*** (0.052)	-0.399*** (0.045)	-0.404*** (0.051)	-0.358*** (0.045)

Table 2.9 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Four-level SRH	W1-2 Men	W1-2 Women	W2-3 Men	W2-3 Women	W3-2 Men	W3-2 Women	W3-4 Men	W3-4 Women
A	-0.712** (0.327)	0.216 (0.293)	-0.039 (0.478)	-0.554 (0.391)	0.129 (0.401)	-0.498 (0.340)	0.489 (0.524)	-0.728* (0.437)
A*Age	0.031** (0.015)	-0.008 (0.012)	0.016 (0.020)	0.020 (0.015)	-0.005 (0.017)	0.003 (0.014)	-0.019 (0.024)	0.023 (0.018)
A*Age squared	-0.029* (0.016)	0.008 (0.013)	-0.015 (0.022)	-0.017 (0.016)	0.009 (0.019)	-0.004 (0.015)	0.023 (0.025)	-0.023 (0.019)
A*Coloured	-0.218* (0.117)	-0.101 (0.108)	-0.056 (0.177)	-0.067 (0.152)	-0.152 (0.127)	-0.047 (0.124)	-0.116 (0.174)	0.134 (0.168)
A*White	0.065 (0.143)	-0.095 (0.136)	0.309 (0.224)	-0.155 (0.192)	0.157 (0.201)	-0.168 (0.184)	-0.043 (0.248)	0.341 (0.227)
A*Married	-0.098 (0.102)	-0.079 (0.088)	-0.214 (0.156)	-0.113 (0.120)	-0.262** (0.125)	-0.014 (0.104)	-0.008 (0.185)	-0.383** (0.149)
A*Div/Sep/Wid	-0.282 (0.192)	-0.032 (0.132)	-0.399 (0.312)	0.145 (0.220)	-0.094 (0.243)	-0.066 (0.154)	0.078 (0.345)	0.010 (0.206)
A*Primary educ	0.056 (0.106)	0.013 (0.099)	-0.143 (0.161)	0.002 (0.146)	-0.064 (0.137)	0.275** (0.126)	-0.072 (0.187)	0.241 (0.170)
A*Secondary educ	-0.108 (0.119)	-0.129 (0.118)	-0.163 (0.182)	-0.001 (0.163)	-0.104 (0.156)	0.339** (0.146)	-0.176 (0.214)	0.345* (0.186)
A*Tertiary educ	-0.086 (0.252)	-0.251 (0.235)	-0.166 (0.379)	0.307 (0.274)	-0.213 (0.316)	0.508** (0.248)	0.261 (0.361)	0.193 (0.280)
A*Traditional geo type	-0.038 (0.107)	-0.116 (0.098)	-0.005 (0.136)	0.015 (0.121)	0.097 (0.117)	-0.201** (0.103)	-0.031 (0.154)	-0.074 (0.138)
A*Farms geo type	-0.149 (0.113)	-0.053 (0.123)	-0.081 (0.167)	0.381*** (0.144)	0.163 (0.190)	0.124 (0.194)	-0.279 (0.257)	-0.087 (0.310)
A*Chronic cond (one)	0.230 (0.197)	-0.154 (0.152)	-0.051 (0.260)	-0.084 (0.188)	-0.134 (0.208)	0.096 (0.167)	0.092 (0.301)	-0.262 (0.243)
A*Chronic cond (two or more)	0.101 (0.147)	-0.101 (0.105)	-0.591** (0.253)	-0.022 (0.170)	-0.268* (0.161)	0.169 (0.131)	-0.422* (0.222)	-0.111 (0.180)
A*Other condition	-0.214 (0.176)	0.040 (0.145)	-0.684** (0.334)	0.269 (0.342)	-0.422* (0.230)	-0.147 (0.176)	0.107 (0.373)	-0.193 (0.269)
A*Regular drinker	0.183 (0.134)	0.488** (0.237)	-0.020 (0.243)	-0.376 (0.299)	0.285 (0.178)	0.289 (0.309)	0.416* (0.239)	0.208 (0.441)

Table 2.9 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	W1-2 Men	W1-2 Women	W2-3 Men	W2-3 Women	W3-2 Men	W3-2 Women	W3-4 Men	W3-4 Women
Four-level SRH								
A*Smoker	-0.061 (0.080)	-0.020 (0.112)	0.005 (0.127)	-0.083 (0.163)	0.141 (0.100)	-0.067 (0.138)	-0.013 (0.134)	0.110 (0.203)
A*Exercise	-0.061 (0.085)	0.190** (0.083)	-0.141 (0.130)	0.193 (0.156)	0.041 (0.100)	-0.061 (0.115)	-0.126 (0.138)	0.002 (0.151)
A*Depressed	-0.157* (0.094)	-0.080 (0.081)	0.105 (0.137)	-0.169 (0.107)	0.015 (0.112)	0.060 (0.096)	0.188 (0.149)	-0.107 (0.128)
A*Symptoms	0.033 (0.082)	0.051 (0.074)	0.073 (0.113)	0.156 (0.105)	-0.125 (0.095)	0.024 (0.087)	0.174 (0.129)	0.199* (0.114)
A*Med consult (1-4 yrs ago)	0.249** (0.114)	0.092 (0.127)	-0.109 (0.151)	-0.157 (0.140)	-0.045 (0.119)	0.270** (0.127)	-0.080 (0.158)	-0.013 (0.158)
A*Med consult (within last yr)	0.302** (0.128)	0.170 (0.120)	0.043 (0.192)	-0.103 (0.173)	0.090 (0.133)	0.261** (0.127)	-0.161 (0.195)	0.148 (0.168)
Cut 1	-2.709*** (0.181)	-2.231*** (0.126)	-2.211*** (0.161)	-2.487*** (0.141)	-2.107*** (0.146)	-2.331*** (0.117)	-2.135*** (0.147)	-2.330*** (0.117)
Cut 2	-1.759*** (0.182)	-1.244*** (0.130)	-1.174*** (0.161)	-1.531*** (0.139)	-0.914*** (0.143)	-1.189*** (0.116)	-0.935*** (0.144)	-1.181*** (0.115)
Cut 3	-0.903*** (0.182)	-0.405*** (0.128)	-0.242 (0.162)	-0.614*** (0.137)	-0.042 (0.143)	-0.288** (0.115)	-0.058 (0.144)	-0.279** (0.115)
Observations	4,714	7,475	4,495	6,782	4,990	7,571	4,782	7,291
Log likelihood	-5417	-8598	-4940	-7839	-5836	-9052	-5599	-8737

Source: Own calculations using NIDS Waves 1 to 4 (2008; 2010-12; 2012; 2014-15).

Notes: Coefficients from ordered probit regression models with attrition dummy variables (A) and interaction terms (A*variable) are presented. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in are shown in parentheses.

Chapter 3

Self-rated health as a predictor of mortality: does gender play a role?

3.1. Introduction

The power of the most subjective health indicator, self-rated health (SRH), as an independent predictor of the most objective one – the likelihood of death – is a paradox that has puzzled researchers for at least four decades. Maddox and Douglas (1973) and Mossey and Shapiro (1982) were among the first to document it. As mentioned in the previous chapter, this predictive ability is one of the most convincing arguments for the reliability of SRH as a health indicator. Hence, “[s]elf-rated health, an individual and subjective conception that is related to the strongest biological indicator, death, constitutes a cross-road between the social world and psychological experiences on the one hand, and the biological world, on the other” (Jylhä, 2009: 308). Evidence from a diverse range of contexts, gathered over follow-up periods of varying length, has shown consistently that poor SRH remains a significant independent predictor of mortality, even after a number of other self-reported and objective health indicators, as well as socioeconomic and lifestyle factors, are taken into account (Benyamini & Idler, 1999; DeSalvo *et al.*, 2006; Idler & Benyamini, 1997).

The majority of studies have analysed this relationship in the context of high-income countries (see the review by Idler and Benyamini (1997), later updated in by Benyamini and Idler (1999), and the meta-analysis by DeSalvo *et al.* (2006)). A more recent thread in the literature is the consideration of low- and middle-income countries, where the evidence remains relatively underexplored. Further, in most studies from developing countries, the data is from elderly sub-populations: see for example, Yu *et al.* (1998) and Falk *et al.* (2017) on China; Frankenberg and Jones (2004) and Ng *et al.* (2012) on Indonesia; Hirve *et al.* (2012) on India and six Latin American countries; and Moreno *et al.* (2017) on Chile. Hence, studies from developing countries and those that consider entire populations, rather than focus only on the elderly sub-group, remain scarce.

In addition, despite a theoretical recognition that gender plays an important role on both sides of the relationship, the bulk of the literature does not examine the gender aspects of the relationship explicitly. Concerning mortality, life expectancy remains higher among women than men,

although the gap has narrowed in recent years, especially in high-income countries (Barford *et al.*, 2006; Goldin & Lleras-Muney, 2018). In addition, the process of aging differs between men and women: men tend to acquire life threatening conditions earlier on in life, while women tend to suffer from multiple non-life-threatening but disabling conditions (Finkel *et al.*, 2016; Wizeman, 2012). Concerning SRH specifically, men's and women's health evaluations differ in important ways as a result of the conditions they suffer from, and the manner in which they experience these conditions, which is filtered through their perceptions and reporting styles (as explored in the previous chapter).

To date, the only nationally-representative analysis on the relationship between SRH and mortality in South Africa is the study by Ardington and Gasealahwe (2014), which utilises data from the first two waves of the National Income Dynamics Study (NIDS) (see Chapter 1). The only other study of this kind using South African data is a comprehensive analysis by Olgiati *et al.* (2012), which explores the relationship over an eight-year horizon in a localised rural setting, controlling for a range of demographic and socioeconomic characteristics, as well as HIV status and anti-retroviral (ARV) uptake. Both studies confirm that less-than-good SRH is a reliable predictor of subsequent mortality. However, neither study interrogates the differences by gender in the relationship between SRH and mortality.

This chapter investigates the relationship between SRH and mortality in South Africa over two time horizons (two years and six years) using logistic regression models on nationally representative data from NIDS waves 1, 2, and 4⁸. The objective is to test two hypotheses. The first is that less-than-good SRH has significant predictive power for mortality in the diverse South African context, even after controlling for other self-reported and measured health indicators, as well as demographic and socioeconomic characteristics, but this predictive power is stronger for a shorter time horizon. As in the previous chapter, given the gender differences in ageing patterns and mortality, psychological and social experiences, access to economic resources, and reporting behaviour, the nature of the relationship is likely to be distinct by gender (Denton *et al.*, 2004; Finkel *et al.*, 2016). Hence, the second hypothesis to be tested is that the predictive ability of SRH

⁸ The decision to exclude wave 3 from the analysis in this chapter is discussed in section 3.3.1.

applies to both men's and women's mortality, but SRH is a more reliable and longer-term predictor for men, which is broadly consistent with international evidence.

This study contributes to the literature on the reliability of self-rated health in four ways. First, it expands the evidence from developing countries. Second, it adds evidence from a nationally representative (rather than more localised or age-restricted) dataset. Third, it considers both a shorter and a longer time horizon in exploring the relationship between SRH and mortality, in order to examine how the predictive capability of SRH changes over time and how these changes differ by gender. Fourth, it explores the gender aspects of the relationship explicitly and in more depth.

The chapter is organised as follows. The next section reviews the literature on the theoretical explanations behind the relationship, the channels through which SRH influences men's and women's mortality, as well as the international and South African empirical evidence. Section 3.3 provides an overview of the methods and key variables used, which is followed by a descriptive analysis in section 3.4 and a discussion of the empirical results in section 3.5. Lastly, section 3.6 outlines the limitations of the study and concludes.

3.2. Literature review

3.2.1 Theoretical foundation

Jylhä (2009) offers a theoretical foundation for the SRH-mortality relationship. To date, hers is the only attempt to develop a multidisciplinary model of health self-assessment, and it rises to the challenges of integrating elements from the clinical and social sciences. A starting point in understanding the usefulness and reliability of SRH as an overarching health indicator is that it reflects information that only the individual has direct access to. In essence, Jylhä's model depicts SRH as aggregating two types of inputs: objective health information (in the form of biological and neurological influences) and subjective "lenses" through which this information is processed (in the form of psychological and social context and conditioning).

Hence, Jylhä's (2009) model brings together the epidemiological and cognitive strands of knowledge to form a theoretical foundation that would be useful both for analysing the strength of the links between SRH and other health indicators (including mortality), and for understanding the underlying mechanisms of influence. The cognitive process of self-evaluation, which is depicted

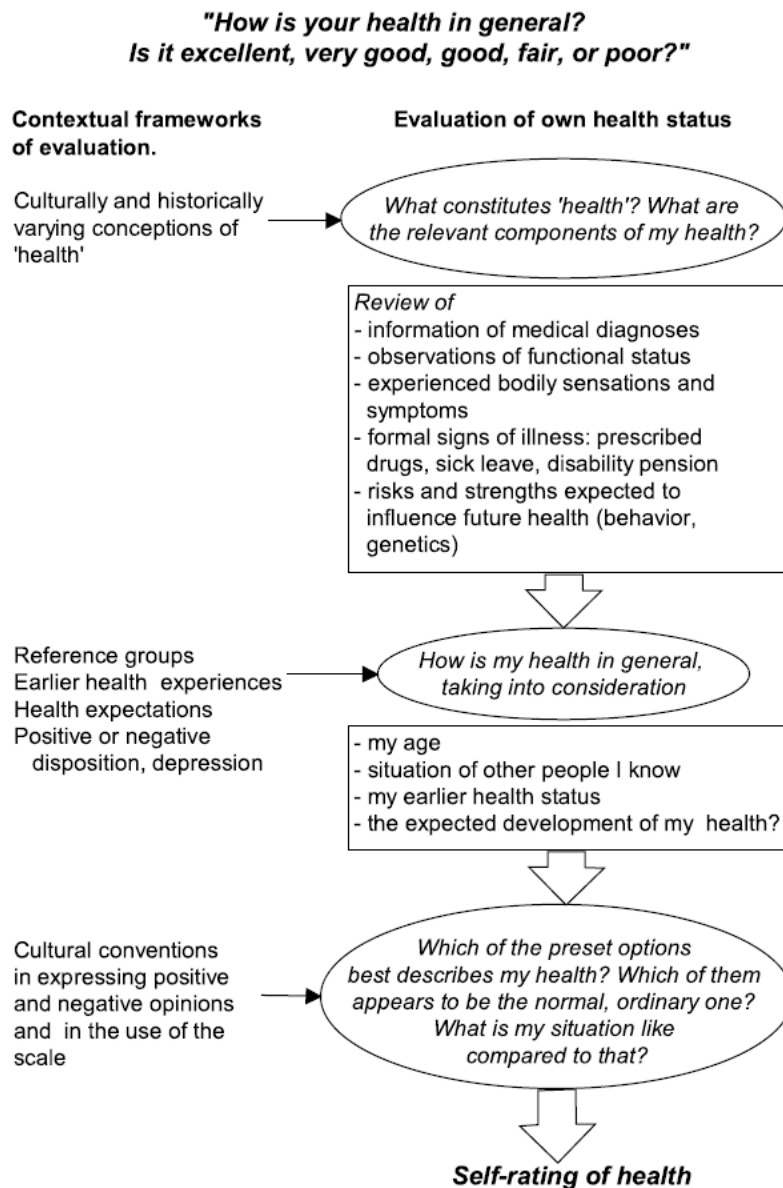
in Figure 3.1 (Jylhä, 2009), shows that an individual does not base their view on a clear definition of health, nor on a well-defined subset of its aspects. The selection of factors is not necessarily conscious, but it integrates physical, social, and cultural forces into one summary statement.

The model recognises other important aspects of health self-assessment, two of which are worth mentioning. First, good health can be regarded as “the state of normalcy, a state where nothing is wrong” (Jylhä, 2009: 310, attributing the idea to philosopher G.H. von Wright). In this sense, good health is the basis for comparison and bad health is seen as any deviation from this state. Hence, the reasons behind a less-than-good health evaluation are likely not to mirror the reasons for a good health evaluation. Reile and Leinsalu (2013) and Reile *et al.* (2017) echo this reasoning. Second, individuals’ reference frameworks are difficult to apply directly to empirical research and are often proxied by age, education, and location, for instance. Psychological disposition and personality also play a role (Moor *et al.*, 2006; Stephan *et al.*, 2020), but these are often difficult to gauge, as such data is not routinely included in large, nationally-representative surveys.

3.2.2 Hypotheses about the links between SRH and mortality – gender aspects

The distinct nature of the SRH-mortality relationship by gender is underpinned by three types of differences: in mortality risk, in the process that generates self-reports of health, and in the SRH-mortality relationship (Idler, 2003). The role of gender is disputed, however. The few studies that use data on twins present contradictory evidence on whether gender matters for the SRH-mortality relationship, once heredity is controlled for (Mosing *et al.*, 2009; Svedberg *et al.*, 2001). The majority of studies do not focus on gender differences: some use gender as a control variable, but only a few conduct separate analyses (Benyamini *et al.*, 2003; Benyamini *et al.*, 2000; Deeg & Bath, 2003). Nevertheless, the independent predictive power of poor SRH for mortality is likely to differ by gender, and its gendered aspects are evident in the light of the four reasons for the predictive power of SRH on mortality, which were put forward by Idler and Benyamini (1997), and later labelled as the following four hypotheses by Wolinsky and Tierney (1998).

Figure 4.1. Cognitive process of health self-evaluation



Source: Jylhä (2009)

The first of these, referred to as “the sponge hypothesis”, suggests that SRH, as an all-encompassing indicator, absorbs the variation that other (less accurate) indicators have left unexplained. The second, “the trajectory hypothesis”, claims that individuals’ ratings take into account the developments in their health over time and its expected progression. The third hypothesis points to the role of self-assessments as behavioural drivers, which determine health

outcomes indirectly, and is named “the intervening hypothesis”. The fourth hypothesis proposes that health outcomes depend on the availability of internal and external, tangible and intangible, sources of support, all of which are reflected in SRH, and hence it is termed “the resource hypothesis”. Each of the hypotheses and its corresponding empirical evidence is considered next. However, while the empirical evidence for the relationship overall is uncontroversial, the specific evidence in support of each specific hypothesis, and its gendered aspects, remains sketchy and inconsistent.

The sponge hypothesis

The sponge hypothesis is the least controversial, though some disagreement regarding its gendered aspects remains. A large number of studies support “the sponge hypothesis” by showing that SRH encompasses a multitude of bodily sensations and symptoms that are may be the precursors of disease, or may reflect its development after diagnosis (Benyamini, 2011; Idler & Benyamini, 1997). Consistent findings from many contexts and populations indicate that SRH correlates with self-reports of various symptoms, health conditions, and functional status (Ardington & Gasealahwe, 2014; Boerma *et al.*, 2016; Idler & Benyamini, 1999; Miilunpalo *et al.*, 1997; Singh-Manoux *et al.*, 2006), as well as biomarkers and physiological processes, some of which may not be conscious (Jylhä *et al.*, 2006; Murdock *et al.*, 2016).

SRH appears to conform to the broader definition of health by the WHO as “not merely the absence of disease or infirmity” (World Health Organization, 1948) because it taps into a self-assessment continuum between good health and illness (Bishop & Yardley, 2010). In addition, some studies point to a stronger correlation between SRH and positive affect as well as good functional status than negative such appraisals (Benyamini *et al.*, 2000; Winter *et al.*, 2007). As discussed in the previous chapter, SRH is related to a wide range of aspects of physical and mental health (Bjorner, 1996) and hence a broader range of factors influence its variability, compared to other indicators.

With regard to gender, SRH has been found to be a broader health assessment for women than for men. The evidence suggests that women take into account factors directly related to health and pay closer attention to disabling conditions, in addition to a wide range of circumstances that may have an indirect influence on health; in contrast, men’s views are shaped mainly by life-threatening conditions and adverse life events that have an immediate bearing on their physical condition (Benyamini *et al.*, 2000; Cobb & Assari, 2020; Idler, 2003).

Theoretically, the inclusion of a broader range of factors in SRH has an ambiguous effect on its predictive power. On the one hand, women's broader self-assessment is more accurate overall, therefore it may be a better predictor of mortality; on the other hand, it may weaken the SRH - mortality link because non-life-threatening or minor conditions introduce more noise (Benyamini *et al.*, 2003).

Most studies find that SRH is a weaker predictor of mortality among women than men (Benyamini *et al.*, 2003; Benyamini *et al.*, 2000; Deeg & Kriegsman, 2003). However, a study from Chile supports the opposite view (Moreno *et al.*, 2017). The study considers ten-year mortality and shows that poor SRH is a stronger predictor of mortality for women, with only a marginally weaker association when other health indicators are included in the analysis. In contrast, men who rate their health as "poor" are at a lower risk of death, with the association losing its statistical significance after other health conditions are taken into account (Moreno *et al.*, 2017). Most studies, including the one by Moreno *et al.* (2017) consider elderly sub-populations, hence it is not clear whether and to what degree the evidence applies to younger ages.

The gender differences in the factors that influence self-assessed health are further highlighted by considering complementary evaluations. For instance, Van Doorn and Kasl (1998) find evidence that wives' evaluations are better independent predictors of husbands' mortality risk than husbands' own ratings, even after controlling for SRH, other self-reported health indicators, and demographic characteristics. In contrast, husbands' such ratings of their wives' mortality risk have no independent predictive power. Van Doorn and Kasl (1998) offer three possible explanations. First, men may underreport on the other health indicators, and hence the wives' ratings fill this gap. Second, wives may have a keener awareness and an enhanced ability to communicate regarding health symptoms and conditions not only for themselves, but also for other family members, which is likely to stem from societal norms and expectations placed on women as caregivers. Third, the differences in reporting by husbands and wives may be based on the intrinsic differences in morbidity and mortality by gender – that is, women's higher likelihood of living with multiple non-lethal conditions (such as osteoporosis or arthritis), in contrast to the heightened risk of life-threatening conditions for men (such as heart disease).

The trajectory hypothesis

It is useful to understand the trajectory hypothesis as encompassing two propositions regarding individuals' perceptions: namely, a backward-looking and a forward-looking health trajectory (Miller & Wolinsky, 2007). The backward-looking trajectory proposition, which is the view that SRH incorporates the individual's perception of her health history, is supported by the scant available evidence. For example, Miller and Wolinsky (2007) find that current SRH is strongly correlated with its past values, but these past ratings exert no independent influence on mortality in addition to current SRH.

In contrast, the forward-looking health trajectory proposition, which is the view that SRH reflects how the individual expects her health to progress in the future, remains in question. Wolinsky and Tierney (1998) focus on the forward-looking trajectory hypothesis and show that the predictive power of poor SRH on adverse outcomes (such as hospitalisation and mortality) is not diminished by the inclusion of a forward-looking trajectory indicator (such as respondents' expectations of worsening health in the future). This finding suggests that SRH and subjective expectations about future health are complementary, rather than overlapping, indicators. Similarly, Bjorner and Kristensen (1999) show that SRH has a strong association with current physical health (especially with physical functioning and chronic disease), but it is only weakly associated with a future-oriented health outlook.

Nevertheless, it is clear that SRH has a dynamic nature. Some studies highlight short-run changes, which reflect daily changes in symptoms (Winter *et al.*, 2007), while others show that SRH is relatively stable over time, even in the face of adverse health developments (e.g. Wilcox *et al.* (1996)). This apparent contradiction can be explained by the phenomenon of "response shift" (Schwartz *et al.*, 2004), which was briefly discussed in Chapter 2. Response shift is a recalibration of the individual's subjective health assessment that is driven by both drastic events and gradual changes that occur with ageing, as well as possible changes in the individual's priorities regarding health (Schwartz *et al.*, 2004).

There is also credibility in the view that the trajectory hypothesis works through the impact of time preferences on health behaviours, rather than forward-looking assessments. As expected, higher subjective discount rates are associated with a range of negative outcomes (e.g. obesity), risky

behaviours (e.g. risky sexual encounters), harmful habits (e.g. smoking), and fewer preventative behaviours (such as vaccinations and mammograms) (Lawless *et al.*, 2013).

Few studies offer gender-specific insights into whether and how trajectory perceptions may be incorporated into SRH. Complementary indicators can shed some light. For example, Van Doorn and Kasl (1998) find that SRH is an independent predictor of mortality only for men. Their results lend little support to the forward-looking trajectory hypothesis, since the addition of self-rated life expectancy, an alternative health trajectory indicator, does not erode the forecasting power of SRH for men. For women, SRH has little forecasting power: it is weakly correlated with the probability of death, but loses its significance in the presence of other health status and lifestyle indicators; there is also no significant association between self-rated life expectancy and mortality. Van Doorn and Kasl speculate that both SRH and self-rated life expectancy “tap different aspects of perhaps the same but broader concept” (1998:S33); for instance, they both indicate elements of optimism or pessimism about one’s health prospects, but remain empirically distinct. A limitation of Van Doorn and Kasl’s (1998) study is the data used, which includes only respondents aged 70 and above.

It is worth noting that despite the relatively weaker empirical support for the forward-looking trajectory hypothesis relative to its backward-looking counterpart, the former may hold higher validity for younger individuals. The explanation for this is related to SRH reflecting a milder evaluation of health that individuals adopt as they age. Siegel *et al.* (2003) show that an age-related response shift in SRH may leave room for self-rated life expectancy to be an independent predictor of mortality at older ages. Siegel *et al.* (2003) compare an older sample (at least one person aged 70 and over in the household) with a middle-aged sample (at least one person aged 51 to 61 in the household). They find that self-rated life expectancy is an independent predictor of mortality (in addition to SRH) only for the older sample. It is also notable that their results for both samples do not differ substantially by gender.

The intervening hypothesis

From the four hypotheses, the intervening hypothesis is the least supported by evidence; moreover, most studies are based on cross-sectional data, preventing the establishment of causality (Benyamini, 2011). Nevertheless, the well-documented associations between SRH and health-related habits, such as smoking, alcohol consumption, physical exercise, and regular check-ups,

suggests a behavioural pathway between SRH and mortality (Mantzavinis *et al.*, 2005; Niedhammer *et al.*, 2013). Many of these associations remain even after genetic, psychological, and socioeconomic factors are taken into account (Svedberg *et al.*, 2006). Importantly, SRH may capture the individual differences in the health impact of similar behaviours. Further, behavioural intentions (for example, in the form of health goals), which drive individuals' actions, are also reflected in SRH, suggesting another pathway (Bailis *et al.*, 2003).

The testing of the intervening hypothesis is complicated by the fact that behavioural factors can be partial confounders in the relationship between SRH and mortality, i.e. personality traits, past and present habits, and behavioural intentions can affect both health perceptions and mortality. For example, negative self-attitudes to ageing are the link between the personality trait neuroticism and poor SRH (Moor *et al.*, 2006), while they are also associated with less physical activity, which heightens mortality risk among middle-aged and older adults (Wurm *et al.*, 2010).

Few studies discuss the gender aspects in the applicability of the intervening hypothesis. The little available evidence points to differences in the association of SRH with BMI (which is often seen as a proxy for nutrition and exercise habits), exercise, and smoking. While being underweight is related to poor health for both genders, high BMI, which represents obesity, is more closely linked to poor SRH for men than for women in a sample from Singapore (Lim *et al.*, 2007). Being underweight is also likely to be associated with lower SRH ratings in South Africa, as some African cultures associate being heavier with success for men and fertility for women (Wittenberg, 2013). Physical inactivity partly explains the relationship between SRH and mortality over the short term and the long term for women, but not for men (Bath, 2003). Regarding smoking, this habit has a significant association with men's poorer health ratings, but not with women's (Lim *et al.*, 2007).

The resource hypothesis

The extent to which access to material, social, and psychological resources have links with health in general, and SRH in particular, spans a large international body of literature. In the South African context, the association of SRH with material resources and disparities, both measured and perceived, is the subject of the next chapter. Specifically with respect to mortality, little attention has been directed to investigating the extent to which the resource-related information contained within SRH sharpens its ability to predict future health and mortality. The likely reason

for this is because SRH has its strongest association with physical functioning, substantially stronger than that with mental health and social functioning (Mavaddat *et al.*, 2011). Hence, the main channel of influence appears to be the degree to which resources make a difference to present physical health, rather than their expected accessibility in the future and their role in shaping other aspects of health, such as mental health. Another complication is that the resource hypothesis is likely to be intertwined with the intervening hypothesis because behavioural factors may be mediators between material and psychosocial resources on the one hand, and health on the other (Niedhammer *et al.*, 2013). Nevertheless, Benyamini *et al.* (2011) contend that expected access to all types of resources needed for health is reflected in SRH. They argue that since these expectations are difficult to measure, they contribute to the statistical connection between SRH and mortality.

As mentioned above, the various kinds of resources are likely to have differential impact on health by gender, as posited in the differential exposure and differential vulnerability hypotheses (Denton *et al.*, 2004; Denton & Walters, 1999). For Canada, Denton *et al.* (2004) find that women's health is better explained by social structural (e.g. occupation, marital status, and social support) and psychosocial (e.g. stress, trauma, and psychological resources, such as self-esteem) factors, while men's health has a closer relationship with behavioural factors (e.g. smoking and alcohol consumption) – hence, the health impact and reliance on corresponding resources differ between men and women. These links are complex, however. For example, Finkel *et al.* (2016) find evidence that marriage plays a protective role for men's health, which cushions the influence of genetic and environmental factors that cause fluctuations in SRH; in comparison, marriage is a weaker buffer against the impact of environmental factors on women's health. With regard to material resources specifically, using data from for Singapore, Lim *et al.* (2007) find that there is a link between low income and poor health only for men (without controlling for occupation), contrary to Leinsalu (2002), whose evidence for Estonia points to a stronger association with women's health, after controlling for occupation.

3.2.3 Evidence from South Africa

In South Africa, the link between SRH and mortality has received attention only recently, and in only two studies: a nationally representative analysis (Ardington & Gasealahwe, 2014) and a study from a rural demographic surveillance site (Olgiati *et al.*, 2012). Based on nationally-

representative panel data from the first two waves of the National Income Dynamics Study (NIDS) (see Chapter 1), Ardington and Gasealahwe (2014) investigate the role of SRH as a predictor of mortality over a two-year horizon using a logit model. Since death is one of the causes of attrition in the panel, NIDS provides data on whether a respondent died between waves, but more accurate information on time of death is lacking. This is the reason the authors use a logistic regression (logit) model, in line with the approach taken by Frankenberg and Jones (2004), instead of a Cox proportional hazard model, which requires accurate data on the date of death and which is more commonly used in other studies using data from developing countries (Falk *et al.*, 2017; Hirve *et al.*, 2012; Moreno *et al.*, 2017; Ng *et al.*, 2012; Yu *et al.*, 1998). Ardington and Gasealahwe (2014) find a significant and graded relationship between less-than-good SRH and the odds of death within two years, even after controlling for a range of other health indicators and socioeconomic variables. They attribute the link to the all-encompassing nature of SRH, and hence its connection to a wide range of more objective measures, as it is associated with the presence of chronic conditions, depression, difficulties with activities of daily living (ADL), and a list of minor illnesses or symptoms, but in addition, it reflects unmeasured health aspects. The study does not focus on gender differences in this relationship, but recognises their role, and hence it uses a single model with gender as a control variable (Ardington & Gasealahwe, 2014).

Olgiati *et al.* (2012) offer an analysis that is more accurate but less generalisable than Ardington and Gasealahwe's (2014). Olgiati *et al.* (2012) utilise data on the time of death and employ a Cox proportional hazards specification over a time horizon of up to eight years. The study by Olgiati *et al.* (2012) is constrained by the sub-population it is based on – it uses data from a rural area of South Africa that is designated as a demographic surveillance region (see Tanser *et al.* (2008) for more details) and the authors limit the age range to between 18 and 54. Olgiati *et al.* (2012) report that SRH strongly predicts mortality within a four-year follow-up period, even after controlling for demographic characteristics (age and gender) and socioeconomic status (years of education, employment status, marital status, household expenditure, and number of household assets), as well as HIV status and ART uptake. They find that HIV status (but not ART uptake) is reflected in SRH and this enhances its predictive power of death in the short term, which the authors define as a four-year period. Hence, controlling for HIV status and ART uptake weakens the relationship between SRH and mortality (that is, it leads to a flatter gradient across all SRH categories) but does not eliminate its independent significance in the short term. However, in the long term (which

Olgiati *et al.* (2012) define as a follow-up period of up to eight years), only the unadjusted negative association between SRH and mortality is apparent – SRH loses its statistical significance in the presence of the control variables.

Olgiati *et al.* (2012) also conduct the analysis stratified by gender and serological condition. Among those who are HIV-negative, they find that for men, SRH is an independent predictor of mortality over both the short- and long-term, while for women, there is only an association in the short term. Among HIV-positive individuals, the gender pattern is reversed: women who report “good”, “fair” or “poor” health have highly significant adjusted hazard ratios for short-term mortality, while this applies only to men who rate their health in the two lowest categories. The adjusted association remains significant over the long-term (eight-year follow-up) for HIV-positive women whose health is “fair” or “poor”, but it disappears for men. However, the null hypothesis of equal coefficients across the subsamples of men and women is not rejected and the authors do not offer an explanation of the differences by gender.

The study by Olgiati *et al.* (2012) is informative in the South African context for three reasons. First, the authors show that the association between SRH and mortality holds over long follow-up periods (up to eight years). Second, the relationship remains significant within a four-year follow-up, even after adjusting for demographic and SES characteristics, as well as after including HIV status and ARV uptake indicators. Third, the authors explore gender-specific patterns and contrasting patterns by HIV status. Among those who are HIV-negative, SRH is an independent longer-term predictor of mortality for men, while among those who are HIV-positive, this applies to women. The limitations of the study are its small geographical scope, absence of other health indicators, and its lack of data on whether respondents knew their HIV status (apart from those on ARV treatment), as the indicator variable reflects “a clinical status, but not necessarily individual awareness of serological condition” (Olgiati *et al.*, 2012: 847).

This chapter builds on and expands Ardington and Gasealahwe’s (2014) analysis. The study contributes to the literature on the independent predictive power of SRH for mortality in several ways. First, it adds to the more scarce evidence from developing countries; second, it uses a nationally representative dataset of adults, while most studies focus only on the elderly; third, it tests the relationship over two time horizons (two years and six years); and fourth, it explores the gender-distinct features of the relationship in more depth.

3.3. Methods

This chapter utilises data from selected waves of NIDS in order to investigate the link between self-rated health and mortality. The sample and estimation method, including the health measures and socioeconomic control variables, are discussed next, followed by descriptive statistics in section 3.4 and logistics regression results in section 3.5.

3.3.1 Sample

The data come from the Waves 1, 2 and 4 of the National Income Dynamics Study (NIDS), the only South African nationally representative panel survey, which has a consistent record of deceased respondents, and which contains information on their previous health status, as well as socioeconomic, demographic, and household characteristics. The data are described in more detail in Chapter 1. The sample used in this chapter is restricted to continuing sample members (CSMs)⁹ (Brown *et al.*, 2012) who are aged 18 and over; also, Asian/Indian respondents are excluded due to few observations over the time dimension of the panel.

The treatment of deceased respondents in NIDS is worth noting, as it was important in the choice of a method of analysis. Household members who have passed away between waves are recorded as deceased in the household roster during the interview for the next wave of NIDS. From a data management perspective, these respondents are regarded as lost because of attrition. Hence, the data contain no information on the precise time of death. This treatment poses limitations on choice of the method for the regression analysis (described in the next section) as well as on the accuracy of estimation. Deaths from natural causes (related to health) and non-natural causes (mostly related to accidents, violence, or crime) can be distinguished but there is a large percentage of missing values in wave 2 (about 29%) and a much smaller percentage (about 0.5%) in wave 4. Hence, the analysis in this chapter is based on the assumption that the share of deaths from non-natural causes in NIDS is roughly in line with the national share, which was between 9% and 10.5% in the 2008 – 2014 period (Statistics South Africa, 2014). This assumption is reasonable,

⁹ CSMs are the resident members of all original households selected to participate in Wave 1. CSMs include children who were living in these households and any children born to or adopted by female CSMs in the following waves. In contrast, temporary sample members (TSMs) are household members who are co-resident with CSMs from Wave 2 onwards (Brown *et al.*, 2012). The latter are excluded from the analysis in this chapter.

since the available NIDS data shows that about 7% of deaths recorded in wave 2 and 11% in wave 4 were a result of accident or violence.

The analysis in this chapter is also constrained by the lack of data on HIV/AIDS related deaths in a country afflicted with one of the highest HIV prevalence rates in the world and faced with challenges in the adherence to ARV treatment. In 2012, the estimated prevalence of HIV in South Africa was 12.2% of the population (that is, 6.4 million individuals), up from 10.6% (or 5.2 million) in 2008 (Shisana *et al.*, 2014). In wave 2 of NIDS, about 7% (or 53) deaths were recorded as caused by HIV/AIDS, while in wave 4, deaths were recorded as resulting from accident or violence or not, but data on specific reasons was not collected.

Non-random attrition for reasons other than death is another limitation of the data (Chinhema *et al.*, 2016), as respondents with unknown vital status are excluded from the analysis. For the purposes of this chapter, ‘unknown vital status’ is assigned to respondents who were not tracked, that is, whose entire households were not interviewed in a particular wave, or who were not located individually.

Table 3.1 presents a breakdown of the status of CSMs who were successfully interviewed in Wave 1. The proportions are unweighted, in order to reveal patterns of attrition for different reasons, including death. The lowest response rates are recorded in Wave 2; the overall attrition rate turns negative in Wave 3, but there is an uptick in Wave 4. In Waves 2 and 3, as expected, a larger proportion of male respondents are recorded as deceased than female. However, in Wave 4, the proportions are approximately the same, most likely due to the gradual effect of survivorship bias among the men. A male survivorship bias is likely because the leading natural causes of mortality for men for the period 2008 to 2014 remained infectious diseases (tuberculosis (TB), influenza and pneumonia, and HIV-related diseases) (Statistics South Africa, 2014). For women, the leading natural causes are similar in the 2008 – 2011 period, but these are gradually overtaken by non-communicable diseases, with diabetes mellitus and cerebrovascular diseases rising to second and third position on the list, after TB, in 2014 (Statistics South Africa, 2014). This national pattern has led to a widening gender mortality gap both in overall rates and in median ages, in contrast to the international trends mentioned above (Aburto *et al.*, 2020; Goldin & Lleras-Muney, 2019).

Table 3.1 Vital status of CSMs interviewed at Wave 1 (percentages)

Subsequent status (%)	Interviewed at Wave 1								
	at Wave 2			at Wave 3			at Wave 4		
	All	Women	Men	All	Women	Men	All	Women	Men
Alive									
Interviewed	78.846	80.148	77.276	82.456	83.791	80.842	81.854	82.826	80.675
Not interviewed	2.170	1.810	2.604	1.288	1.077	1.542	1.478	1.394	1.579
Dead	3.115	2.979	3.279	2.170	2.014	2.360	2.711	2.723	2.696
Unknown	15.869	15.064	16.841	14.086	13.118	15.257	13.957	13.057	15.050
Total	100	100	100	100	100	100	100	100	100

Source: Own calculations using NIDS Waves 1, 2 and 4.

Notes: The percentages are based on totals, which include all CSMs (adults and children). CSMs with unknown vital status are those who were not tracked or who belong to households that were not interviewed.

The overall mortality rate for the two-year period between Wave 1 and Wave 2 was 2.70%, which aligns roughly with the national mortality rates recorded by StatsSA for 2008 and 2009; however, the rate is 3.34% when the respondents with unknown vital status are excluded (Ardington & Gasealahwe, 2014). The CSM sample is affected by non-random attrition. Between Waves 1 and 2, as well as between Waves 3 and 4, the positive attrition was driven by higher rates of non-response for individuals who were White or Asian/Indian, those from the highest income decile, and those living in the Western Cape (Brown *et al.*, 2012)¹⁰. However, Wave 3 saw negative attrition due to the concerted efforts of the NIDS team to track down and interview CSMs who were not reached in Wave 2 (De Villiers *et al.*, 2013). Hence, the pattern of negative attrition between Wave 2 and 3 is the opposite, with more respondents from the groups mentioned above providing information. This discrepancy, together with the treatment of death solely as a cause of attrition in NIDS, means that two-year mortality patterns (between Wave 1 and 2) are comparable with six-year mortality patterns (between Wave 1 and 4), since they are both affected by similar groups who are less likely to respond. However, comparison with four-year mortality (between Wave 1 and 3), which is affected by negative attrition, is tenuous. This chapter, therefore, focuses on two-year and six-year mortality.

¹⁰ Since individuals in these categories were less likely to die in any given year over this period (Statistics South African, 2014), further comparisons with the national crude mortality rates for the period 2010 to 2014 would not be meaningful.

3.3.2 Logistic regression method

Logistic regression is employed to estimate the relationship between individual characteristics at baseline and two-year or six-year mortality. The models are reported separately by gender. The Cox proportional hazard model is a more commonly used methodology in similar studies; however, this approach is not feasible with the NIDS data, as the exact time of death is frequently unknown¹¹ and hence logistic regression is more suitable (see, for example, Frankenberg and Jones (2004)). In this chapter, the dependent variable in the logistic regression is an indicator of whether the respondent died within two years or within six years from the baseline, which is Wave 1 (2008). The F-test and corresponding p-value from an adjusted Hosmer-Lemeshow goodness-of-fit test (Hosmer & Lemeshow, 1980; Hosmer Jr *et al.*, 2013) are included for each model. This test compares the predicted outcomes with the observed ones in the data; it also tests whether the structure of the residuals contributes systematically to the differences between the model and the data. The conventional Pearson's chi-squared test, which is used to indicate goodness of fit in logistic regression models, is sensitive to the sample size, and hence also sensitive to the way in which the sampling weights inflate the sample to the population size. The adjusted Hosmer-Lemeshow test takes the survey design of the data into account without the distortions applicable to the Pearson's chi-squared test (Archer & Lemeshow, 2006). The null hypothesis for the Hosmer-Lemeshow F-test is that the model is specified correctly.

Apart from the variable of interest, self-rated health, a number of health indicators, as well as demographic and socio-economic characteristics, are included in the regression analysis as control variables, in order to reveal the independent predictive capacity of self-rated health on mortality. The relevant variables are described next and their measures are summarised in Tables 3.2 and 3.3.

3.3.3 Health measures

Self-rated health

As in the previous chapter, self-rated health (SRH) is reflected in the NIDS question (J1): "How would you describe your health at present? Would you say it is excellent, very good, good, fair, or poor?". For the purposes of this chapter, the distinction between the categories reflecting worst

¹¹ NIDS does contain a question about the exact date of death of a household member, but it relies on other family members' recall and a large proportion of these data are missing.

health (“fair” and “poor”) is important for understanding the relationship between SRH and mortality risk, hence the five-level SRH measure is used.

The regression analysis controls for a number of quasi-objective health indicators, which are described next. These controls relate to health conditions and behaviours that are likely to be linked to mortality directly, while environmental factors (such as living conditions in informal housing, poor sanitation, inadequate nutrition, reliance on modes of heating and cooking that causes indoor air pollution and unreliable or inconvenient access to clean water) are not incorporated for simplicity. The variables for chronic conditions, other condition or disability, regular drinker, exercise habits, and depression are defined in the same way as in Chapter 2. Regardless, brief descriptions of all variables are provided next for convenience.

Chronic conditions

This categorical variable is based on the question (J13): “Have you ever been told by a doctor, nurse, or healthcare professional that you have [...]”. Respondents could select one or more from a list of seven conditions: tuberculosis (TB), high blood pressure, diabetes, stroke, asthma, heart problems, and/or cancer. The variable used here has three categories: no known chronic conditions, exactly one, or two or more. It is worth noting that the reliability of this indicator is likely to be affected by the inconsistency of this variable with the measured indicators in NIDS and its non-negligible fluctuation between the waves (Ardington & Case, 2009; Ardington & Gasealahwe, 2014).

Other condition or disability

This binary variable draws from the follow-up question (J17) to the question about chronic conditions, which is worded as follows: “Do you have any other major illnesses or disability not mentioned above?”. Any spontaneous responses were recorded – some of the likely answers included any form of disability (e.g. sight, hearing, or speech), psychological or psychiatric disorders, HIV/AIDS, epilepsy, Alzheimer’s disease, etc. The binary indicator used in the regression analysis equals one if the respondent had one or more other condition or disability, and zero otherwise.

Regular drinker

The binary variable for a regular drinker is based only on the frequency of alcohol consumption – it is equal to one if the individual consumed alcohol three or more times per week. This variable is described in more detail in Chapter 2.

Ever smoked

This binary variable reflects whether the individual smoked cigarettes previously or smokes currently. Since this chapter analyses the probability of death, both past and current behaviour is assumed to be important (US Department of Health and Human Services, 2014).

Exercise

This variable is based on the survey question, “How regularly do you exercise?” (J25). It is a binary indicator of whether the individual exercises at least once a week. The rationale behind the construction of this variable is given in Chapter 2.

Depressed

The NIDS questionnaire allows for the assessment of mild depression, as it includes a ten-question section on emotional health, which evaluates symptoms of depression experienced in the last week. These ten questions comprise a scale, developed by the Centre for Epidemiological Studies, which is known as the CES-D10 scale (Radloff, 1977). An individual can be said to suffer from mild depression if she scores 10 or higher, out of the possible maximum 30, on the ten-question scale (Radloff, 1977). Hence, the binary indicator used in the analysis is equal to one if the CES-D10 score was 10 or higher, and zero otherwise. In addition to its validation for English-speaking individuals (Radloff, 1977), the scale has been validated for use with Zulu, Xhosa, and Afrikaans-speaking individuals in South Africa (Baron *et al.*, 2017).

Symptoms

The health section of the NIDS questionnaire also assesses short-term health through the list of 24 symptoms the respondent may have experienced in the last 30 days. This list is condensed into a binary variable, showing whether the individual experienced at least one of the symptoms.

Last medical consultation

This indicator of health-care seeking behaviour relates to the time elapsed since the respondent's last medical consultation. The variable used in the analysis reduces the eight categories the respondents were asked to choose from, into three. These are: "five or more years ago or never", "one to four years ago", and "in the last year".

Table 3.2 Self-reported health measures

Variable / Measure	Description
Vital status (dependent variable)	Binary variable, reflecting whether the respondent died between the preceding Wave and the current one 0 = alive; 1 = dead
Self-rated health (SRH)	Five-level self-reported health measure, coded as: 1 = excellent*; 2 = very good; 3 = good; 4 = fair; 5 = poor
Chronic conditions	Three-level categorical variable, based on the number of chronic conditions from a list of seven conditions (such as tuberculosis, hypertension, diabetes, asthma, and heart problems): 0 = none*; 1 = one; 2 = two or more
Other condition or disability	Binary variable: 0 = none*; 1 = at least one
Symptoms in last 30 days	Binary variable, based on the number of symptoms experienced in the last 30 days, from a list of 24 possible symptoms: 0 = none*; 1 = at least one
Exercise	Binary variable: 0 = never or infrequently*; 1 = at least once a week
Regular alcohol consumption	Binary indicator of regular alcohol consumption: 0 = never consumes alcohol or does it infrequently (less than two days a week)*; 1 = consumes alcohol regularly (at least 3 days a week)
Ever smoked	Binary indicator of whether the respondent has ever smoked cigarettes regularly or is a smoker currently: 0 = never smoked*; 1 = a regular smoker in the past or presently
Mildly depressed	Binary variable for mildly depressed using a cut-off value of 10 on the CES-D10 depression scale. A score of at least 10 is considered mildly depressed (Radloff, 1977). 0 = not depressed*; 1 = mildly depressed
Last medical consultation	Time elapsed since the last medical consultation 0 = more than five years ago or never*; 1 = one to four years ago; 2 = within the last year

Notes: *denotes the reference (base) category for categorical variables.

NIDS contains data on direct measurements of respondents' weight, height, waist circumference, and blood pressure, which were repeated twice for accuracy (Ardington & Case, 2009; Ardington

& Gasealahwe, 2012). The logistic regression analysis in this chapter is conducted first excluding and then including two measured indicators – namely, body mass index (BMI) category and hypertension. The reason for this is two-fold: data on the measured health indicators is missing more frequently than on the self-reported ones; in addition, the patterns of missing values are non-random (see Chapter 2). Hence, both the BMI and the hypertension variables contain a category for missing values.

Body mass index (BMI) categories

The body mass index (BMI) is calculated as the individual's weight (in kilograms) divided by the square of her height (in metres). It reflects nutritional status and it is more understandable when presented into four categories, in line with the WHO classification: underweight (BMI below 18.5), normal (BMI between 18.5 and 24.9), overweight (BMI between 25 and 29.9), and obese (BMI above 30). These categories are defined only for ages 20 and older (WHO, 2000). Here, for respondents with two non-missing measurements, the BMI calculation is based on the average weight and height. Observations with a BMI below 10 or above 50 in both assessments are omitted from the analysis, as these are likely the result of measurement errors. Since missing values for the measured indicators are non-random, an indicator for a missing measurement is included in the categorical variable for BMI.

Hypertension

The indicator for hypertension utilises the average of the two blood pressure measurements, where available. For the purposes of this chapter, hypertension is defined as a systolic reading above 160mmHg and/or her average diastolic reading is above 100mmHg. The guidelines of the Southern African Hypertension Society (SAHS) define these levels as the lower thresholds of Grade 2 hypertension, which requires treatment with a combination of two drugs and lifestyle changes (Seedat *et al.*, 2014). An indicator for missing readings is also included in the categorical variable for hypertension.

Table 3.3 Measured health indicators

Variable / Measure	Description	Notes
Body Mass Index (BMI)	Categorical variable, based on the BMI index: 0 = underweight ($10 < \text{BMI} < 18.5$); 1 = normal ($18.5 \leq \text{BMI} < 25$)*; 2 = overweight ($25 \leq \text{BMI} < 30$); 3 = obese ($30 \leq \text{BMI} < 50$); 4 = missing	Based on two height and weight measures done by interviewer
Hypertension	Categorical variable, based on systolic and diastolic blood pressure measurements: 0 = not hypertensive* (systolic BP ≤ 159 ; or diastolic BP ≤ 99); 1 = hypertensive (systolic BP > 160 ; or diastolic BP > 100); 2 = missing	Based on two blood pressure measures done by interviewer

Notes: *denotes the reference (base) category for categorical variables.

3.3.4 Demographic and socioeconomic characteristics

In addition to the health measures, the logistic regressions control for a number of demographic and socioeconomic characteristics, which are similar to the ones in Chapter 2. They are described again briefly for convenience. Table 3.4 contains a summary of these characteristics.

An individual's mortality likelihood is influenced by age – this may not be a linear relationship, hence, and in line with similar studies, age enters as a quadratic (Ardington & Gasealahwe, 2014; Frankenberg & Jones, 2004). The control variable for race is based on the four population groups used in South African official statistics: African, Coloured, Asian/Indian, and White. The sample size of Asian/Indian respondents who can be followed across the waves is small; hence, this population group is excluded from the analysis.

The five marital status categories available in the NIDS questionnaire are transformed into three: 'single' (never married), 'married or cohabiting', and 'divorced, separated, or widowed'. The geographic area type where the individual resides is classified as either urban, traditional, or farms. The analysis in this chapter includes a more condensed measure of education than in Chapter 2, with three levels, namely: no schooling or incomplete primary (up to 6 years of education), primary or incomplete secondary (between 7 and 11 years), and secondary or some level of tertiary (12 years of schooling or more).

The resources available to households enter in two ways: as household expenditure per capita, which is a proxy for disposable income, and as an asset index, which is a proxy for wealth. The household expenditure measure is real monthly household expenditure per capita, calculated using the derived total household expenditure variable from NIDS (imputed to cover all surveyed households (Argent, 2009)), which is adjusted for the number of household members and for inflation. All values are inflated to the price level prevailing in November 2014, the last month of interviews for Wave 4. The asset index is calculated from a count of the household's assets (from a list of possible 27 durable goods in the household questionnaire) using principal component analysis. The asset index terciles are included in the regression, where the first tercile reflects the lowest level of assets and the third the highest.

Table 3.4 Demographic and socioeconomic characteristics

Variable	Description
Age and age squared	Age in years at last birthday
Race	Coded as 1 = African*; 2 = Coloured; 3 = White (Asian/Indian respondents are omitted from the analysis due to small sample sizes across time.)
Education	Binary indicator: 0 = none or primary (up to an incomplete secondary education)*; 1 = secondary or tertiary (completed at least secondary education)
Log of household expenditure per capita	Household monthly expenditure per capita, using the variable with full imputations in the NIDS derived variables dataset, in log form
Assets	Three-level categorical variable using the terciles from an index of household assets. The index was derived using principal component analysis from a list of household assets. The first tercile* indicates the third of households with the lowest level of assets.
Geo type	Type of area the respondent lives in according to the Census 2011 classification: 1 = urban*; 2 = traditional; 3 = farms
Marital status	1 = never married*; 2 = married or cohabiting; 3 = divorced, separated or widowed

Notes: *denotes the reference (base) category for categorical variables.

3.4. Descriptive statistics

Tables 3.5, 3.6, and 3.7 show descriptive statistics, presented separately by gender and vital status. The estimation sample encompasses all observations from CSMs who provided full information on the variables of interest in Wave 1. The Wave 2 and Wave 4 vital status information was merged into Wave 1, in order to identify CSMs who are deceased within two years and within six years, as well as CSMs who cannot be tracked and whose vital status is therefore unknown. The three

tables of descriptive statistics allow for the examination of within-gender differences by vital status; t-tests are used to verify whether there are statistically significant differences between respondents who remain alive, on the one hand, and those who die or those with unknown vital status, on the other. Table 3.5 presents descriptive statistics on the self-reported health measures, Table 3.6 on the measured health indicators, and Table 3.7 on the demographic and socioeconomic characteristics.

There are substantial differences between men and women in their health, demographic, and socioeconomic characteristics – these are discussed in Chapter 2. Table 3.5 shifts the focus to the within-gender differences between respondents with different vital status (alive, dead, or unknown), in order to assess the effect of the inevitable exclusion of respondents who could not be tracked on the logistic regression results.

Considering the self-reported health measures summarised in Table 3.5, men with unknown vital status in Wave 2 or Wave 4 reported similar patterns of SRH at baseline (Wave 1), compared to those who were alive – the differences between these groups of observations are either significant only at the 10% level or statistically insignificant. At baseline, men with subsequent unknown vital status were more likely to report having no chronic conditions, no other conditions, and not having experienced any symptoms of illness in the last 30 days, compared to individuals who were known to be alive. In addition, men who could not be tracked were also significantly more likely to exercise regularly, to be non-smokers, and to be in good emotional health. Hence, it appears more probable that these respondents would have relocated within South Africa, or emigrated out of the country, rather than died, since their characteristics bear more similarity to respondents with ‘alive’ status than those who were recorded as dead.

Not surprisingly, for men who were recorded dead in Wave 2 or Wave 4, almost all indicators at baseline point to worse health, compared to those who were alive. Men who died were less likely to describe their overall health as “excellent” or “very good”, and tended more towards “fair” or “poor”. Larger proportions of men who died suffered from at least one chronic condition, as well as from other conditions or disabilities, and experienced symptoms of illness and of depression, relative to those who were alive. In addition, adverse health-related behaviours (alcohol consumption, smoking, and lack of exercise) were substantially more common among the

deceased group, and a greater proportion of this group sought medical assistance within the preceding four years.

In contrast to the men, the women with unknown vital status had significantly better self-evaluations of health than the women who were alive (and interviewed) for Wave 2 and Wave 4. The other health indicators do not confirm this better overall health evaluation for women who could not be tracked consistently. They were less likely to have been diagnosed with chronic conditions and to be depressed; and more likely to have good exercise habits. However, women with unknown vital status were also more likely to consume alcohol regularly and to have smoked.

The self-reported health indicators for women and men who died show a similar pattern of differences when compared with the corresponding groups who were alive. Two notable exceptions are with regard to depression and alcohol consumption. The proportion of deceased women with symptoms of depression was only slightly larger and differed only at the 10% significance level from that for women who were interviewed; similarly, the proportions of regular drinkers among women who were alive or died were statistically indistinguishable.

Table 3.5 Descriptive statistics for self-reported health indicators by vital status

Variable		Men			Women		
		Alive	Dead	Unknown	Alive	Dead	Unknown
Self-rated health (5-level)	Excellent [#]	0.359 (0.015)	0.203*** (0.025)	0.367 (0.028)	0.271 (0.013)	0.146*** (0.022)	0.322** (0.021)
	Very good	0.280 (0.013)	0.199*** (0.029)	0.340* (0.031)	0.248 (0.010)	0.192** (0.022)	0.294** (0.024)
	Good	0.221 (0.012)	0.225 (0.026)	0.201 (0.022)	0.260 (0.011)	0.242 (0.023)	0.244 (0.021)
	Fair	0.095 (0.008)	0.200*** (0.026)	0.064* (0.015)	0.140 (0.008)	0.246*** (0.024)	0.097*** (0.013)
	Poor	0.044 (0.005)	0.173*** (0.021)	0.028* (0.007)	0.081 (0.007)	0.173*** (0.018)	0.044*** (0.009)
Chronic conditions	None [#]	0.877 (0.011)	0.707*** (0.026)	0.906* (0.014)	0.773 (0.010)	0.643*** (0.027)	0.846*** (0.016)
	One	0.043 (0.006)	0.076** (0.012)	0.038 (0.009)	0.066 (0.006)	0.073 (0.013)	0.053 (0.011)
	At least two	0.080 (0.007)	0.217*** (0.026)	0.057* (0.009)	0.161 (0.009)	0.284*** (0.026)	0.102*** (0.013)
Other condition/disability	No [#]	0.925 (0.008)	0.877** (0.018)	0.959*** (0.008)	0.910 (0.007)	0.874** (0.018)	0.935* (0.012)
	Yes	0.075 (0.008)	0.123** (0.018)	0.041*** (0.008)	0.090 (0.007)	0.126** (0.018)	0.065* (0.012)
Symptoms	None [#]	0.464 (0.017)	0.341*** (0.033)	0.570*** (0.025)	0.348 (0.013)	0.280*** (0.027)	0.390 (0.025)
	At least one	0.536 (0.017)	0.659*** (0.033)	0.430*** (0.025)	0.652 (0.013)	0.720*** (0.027)	0.610 (0.025)
Exercise (at least once a week)	No [#]	0.595 (0.015)	0.774*** (0.026)	0.531* (0.029)	0.820 (0.012)	0.903*** (0.020)	0.709*** (0.026)
	Yes	0.405 (0.015)	0.226*** (0.026)	0.469* (0.029)	0.180 (0.012)	0.097*** (0.020)	0.291*** (0.026)

Table 3.5 (continued)

Variable		Men			Women			
		Alive	Dead	Unknown	Alive	Dead	Unknown	
Regular drinker (at least 3 days/week)	No [#]	0.943 (0.007)	0.876*** (0.022)	0.94 (0.012)	0.989 (0.003)	0.976 (0.013)	0.964** (0.011)	
	Yes	0.057 (0.007)	0.124*** (0.022)	0.060 (0.012)	0.011 (0.003)	0.024 (0.013)	0.036** (0.011)	
Ever smoked	No [#]	0.573 (0.015)	0.445*** (0.028)	0.489*** (0.030)	0.891 (0.010)	0.839** (0.026)	0.793*** (0.026)	
	Yes	0.427 (0.015)	0.555*** (0.028)	0.511*** (0.030)	0.109 (0.010)	0.161** (0.026)	0.207*** (0.026)	
Mildly depressed	No [#]	0.721 (0.015)	0.602*** (0.029)	0.788*** (0.022)	0.620 (0.013)	0.571* (0.028)	0.710*** (0.024)	
	Yes	0.279 (0.015)	0.398*** (0.029)	0.212*** (0.022)	0.380 (0.013)	0.429* (0.028)	0.290*** (0.024)	
Last medical consultation	More than 5 yrs ago or never [#]	0.227 (0.017)	0.219 (0.035)	0.186* (0.022)	0.148 (0.009)	0.103** (0.020)	0.122 (0.019)	
		0.406 (0.015)	0.285*** (0.032)	0.457 (0.033)	0.323 (0.013)	0.265** (0.026)	0.318 (0.027)	
	1 to 4 yrs ago	0.367 (0.017)	0.496*** (0.034)	0.357 (0.029)	0.529 (0.013)	0.632*** (0.025)	0.559 (0.027)	
		Within the last year						
	N		3396	701	896	5863	841	1060

Source: Own calculations based on Waves 1 (2008), 2 (2010), and 4 (2014/15) of NIDS

Notes: The sample consists of all CSMs aged 18 and over, excluding Asian/Indian respondents. *** Mean or proportion difference from those who are alive is statistically significant at the 1% level ($p < 0.01$), ** 5% level ($p < 0.05$), or * 10% level ($p < 0.1$). # denotes the omitted (base) category for categorical variables. Standard errors are shown in parentheses. Estimates are weighted using the post-stratified weights.

The measured health indicators in Table 3.6 reveal some gender-specific differences. Compared to men who were successfully interviewed in Waves 2 and 4, men with unknown vital status are less likely to be underweight, but there was no difference in the prevalence of obesity. In addition, greater proportions of the latter group were hypertensive. Refusal to have their height, weight, and blood pressure measurements taken at baseline was more frequent among men who were not tracked subsequently. Men who died were more than twice as likely to be underweight and had a greater prevalence of hypertension than those who were alive.

The proportion of underweight women among those with unknown vital status was half of that for women who were alive; however, and in contrast to men, obesity was also less prevalent. Women who were not tracked after Wave 1 were less likely to fall in the range for hypertension. Similarly to men, refusal to have measurements taken was more common among the latter group of women. Being underweight was more common among women who died and the proportion with hypertension was almost twice that of women who were alive.

On the whole, individuals with unknown vital status appeared to be healthier at baseline than both those who were interviewed in subsequent waves, and those who died. If mobility is associated with both economic and health resources, then respondents with unknown vital status were likely to be more mobile adults and therefore more likely to emigrate. Hence, even though the pattern of attrition due to non-response is not random, the regression results are likely to understate the links between SRH and mortality, since the observations from those found to be alive and those found to be deceased are closer in their characteristics than observations from individuals who could not be tracked.

Table 3.6 Descriptive statistics for measured health indicators by vital status

Variable		Men			Women		
		Alive	Dead	Unknown	Alive	Dead	Unknown
BMI	Underweight	0.069	0.149***	0.035***	0.031	0.056**	0.016**
		(0.007)	(0.020)	(0.008)	(0.004)	(0.010)	(0.006)
	Normal	0.447	0.458	0.414	0.261	0.287	0.271
		(0.017)	(0.033)	(0.030)	(0.010)	(0.024)	(0.018)
	Overweight	0.189	0.149	0.217	0.228	0.204	0.235
		(0.012)	(0.027)	(0.024)	(0.009)	(0.021)	(0.020)
	Obese	0.103	0.072*	0.117	0.320	0.305	0.234***
		(0.010)	(0.013)	(0.019)	(0.010)	(0.029)	(0.019)
Missing	0.191	0.171	0.217	0.160	0.147	0.244***	
	(0.013)	(0.022)	(0.020)	(0.010)	(0.020)	(0.020)	
Hypertension	Not hypertensive	0.826	0.755**	0.792	0.804	0.706***	0.732***
		(0.013)	(0.026)	(0.022)	(0.009)	(0.025)	(0.022)
	Hypertensive	0.085	0.133**	0.055**	0.115	0.195***	0.084**
		(0.008)	(0.018)	(0.012)	(0.006)	(0.020)	(0.013)
	Missing	0.089	0.112	0.153***	0.081	0.099	0.184***
		(0.011)	(0.020)	(0.020)	(0.008)	(0.018)	(0.021)
N		3358	692	891	5749	828	1043

Source: Own calculations based on Waves 1 (2008), 2 (2010), and 4 (2014/15) of NIDS

Notes: The sample consists of all CSMs aged 18 and over, excluding Asian/Indian respondents. *** Mean or proportion difference from those who are alive is statistically significant at the 1% level ($p < 0.01$), ** 5% level ($p < 0.05$), or * 10% level ($p < 0.1$). # denotes the omitted (base) category for categorical variables. Standard errors are shown in parentheses. Estimates are weighted using the post-stratified weights.

Some distinct gender patterns are evident in the demographic and socioeconomic characteristics, presented in Table 3.7, too. As expected, men were more likely to die. On average, a smaller proportion of men had no education and a larger proportion were single or married, while the previously married categories applied to a bigger percentage of women. Men also appeared to have greater access to resources (in terms of both household expenditure and assets) than women.

A typical man with unknown vital status in Wave 2 or Wave 4 was white, previously married, had a secondary or tertiary education, and lived in a relatively well-off household (in terms of both per capita expenditure and assets), which was based in an urban or commercial farm area. Compared to the average woman who was alive, a typical woman with unknown vital status had similar characteristics to that of a man with that status, except she was younger, coloured or white, married, and lives in an urban area.

Larger proportions of both men and women who died were older, had no education, and lived in less wealthy households (in terms of assets). They were also more likely to be based in a traditional rather than an urban, area. Gender differences were present in per capita household expenditure and marital status. Deceased men were more likely to be married and to live in households with much lower than average expenditure, while deceased women were more likely to be previously married. This difference is to be expected, since women are more likely to be widowed, given their persistently longer life expectancy in South Africa.

3.5. Results

In the logistic regressions presented in Table 3.8, Table 3.9, and Table 3.10, the dependent variable is whether the respondent is alive or deceased within two years or six years of their first interview in 2008 (hence, respondents with unknown vital status are omitted from the analysis). The explanatory variable of primary interest is SRH.

Table 3.7 Descriptive statistics for demographic and socioeconomic indicators by vital status

Variable		Men			Women		
		Alive	Dead	Unknown	Alive	Dead	Unknown
Overall proportion		0.667 (0.016)	0.114 (0.006)	0.218 (0.016)	0.728 (0.012)	0.090 (0.004)	0.182 (0.011)
Age		36.491 (0.501)	48.614*** (1.140)	35.942 (0.623)	38.482 (0.348)	49.547*** (0.884)	36.945** (0.725)
Race	African	0.847 (0.020)	0.830 (0.030)	0.649*** (0.040)	0.846 (0.019)	0.840 (0.028)	0.571*** (0.042)
		0.074 (0.012)	0.072 (0.014)	0.105 (0.024)	0.079 (0.014)	0.079 (0.015)	0.128** (0.025)
	Coloured	0.079 (0.016)	0.098 (0.028)	0.246*** (0.036)	0.075 (0.014)	0.081 (0.025)	0.301*** (0.043)
	White						
Education	None	0.202 (0.012)	0.440*** (0.030)	0.149** (0.021)	0.244 (0.011)	0.405*** (0.023)	0.126*** (0.017)
	Primary/Incomplete secondary	0.48 (0.016)	0.384** (0.033)	0.395*** (0.028)	0.469 (0.011)	0.429 (0.027)	0.428 (0.028)
	Complete secondary/Tertiary	0.318 (0.018)	0.175*** (0.026)	0.456*** (0.035)	0.286 (0.013)	0.166*** (0.028)	0.445*** (0.031)
Per capita hh expenditure		2,394.411 (291.773)	1,721.273** (210.749)	4,202.013*** (555.887)	1,711.894 (155.989)	1,339.165 (302.514)	4,716.928*** (742.077)
Asset index	First (lowest) tercile	0.294 (0.020)	0.399*** (0.034)	0.279 (0.030)	0.292 (0.016)	0.357*** (0.027)	0.212*** (0.027)
	Second tercile	0.323 (0.017)	0.308 (0.033)	0.236*** (0.030)	0.340 (0.015)	0.389* (0.030)	0.212*** (0.025)
	Third (highest) tercile	0.383 (0.020)	0.293*** (0.032)	0.485*** (0.039)	0.367 (0.018)	0.255*** (0.030)	0.576*** (0.038)
Geo type	Urban	0.638 (0.027)	0.568** (0.038)	0.751*** (0.031)	0.588 (0.027)	0.536** (0.036)	0.791*** (0.030)
	Traditional	0.306 (0.026)	0.380** (0.038)	0.156*** (0.026)	0.375 (0.026)	0.423** (0.035)	0.157*** (0.028)
	Farms	0.056 (0.012)	0.051 (0.013)	0.093** (0.017)	0.037 (0.007)	0.041 (0.009)	0.052 (0.012)

Table 3.7 (continued)

Variable	Men			Women		
	Alive	Dead	Unknown	Alive	Dead	Unknown
Marital status	Never married	0.514	0.365***	0.448**	0.433	0.343***
		(0.017)	(0.029)	(0.033)	(0.013)	(0.029)
	Married/cohabiting	0.449	0.520**	0.487	0.421	0.342***
		(0.016)	(0.032)	(0.033)	(0.011)	(0.030)
	Divorced/separated/widowed	0.037	0.115***	0.065**	0.147	0.315***
		(0.005)	(0.017)	(0.013)	(0.007)	(0.023)
N	3396	701	896	5863	841	1060

Source: Own calculations based on Waves 1 (2008), 2 (2010), and 4 (2014/15) of NIDS

Notes: The sample consists of all CSMs aged 18 and over, excluding Asian/Indian respondents. *** Mean or proportion difference from those who are alive is statistically significant at the 1% level ($p < 0.01$), ** 5% level ($p < 0.05$), or * 10% level ($p < 0.1$). # denotes the omitted (base) category for categorical variables. Standard errors are shown in parentheses. Estimates are weighted using the post-stratified weight.

The results of three models are reported. Model 1 presents the age-adjusted association between SRH and mortality. Model 2 and Model 3 show the independent predictive power of SRH for mortality. Model 2 includes the other self-reported health measures, possibly deemed more objective than SRH, and controls for individual demographic and socioeconomic characteristics. Model 3 further adds the measured health indicators for BMI and hypertension. As discussed above, the regressions are conducted separately by gender.

Table 3.8 presents the two-year mortality logistic regression results for Model 1 and Model 2. The first and third columns show the two-year mortality odds in relation to SRH, adjusted only for age. For both men and women, “fair” or “poor” SRH is associated with a graded increase in mortality risk in the two-year period between Wave 1 and Wave 2, compared to “excellent” health at baseline (in Wave 1), but the relationship is stronger for men.

Model 2 (presented in the second and fourth columns) shows that the odds of death within two years for men in “fair” or “poor” health at baseline are 2.2 and 2.3 times greater, respectively, than for those whose perceived health was “excellent”, even after taking other self-reported health measures into account and after controlling for demographic and socioeconomic characteristics. For women, the statistically significant rise in two-year mortality risk is only related to those who rated their health as “poor” at baseline – their mortality odds are twice those of women who rated their health as “excellent” – and only significant at the 10% level.

Men living with two or more chronic conditions have heightened odds of death within two years, but good exercise habits have a protective effect. For women, being married and living in a relatively wealthy household (at the highest tercile of the asset index) reduce the mortality odds (though the coefficients for these characteristics are only significant at the 10% level), while smoking (currently or in the past) heightens these odds. Despite the higher prevalence of depression among women in most countries, including South Africa (Culbertson, 1997; Thapa *et al.*, 2014), there is an uptick in the two-year mortality odds for men who scored 10 or higher on the CES-D scale, which is significant at the 5% level, but no effect for women.

Table 3.8 Logistic regression of two-year mortality including self-reported health indicators only

Dep var: deceased in ... years		Men		Women	
		Two years Model 1	Two years Model 2	Two years Model 1	Two years Model 2
SRH					
	Very good	1.472 (0.454)	1.359 (0.411)	1.144 (0.334)	1.013 (0.305)
	Good	1.681 (0.543)	1.236 (0.442)	1.510 (0.426)	1.202 (0.340)
	Fair	3.549*** (1.154)	2.226** (0.714)	2.194** (0.689)	1.578 (0.530)
	Poor	4.698*** (1.477)	2.230** (0.708)	3.311*** (1.027)	1.985* (0.706)
Age		1.015 (0.033)	1.020 (0.038)	0.998 (0.018)	1.021 (0.022)
Age squared x 100		1.006 (0.032)	1.005 (0.037)	1.022 (0.017)	0.997 (0.019)
Race					
	Coloured		0.801 (0.259)		0.796 (0.280)
	White		0.877 (0.659)		0.517 (0.419)
Education					
	Primary		1.108 (0.291)		1.330 (0.337)
	Secondary or tertiary		1.088 (0.433)		0.814 (0.306)
Marital status					
	Married		0.675 (0.162)		0.665* (0.158)
	Div/Sep/Widowed		0.771 (0.300)		1.418 (0.338)
Geo type					
	Traditional		1.008 (0.195)		0.938 (0.202)
	Farms		0.878 (0.280)		0.848 (0.355)
Log PC HH expenditure			0.982 (0.117)		0.820 (0.119)
Assets terciles					
	Second tercile		0.899 (0.194)		1.126 (0.219)
	Third (highest) tercile		0.838 (0.248)		0.607* (0.173)

Source: Own calculations based on NIDS Wave 1 (2008), 2 (2010), and 4 (2014/15).

Notes: Odds ratios are reported. The estimated are weighted. Standard errors are in parentheses.

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

Table 3.8 (continued)

Dep var: deceased in ... years	Men		Women	
	Two years Model 1	Two years Model 2	Two years Model 1	Two years Model 2
Chronic conditions				
One		1.275 (0.407)		0.805 (0.294)
Two or more		1.877** (0.508)		1.118 (0.260)
Other conditions/disabilities		1.155 (0.332)		1.053 (0.251)
Symptoms in last 30 days (at least one)		1.556 (0.431)		0.947 (0.197)
Exercise at least once/wk		0.505** (0.147)		0.738 (0.253)
Regular alcohol consumption		1.281 (0.525)		0.494 (0.300)
Smoking		1.101 (0.210)		1.806** (0.536)
Depressed		1.352* (0.237)		0.984 (0.179)
Last medical consultation				
1 to 4 years ago		0.642 (0.201)		1.159 (0.406)
Within the last year		0.711 (0.177)		1.408 (0.412)
Constant	0.015*** (0.012)	0.021*** (0.023)	0.014*** (0.006)	0.038*** (0.039)
N	14,691	14,330	15,362	14,849
Adj. F-stat	6.470	9.379	2.020	2.168
Prob>F	0.000	0.000	0.037	0.024

Source: Own calculations based on NIDS Wave 1 (2008), 2 (2010), and 4 (2014/15).

Notes: Odds ratios are reported. The estimated are weighted. Standard errors are in parentheses.

*** p < 0.01, ** p < 0.05, * p < 0.1. Adjusted F-statistic and p-value are reported for the Hosmer-Lemeshow goodness-of-fit test.

The p-values of the Hosmer-Lemeshow goodness-of-fit test indicate that the null hypothesis (which states that the model is correctly specified) cannot be rejected only for the models for women in the third and fourth columns, at the 1% level of significance. The models for men are a poorer reflection of the data.

The logistic regression results for six-year mortality are reported in Table 3.9. The association adjusted only for age shows that rating one's health as "poor" is predictive of men's longer-term mortality, but not women's. After including the other health indicators and controlling for demographic and socioeconomic characteristics, women's baseline ratings are not predictive of mortality over a six-year period (between Wave 1 and Wave 4), while men's "poor" health ratings still hold predictive power, which is statistically significant at the 5% level. The odds of dying within six years for men who perceive themselves to be in "poor" health are 3.4 times higher than for men in "excellent" health, all else equal.

Education is expected to enhance health through a number of channels (Cutler & Lleras-Muney, 2006). While the results in Table 3.8 do not point to any short-term (two-year) reduction in mortality risk, Table 3.9 shows that there are likely to be longer-term (six-year) benefits of having completed primary education for men. Contrary to expectations, however, the odds of death over a six-year horizon are higher for women with secondary or tertiary education, compared to those with no education, but this coefficient is only statistically significant at the 10% level.

For both men or women, marriage does not confer a longer-term protective effect. There is also no excess mortality risk independently associated with geo type or the material circumstances of the household that the individual resides in.

The health indicators are more predictive of mortality than the demographic and socio-economic characteristics, which may suggest that the demographic and socio-economic characteristics are absorbed in the health indicators, especially in SRH. For men, living with one chronic condition has a protective effect over the six-year term, compared to men who reported no diagnosed chronic conditions. This appears counter-intuitive, but may be related to the lack of awareness of chronic illnesses, especially for men who are less likely to engage in health-seeking behaviour than women, in a setting where access to healthcare and the quality of healthcare available for the majority of the population leave much room for improvement (Burger & Christian, 2020). Hence,

men living with one chronic illness may lead healthier lifestyles and seek appropriate treatment, compared to those with no known chronic conditions.

Compared to individuals with irregular or infrequent exercise habits, exercising at least once a week has a protective effect for men over the two-year time horizon, halving their odds of death. The protective effect for women is over the longer term, reducing their six-year mortality odds by just over a half, though this coefficient is only significant at the 10% level.

Alcohol consumption at least three days a week raises men's six-year mortality odds by a factor of 2.5, compared to men who never drink, or do so infrequently. Smoking cigarettes or having been a regular smoker in the past has a larger negative effect on women than on men. It heightens women's two-year and six-year mortality risks, while its consequences appear only over the longer-term horizon for men.

None of the models in Table 3.9 appear to fit the data well. The null hypothesis of the Hosmer-Lemeshow goodness-of-fit test cannot be rejected, at the 1% level of significance, only for the model for women with more covariates in the fourth column.

Table 3.9 Logistic regression of six-year mortality including self-reported health indicators only

Dep var: deceased in ... years		Men		Women	
		Six years Model 1	Six years Model 2	Six years Model 1	Six years Model 2
SRH					
	Very good	0.936 (0.308)	0.908 (0.327)	0.970 (0.363)	0.981 (0.356)
	Good	1.012 (0.289)	1.057 (0.346)	1.129 (0.425)	0.983 (0.382)
	Fair	1.552 (0.429)	1.463 (0.531)	1.604 (0.685)	1.186 (0.552)
	Poor	3.728*** (1.460)	3.393** (1.687)	1.833 (0.720)	1.471 (0.685)
Age		0.937* (0.034)	0.900** (0.042)	0.995 (0.027)	1.000 (0.031)
Age squared x 100		1.130*** (0.044)	1.181*** (0.052)	1.047* (0.026)	1.050* (0.030)
Race					
	Coloured		1.257 (0.440)		0.758 (0.222)
	White		0.860 (0.474)		0.676 (0.405)
Education					
	Primary		0.573** (0.162)		1.430 (0.335)
	Secondary or tertiary		0.640 (0.256)		2.105* (0.860)
Marital status					
	Married		0.740 (0.253)		0.985 (0.289)
	Div/Sep/Widowed		1.359 (0.708)		0.901 (0.253)
Geo type					
	Traditional		1.414 (0.382)		0.989 (0.213)
	Farms		0.729 (0.288)		0.755 (0.240)
Log PC HH expenditure			0.873 (0.093)		1.068 (0.135)
Assets terciles					
	Second tercile		0.983 (0.263)		1.062 (0.236)
	Third (highest) tercile		1.118 (0.324)		0.604 (0.209)

Table 3.9 (continued)

Dep var: deceased in ... years	Men		Women	
	Six years Model 1	Six years Model 2	Six years Model 1	Six years Model 2
Chronic conditions				
One		0.367** (0.165)		1.001 (0.320)
Two or more		0.825 (0.242)		1.444 (0.389)
Other conditions/disabilities		0.617 (0.230)		1.416 (0.598)
Symptoms in last 30 days (at least one)		0.861 (0.216)		1.427 (0.354)
Exercise at least once/wk		0.840 (0.228)		0.459* (0.192)
Regular alcohol consumption		2.539*** (0.777)		0.736 (0.439)
Smoking		1.580** (0.347)		1.932** (0.580)
Score on CES-D depression scale		1.351 (0.356)		0.910 (0.142)
Last medical consultation				
1 to 4 years ago		0.837 (0.249)		1.148 (0.469)
Within the last year		1.060 (0.336)		0.892 (0.419)
Constant	0.040*** (0.032)	0.250 (0.322)	0.013*** (0.007)	0.005*** (0.006)
N	14,180	13,852	14,805	14,323
Adj. F-stat	4.451	5.400	3.631	2.409
Prob>F	0.000	0.000	0.000	0.012

Source: Own calculations based on NIDS Wave 1 (2008), 2 (2010), and 4 (2014/15).

Notes: Odds ratios are reported. The estimated are weighted. Standard errors are in parentheses.

*** p < 0.01, ** p < 0.05, * p < 0.1. Adjusted F-statistic and p-value are reported for the Hosmer-Lemeshow goodness-of-fit test.

Including the measured health indicators in the logistic regression specification does not alter the results substantially, but reveals more distinct gender patterns. In relation to two-year mortality for men, “fair” or “poor” SRH is still independently predictive of mortality, but the relationships are weaker than in Model 2. For women, including the measured indicators eliminates the independent predictive power of SRH. These findings are in line with international evidence that SRH is a broader measure, encompassing various aspects of health for women, while for men, it incorporates mostly physical aspects (Benyamini *et al.*, 2003; Benyamini *et al.*, 2000; Deeg & Kriegsman, 2003).

The results of Model 3 reflect gender differences with regard to education, marital status, wealth, and some of the health indicators: specifically chronic conditions, recent symptoms, exercise, smoking, depression, and BMI. As with the Model 2 results, primary education reduces the short-term mortality risk for men, but has no effect for women. Marital status matters only for women’s two-year mortality: the risk is lower for married women, while those who are previously married face a heightened risk. Living in a household that is among the wealthiest third is also protective for women.

With regard to the health indicators, suffering from two or more chronic conditions and experiencing recent symptoms of illness worsens men’s mortality odds, as do being depressed or underweight. Good exercise habits or being obese appear to be protective for men within a two-year horizon. Surprisingly, the coefficient on ‘obese’ is only significant at the 10% level. For women, however, these factors have no independent influence. In Model 3, a present or past smoking habit is the only health indicator with independent predictive power for women’s two-year mortality.

In the six-year mortality model, SRH holds its predictive power only for men who described their health as “poor” at baseline (Wave 1). Education appears to heighten mortality risk for women with completed secondary or tertiary qualifications, but this coefficient is significant only at the 10% level. The effects of the health indicators differ by gender. Smoking is the only exception – it is likely to be harmful to all individuals, but carries a bigger risk for women. The independent benefits of regular exercise extend only to women over the six-year horizon. For men, living with one chronic condition appears to be protective (also shown in Model 2). Being overweight also reduces the mortality odds, though this result is only weakly significant. The latter finding, though

surprising on the surface, may fit into the South African context where weight is considered a symbol of prosperity in some cultural settings (Wittenberg, 2013).

Similarly to the other models, the results for women in Table 3.10 fit the data better than those for men. In particular, the Hosmer-Lemeshow test indicates that the more extensive six-year mortality model for women in the fourth column is correctly specified at all conventional significance levels.

3.6. Conclusion

A substantial argument in favour of the purely subjective SRH as a overall health self-assessment is its independent ability to predict mortality, even when used in addition to a range of more objective health measures, such as indicators of chronic conditions, functioning limitations, healthcare utilisation, smoking, and alcohol consumption, among others (Ardington & Gasealahwe, 2014; DeSalvo *et al.*, 2006; Idler & Benyamini, 1997). This chapter presents evidence that this kind of relationship between SRH and mortality also exists in South Africa. The study uses nationally representative data from NIDS Waves 1, 2 and 4 and includes all adults (aged at least 18 years), in contrast with most similar studies, which focus on the elderly subset of the population. Two follow-up periods, two years and six years, are analysed, which adds to the evidence on distinguishing the shorter- and longer-term features of this relationship for developing countries more broadly and for South Africa in particular. The analysis is conducted separately by gender, in order to highlight differences in the aspects of health captured by SRH for men and women.

The logistic regressions indicate that less-than-good SRH has significant predictive power for both men's and women's mortality, but it is a more reliable and a longer-term predictor for men, which is broadly consistent with international evidence. SRH remains an independent predictor for men, even after controlling for a range of demographic and socioeconomic characteristics and other health indicators, both self-reported and measured. This finding is driven by the gender gap in mortality, which shows no signs of closing for the South African population. It is also driven by the gender differences in the aspects of health that SRH reflects – it captures mainly physical health for men, while it is a broader, all-encompassing health indicator for women.

Table 3.10 Logistic regression of two-year and six-year mortality including self-reported and measured health indicators

Dep var: deceased in ... years		Men		Women	
		Two years Model 3	Six years Model 3	Two years Model 3	Six years Model 3
SRH					
	Very good	1.361 (0.418)	0.911 (0.333)	0.988 (0.297)	0.975 (0.365)
	Good	1.173 (0.414)	1.026 (0.339)	1.167 (0.327)	0.994 (0.396)
	Fair	1.857* (0.586)	1.288 (0.476)	1.337 (0.459)	1.169 (0.562)
	Poor	1.995** (0.612)	3.157** (1.581)	1.729 (0.618)	1.481 (0.698)
Age		1.038 (0.035)	0.917* (0.047)	1.021 (0.024)	1.010 (0.033)
Age squared x 100		0.986 (0.033)	1.163*** (0.055)	0.996 (0.022)	1.039 (0.031)
Race					
	Coloured	0.727 (0.232)	1.221 (0.432)	0.870 (0.307)	0.742 (0.220)
	White	0.875 (0.705)	0.652 (0.363)	0.755 (0.569)	0.653 (0.394)
Education					
	Primary	1.129 (0.289)	0.570* (0.164)	1.280 (0.310)	1.442 (0.334)
	Secondary or tertiary	1.066 (0.437)	0.695 (0.280)	0.825 (0.319)	2.126* (0.875)
Marital status					
	Married	0.712 (0.174)	0.752 (0.264)	0.635* (0.162)	1.034 (0.300)
	Div/Sep/Widowed	0.809 (0.319)	1.394 (0.736)	1.607* (0.396)	0.929 (0.258)
Geo type					
	Traditional	1.058 (0.205)	1.380 (0.370)	0.981 (0.216)	1.015 (0.225)
	Farms	0.881 (0.287)	0.702 (0.282)	0.857 (0.359)	0.770 (0.247)
Log PC HH expenditure		1.036 (0.132)	0.901 (0.090)	0.795 (0.120)	1.069 (0.136)
Assets terciles					
	Second tercile	0.900 (0.193)	0.967 (0.259)	1.216 (0.232)	1.103 (0.264)
	Third tercile	0.909 (0.276)	1.172 (0.346)	0.549** (0.158)	0.630 (0.232)

Table 3.10 (continued)

Dep var: deceased in ... years	Men		Women	
	Two years Model 3	Six years Model 3	Two years Model 3	Six years Model 3
Chronic conditions				
One	1.150 (0.369)	0.384** (0.163)	0.815 (0.313)	1.015 (0.330)
Two or more	2.070*** (0.563)	0.897 (0.271)	1.028 (0.257)	1.514 (0.396)
Other conditions/disabilities	1.153 (0.331)	0.617 (0.227)	1.133 (0.259)	1.444 (0.620)
Symptoms in last 30 days (at least one)	1.707** (0.441)	0.819 (0.206)	0.930 (0.193)	1.428 (0.360)
Exercise at least once/wk	0.460** (0.145)	0.826 (0.229)	0.814 (0.275)	0.449* (0.185)
Regular alcohol consumption	1.247 (0.522)	2.519*** (0.762)	0.480 (0.292)	0.760 (0.464)
Smoking	1.005 (0.210)	1.467* (0.314)	1.763* (0.542)	1.812** (0.537)
Depressed	1.406* (0.245)	1.346 (0.353)	1.076 (0.185)	0.921 (0.149)
Last medical consultation				
1 to 4 years ago	0.677 (0.215)	0.827 (0.253)	1.229 (0.428)	1.135 (0.476)
Within the last year	0.684 (0.176)	1.117 (0.359)	1.458 (0.428)	0.890 (0.430)
BMI				
Underweight	2.489*** (0.736)	1.258 (0.364)	1.593 (0.554)	1.756 (0.671)
Overweight	0.860 (0.336)	0.554* (0.177)	0.925 (0.226)	0.850 (0.245)
Obese	0.531* (0.195)	0.700 (0.306)	0.685 (0.174)	0.834 (0.261)
Missing	1.486 (0.523)	1.344 (0.556)	0.910 (0.316)	1.020 (0.316)
Hypertension				
Yes	1.161 (0.358)	0.707 (0.212)	1.294 (0.308)	1.146 (0.255)
Missing	0.974 (0.442)	0.614 (0.297)	0.609 (0.248)	1.279 (0.429)
Constant	0.009*** (0.010)	0.149 (0.207)	0.049*** (0.048)	0.004*** (0.005)
N	14,278	13,806	14,705	14,188
Adj. F-stat	4.933	3.806	2.517	1.183
Prob>F	0.000	0.000	0.008	0.305

Source: Own calculations based on NIDS Wave 1 (2008), 2 (2010), and 4 (2014/15).

Notes: Odds ratios are reported. The estimated are weighted. Standard errors are in parentheses.

*** p < 0.01, ** p < 0.05, * p < 0.1. Adjusted F-statistic and p-value are reported for the Hosmer-Lemeshow goodness-of-fit test.

In this study, the two follow-up periods, two years and six years, highlight how the gender distinct aspects of SRH are reflected over different time horizons. SRH has stronger links with mortality in the shorter follow-up period, where it is an independent predictor for both men and women even after individual characteristics, as well as a number of other self-reported health indicators are taken into account. Once measured health indicators are included, the independent SRH-mortality association for women becomes insignificant over both time horizons. In contrast, the link remains over the two-year horizon for men in “fair” or “poor” health, and over the six-year horizon for men in “poor” health.

On the whole, the results imply that the “sponge hypothesis” may hold more relevance for women’s SRH than men’s. This hypothesis suggests that SRH encompasses a broad range of conditions and bodily sensations, including some that evade medical diagnosis. An extended version of the hypothesis points to women’s self-assessments containing aspects of both physical and emotional health, while men’s self-assessments focussing on physical conditions, which are more likely to be life threatening. Further, the evidence supports the relevance of “the trajectory hypothesis” (which proposes that individuals consider their past and future health trajectories when choosing a SRH category) for men’s SRH, since it retains its independent predictive power over a longer time horizon.

It is worth noting that very few of the socio-economic and demographic characteristics for both men and women are independently predictive of mortality in the regressions (which also include controls for health). This finding is likely to lend support to “the resource hypothesis”; that is, SRH is likely to reflect the range of resources – material, social, and psychological – needed to prevent health deterioration or to aid a recovery.

The analysis has a number of limitations. The more accurate alternative methodology, the Cox proportional odds model, could not be applied to the South African data, since the death of respondents is recorded as having occurred within a two-year period between the waves of NIDS, and hence the exact date of date is unavailable or unreliable. The cause of death is also not recorded in NIDS and therefore deaths from natural or other causes cannot be distinguished, but the bulk of cases are likely to be from natural causes, in line with national trends. The logistic regression results focus on the effect of SRH, as reported at baseline, on mortality risk, and not on an

adjustment process that is likely to be dynamic (Bath, 2003). However, this limitation implies the results are under-estimates, especially over the longer follow-up period.

Even in the diverse South African context and despite the heterogeneous reporting patterns found in Chapter 2, “SRH may be a finely-tuned indicator of physical well-being; or persons with a durable advantage derived from protective health habits are the ones who report good SRH for any current level of objective health; emotional health, including positive feelings, could also be reflected in SRH and its correlation with longevity” (Muller, 1982: 789). This makes it a useful and internally-consistent indicator of health for each individual over time, albeit with gender-distinct features, and therefore suitable for the analysis of the relationship between health, social status and inequality, which is conducted in the next chapter.

Chapter 4

Are measured or perceived rank and inequality more closely linked to health in a highly unequal country? Evidence from South Africa

4.1. Introduction

In individuals' assessments of health and well-being, context and perceptions of socioeconomic environment and position have been shown to matter considerably (Posel & Casale, 2011; Sen, 2002; Singh-Manoux *et al.*, 2005). In this chapter, the focus is on the relationship between health and both measured and perceived socioeconomic rank and inequality. The National Income Dynamics Study (NIDS) has presented new opportunities for research in the realm of the socioeconomic correlates of health, as data on a range of both health and socioeconomic indicators is collected through a nationally representative panel survey.

Thus far, only a fledgling South African literature on the socioeconomic correlates of health exists, mainly due to data constraints. Chapters 2 and 3 interrogated the usefulness and reliability of self-rated health (SRH) as an indicator and presented evidence that SRH is a health measure with important credibility advantages. SRH suffers from reporting heterogeneity and hence it is a less useful measure of differences between individuals and between groups. However, for each person, it is part of an internally consistent self-identity over time and thus it is an independent predictor of mortality. Hence, SRH is a reliable indicator of general health when the same individual is observed over time and therefore, it can be employed meaningfully in individual-level panel data analysis.

Building on this understanding of individuals' perceptions of their own health, Chapter 4 explores the relationship between self-rated health, on the one hand, and indicators of absolute material well-being, relative material well-being, and inequality, both measured and perceived, on the other. This research fills only part of the bigger research gap in understanding how broader ideas of welfare relate to current mainstream proxies (such as income and expenditure) in South Africa. Research to date has investigated some of the aspects of the health-socioeconomic status (SES) relationship in South Africa, but this has not included the role of measured and perceived rank and

inequality. This chapter explores the co-movements between material and health aspects of well-being in a society, which is among the most unequal in the world.

In particular, the research addresses a number of questions in the South African context. The absolute income hypothesis poses the first: is there a relationship between health and absolute income? The second is linked to the relative income hypothesis: is there a relationship between health and relative income, which is a proxy for rank? The income inequality hypothesis puts forward the third question: is there a relationship between health and inequality? The chapter explores further whether in the latter two relationships, the association between SRH is stronger with rank as objectively measured or as perceived by the individual, and similarly for inequality.. An additional focus is the gender-distinct nature of these relationships, as gender remains a major stratifying factor with regard to both material and health disparities in the South African context (Casale *et al.*, 2021; Herman *et al.*, 2009; Mayosi *et al.*, 2012; Stats SA, 2019). In exploring these questions, the chapter seeks only to investigate statistical associations and does not make any inferences about causality.

The chapter is organised as follows. Section 4.2 reviews the theoretical strands about the relationship between health and material aspects of welfare, as well as relevant international and South African empirical studies. Section 4.3 details the methodology used in the panel ordered probit regression models, the results of which are presented and discussed in Section 4.4. The regression models were tested for the effects of attrition bias and section 4.5 contains the outcomes of these tests. Section 4.6 summarises the main findings and concludes the chapter.

4.2. Literature review

This chapter draws from the literature regarding the socioeconomic determinants of health. For the purposes of this thesis, the focus is on the associations between health and various indicators of socioeconomic status and inequality, but not on issues concerning causality, which is likely to run in both directions. The major ideas behind these relationships are reviewed in turn.

“The gradient” – what it is and Deaton’s critique

The idea, known as “the gradient”, which spawned the study of the socioeconomic correlates of health, is more than a century old (Cutler *et al.*, 2008). In a seminal paper that examined data from the Whitehall I study of British civil servants, it was referred to as “the class gradient in disease”

(Marmot *et al*, 1978: 244). Over the seven and a half year duration of the study, Marmot *et al*. (1978) recorded that men in the lowest ranking occupations had 3.6 times higher mortality rates due to coronary heart disease (CHD), compared to men in the highest grades. Moreover, occupational grade had the highest predictive power, even after controlling for a number of important coronary risk factors, from plasma cholesterol to leisure exercise habits.

The notion of “the gradient” is understood more broadly to mean that the poorest suffer the worst health. Looking at the world as a whole, and within countries, a lower socioeconomic status is associated with poorer health outcomes (World Health Organization, 2008). Various studies have presented evidence of an association between different indicators of socioeconomic status (SES) and a wide range of mortality causes, finding similar evidence (e.g., Adler *et al*, 1994; Link and Phelan, 1995; the Whitehall II study, discussed in Marmot *et al*, 1991). However, more recent challenges to the concept of “the gradient” have highlighted the multidimensional nature of socioeconomic status and emphasized the importance of exploring the diverse pathways of association with health (Case and Deaton, 2005; Cutler *et al*., 2008; Deaton, 2013a; Deaton, 2013b). Deaton (2013b: 266) explains that “...there is no general benefit from status *in and of itself*, and ... power and money are useless against the force of mortality without weapons to fight” (emphasis in the original text).

Hypotheses about the links between socioeconomic indicators and health

Three kinds of hypotheses about the relationship between SES (usually expressed in terms of income, but other frequently used markers are assets, occupation, and education) and health have been formulated and investigated. The hypotheses differ in terms of which concept matters: absolute SES (e.g. the level of income or wealth); relative position (e.g., the position in the relevant income distribution) or inequality (e.g. a measure of the dispersion of the income distribution). Another strand of research deals with a further distinction about whether measured or perceived social status is more closely tied with health. It is important to note that causality is likely to run in both directions between SES and health. For example, higher income earners are likely to have the resources necessary to protect and care for their health; also, better health may improve the possibilities of getting and keeping higher paying jobs. This possible two-way influence adds another level of complexity to the debate. Here, the focus is on the notion of SES more closely

related to health and not on the direction of causality. Next, the three hypotheses are outlined briefly in turn.

The absolute income hypothesis

The absolute income hypothesis claims that health improves with higher levels of income, but at a decreasing rate, and hence health can be seen as a normal good (Grossman, 1972). The Grossman model considers only the direct effect of an individual's own income on the individual's health, and not the possible indirect relationship with others' incomes (Wilkinson, 1998). That is, the utility function in the Grossman model does not cater for utility in relation to other agents, i.e. relative utility from rank (status) and inequality concerns is not incorporated. This is one among several other limitations of the Grossman model, which make it unsuitable for testing the relative income hypothesis and the income inequality hypothesis. Hence, this chapter does not draw exclusively on the Grossman model as a theoretical foundation, but rather on various strands from the literature in economics, sociology, and psychology.

Two other limitations of the Grossman model that are relevant to this chapter are as follows. First, the role of perceptions is absent from the model, including perceptions about health, status and inequality. Second, the Grossman model is conceptualised as an investment model, and while some of the mechanisms at work in the relationship between health and material well-being can be thought of as incentives or disincentives for investment, alternative frameworks are available and likely to be relevant. These include a game-theoretic framework with positional externalities, introduced by Frank (2005) and a psychosocial framework (Marmot *et al.*, 1978; Singh-Manoux *et al.*, 2005; Wilkinson, 1996).

With regard to the absolute income hypothesis, Deaton (2013a) shows that an apparent nonlinear relationship between *the level* of price-adjusted GDP per capita and life expectancy appears to hold at a cross-country macroeconomic level. As countries emerge out of poverty, deaths due to infectious diseases decline and life expectancy rises rapidly, but once a critical (average) income level is reached (where the main causes of mortality are chronic conditions), further increases seem to bring diminishing returns. Nevertheless, and despite the relationship being far from exact, it is

clear that *proportional* increases in income are associated with additional years of life both for rich and poor countries (Deaton, 2013a).

A nonlinear relationship between income and health is also evident in numerous microeconomic studies, with the strongest effects of income on health among the poor (Smith, 1999). For example, Ecob and Davey Smith (1999) find an inverted-U relationship for England, Wales, and Scotland, such that increases in income bring health improvements at the low end of the distribution, but health declines with further income increments at the high end of the scale.

Relative income (relative deprivation) hypothesis

Despite acknowledging the positive association between absolute income and health, other studies place additional importance on the individual's relative income or social position (Marmot *et al.*, 1991; Wilkinson, 1998). The relative income hypothesis states that an individual's health is affected by the incomes of others around him or her, through complex social mechanisms. Socioeconomic rank is commonly measured by the mean or median income of the country, district, or neighbourhood, race or ethnic group, or the individual's position in the relevant income distribution. These measures make assumptions about the appropriate reference group that individuals compare themselves to. As with self-rated health, the actual reference groups are difficult to ascertain, and in practice, comparisons with the national population or those living in the immediate geographical area are frequently used in empirical studies (Deaton, 2001).

Furthermore, both the individual's actual position and perceived position are found to be important correlates of a wide range of health outcomes (Singh-Manoux *et al.*, 2005), a finding shown to be valid in the contexts of the UK and US (Adler *et al.*, 2008). For South Africa, Posel and Rogan (2014) found that the differences in overall objective poverty rates (based on R577 per capita per month at 2008 prices) and subjective self-reported poverty rates are small, but statistically significant. Interestingly, however, only 60 percent of objectively poor households perceive themselves as such. Posel and Rogan's results show a negative association between subjective poverty and average self-rated health in the household – on average, people who are healthier are less likely to see themselves as poor.

Perceived social position is an important contributor to well-being. In relation to subjective well-being in South Africa, using data from the first wave of the NIDS, Posel and Casale (2011) show

that an individual's perceived ranking in the income distribution is a significantly more important contributor to subjective well-being (measured as life satisfaction) than an income-based objective rank measure. In addition, Posel and Casale's results indicate that rank within the more narrowly defined geographical reference group (those living in their village or suburb) is more relevant to subjective well-being for South Africans, compared to rank in the broader national reference group.

Von Fintel (2015) sheds more light on the composition and size of reference groups in the South African context. She investigates reference groups related to subjective well-being (SWB), using data from NIDS wave 1 (2008). Von Fintel (2015) finds that the cluster is a proxy for close neighbours who have similar characteristics to the individual, while the district is a proxy for 'more distant others' (Kingdon & Knight, 2007), who have a more diverse set of characteristics. Von Fintel (2015) confirms Kingdon and Knight's (2007) results (based on South African data from 1993) that the welfare of households in close proximity may spark altruism and hence improves one's SWB, while the welfare of 'more distant others' is associated with negative comparisons and so it is negatively associated with one's SWB. However, she further shows that reference groups have evolved over time, becoming less racially homogeneous.

Income inequality hypothesis

This hypothesis claims that large socioeconomic differentials have a negative effect on health (Wilkinson, 1996). Various mechanisms behind the relationship have been suggested, including a range of 'psychosocial' pathways that undermine social cohesion (Wilkinson, 1996), lead to stressful social comparisons (Cohen *et al.*, 1991; James, 1998), and to the erosion of social capital (Kawachi & Kennedy, 1999). In the US, states with higher income inequality also record lower investments in human capital, such as education spending (Kaplan *et al.*, 1996).

Apart from the biological, psychological, and sociological explanations, Frank (2005) suggests purely economic reasoning, based on the proposition that utility is affected by absolute as well as relative consumption, and he refers to the role of positional goods - those for which relative consumption matters more than absolute consumption (e.g. housing). In his model, the widening gap between the rich and poor is likely to lead to negative externalities associated with the consumption of positional goods. For instance, assuming that better schools are located in

neighbourhoods where property is more expensive, a wealthier family will spend more on housing, in order to send their children to the best schools. Considering this, a less-well-off family has an incentive to increase their housing spending too (by probably saving less for retirement) or their children will be left with substantially inferior schooling options. However, if all families respond in the same way, the benefit of this decision is negated – the incentives are similar to those that lock countries in international arms races, leading to futile and wasteful outcomes (Frank, 2005).

Though the evidence for the income inequality hypothesis was initially thought to amount to a consensus (Wilkinson, 1996), more recent reviews see the hypothesis as more of a controversy and recommend the use of individual-level longitudinal data to address the gaps in cross-country and regional studies (Wagstaff & van Doorslaer, 2000; Wilkinson & Pickett, 2006).

South African studies

There is only a fledgling South African literature on the links between SES, health and well-being, including the studies mentioned above (Posel & Rogan, 2014; Posel & Casale, 2011). An early contribution by McIntyre and Gilson (2002) seeks to bring attention to South African health inequalities and set the policy agenda for addressing them. McIntyre and Gilson (2002) also indirectly promote a research agenda about the linkages between health inequalities and poverty, government resource allocation, and the practical aspects of distributional and procedural justice.

Other studies offer different perspectives, but they are connected by the common thread that the burden of disease falls predominantly on the poor in South Africa. In order to assess inequality in the distribution of ill health and disability related to socioeconomic disparities, Ataguba *et al.* (2011) estimate concentration indices and track changes since the early 2000's using General Household Survey data. They confirm that the poor carry a disproportionately higher burden of disease; and further, they find that even for diseases that are predominant among the more affluent, such as flu and diabetes, the concentration indices are falling over time.

Another complication is that the various SES indicators may have different relationships with health measures. Using data from the first wave of NIDS (2008), Alaba and Chola (2013) show that educated and employed individuals are less likely to suffer from one or more chronic diseases. Their results, however, indicate a positive relationship between household income and

multimorbidity (defined as the simultaneous occurrence of two or more chronic health conditions), but this relationship does not hold for individuals who suffer from a single chronic disease.

Gender aspects

The factors (biological, statistical, and social) shaping gender inequalities in health were discussed in Chapter 2, together with the theoretical framework, developed by Denton *et al.* (2004), which proposes two hypotheses about the reasons why the impact of socioeconomic factors varies by gender: the differential exposure hypothesis and the differential vulnerability hypothesis. A brief overview of some of the mechanisms behind the relationship of rank and inequality with health follows, showing why this relationship may be distinct by gender.

Stiglitz (2012) draws attention to economic discrimination (e.g. along gender or racial lines) as one of the forces behind widening inequality between societal groups. Importantly, he also emphasises that discriminatory mechanisms are self-enforcing – that is, they play a role in shaping the perceptions about the productivity and social position of both the discriminating and discriminated groups (Altonji & Blank, 1999) with “statistical discrimination” closing a feedback loop (Phelps, 1972). On a related note, Wilkinson and Pickett (2020) argue that meritocracy is a misconception, that is, they challenge the popular notion status and access to material resources stem from natural ability and not much more. Taking a psychological perspective, one of the factors that Wilkinson and Pickett (2020) highlight is stereotyping (including by gender, race, or age); for example, they point out that priming according to well-known stereotypes has been shown to cause experimental subjects to align their behaviour to these. These channels of influence can also be reasons for the differential impact of rank and inequality on men’s and women’s health.

Some channels of influence may have opposite effects on men and women. For example, as discussed in Chapter 2, marriage may confer health benefits more uniformly to men (Guner *et al.*, 2014). The effect on women’s health and life satisfaction depends on the quality of the relationship: women enjoy greater gains from well-functioning relationships, but are also more vulnerable to marriage-related stress, than men (Kiecolt-Glaser & Newton, 2001).

Differences in labour market participation, occupations, and opportunities for advancement at work are both a cause and consequence of inequality and are likely to shape the differences in its relationship with health by gender. Bartley (2016) describes one of the materialist drivers of health

inequality as being the historically higher and more consistent labour force participation and employment of men, which exposes them to higher risks of various occupational hazards than women. Further, she explains the more complex nature of this relationship in recent decades, as greater proportions of women have entered and engaged more actively in the labour market, but they have often taken on safer, yet lower-paid occupations and less secure jobs, which are less likely to ensure financial independence. This pattern refers to industrialised nations post World War II, but has also been evident in South Africa, where gender disparities in the workplace were enforced by the policies of the apartheid regime, but women's participation in the labour market has increased dramatically since the advent of democracy in 1994 (Casale, 2004; Casale & Posel, 2002; Posel & Casale, 2019; Posel & Muller, 2008). Bartley (2016) sums up the consequences: "One result of this may have been the higher rates of anxiety and depression seen in women in many surveys. It may be that financial dependency, enforced by law, tradition and lack of child care, has protected women against material hazards but posed greater psychological risk" (Bartley, 2016:145).

It is also worth noting that the methods of measuring rank and material inequality are likely to matter considerably in determining the gender-distinct nature and strength of their relationships with health. For example, using longitudinal data from England and Wales over the period from 1986 to 1996, Sacker *et al.* (2000) show that a rank (class) and inequality measure, based on the individual's occupation and employment relations, explains the varying life expectancy between men of different rank, but reflects substantially lower inequality in women and has no explanatory power. In contrast, a measure based on the social position and lifestyle of the household is as closely associated with inequality in women's life expectancy as with inequality in men's (Sacker *et al.*, 2000).

Conclusions and contribution

In the last two decades, the international debates about the links between health, SES, and inequality have become more detailed and nuanced, seeking to understand how individuals are impacted over time. Since health and socioeconomic data have rarely been collected in the same survey, the literature exploring the links between socioeconomic indicators and health is still at its early stages of development in South Africa. This chapter uses unique data collected in a South African panel study and contributes to the international and South African literature by adding

evidence on the associations between health on the one hand and measured or perceived SES and inequality on the other, in an environment plagued by enormous disparities. The chapter considers also whether these associations differ by gender.

4.3. Data and methods

This chapter employs descriptive and regression analysis. The data and key measures are described next, followed by a brief overview of the panel ordered probit model used in the regression analysis.

Data

As in the previous chapters, the data for this chapter come from the first four waves of NIDS. The dataset is described in Chapter 1. The questionnaire includes questions on health as well as a range of questions about material welfare and socioeconomic status, both money-metric and perceived, which makes NIDS suitable for testing the three hypotheses posed in this chapter. The longitudinal nature of the survey allows the use of self-rated health (SRH) as a measure of overall health, since SRH is understood to be part of the individual's self-concept; hence, it is likely to be a consistent notion for each individual over time (see Chapters 2 and 3). An unbalanced panel of the first four waves of NIDS is employed in the analysis and the sample is restricted to adults (here defined as aged 18 and over) and continuing sample members (CSMs)¹² only.

Measure of health

Self-rated health (SRH) is employed as an internally consistent reflection of perceived general health. Since the analysis is conducted using panel data methods, the reporting heterogeneity in the health measure is addressed by considering within-individual variation in a fixed effects ordered probit (FEOP) estimation, which is described below in this section.

As identified previously, the NIDS question eliciting the individual's subjective rating is J1: "How would you describe your health at present? Would you say it is excellent, very good, good, fair, or

¹² CSMs are the resident members of all original households selected to participate in Wave 1. CSMs include children who were living in these households and any children born to or adopted by female CSMs in the following waves. In contrast, temporary sample members (TSMs) are household members who are co-resident with CSMs from Wave 2 onwards (Brown *et al*, 2012). The latter are excluded from the analysis in this chapter.

poor?”. Following the approach in Chapter 2, the bottom two categories, “fair” and “poor” are combined to produce a four-level SRH measure because relatively few respondents throughout the panel chose the lowest category.

Measure of absolute income

The proxy for absolute income used in the analysis is real monthly household non-rent income per capita. Given the high unemployment rate in South Africa, which varied between 22 and 25% (using the strict definition¹³) during the period 2008 – 2015, the relatively young population, and the even higher unemployment rates among the youth, an individual’s level of material welfare is especially likely to be tied to their household’s. The NIDS household income per capita with full imputations is used (Argent, 2009). The imputed (implied) rent of homeowners is removed from the income measure, which makes it more reliable (containing less measurement error) and more consistent over time (Leibbrandt *et al.*, 2010). Income is also adjusted for household size and for inflation (all values are deflated to November 2014 as a base month).

Real income enters the regression specifications in a non-linear fashion – in this case, quadratic – in order to test the absolute income hypothesis, which implies diminishing returns of health capital to absolute income (Grossman, 1972). As a robustness check, the analysis is also conducted using household expenditure per capita as a proxy for disposable income, as well as using the corresponding measures of rank and inequality, instead of the income-based ones. These results are presented in Appendix 4.A.

Reference groups

The reference groups used in the analysis are assumed to be geographical in nature, similarly to the approach taken by Lorgelly and Lindley (2008). The NIDS data comprise 53 district municipalities, made up of 400 clusters. For both the rank and inequality measures, the (municipal) district is assumed to be the relevant reference group, based on Von Fintel’s (2015) findings that

¹³ NIDS follows the International Labour Organization’s definition for employment status, which has four categories: employed, unemployed (strict definition), unemployed (broad definition), and not economically active. According to the strict definition, an unemployed individual is someone between the ages of 15 and 64, who is without a job, available to work, and searching for a job actively. In contrast, unemployed individuals not taking steps to look for a job are included in the broad definition (Brown *et al.*, 2012).

the district, as a broader reference group that is still within the individual's observable distance, which may be the benchmark for negative comparisons. Hence, this is an appropriate reference group for testing the relative income hypothesis and the inequality hypothesis.

From an econometric perspective, the measures of rank and inequality can be calculated credibly at district level for the following reasons. First, a stratified, two-stage, cluster sample design was implemented to select the original NIDS sample. The strata for this design are the 53 district councils (Leibbrandt *et al.*, 2009) and therefore the survey is likely to be representative at the district level, provided the appropriate sampling weights are used in the estimation (see, for example, Kollamparambil (2017)). Second, the sample sizes per district are adequate – they are no smaller than about 40 observations in every wave, but are most frequently above 100 observations. One district was excluded from the analysis below (District 554, Umzinyathi), as it only had a single observation in Wave 3.

Measures of rank

The Deaton index is employed as an indicator of measured rank, or relative deprivation. The underlying measure of material affluence is non-rent household income per capita (described above) and the (municipal) district is assumed to be the relevant reference group. This index is a modified version of Yitzhaki's (1979) upward-looking measure of status. Yitzhaki's index defines individual i 's relative deprivation (RD_i) as the average distance between the individual's material affluence (y_i) and the affluence of those in individual i 's reference group who are better off (y_j):

$$RD_i = D(y_i) = \int_{y_i}^{y^*} [1 - F(z)] dz \quad (4.1)$$

where y^* is the highest level of affluence in the reference group, D_i indicates a measure of distance, and $F(z)$ is the cumulative distribution of affluence in the reference group.

Since the values of Yitzhaki's index are dependent on the units that affluence is measured in, they are not comparable between groups that use different currencies, for example, or across time. The Deaton index is an alternative measure, which overcomes this limitation by dividing the Yitzhaki index by the mean affluence of the reference group (μ_i) (Deaton, 2001).

$$RD_i = \frac{D(y_i)}{\mu_i} = \frac{\int_{y_i}^{y^*} [1-F(z)]dz}{\mu_i} \quad (4.2)$$

This adjustment results in a unitless measure, which takes any further differences into account – for example, variations in purchasing power across distance and time and the prevalence of payments in kind or subsistence agriculture. The average value of the Deaton index in a reference group is the same as the Gini coefficient. In order to make measured rank (relative deprivation) somewhat comparable with perceived rank, the quintiles of the Deaton index are used.

The measure of perceived rank is based on the survey question (M2), "How would you classify your household in terms of income, compared to other households in your village/suburb?" Respondents can select one of the five categories shown in Table 4.1. It is worth noting that this question implies a smaller reference group that is closer in proximity, compared to the municipal district.

Measures of inequality

The main indicator of measured inequality employed in the analysis is the Gini coefficient. The most widely used measures satisfy a set of desirable properties: the Pigou-Dalton Transfer Principle¹⁴, Income Scale Independence¹⁵, Principle of Population¹⁶, Anonymity¹⁷, and Decomposability¹⁸ (Litchfield, 1999). The intuition behind these properties is that the inequality measures should reflect, in real terms, a widening of the gap in access to material resources between the poorest and the richest members of a society. Hence, the properties ensure that theoretical notions of inequality are reflected as accurately as possible by aligning the economic and statistical features of the measures (Cowell & Victoria-Feser, 1996). Any measure that satisfies these properties belongs to the class of Generalised Entropy (GE) measures of inequality, such as

¹⁴ This axiom states that the inequality measure must increase with a rise in (mean-reserving) spread, i.e. an income transfer from one who is poorer to one who is richer should register as a rise in inequality and the opposite transfer should register as a fall.

¹⁵ This axiom requires the income measure not to be influenced by proportional changes (in income, say) that affect all individuals.

¹⁶ This principle requires the inequality measure to be invariant to identical replications of the population – e.g. merging identically distributed populations should leave inequality unchanged.

¹⁷ Also known as symmetry, this axiom requires the inequality measure to be independent of any individual characteristics other than the relevant one (e.g. to depend only on income).

¹⁸ This property requires overall inequality to relate to parts of the distribution (e.g. subgroups) in a consistent manner. This allows for some measures to be decomposed to within-group and between-group inequality.

the Gini coefficient and the Atkinson measures. GE measures are sensitive to changes in different parts of the income distribution, which enables the evaluation of different types of inequalities. For example, the Gini coefficient is most sensitive to inequalities about the mean of the income distribution, while the Atkinson Index (and the Generalised Entropy Index) family of indicators contain a parameter that can be adjusted to increase sensitivity to changes in other parts of the distribution (De Maio, 2007). Using per capita household income, Gini coefficient values are calculated at (municipal) district level. It is worth noting that more refined metrics for measured rank and inequality that apply to the neighbourhood or village (e.g. at the cluster level) are not possible to calculate reliably because of small sample sizes and because the data are not representative at sub-district levels.

Perceived inequality is measured indirectly using Cowell and Flachaire's (2017) metric designed for ordered categorical data, which is applied to the perceived rank variable (the five-step perceived village (or neighbourhood) income comparison variable (M2) described above). Hence, the link between the perceived inequality measure and the perceived rank indicator is somewhat similar to that between the Gini coefficient and the Deaton index.

The metric developed by Cowell and Flachaire (2017) was chosen because of the advantages it offers in addressing the problems of measuring inequality using ordered categorical data. One such problem is that the underlying concept may not be measurable, or if it is, the measurement scale is likely to be unknown (Cowell & Flachaire, 2017). To address this, Cowell-Flachaire's (2017) metric incorporates the concept of upward- or downward-looking status within a distribution and it uses maximum status as a reference point, thus avoiding the problems associated with the sensitivity of means and medians of categorical variables. The metric's further advantages include that it complies with the set of five axioms regarding the desirable properties of inequality measures, and it is easy to implement empirically. The Cowell-Flachaire metric takes on values between zero and one, making it roughly comparable to the Gini coefficient.

For 'downward-looking' status, the Cowell-Flachaire metric is:

$$I_{\alpha} = \frac{1}{1-\alpha} \left[\sum_{i=1}^K p_i \left[\sum_{j=1}^i p_j \right]^{\alpha} - 1 \right] \quad \text{if } \alpha \neq 0,1 \quad (4.3)$$

$$I_{\alpha} = - \sum_{i=1}^K p_i \log \left[\sum_{j=1}^i p_j \right] \quad \text{if } \alpha=0$$

where α is the sensitivity of the inequality metric to high-status inequality; K is the number of categories; and p_i is the proportion of observations in category i . The metric used in this analysis was generated with $\alpha = 0$, which implies least sensitivity – i.e. changes in low-status inequality and high-status inequality usually have similar effects¹⁹ (Cowell & Flachaire, 2017). The Gini coefficient has a similar property – it responds most readily to changes in the middle of the income distribution (De Maio, 2007).

Control variables

The regression analysis controls for some key demographic characteristics of the individual and the household. The individual's age (in completed years) enters in a quadratic fashion, as the path of individuals' health perceptions over time is assumed to be non-linear (see Chapter 2). The four population groups used are those commonly delineated in official South African surveys, namely African, Coloured, Asian/Indian, and White. The Asian/Indian respondents are included in this chapter, as the methods of analysis (and therefore sample size requirements) differ from those in previous chapters.

Marital status is reduced to three categories: single (never married), married or cohabiting, and divorced, separated, or widowed. Education is included as a four-level variable with categories for 'no education', 'completed primary', 'completed secondary', and 'some level of tertiary education'. Given the historical geographic segregation in South Africa, another important control variable is geographical type (geo-type) – in line with the new official classification introduced in the 2011 Census, the geo-type can be urban, traditional, or farms. Urban areas are defined as built-up cities and towns, including formal and informal settlements; traditional areas are villages on community-owned land, which is under traditional leaders' authority (these areas were part of the former "homelands" or "Bantustans"); and farms are commercial farming areas (Chinhema *et al.*, 2016). The number of children under the age of 7 in the household is also included as a control, as

¹⁹ Even with $\alpha=0$, Cowell and Flachaire (2017) show that their metric does not always produce this symmetrical effect because the mean or median of the distribution may not always be clear or meaningful, depending on the underlying categorical variable used, or on the skewness of the distribution.

their susceptibility to illness (because of developing immune systems) and their care needs can have an effect on adults' health.

The panel ordered probit model

In order to test the three hypotheses stated above, the regression analysis employs panel ordered probit models, estimated separately gender. In all the regression models, four-level SRH is the dependent variable and the explanatory variables include a measure of absolute income (household income per capita and income squared); a measure of rank (or relative deprivation); a measure of inequality; and control variables.

The ordered probit estimation equation is:

$$Y_{it}^* = X_{it}\beta + \alpha_i + \varepsilon_{it} \quad (4.5)$$

where Y_{it}^* is an latent dependent variable (not directly observable), such as true health, which is assumed to be continuous; X_{it} is a vector of explanatory variables; β is a vector of parameters to be estimated; ε_{it} is an idiosyncratic error term; $i = 1, \dots, N$ is an index of individuals; and $t = 1 \dots, T$ is a time index (Wooldridge, 2010).

A categorical variable, Y_{it} (such as SRH), with J categories is observed instead of the latent and continuous Y_{it}^* (such as true health), such that:

$$\begin{aligned} Y_{it} &= 0 \text{ if } Y^* \leq 0 \\ Y_{it} &= 1 \text{ if } 0 < Y^* \leq \tau_1 \\ Y_{it} &= 2 \text{ if } \tau_1 < Y^* \leq \tau_2 \\ &\cdot \\ &\cdot \\ Y_{it} &= J \text{ if } \tau_{J-1} \leq Y^* \leq \tau_J \end{aligned} \quad (4.6)$$

where $\tau_1 < \tau_2 < \dots < \tau_J$ are unknown threshold parameters.

Assuming that latent health, Y_{it} , is normally distributed, the coefficient vector and the vector of threshold parameters can be estimated using the Maximum Likelihood method.

For each of the specifications in Tables 4.2 to 4.5, a pooled ordered probit (POP), random-effects ordered probit (REOP), and a fixed-effects ordered probit (FEOP) are estimated. The pooled model provides population-averaged coefficients, which are consistent if X_{it} is independent of ε_{it} . The random-effects (RE) model allows for unobserved heterogeneity between individuals (thus recognising the panel structure of the data), but assumes that individual-specific heterogeneity is distributed randomly across the population (Wooldridge, 2010). The fixed effects model allows for correlation between X_{it} and the individual-specific α_i ; therefore, the model removes time-invariant characteristics and produces less biased estimates by eliminating variables difficult or impossible to observe (Cameron & Trivedi, 2009).

Since the ordered probit model is non-linear, the conventional approaches to generate fixed effects estimates (e.g. by mean-differencing of all variables, in order to remove time-invariant influences) are not possible to implement²⁰. Fixed-effects estimation for non-linear models is not well-established. This chapter implements the Chamberlain-Mundlak approach (also known as the correlated random effects (CRE) model), which was originally suggested by Mundlak (1978), and was later extended by Chamberlain (1984). The essence of the approach is outlined below.

The starting point is the linear panel model

$$y_{it} = \beta_0 + \beta_1 x_{it} + \beta_2 c_i + \mu_i + \varepsilon_{it} \quad (4.7)$$

where the i denotes individuals; t denotes time; y_{it} and x_{it} are variables that vary between individuals as well as over time; c_i is a time-invariant variable (varies only between individuals); μ_i is an individual-level error (also referred to as a random intercept); and ε_{it} is an idiosyncratic error.

The conditional distribution of μ_i is assumed to be $\mu_i | x_{it}, c_i \sim N(0, \sigma_\mu^2)$. This assumption ensures the model produces consistent estimates if $E(\mu_i | x_{it}, c_i) = 0$.

The model in (4.7) contains both within-individual and between-individual variation. The model containing only between-individual variation is

²⁰ There have been attempts to produce bias-corrected versions of a fixed effects estimator for non-linear models, including the ordered probit (e.g. Fernandez-Val and Weidner, 2016), but the corresponding empirical applications are few and have been limited to binary outcome models (e.g. Cruz-Gonzalez *et al*, 2017).

$$\bar{y}_{it} = \beta_0 + \beta_1 \bar{x}_{it} + \beta_2 c_i + \mu_i + \bar{\varepsilon}_{it} \quad (4.8)$$

Subtracting (4.8) from (4.7) gives the standard fixed-effects (demeaned) model, which does not contain the individual-level error, μ_i , or any time-invariant variables.

$$y_{it} - \bar{y}_{it} = \beta_1 (x_{it} - \bar{x}_{it}) + (\varepsilon_{it} - \bar{\varepsilon}_{it}) \quad (4.9)$$

An algebraically equivalent estimate of β_1 can be found using Chamberlain's (1984) generalisation of Mundlak's (1978) approach, which gives rise to the following model:

$$y_{it} = \beta_1 x_{it} + \beta_3 \bar{x}_i + \omega_{it} \quad (4.10)$$

where $\omega_{it} = \mu_i + \varepsilon_{it}$.

This is the Chamberlain-Mundlak estimating equation. Equation (4.10) is estimated using random effects, hence the model is sometimes referred to as “between-within”. This approach is mainly of interest in non-linear models (such as the ordered probit) rather than in linear ones, as it opens up a way of implementing a form of fixed effects estimation that is intuitive and simple to apply²¹

As with conventional approaches to fixed effects estimation, the Hausman test can be used to assess whether the REOP or FEOP is a more appropriate model, given the data. It tests the null hypothesis that the random effects estimators are consistent (and efficient) against the alternative hypothesis that the fixed effects estimators are consistent (yet inefficient) (Hausman, 1978). The descriptive and regression results are presented in the next section.

4.4. Results

Table 4.1 presents summary statistics of the measures of health, absolute income, measured and perceived relative income and income inequality, as well as a range of individual and household characteristics, by the gender of adults. Tables 4.2, 4.3, and 4.4 introduce the econometric results, which test the three hypotheses about the relationships between absolute income, relative income, and income inequality, on the one hand, with health, on the other.

²¹ The algebraic equivalence of the FE and the Chamberlain-Mundlak estimators applies only to linear models. Where they can be defined explicitly, the FE and Chamberlain-Mundlak estimates in non-linear models (such as in the logit model) are not algebraically equivalent.

As expected, and in line with the patterns observed in Chapter 2, it is evident from Table 4.1 that a larger proportion of women occupy the lower categories of self-rated health, with the differences in the proportions of men and women who selected each category being highly statistically significant. The material well-being measures also reveal a different pattern by gender. On average, women live in households with lower income per capita. This is partly due to differences in household size – in the pooled sample, the average number of household members is 5.07 for women, compared to 3.99 for men. The typical household for women also contains a greater number of children under age 7. In South Africa, single parenting is common, as a large share of the adult population is unmarried: more than two out of five women, compared to just over half of men; but women are more than twice as likely as men to be divorced, separated or widowed (6% of men vs 15.1% of women) (Hatch & Posel, 2018; Posel & Rudwick, 2014). In addition, women are more likely to be based in poorer districts and in areas under the authority of traditional leaders (the former Bantustan areas under apartheid, which are rural). Unsurprisingly, then, greater proportions of women occupy the two most deprived quintiles of Deaton’s relative deprivation index, while a larger proportion of men occupy the least deprived quintile. This is in line with the portrait of South African poverty in previous studies (Posel & Rogan, 2009; Rogan, 2013). However, there is no statistically significant difference by gender in inequality at district level, as measured by the Gini coefficient; the same applies to perceived inequality, given by the Cowell and Flachaire (2017) metric.

As expected, perceptions of position in the income distribution diverge from measured positions (Posel & Casale, 2011). While there are no statistically significant differences in the proportions of men and women who believe their household to be “much above average income” or “above average income”, women were more likely than men to report belonging to a household with income “below” or “much below” that of others in their village or suburb.

Table 4.1 Descriptive statistics by gender (means or proportions for the pooled sample)

Variable	Definition		Mean or proportion	
			Men	Women
Self-rated health (4-level)	Self-rated health	Fair or poor	0.103	0.159***
	1 if fair or poor		(0.004)	(0.005)
	2 if good	Good	0.233	0.260***
	3 if very good		(0.006)	(0.005)
	4 if excellent	Very good	0.296	0.282**
			(0.007)	(0.006)
		Excellent	0.368	0.299***
			(0.009)	(0.007)
Household income per capita	Non-rent household income per capita (R1000s)		3.453	2.494***
			(0.349)	(0.242)
District average income	District average household income (10,000s)		0.177	0.169***
			(0.005)	(0.005)
Deaton index	Index of relative deprivation (quintiles)			
		Quintile 1	0.172	0.129***
		(least deprived)	(0.011)	(0.010)
		Quintile 2	0.167	0.167
			(0.009)	(0.009)
		Quintile 3	0.184	0.189
			(0.009)	(0.009)
		Quintile 4	0.226	0.242***
			(0.012)	(0.012)
		Quintile 5	0.251	0.273***
		(most deprived)	(0.019)	(0.019)

Table 4.1 (continued)

Variable	Definition		Mean or proportion	
			Men	Women
Perceived relative income	Based on the question: "How would you classify your household in terms of income, compared to other households in your village/suburb?"	Much above avg income	0.037 (0.003)	0.034 (0.003)
		Above average income	0.098 (0.006)	0.093 (0.005)
		Average income	0.435 (0.011)	0.417** (0.009)
		Below average income	0.272 (0.007)	0.288** (0.007)
		Much below avg income	0.158 (0.008)	0.168* (0.008)
Gini at district level (income)	Gini coefficient based on non-rent household income		0.579 (0.002)	0.578 (0.003)
Perceived inequality	Cowell-Flachaire inequality metric		0.578 (0.001)	0.578 -0.001
Age	Age in years		38.147 (0.422)	40.012*** (0.311)
Race	Population group classification, beased on commonly-used categories in national surveys	African	0.784 (0.026)	0.767** (0.026)
		Coloured	0.086 (0.017)	0.094* (0.018)
		Indian / Asian	0.027 (0.014)	0.028 (0.012)
		White	0.103 (0.017)	0.111 (0.017)

Table 4.1 (continued)

Variable	Definition	Mean or proportion	
		Men	Women
Marital status	Never married	0.530 (0.016)	0.450*** (0.013)
	Married / cohabiting	0.409 (0.015)	0.400 (0.012)
	Divorced, separated, or widowed	0.060 (0.007)	0.151*** (0.005)
Education	Based on years of schooling:		
	None or incomplete primary (0-6 yrs)	0.182 (0.010)	0.201* (0.010)
	Primary or incomplete secondary (7-11 yrs)		
	Primary	0.470 (0.012)	0.459 (0.010)
	Secondary or incomplete tertiary (12-14 yrs)		
	Tertiary (15 years or more)	0.308 (0.013)	0.296 (0.010)
Geo type			
	Urban	0.665 (0.029)	0.631*** (0.029)
	Traditional	0.274 (0.026)	0.324*** (0.028)
	Farms	0.061 (0.015)	0.045*** (0.011)
Number of children aged under 7		0.488 (0.025)	0.879*** (0.032)
Observations		20,573	30,594

Source: Own calculations using NIDS Waves 1 to 4 (2008; 2010-12; 2012; 2014-15).

Notes: Means or proportions between men and women are statistically significant at the *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. # denotes the omitted (base) category for categorical variables. Robust standard errors are shown in parentheses. Estimates are weighted using the post-stratified weights.

The three tables of regression results below focus in turn on measured rank and inequality (Table 4.2), perceived rank (Table 4.3), and perceived inequality (Table 4.4). Each table presents the three different panel-data probit specifications (POP, RE, and FE) separately by gender. Due to space considerations, for all the specifications, the wave (time) dummy variables and intercepts have been excluded from the tables. In addition, for the fixed effects specifications, which are based on the Chamberlain-Mundlak approach, the variables representing within-individual means of time-varying regressors have also been omitted from the tables.

In Table 4.2, the results lend limited support for the absolute income hypothesis – the coefficients of the quadratic in household income per capita are statistically significant at the 10% level, and only in the POP and REOP models. However, the Hausman test indicates that the null hypothesis of no systematic difference between the coefficients of the REOP and FEOP models can be rejected at all conventional significance levels ($\chi^2=65.76$ for men and $\chi^2=189.64$ for women), hence the FEOP model is preferable. The fixed-effects results consider the relationship between health and within-individual income variability only, in order to control for unobserved individual heterogeneity. These results show that the positive relationship, based on income variations between individuals (or groups) becomes insignificant when this heterogeneity is taken into account. Hence, in South Africa, the absolute income hypothesis receives weak support when comparing different groups (Wilkinson & Pickett, 2010), but not when tracking individuals over time, in line with evidence for the United Kingdom (Lorgelly & Lindley, 2008).

A possible reason for the lack of evidence for the absolute income hypothesis at the individual level is the underestimation of economic resources in per capita measures, which overlook the lower requirements of children and the economies of scale in consumption enjoyed by larger households (Posel *et al.*, 2016). Another reason is the provision of government-funded basic healthcare to the predominant share of the population, though considerable challenges related to accessibility remain, especially in remote and rural areas (Burger & Christian, 2020). A third reason relates to the possibility that the first four waves of the NIDS panel span an eight-year period, which is not sufficient to estimate the independent association between inflation-adjusted income per capita and individual health.

The FEOP results provide no evidence for the relative income hypothesis on the basis of measured relative rank. That is, measured relative deprivation has no independent relationship to SRH, as

the coefficients of all quintiles of the Deaton index are not statistically significant, with the notable exception of men in the most deprived (fifth) quintile, for whom the link between rank and health is favourable. This result is contrary to expectations.

Measured inequality has a positive effect on SRH in the pooled and random effects models, but this influence is weakened when unobserved individual heterogeneity is taken into account. In the fixed-effects models, the coefficient is positive for both men and women, but only significant for women at the 10% level. This is contrary some to previous studies from developing countries using panel data – for example, by Rasella *et al.* (2013) for Brazil and by Pei and Rodriguez (2006) for China – but in line with Lorgelly and Lindley’s (2008) findings for the UK. It is also likely that in the South African context, a higher Gini coefficient may highlight districts that present better equality of opportunity or the better provision of services (compared to districts that are poor with low levels of inequality) (Turok *et al.*, 2017), even though the Gini coefficient is designed and used as a measure of inequality of outcome.

Perceived rank is added as a key indicator in Table 4.3, instead of measured rank. In contrast to measured relative rank, perceived rank lends support to the relative income hypothesis. Regarding the categorical variable representing perceived rank, it is worth noting that the reference group is individuals who reported belonging to a household with “much above average income”. For Table 4.3, again, the Hausman test leads to the conclusion that the difference between the REOP and FEOP coefficients is not incidental ($\chi^2 = 78.30$ for men and $\chi^2 = 126.96$ for women), hence the FEOP model is preferable.

After taking individual heterogeneity into account, for men, the estimated coefficients for the bottom three categories of perceived rank are negative and statistically significant at all conventional levels; while for women, this applies to all categories. Hence, reporting one’s household to be in one of the lower-income rungs, relative to those in the immediate vicinity, is associated with worse health for both men and women, but this relationship is increasingly stronger for women the closer to the bottom of the income pyramid they perceive their households to be. This finding is consistent with the theoretical frameworks developed by Marmot *et al.* (1991), spawned by the British Whitehall study of civil servants, which began in 1967, and in line with empirical studies conducted in a wide range of contexts (Gerdtham & Johannesson, 2004; Gravelle & Sutton, 2009; Miller & Paxson, 2006; Roy *et al.*, 2016).

Table 4.2 Ordered probit models with measured rank and inequality

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Four-level SRH	POP Men	POP Women	RE Men	RE Women	FE Men	FE Women
Gini (on non-rent income)	0.288*	0.530***	0.238	0.538***	0.005	0.350*
	(0.174)	(0.148)	(0.187)	(0.157)	(0.255)	(0.200)
Relative deprivation (Deaton index quintiles)						
Quintile 2	0.055	0.009	0.055	0.013	0.039	0.031
	(0.040)	(0.035)	(0.043)	(0.037)	(0.049)	(0.040)
Quintile 3	0.021	-0.016	0.024	-0.009	0.031	0.030
	(0.041)	(0.036)	(0.045)	(0.038)	(0.054)	(0.043)
Quintile 4	-0.003	-0.045	-0.005	-0.047	-0.003	-0.023
	(0.045)	(0.037)	(0.049)	(0.039)	(0.058)	(0.044)
Quintile 5	0.019	-0.048	0.044	-0.034	0.126**	0.042
	(0.044)	(0.038)	(0.048)	(0.041)	(0.058)	(0.046)
Non-rent PC HH income(R10,000s)	0.160***	0.117***	0.151***	0.109**	-0.000	0.021
	(0.041)	(0.045)	(0.043)	(0.046)	(0.055)	(0.049)
Non-rent PC HH income (R10,000s) squared	-0.007***	-0.002***	-0.006**	-0.002**	-0.000	-0.000
	(0.002)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
Age	-0.023***	-0.029***	-0.024***	-0.030***	-0.079***	-0.049***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.020)	(0.018)
Age squared/100	-0.002	0.007*	-0.002	0.006	0.006	0.006
	(0.005)	(0.004)	(0.005)	(0.004)	(0.016)	(0.012)
Marital status						
Married	0.095***	0.044	0.103***	0.035	0.065	-0.092*
	(0.034)	(0.028)	(0.037)	(0.030)	(0.069)	(0.053)
Div/sep/widowed	-0.074	-0.041	-0.086	-0.058	-0.131	-0.133*
	(0.067)	(0.039)	(0.073)	(0.042)	(0.112)	(0.068)
Education						
Primary	0.206***	0.227***	0.239***	0.254***	0.058	0.032
	(0.038)	(0.033)	(0.041)	(0.036)	(0.118)	(0.106)
Secondary	0.368***	0.474***	0.420***	0.526***	0.126	0.135
	(0.044)	(0.039)	(0.048)	(0.043)	(0.143)	(0.132)
Tertiary	0.609***	0.608***	0.697***	0.667***	0.222	0.052
	(0.102)	(0.087)	(0.111)	(0.094)	(0.239)	(0.236)

Table 4.2 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Four-level SRH	POP Men	POP Women	RE Men	RE Women	FE Men	FE Women
Geo type						
Traditional	0.001 (0.028)	0.106*** (0.023)	0.001 (0.030)	0.116*** (0.025)	0.089 (0.072)	0.076 (0.067)
Farms	0.069 (0.049)	-0.032 (0.055)	0.082 (0.054)	-0.050 (0.059)	0.266* (0.137)	-0.194 (0.126)
No. of children younger than 7	-0.020* (0.034)	0.006 (0.027)	-0.025** (0.037)	0.003 (0.029)	-0.037** (0.109)	-0.008 (0.102)
Race (POP and RE only)						
Coloured	-0.079* (0.045)	0.121*** (0.042)	-0.084* (0.049)	0.134*** (0.046)		
Indian/ Asian	-0.091 (0.110)	-0.080 (0.104)	-0.099 (0.123)	-0.065 (0.113)		
White	-0.108* (0.056)	0.189*** (0.062)	-0.104* (0.063)	0.222*** (0.066)		
Observations	21,605	32,091	21,605	32,091	21,605	32,091
Log likelihood	-6.680e+07	-8.290e+07	-6.630e+07	-8.220e+07	-6.620e+07	-8.210e+07
Number of pid			8,641	11,140	8,641	11,140
Sigma u			0.431	0.446	0.433	0.447

Source: Own calculations using NIDS Waves 1 to 4 (2008; 2010-12; 2012; 2014-15).

Notes: Selected coefficients from panel ordered probit regression models are presented. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in are shown in parentheses. Estimates are weighted using panel weights.

In Table 4.4, the focus is on perceived inequality, as reflected in the metric designed by Cowell and Flachaire (2017). Here the relative income hypothesis is reflected in the inclusion of the district average income. The relationship of this inequality measure with health differs by gender. The coefficients of perceived inequality are positive, but statistically insignificant in all the models for men; in contrast, they are negative and statistically significant in all the models for women. The size of the coefficient decreases when individual heterogeneity is accounted for, but the coefficients remain statistically significant at the 10% level. This finding signifies that the inequality hypothesis holds for women, but only with regard to perceived inequality. The broader notion of health that SRH represents for women, compared to mostly physical aspects of health for men, may explain the lack of a relationship for men. The Hausman test indicates that, at all conventional significance levels, the FEOP model is preferable to the REOP ($\chi^2 = 61.50$ for men and $\chi^2 = 108.93$ for women).

District average income per capita is used as an implicit measure of relative rank in Table 4.4 (Lorgelly & Lindley, 2008). However, Table 4.4 presents no evidence in support of the relative income hypothesis. The coefficient of district average income is positive and significant at the 5% level in the POP and REOP models for men and women, but insignificant in the FEOP models. The district average income also reflects the individual's socioeconomic environment. Its positive association with SRH may suggest that it captures opportunities to live a better lifestyle (through better work or recreation), or to obtain higher-quality healthcare, in districts where individuals, on average, have more resources. Districts with a higher average income are also likely to be more unequal – both of these material well-being dimensions may be related to access to better opportunities.

The results for a few of the other covariates in the FEOP models may be worth noting. Compared to being single, a change in status to married or previously married has a weakly significant and negative association with women's health, but there is no link for men. This finding is not in discord with the international literature (Guner *et al.*, 2014; Kiecolt-Glaser & Newton, 2001). Men who move to commercial farms tend to be healthier, compared to those in urban locations, but geo type is not connected to women's health. Contrary to expectations, living with an increasing number of young children (under age 7) is related to worse SRH for men, but not for women. This is surprising, given that, on average, women live in households with more children (Table 4.1) and

women are also much more likely to be primary physical caregivers to the children who reside with them (Hatch & Posel, 2018). These coefficients are largely robust across the different specifications.

Table 4.3 Ordered probit models with perceived rank

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Four-level SRH	POP Men	POP Women	RE Men	RE Women	FE Men	FE Women
Gini (on non-rent income)	0.284* (0.157)	0.432*** (0.132)	0.290* (0.169)	0.480*** (0.142)	0.285 (0.246)	0.487** (0.195)
Perceived rank						
Above average income	-0.120 (0.074)	-0.176*** (0.066)	-0.115 (0.080)	-0.202*** (0.070)	-0.065 (0.098)	-0.208** (0.083)
Average income	-0.215*** (0.065)	-0.300*** (0.056)	-0.231*** (0.070)	-0.330*** (0.060)	-0.253*** (0.086)	-0.340*** (0.069)
Below average income	-0.256*** (0.067)	-0.364*** (0.057)	-0.268*** (0.072)	-0.388*** (0.061)	-0.258*** (0.089)	-0.346*** (0.070)
Much below average income	-0.323*** (0.069)	-0.387*** (0.059)	-0.328*** (0.074)	-0.410*** (0.063)	-0.251*** (0.091)	-0.360*** (0.072)
Non-rent PC HH income (R10,000s)	0.142*** (0.040)	0.115** (0.045)	0.129*** (0.043)	0.113** (0.047)	-0.028 (0.055)	0.021 (0.051)
Non-rent PC HH income (R10,000s) squared	-0.006** (0.002)	-0.002** (0.001)	-0.005** (0.003)	-0.002** (0.001)	0.001 (0.003)	-0.000 (0.001)
Age	-0.023*** (0.004)	-0.030*** (0.004)	-0.024*** (0.005)	-0.031*** (0.004)	-0.075*** (0.021)	-0.033* (0.019)
Age squared/100	-0.002 (0.005)	0.007* (0.004)	-0.002 (0.005)	0.006 (0.004)	0.012 (0.016)	0.005 (0.012)
Marital status						
Married	0.090*** (0.035)	0.052* (0.029)	0.096** (0.037)	0.045 (0.030)	0.083 (0.071)	-0.079 (0.054)
Div/sep/widowed	-0.066 (0.066)	-0.026 (0.039)	-0.081 (0.073)	-0.040 (0.042)	-0.110 (0.115)	-0.104 (0.068)
Education						
Primary	0.195*** (0.039)	0.217*** (0.033)	0.225*** (0.041)	0.242*** (0.036)	0.063 (0.119)	0.021 (0.109)
Secondary	0.352*** (0.046)	0.457*** (0.040)	0.403*** (0.049)	0.508*** (0.043)	0.161 (0.145)	0.134 (0.136)
Tertiary	0.577*** (0.106)	0.600*** (0.089)	0.661*** (0.116)	0.660*** (0.096)	0.318 (0.243)	0.127 (0.242)

Table 4.3 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Four-level SRH	POP Men	POP Women	RE Men	RE Women	FE Men	FE Women
Geo type						
Traditional	0.018 (0.029)	0.120*** (0.024)	0.017 (0.030)	0.126*** (0.026)	0.095 (0.075)	0.037 (0.066)
Farms	0.065 (0.050)	-0.005 (0.056)	0.076 (0.054)	-0.023 (0.060)	0.238* (0.133)	-0.199 (0.126)
No. of children younger than 7	-0.028** (0.012)	0.006 (0.009)	-0.032** (0.013)	0.004 (0.009)	-0.046** (0.018)	-0.002 (0.015)
Race (POP and RE only)						
Coloured	-0.090** (0.045)	0.124*** (0.043)	-0.093* (0.049)	0.133*** (0.047)		
Indian/ Asian	-0.075 (0.114)	-0.124 (0.107)	-0.072 (0.126)	-0.110 (0.115)		
White	-0.110* (0.058)	0.198*** (0.062)	-0.107* (0.064)	0.224*** (0.066)		
Observations	20,573	30,594	20,573	30,594	20,573	30,594
Log likelihood	-6.310e+07	-7.840e+07	-6.280e+07	-7.780e+07	-6.270e+07	-7.780e+07
Number of pid			8,527	11,019	8,527	11,019
Sigma u			0.412	0.442	0.415	0.446

Source: Own calculations using NIDS Waves 1 to 4 (2008; 2010-12; 2012; 2014-15).

Notes: Selected coefficients from panel ordered probit regression models are presented. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in are shown in parentheses. Estimates are weighted using panel weights.

Table 4.4 Ordered probit models with perceived inequality

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Four-level SRH	POP Men	POP Women	RE Men	RE Women	FE Men	FE Women
Perceived inequality	0.085 (0.220)	-0.443** (0.178)	0.155 (0.236)	-0.439** (0.191)	0.353 (0.271)	-0.379* (0.215)
District average non-rent income (R10,000s)	0.508*** (0.171)	0.334** (0.145)	0.482** (0.187)	0.343** (0.156)	0.050 (0.339)	0.228 (0.247)
Non-rent PC HH income(R10,000s)	0.154*** (0.038)	0.131*** (0.044)	0.141*** (0.041)	0.119*** (0.045)	-0.017 (0.053)	0.015 (0.049)
Non-rent PC HH income (R10,000s) squared	-0.006*** (0.002)	-0.003*** (0.001)	-0.005** (0.002)	-0.002*** (0.001)	0.001 (0.003)	-0.000 (0.001)
Age	-0.023*** (0.004)	-0.029*** (0.004)	-0.025*** (0.005)	-0.031*** (0.004)	-0.073*** (0.020)	-0.048*** (0.018)
Age squared/100	-0.002 (0.005)	0.007* (0.004)	-0.002 (0.005)	0.006 (0.004)	0.008 (0.016)	0.008 (0.012)
Marital status						
Married	0.094*** (0.034)	0.044 (0.028)	0.101*** (0.037)	0.035 (0.030)	0.069 (0.069)	-0.094* (0.053)
Div/sep/widowed	-0.071 (0.067)	-0.042 (0.039)	-0.085 (0.073)	-0.060 (0.042)	-0.129 (0.112)	-0.135** (0.068)
Education						
Primary	0.203*** (0.038)	0.225*** (0.032)	0.235*** (0.041)	0.252*** (0.035)	0.063 (0.119)	0.037 (0.107)
Secondary	0.359*** (0.044)	0.474*** (0.039)	0.410*** (0.048)	0.525*** (0.043)	0.134 (0.144)	0.138 (0.133)
Tertiary	0.611*** (0.101)	0.611*** (0.086)	0.696*** (0.111)	0.670*** (0.093)	0.246 (0.239)	0.060 (0.236)

Table 4.4 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Four-level SRH	POP Men	POP Women	RE Men	RE Women	FE Men	FE Women
Geo type						
Traditional	0.044 (0.031)	0.137*** (0.025)	0.041 (0.033)	0.148*** (0.027)	0.087 (0.076)	0.088 (0.070)
Farms	0.089* (0.050)	-0.020 (0.056)	0.100* (0.054)	-0.039 (0.059)	0.258* (0.136)	-0.201 (0.126)
No. of children younger than 7	-0.019* (0.012)	0.006 (0.009)	-0.024* (0.013)	0.003 (0.009)	-0.036** (0.018)	-0.007 (0.014)
Race (POP and RE only)						
Coloured	-0.082* (0.045)	0.104** (0.042)	-0.087* (0.049)	0.116** (0.046)		
Indian/ Asian	-0.075 (0.109)	-0.066 (0.105)	-0.079 (0.122)	-0.047 (0.114)		
White	-0.120** (0.057)	0.180*** (0.062)	-0.116* (0.063)	0.214*** (0.066)		
Observations	21,605	32,091	21,605	32,091	21,605	32,091
Log likelihood	-6.680e+07	-8.290e+07	-6.630e+07	-8.220e+07	-6.630e+07	-8.220e+07
Number of pid			8,641	11,140	8,641	11,140
Sigma_u			0.428	0.445	0.430	0.447

Source: Own calculations using NIDS Waves 1 to 4 (2008; 2010-12; 2012; 2014-15).

Notes: Selected coefficients from panel ordered probit regression models are presented. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in are shown in parentheses. Estimates are weighted using panel weights.

4.5. Tests for attrition bias

The specifications in Tables 4.2 to 4.4 were tested for attrition bias by applying the Beckett, Gould, Lillard, and Welch (BGLW) test (Beckett *et al.*, 1988). This test investigates the effects of attrition in the future period on the outcome variable in the present period. The BGLW test involves including a binary indicator for whether the respondent attrited in the subsequent wave (that is, a binary variable which equals one if the individual was not interviewed successfully for any reason, and equals zero otherwise), as well as interaction terms of this binary variable with all the regressors, into the regression results for the baseline wave (Baulch & Quisumbing, 2011). The BGLW test was conducted for each pair of consecutive waves, as non-random patterns of (positive) attrition were recorded between waves 1 and 2, and also between waves 3 and 4 (Brown *et al.*, 2012; Chinhema *et al.*, 2016).

In addition, the test was applied in the conventional way and in reverse for waves 2 and 3 because of the negative attrition recorded between wave 2 and wave 3 of NIDS (De Villiers *et al.*, 2013). The ‘reverse’ test for the effect of the negative attrition between W2 and W3 was conducted by setting W3 as the ‘baseline wave’ and including a binary variable for individuals who were interviewed in wave 3 but not in wave 2, as well as interactions of this variable with the other explanatory variables, into the regression results for wave 3.

The BGLW test results are presented in Table 4.5. They suggest that attrition does not affect the regression results for the most part, with the two consistent exceptions being W1-W2 attrition for men and W2-W3 attrition for women. The complete results of the BGLW test are included in Appendix 4.B.

Table 4.5 BGLW test for attrition in regression models

Attrition check for measured rank and inequality models in Table 4.2

	Men			Women		
	Chi2	df	p-value	Chi2	df	p-value
Wave 1-2	48.737	21.000	0.001	27.687	21.000	0.149
Wave 2-3	22.569	21.000	0.367	40.700	21.000	0.006
Wave 3-2	17.277	21.000	0.694	23.360	21.000	0.325
Wave 3-4	22.984	21.000	0.345	28.258	21.000	0.133

Attrition check for perceived rank models in Table 4.3

	Men			Women		
	Chi2	df	p-value	Chi2	df	p-value
Wave 1-2	59.041	21.000	0.000	24.341	21.000	0.277
Wave 2-3	27.758	21.000	0.147	36.384	21.000	0.020
Wave 3-2	16.571	21.000	0.737	29.584	21.000	0.101
Wave 3-4	27.885	21.000	0.143	24.246	21.000	0.281

Attrition check for perceived rank models in Table 4.4

	Men			Women		
	Chi2	df	p-value	Chi2	df	p-value
Wave 1-2	59.041	21.000	0.000	24.341	21.000	0.277
Wave 2-3	27.758	21.000	0.147	36.384	21.000	0.020
Wave 3-2	16.571	21.000	0.737	29.584	21.000	0.101
Wave 3-4	27.885	21.000	0.143	24.246	21.000	0.281

Source: Own calculations using NIDS Waves 1 to 4 (2008; 2010-12; 2012; 2014-15).

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in are shown in parentheses.

4.6. Conclusion

The aim of this chapter was to gain insight into the relationship between health and material dimensions of well-being by testing three hypotheses about the links between health and absolute income, relative income (also referred to as rank, or relative deprivation), and income inequality. The latter two hypotheses were expanded to compare the role of measured rank and inequality with that of perceptions about rank and inequality. The analysis was conducted separately by gender, given some significant differences in the average characteristics of women and men in South Africa and given that the nature of the relationships is likely to be distinct by gender. The panel ordered probit models took into account the structure of the data and unobserved individual heterogeneity was addressed using the Chamberlain-Mundlak approach in the fixed-effects ordered probit models (Chamberlain, 1984; Mundlak, 1978).

For both men and women, the results provide no evidence in support of the absolute income hypothesis when unobserved individual heterogeneity is taken into account. There are three possible reason for this result. First, per capita measures may underestimate available economic resources, since the lower requirements of children compared to adults and the economies of scale in consumption enjoyed by larger households are not accounted for. Second, the benefits of the government-funded healthcare in South Africa are not imputed into direct income measures. Third, the relationship between access to material resources and health is likely to manifest over long periods; hence, the six-year horizon, covered by the first four waves of NIDS, may be too short to establish this relationship using real (inflation-adjusted) per capita income and perceived health as measures. Similarly, relative income, based on Deaton's relative deprivation index, generated using the same per capita measure of income, also shows no link to health.

Further, there is little support for the income inequality hypothesis – on the contrary, in the case of women, a higher Gini coefficient at district level may be associated with better health. It is possible that in the South African context, a higher Gini coefficient may proxy better job opportunities, more effective service provision, or access to higher quality (government-funded) healthcare (Turok *et al.*, 2017). Further research can shed more light on these links. The Roy-Borjas model may point to another possible explanation for the positive relationship between measured inequality and health perceptions. The model posits that more unequal regions signal the possibility of higher wages, especially for workers endowed with substantial human capital (Borjas, 1987; Stolz & Baten, 2012). This is also an avenue for future research.

In contrast, measures of perceived rank and inequality have stronger links with health. For both genders, self-reporting lower than the top rank on the income ladder, compared to neighbours in the near vicinity, is associated with worse SRH. A measure of perceived inequality, generated using the inequality measure for ordinal data, suggested by Cowell and Flachaire (2017), produces different results by gender. It has no significant relationship with men's health, but a negative relationship with women's. These findings are likely to suggest that while measured rank and inequality are indicators of disparities in access to material resources as an outcome, perceived rank and inequality are better reflections of disparities in opportunities available to individuals. Hence, the latter are more likely to be related, via negative psychosocial pathways, to health. The results are consistent with another South African studies, which find that perceived rank is a better

predictor of well-being than rank based on measured income (Posel & Rogan, 2014; Posel & Casale, 2011).

Some of the limitations of the study include the following. As mentioned in the methodology section, the rank and inequality measures are at the district level. Less granular measures, with neighbourhoods or villages as reference groups (e.g. at the cluster level) are not possible to implement because the NIDS samples at those levels are small and lack representability. Nevertheless, Pickett and Wilkinson (2015) suggest that measures involving broader geographical areas are more appropriate in studies similar to this. Another limitation is that the results do not shed light on the direction of causality in the relationships that are investigated. This is another worthwhile area for further research.

Appendix 4.A

Table 4.6 Ordered probit models with measured expenditure rank and inequality

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Four-level SRH	POP Men	POP Women	RE Men	RE Women	FE Men	FE Women
Gini (PC HH expenditure)	0.195 (0.188)	0.214 (0.159)	0.144 (0.200)	0.128 (0.167)	0.107 (0.256)	-0.285 (0.213)
Relative deprivation (Deaton index quintiles)						
Quintile 2	0.067 (0.042)	0.006 (0.035)	0.067 (0.045)	0.013 (0.037)	0.045 (0.052)	0.044 (0.040)
Quintile 3	0.014 (0.043)	-0.006 (0.038)	-0.002 (0.046)	-0.009 (0.040)	-0.042 (0.052)	0.005 (0.043)
Quintile 4	0.065 (0.044)	-0.052 (0.038)	0.071 (0.047)	-0.051 (0.041)	0.076 (0.055)	-0.027 (0.045)
Quintile 5	0.076* (0.046)	0.003 (0.040)	0.082* (0.050)	0.017 (0.042)	0.097* (0.058)	0.063 (0.048)
PC HH expenditure (R10,000s)	0.152** (0.061)	0.129* (0.075)	0.133** (0.066)	0.099 (0.076)	-0.093 (0.095)	-0.118 (0.085)
PC HH expenditure (R10,000s) squared	-0.011 (0.007)	-0.010 (0.011)	-0.009 (0.008)	-0.005 (0.011)	0.013 (0.013)	0.022* (0.011)
Age	-0.021*** (0.004)	-0.029*** (0.004)	-0.023*** (0.005)	-0.030*** (0.004)	-0.080*** (0.020)	-0.050*** (0.018)
Age squared/100	-0.004 (0.005)	0.007 (0.004)	-0.004 (0.005)	0.006 (0.004)	0.006 (0.016)	0.006 (0.012)
Marital status						
Married	0.101*** (0.034)	0.050* (0.028)	0.107*** (0.037)	0.042 (0.030)	0.062 (0.069)	-0.087* (0.053)
Div/sep/widowed	-0.065 (0.067)	-0.042 (0.039)	-0.079 (0.073)	-0.058 (0.042)	-0.127 (0.113)	-0.124* (0.068)

Table 4.6 (continued)

Dependent variable		(1)	(2)	(3)	(4)	(5)	(6)
Four-level SRH		POP Men	POP Women	RE Men	RE Women	FE Men	FE Women
Education							
	Primary	0.210*** (0.038)	0.228*** (0.033)	0.243*** (0.041)	0.257*** (0.036)	0.064 (0.120)	0.032 (0.107)
	Secondary	0.385*** (0.045)	0.480*** (0.040)	0.438*** (0.049)	0.536*** (0.043)	0.132 (0.145)	0.135 (0.132)
	Tertiary	0.669*** (0.100)	0.639*** (0.086)	0.755*** (0.110)	0.703*** (0.093)	0.231 (0.239)	0.068 (0.235)
Geo type							
	Traditional	0.011 (0.029)	0.105*** (0.024)	0.010 (0.031)	0.113*** (0.026)	0.100 (0.073)	0.049 (0.068)
	Farms	0.071 (0.050)	-0.035 (0.055)	0.083 (0.054)	-0.055 (0.060)	0.261* (0.136)	-0.212* (0.126)
No. of children younger than 7		-0.026** (0.012)	0.005 (0.009)	-0.030** (0.013)	0.001 (0.009)	-0.040** (0.018)	-0.010 (0.014)
Race (POP and RE only)							
	Coloured	-0.092** (0.046)	0.115*** (0.042)	-0.098** (0.050)	0.129*** (0.046)		
	Indian/ Asian	-0.103 (0.110)	-0.084 (0.107)	-0.102 (0.124)	-0.056 (0.115)		
	White	-0.101* (0.059)	0.183*** (0.067)	-0.092 (0.066)	0.227*** (0.071)		
Observations		21,605	32,091	21,605	32,091	21,605	32,091
Log likelihood		-6.680e+07	-8.290e+07	-6.640e+07	-8.220e+07	-6.630e+07	-8.220e+07
Number of pid				8,641	11,140	8,641	11,140
Sigma u				0.436	0.447	0.439	0.449

Source: Own calculations using NIDS Waves 1 to 4 (2008; 2010-12; 2012; 2014-15).

Notes: Selected coefficients from panel ordered probit regression models are presented. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in are shown in parentheses. Estimates are weighted using panel weights.

Table 4.7 Ordered probit models with perceived rank

		(1)	(2)	(3)	(4)	(5)	(6)
Four-level SRH		POP Men	POP Women	RE Men	RE Women	FE Men	FE Women
Gini (PC HH expenditure)		0.383** (0.165)	0.254* (0.137)	0.361** (0.177)	0.203 (0.146)	0.306 (0.252)	-0.136 (0.208)
Perceived rank							
	Above average income	-0.111 (0.074)	-0.173*** (0.066)	-0.107 (0.080)	-0.198*** (0.071)	-0.063 (0.098)	-0.206** (0.083)
	Average income	-0.214*** (0.065)	-0.300*** (0.056)	-0.232*** (0.070)	-0.329*** (0.060)	-0.252*** (0.086)	-0.337*** (0.069)
	Below average income	-0.260*** (0.067)	-0.365*** (0.057)	-0.272*** (0.072)	-0.388*** (0.061)	-0.257*** (0.089)	-0.342*** (0.070)
	Much below average income	-0.334*** (0.069)	-0.390*** (0.059)	-0.338*** (0.074)	-0.412*** (0.063)	-0.252*** (0.091)	-0.360*** (0.072)
PC HH expenditure (R10,000s)		0.088 (0.060)	0.150* (0.077)	0.069 (0.065)	0.126 (0.079)	-0.136 (0.097)	-0.066 (0.094)
PC HH expenditure (R10,000s) squared		-0.006 (0.008)	-0.019 (0.014)	-0.004 (0.009)	-0.014 (0.014)	0.016 (0.014)	0.012 (0.016)
Age		-0.022*** (0.004)	-0.030*** (0.004)	-0.023*** (0.005)	-0.031*** (0.004)	-0.079*** (0.021)	-0.037** (0.019)
Age squared/100		-0.003 (0.005)	0.007* (0.004)	-0.004 (0.005)	0.006 (0.004)	0.011 (0.016)	0.005 (0.012)
Marital status							
	Married	0.093*** (0.035)	0.054* (0.028)	0.099*** (0.037)	0.048 (0.030)	0.078 (0.071)	-0.078 (0.054)
	Div/sep/widowed	-0.057 (0.066)	-0.028 (0.039)	-0.072 (0.072)	-0.041 (0.042)	-0.109 (0.116)	-0.099 (0.068)
Education							
	Primary	0.195*** (0.039)	0.215*** (0.033)	0.227*** (0.041)	0.241*** (0.036)	0.067 (0.120)	0.019 (0.109)
	Secondary	0.364*** (0.046)	0.456*** (0.040)	0.416*** (0.049)	0.510*** (0.044)	0.166 (0.146)	0.134 (0.136)
	Tertiary	0.633*** (0.104)	0.615*** (0.089)	0.717*** (0.114)	0.681*** (0.096)	0.316 (0.244)	0.142 (0.242)

Table 4.7 (continued)

Dependent variable		(1)	(2)	(3)	(4)	(5)	(6)
Four-level SRH		POP Men	POP Women	RE Men	RE Women	FE Men	FE Women
Geo type							
	Traditional	0.018 (0.029)	0.119*** (0.024)	0.016 (0.031)	0.120*** (0.026)	0.091 (0.076)	0.011 (0.068)
	Farms	0.061 (0.050)	-0.007 (0.056)	0.072 (0.055)	-0.027 (0.060)	0.241* (0.133)	-0.211* (0.127)
No. of children younger than 7		-0.032*** (0.012)	0.007 (0.009)	-0.036*** (0.013)	0.004 (0.009)	-0.048*** (0.018)	-0.003 (0.015)
Race (POP and RE only)							
	Coloured	-0.098** (0.045)	0.115*** (0.042)	-0.101** (0.049)	0.124*** (0.046)		
	Indian/ Asian	-0.083 (0.116)	-0.132 (0.110)	-0.078 (0.128)	-0.109 (0.118)		
	White	-0.103* (0.062)	0.182*** (0.067)	-0.095 (0.068)	0.216*** (0.072)		
Observations		20,573	30,594	20,573	30,594	20,573	30,594
Log likelihood		-6.310e+07	-7.840e+07	-6.280e+07	-7.780e+07	-6.270e+07	-7.780e+07
Number of pid				8,527	11,019	8,527	11,019
Sigma_u				0.416	0.442	0.419	0.445

Source: Own calculations using NIDS Waves 1 to 4 (2008; 2010-12; 2012; 2014-15).

Notes: Selected coefficients from panel ordered probit regression models are presented. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in are shown in parentheses. Estimates are weighted using panel weights.

Table 4.8 Ordered probit models with perceived inequality

Dependent variable		(1)	(2)	(3)	(4)	(5)	(6)
Four-level SRH		POP Men	POP Women	RE Men	RE Women	FE Men	FE Women
Perceived inequality (based on M2)		0.126 (0.220)	-0.442** (0.178)	0.190 (0.237)	-0.439** (0.192)	0.366 (0.270)	-0.382* (0.215)
District average PC HH expenditure (R10,000s)		0.773*** (0.201)	0.378** (0.181)	0.751*** (0.216)	0.397** (0.194)	0.329 (0.378)	0.301 (0.327)
PC HH expenditure (R10,000s)		0.109* (0.058)	0.132* (0.071)	0.089 (0.063)	0.096 (0.072)	-0.125 (0.094)	-0.140* (0.083)
PC HH expenditure (R10,000s) squared		-0.007 (0.008)	-0.010 (0.011)	-0.005 (0.009)	-0.005 (0.011)	0.016 (0.014)	0.024** (0.011)
Age		-0.021*** (0.004)	-0.029*** (0.004)	-0.023*** (0.005)	-0.030*** (0.004)	-0.079*** (0.020)	-0.047** (0.018)
Age squared/100		-0.003 (0.005)	0.007* (0.004)	-0.003 (0.005)	0.006 (0.004)	0.008 (0.016)	0.007 (0.012)
Marital status							
	Married	0.097*** (0.034)	0.046* (0.028)	0.103*** (0.037)	0.038 (0.030)	0.065 (0.069)	-0.090* (0.053)
	Div/sep/widowed	-0.064 (0.067)	-0.046 (0.039)	-0.079 (0.073)	-0.063 (0.042)	-0.128 (0.112)	-0.131* (0.069)
Education							
	Primary	0.203*** (0.038)	0.222*** (0.033)	0.235*** (0.041)	0.250*** (0.036)	0.064 (0.119)	0.037 (0.107)
	Secondary	0.370*** (0.045)	0.475*** (0.039)	0.421*** (0.048)	0.529*** (0.043)	0.136 (0.145)	0.136 (0.133)
	Tertiary	0.668*** (0.100)	0.634*** (0.086)	0.752*** (0.109)	0.697*** (0.093)	0.243 (0.239)	0.076 (0.236)

Table 4.8 (continued)

Dependent variable		(1)	(2)	(3)	(4)	(5)	(6)
Four-level SRH		POP Men	POP Women	RE Men	RE Women	FE Men	FE Women
Geo type							
	Traditional	0.057* (0.031)	0.138*** (0.026)	0.054 (0.034)	0.148*** (0.029)	0.100 (0.075)	0.086 (0.071)
	Farms	0.097* (0.050)	-0.019 (0.056)	0.108** (0.055)	-0.040 (0.060)	0.263* (0.136)	-0.203 (0.126)
No. of children younger than 7		-0.023* (0.012)	0.006 (0.009)	-0.027** (0.013)	0.002 (0.009)	-0.039** (0.018)	-0.009 (0.014)
Race (POP and RE only)							
	Coloured	-0.090** (0.045)	0.102** (0.042)	-0.094* (0.049)	0.116** (0.046)		
	Indian/ Asian	-0.076 (0.110)	-0.070 (0.108)	-0.078 (0.123)	-0.043 (0.117)		
	White	-0.117** (0.059)	0.175*** (0.067)	-0.110* (0.066)	0.218*** (0.071)		
Observations		21,605	32,091	21,605	32,091	21,605	32,091
Log likelihood		-6.680e+07	-8.290e+07	-6.640e+07	-8.220e+07	-6.630e+07	-8.220e+07
Number of pid				8,641	11,140	8,641	11,140
Sigma_u				0.430	0.446	0.434	0.448

Source: Own calculations using NIDS Waves 1 to 4 (2008; 2010-12; 2012; 2014-15).

Notes: Selected coefficients from panel ordered probit regression models are presented. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in are shown in parentheses. Estimates are weighted using panel weights.

Appendix 4.B

Table 4.9 BGLW test for attrition bias on ordered probit models with measured rank and inequality

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	W1-2 Men	W1-2 Women	W2-3 Men	W2-3 Women	W3-2 Men	W3-2 Women	W3-4 Men	W3-4 Women
Four-level SRH								
Gini (on non-rent income)	0.275 (0.295)	0.472* (0.284)	0.234 (0.404)	0.280 (0.386)	0.286 (0.314)	0.717*** (0.245)	0.311 (0.305)	0.600** (0.241)
Relative deprivation (Deaton index quintiles)								
Quintile 2	0.022 (0.060)	-0.005 (0.057)	0.017 (0.086)	0.048 (0.099)	0.015 (0.059)	0.021 (0.047)	0.027 (0.059)	0.025 (0.048)
Quintile 3	0.040 (0.073)	0.040 (0.065)	0.038 (0.094)	0.056 (0.110)	-0.113* (0.060)	-0.076 (0.049)	-0.102* (0.059)	-0.080 (0.049)
Quintile 4	-0.033 (0.076)	0.039 (0.064)	-0.048 (0.097)	0.033 (0.115)	-0.089 (0.067)	-0.099* (0.052)	-0.093 (0.065)	-0.123** (0.052)
Quintile 5	0.071 (0.074)	0.087 (0.070)	0.032 (0.112)	0.127 (0.128)	-0.012 (0.067)	-0.032 (0.055)	-0.006 (0.065)	-0.016 (0.055)
Non-rent PC HH income(R10,000s)	0.239** (0.100)	0.372*** (0.126)	0.145* (0.084)	0.164 (0.153)	0.097 (0.098)	0.056 (0.113)	0.109 (0.094)	0.031 (0.111)
Non-rent PC HH income (R10,000s) squared	-0.015 (0.010)	-0.050*** (0.018)	-0.007* (0.004)	0.027 (0.048)	0.012 (0.019)	-0.006 (0.035)	0.002 (0.018)	-0.011 (0.036)
Age	-0.052*** (0.007)	-0.036*** (0.005)	-0.027*** (0.006)	-0.036*** (0.005)	-0.025*** (0.006)	-0.026*** (0.004)	-0.026*** (0.006)	-0.027*** (0.004)
Age squared/100	0.026*** (0.007)	0.010** (0.005)	0.002 (0.007)	0.012*** (0.005)	-0.003 (0.006)	0.002 (0.004)	-0.000 (0.006)	0.003 (0.004)
Race								
Coloured	0.030 (0.063)	0.229*** (0.055)	0.040 (0.066)	0.193*** (0.065)	0.011 (0.052)	0.046 (0.042)	-0.018 (0.050)	0.024 (0.041)
Indian/ Asian	-0.621*** (0.092)	-0.397*** (0.138)	0.108 (0.213)	0.123 (0.171)	-0.416*** (0.157)	-0.180 (0.131)	-0.336** (0.163)	-0.207 (0.128)
White	-0.116 (0.111)	0.145 (0.109)	0.266** (0.111)	0.291** (0.118)	-0.149 (0.111)	0.127 (0.095)	-0.140 (0.104)	0.028 (0.090)

Table 4.9 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Four-level SRH	W1-2 Men	W1-2 Women	W2-3 Men	W2-3 Women	W3-2 Men	W3-2 Women	W3-4 Men	W3-4 Women
Marital status								
Married	0.192*** (0.053)	0.114*** (0.036)	0.165*** (0.057)	0.076* (0.040)	0.197*** (0.050)	0.109*** (0.034)	0.170*** (0.049)	0.119*** (0.034)
Div/sep/widowed	0.018 (0.100)	0.040 (0.053)	-0.012 (0.109)	-0.002 (0.052)	0.094 (0.090)	0.052 (0.046)	0.098 (0.091)	0.046 (0.046)
Education								
Primary	0.240*** (0.054)	0.290*** (0.042)	0.251*** (0.051)	0.173*** (0.042)	0.218*** (0.048)	0.201*** (0.037)	0.215*** (0.048)	0.221*** (0.037)
Secondary	0.446*** (0.066)	0.597*** (0.053)	0.417*** (0.060)	0.409*** (0.055)	0.395*** (0.059)	0.411*** (0.047)	0.419*** (0.058)	0.432*** (0.046)
Tertiary	0.797*** (0.156)	0.765*** (0.134)	0.291** (0.128)	0.431*** (0.108)	0.618*** (0.133)	0.341*** (0.110)	0.514*** (0.134)	0.420*** (0.108)
Geo type								
Traditional	0.013 (0.060)	0.145*** (0.055)	0.043 (0.057)	0.174*** (0.053)	-0.023 (0.041)	-0.012 (0.032)	-0.028 (0.040)	-0.033 (0.032)
Farms	0.119 (0.075)	0.080 (0.066)	-0.079 (0.059)	-0.158** (0.070)	0.164** (0.065)	0.047 (0.058)	0.207*** (0.064)	0.051 (0.057)
No. of children younger than 7	-0.014 (0.020)	0.012 (0.016)	0.008 (0.019)	0.005 (0.013)	-0.031* (0.018)	0.011 (0.012)	-0.026 (0.018)	0.007 (0.012)
A (attrition dummy variable)	-0.649* (0.351)	0.139 (0.320)	0.203 (0.610)	-0.346 (0.423)	0.554 (0.576)	0.109 (0.506)	0.891 (0.612)	-0.019 (0.547)
A*Gini	0.486 (0.413)	-0.291 (0.393)	-1.036 (0.835)	0.606 (0.636)	-0.089 (0.162)	-0.049 (0.158)	-0.187 (0.165)	-0.100 (0.146)

Table 4.9 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	W1-2 Men	W1-2 Women	W2-3 Men	W2-3 Women	W3-2 Men	W3-2 Women	W3-4 Men	W3-4 Women
Four-level SRH								
A*RD quintile 2	0.190*	0.048	0.328	-0.040	0.016	-0.138	-0.023	-0.217
	(0.107)	(0.101)	(0.205)	(0.167)	(0.157)	(0.153)	(0.172)	(0.158)
A*RD quintile 3	0.041	-0.027	0.370*	-0.114	-0.086	-0.126	-0.052	0.077
	(0.123)	(0.112)	(0.210)	(0.165)	(0.169)	(0.162)	(0.188)	(0.169)
A*RD quintile 4	-0.146	-0.082	0.116	-0.146	0.048	-0.045	0.036	-0.149
	(0.138)	(0.123)	(0.221)	(0.186)	(0.172)	(0.170)	(0.192)	(0.173)
A*RD quintile 5	-0.072	-0.055	0.170	-0.221	-0.985	-0.533	-1.397	0.067
	(0.143)	(0.128)	(0.223)	(0.194)	(0.798)	(0.738)	(0.918)	(0.851)
A*PC HH income	0.237	-0.148	0.007	0.418	0.053	0.041	-0.006	0.374
	(0.170)	(0.200)	(0.185)	(0.316)	(0.241)	(0.321)	(0.307)	(0.335)
A*PC HH income squared	-0.026	0.011	-0.004	-0.192	-0.040	0.004	0.010	-0.060
	(0.023)	(0.049)	(0.014)	(0.135)	(0.046)	(0.117)	(0.069)	(0.100)
A*Age	0.016	0.004	0.003	-0.001	0.002	0.004	0.003	-0.003
	(0.013)	(0.010)	(0.016)	(0.012)	(0.017)	(0.014)	(0.016)	(0.013)
A*Age squared	-0.018	-0.003	-0.001	0.002	0.001	-0.004	-0.005	-0.000
	(0.013)	(0.010)	(0.017)	(0.012)	(0.018)	(0.014)	(0.015)	(0.012)
A*Coloured	-0.084	-0.049	-0.033	-0.201*	-0.175	-0.080	-0.064	0.081
	(0.104)	(0.095)	(0.133)	(0.121)	(0.123)	(0.115)	(0.144)	(0.130)
A*Indian/Asian	0.530***	0.484***	-0.582	-0.290	0.510	-0.336	0.177	-0.127
	(0.172)	(0.149)	(0.455)	(0.332)	(0.384)	(0.305)	(0.348)	(0.338)
A*White	0.092	0.146	-0.184	-0.061	0.104	-0.270	0.097	0.149
	(0.157)	(0.124)	(0.194)	(0.192)	(0.207)	(0.189)	(0.239)	(0.204)
A*Married	-0.055	-0.144*	-0.091	0.012	-0.265**	0.003	-0.180	-0.132
	(0.089)	(0.078)	(0.128)	(0.104)	(0.122)	(0.101)	(0.137)	(0.113)
A*Div/Sep/Wid	-0.038	-0.107	-0.134	0.242	-0.182	-0.052	-0.202	-0.014
	(0.163)	(0.114)	(0.236)	(0.159)	(0.235)	(0.149)	(0.227)	(0.145)

Table 4.9 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	W1-2 Men	W1-2 Women	W2-3 Men	W2-3 Women	W3-2 Men	W3-2 Women	W3-4 Men	W3-4 Women
Four-level SRH								
A*Primary educ	0.055 (0.094)	0.133 (0.092)	0.080 (0.126)	-0.033 (0.115)	-0.042 (0.133)	0.303** (0.121)	0.018 (0.137)	0.101 (0.122)
A*Secondary educ	-0.130 (0.116)	0.019 (0.107)	0.096 (0.148)	-0.020 (0.135)	-0.025 (0.154)	0.340** (0.145)	-0.241 (0.173)	0.156 (0.150)
A*Tertiary educ	-0.295 (0.237)	0.184 (0.246)	0.230 (0.338)	0.148 (0.266)	-0.100 (0.333)	0.435* (0.253)	0.443 (0.336)	0.008 (0.264)
A*Traditional geo type	-0.020 (0.088)	-0.061 (0.082)	-0.103 (0.106)	-0.003 (0.101)	0.027 (0.118)	-0.211** (0.107)	0.012 (0.128)	-0.049 (0.110)
A*Farms geo type	-0.037 (0.106)	-0.023 (0.100)	-0.015 (0.154)	0.230* (0.130)	0.024 (0.185)	-0.007 (0.188)	-0.440** (0.198)	-0.057 (0.206)
A*No. of children younger than 7	-0.066 (0.044)	0.031 (0.031)	0.051 (0.047)	-0.067* (0.034)	0.037 (0.049)	-0.039 (0.041)	-0.024 (0.055)	0.002 (0.045)
Cut 1	-2.042*** (0.219)	-1.241*** (0.196)	-1.950*** (0.256)	-1.866*** (0.228)	-1.982*** (0.210)	-1.582*** (0.165)	-1.967*** (0.208)	-1.648*** (0.164)
Cut 2	-1.253*** (0.221)	-0.398** (0.199)	-1.081*** (0.255)	-1.032*** (0.227)	-0.901*** (0.209)	-0.530*** (0.164)	-0.884*** (0.207)	-0.596*** (0.163)
Cut 3	-0.492** (0.223)	0.353* (0.200)	-0.246 (0.255)	-0.210 (0.227)	-0.072 (0.209)	0.322** (0.164)	-0.055 (0.207)	0.256 (0.163)
Observations	5,394	8,365	5,131	7,574	5,099	7,717	5,099	7,717
Log likelihood	-6750	-10430	-6124	-9435	-6243	-9655	-6240	-9653

Source: Own calculations using NIDS Waves 1 to 4 (2008; 2010-12; 2012; 2014-15).

Notes: Coefficients from ordered probit regression models with attrition dummy variables (A) and interaction terms (A*variable) are presented. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in are shown in parentheses.

Table 4.10 BGLW test for attrition bias on ordered probit models with perceived rank

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	W1-2 Men	W1-2 Women	W2-3 Men	W2-3 Women	W3-2 Men	W3-2 Women	W3-4 Men	W3-4 Women
Four-level SRH								
Gini (on non-rent income)	0.290 (0.276)	0.652** (0.274)	0.182 (0.348)	0.455 (0.323)	0.197 (0.267)	0.565*** (0.209)	0.193 (0.262)	0.464** (0.208)
Perceived rank								
Above average income	-0.373** (0.158)	-0.277** (0.129)	-0.212** (0.093)	-0.076 (0.098)	-0.044 (0.136)	-0.119 (0.099)	0.058 (0.136)	-0.090 (0.099)
Average income	-0.468*** (0.148)	-0.306*** (0.116)	-0.192** (0.089)	-0.300*** (0.093)	-0.142 (0.126)	-0.197** (0.089)	-0.013 (0.125)	-0.195** (0.088)
Below average income	-0.633*** (0.147)	-0.429*** (0.116)	-0.265*** (0.092)	-0.377*** (0.094)	-0.114 (0.127)	-0.222** (0.089)	-0.010 (0.126)	-0.231*** (0.089)
Much below average income	-0.611*** (0.151)	-0.501*** (0.121)	-0.362*** (0.098)	-0.462*** (0.098)	-0.189 (0.129)	-0.243*** (0.091)	-0.054 (0.129)	-0.217** (0.090)
Non-rent PC HH income(R10,000s)	0.144 (0.090)	0.285** (0.117)	0.176** (0.085)	-0.017 (0.152)	0.134 (0.094)	0.087 (0.110)	0.140 (0.091)	0.073 (0.107)
Non-rent PC HH income (R10,000s) squared	-0.005 (0.009)	-0.049** (0.021)	-0.009** (0.005)	0.076 (0.057)	0.007 (0.019)	-0.014 (0.035)	-0.003 (0.018)	-0.021 (0.036)
Age	-0.051*** (0.007)	-0.036*** (0.005)	-0.029*** (0.007)	-0.040*** (0.005)	-0.024*** (0.006)	-0.026*** (0.004)	-0.025*** (0.006)	-0.027*** (0.004)
Age squared/100	0.024*** (0.007)	0.010** (0.005)	0.003 (0.007)	0.016*** (0.005)	-0.004 (0.006)	0.001 (0.004)	-0.001 (0.006)	0.004 (0.004)
Race								
Coloured	0.005 (0.063)	0.230*** (0.056)	0.037 (0.070)	0.227*** (0.068)	-0.006 (0.052)	0.027 (0.042)	-0.033 (0.050)	0.005 (0.041)
Indian/ Asian	-0.634*** (0.090)	-0.386*** (0.144)	0.125 (0.231)	0.205 (0.195)	-0.374** (0.158)	-0.159 (0.130)	-0.294* (0.164)	-0.178 (0.128)
White	-0.096 (0.116)	0.190* (0.103)	0.246* (0.127)	0.357*** (0.109)	-0.155 (0.112)	0.115 (0.096)	-0.165 (0.104)	-0.013 (0.091)

Table 4.10 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Four-level SRH	W1-2 Men	W1-2 Women	W2-3 Men	W2-3 Women	W3-2 Men	W3-2 Women	W3-4 Men	W3-4 Women
Marital status								
Married	0.171*** (0.055)	0.118*** (0.037)	0.182*** (0.060)	0.084** (0.041)	0.188*** (0.050)	0.103*** (0.034)	0.161*** (0.049)	0.116*** (0.034)
Div/sep/widowed	-0.029 (0.101)	0.046 (0.053)	0.016 (0.113)	0.022 (0.054)	0.103 (0.091)	0.063 (0.046)	0.105 (0.092)	0.059 (0.047)
Education								
Primary	0.187*** (0.057)	0.277*** (0.044)	0.233*** (0.054)	0.164*** (0.043)	0.215*** (0.049)	0.189*** (0.037)	0.215*** (0.048)	0.210*** (0.037)
Secondary	0.398*** (0.069)	0.555*** (0.056)	0.371*** (0.063)	0.374*** (0.056)	0.385*** (0.059)	0.398*** (0.047)	0.412*** (0.058)	0.424*** (0.047)
Tertiary	0.722*** (0.165)	0.718*** (0.138)	0.225 (0.141)	0.397*** (0.114)	0.607*** (0.135)	0.340*** (0.111)	0.502*** (0.135)	0.431*** (0.109)
Geo type								
Traditional	0.050 (0.061)	0.180*** (0.055)	0.054 (0.062)	0.140** (0.056)	-0.014 (0.041)	-0.006 (0.032)	-0.022 (0.040)	-0.027 (0.032)
Farms	0.124 (0.077)	0.085 (0.067)	-0.107* (0.064)	-0.168** (0.078)	0.170*** (0.066)	0.042 (0.059)	0.205*** (0.065)	0.041 (0.058)
No. of children younger than 7	-0.016 (0.021)	0.019 (0.016)	-0.002 (0.020)	0.002 (0.014)	-0.034* (0.018)	0.008 (0.012)	-0.030* (0.018)	0.004 (0.012)
A (attrition dummy variable)	-0.764 (0.499)	0.380 (0.387)	0.914 (0.616)	-0.320 (0.490)	0.166 (0.687)	0.021 (0.588)	1.563** (0.710)	-0.235 (0.633)
A*Gini	0.034 (0.390)	-0.632* (0.373)	-0.940 (0.727)	0.290 (0.543)	-0.858 (0.723)	-0.578 (0.657)	-1.099 (0.811)	0.005 (0.701)

Table 4.10 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	W1-2 Men	W1-2 Women	W2-3 Men	W2-3 Women	W3-2 Men	W3-2 Women	W3-4 Men	W3-4 Women
Four-level SRH								
A*RD quintile 2	0.169 (0.352)	0.050 (0.250)	-0.288 (0.206)	-0.054 (0.228)	0.408 (0.429)	0.207 (0.357)	-0.507 (0.423)	-0.081 (0.390)
A*RD quintile 3	0.240 (0.333)	0.023 (0.235)	-0.199 (0.198)	0.058 (0.194)	0.358 (0.406)	0.056 (0.332)	-0.808** (0.391)	0.103 (0.363)
A*RD quintile 4	0.341 (0.341)	-0.030 (0.244)	-0.427** (0.187)	-0.043 (0.195)	0.261 (0.407)	-0.081 (0.333)	-0.741* (0.397)	0.029 (0.366)
A*RD quintile 5	0.142 (0.351)	-0.031 (0.242)	-0.530** (0.215)	-0.135 (0.228)	0.294 (0.414)	0.166 (0.338)	-0.948** (0.403)	-0.047 (0.371)
A*PC HH income	0.297* (0.172)	-0.135 (0.188)	-0.095 (0.179)	0.644* (0.343)	0.026 (0.232)	0.062 (0.312)	0.039 (0.300)	0.265 (0.326)
A*PC HH income squared	-0.023 (0.042)	0.021 (0.052)	0.001 (0.013)	-0.298 (0.197)	-0.030 (0.047)	0.003 (0.117)	0.002 (0.069)	-0.027 (0.098)
A*Age	0.020 (0.013)	0.002 (0.010)	0.005 (0.016)	0.002 (0.013)	0.001 (0.017)	0.002 (0.014)	-0.002 (0.016)	0.004 (0.013)
A*Age squared	-0.021 (0.013)	-0.001 (0.010)	-0.005 (0.017)	-0.001 (0.014)	0.002 (0.018)	-0.001 (0.015)	-0.002 (0.015)	-0.007 (0.013)
A*Coloured	-0.059 (0.108)	-0.076 (0.098)	-0.035 (0.132)	-0.247* (0.132)	-0.171 (0.124)	-0.095 (0.114)	-0.050 (0.146)	0.024 (0.129)
A*Indian/Asian	0.550*** (0.187)	0.428*** (0.158)	-0.193 (0.348)	-0.304 (0.305)	0.454 (0.385)	-0.392 (0.305)	0.142 (0.347)	-0.228 (0.334)
A*White	0.040 (0.161)	0.079 (0.125)	0.014 (0.201)	-0.213 (0.216)	0.075 (0.207)	-0.322* (0.191)	0.097 (0.238)	0.174 (0.206)
A*Married	0.007 (0.092)	-0.141* (0.079)	-0.216 (0.131)	-0.013 (0.106)	-0.258** (0.124)	0.026 (0.102)	-0.148 (0.139)	-0.146 (0.115)
A*Div/Sep/Wid	0.008 (0.168)	-0.065 (0.111)	-0.193 (0.240)	0.215 (0.162)	-0.200 (0.236)	-0.020 (0.151)	-0.200 (0.233)	0.003 (0.145)

Table 4.10 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	W1-2 Men	W1-2 Women	W2-3 Men	W2-3 Women	W3-2 Men	W3-2 Women	W3-4 Men	W3-4 Women
Four-level SRH								
A*Primary educ	0.155 (0.098)	0.117 (0.095)	-0.093 (0.132)	-0.066 (0.129)	-0.020 (0.132)	0.324*** (0.123)	0.020 (0.138)	0.121 (0.123)
A*Secondary educ	-0.050 (0.119)	0.015 (0.110)	-0.107 (0.154)	-0.076 (0.152)	-0.020 (0.156)	0.380*** (0.147)	-0.283 (0.175)	0.169 (0.154)
A*Tertiary educ	-0.236 (0.248)	0.192 (0.252)	-0.094 (0.360)	0.186 (0.288)	-0.166 (0.334)	0.489* (0.257)	0.354 (0.338)	0.024 (0.265)
A*Traditional geo type	-0.078 (0.094)	-0.104 (0.085)	-0.127 (0.113)	0.009 (0.107)	0.017 (0.116)	-0.202* (0.105)	0.044 (0.128)	-0.057 (0.109)
A*Farms geo type	-0.008 (0.106)	-0.035 (0.105)	-0.096 (0.153)	0.150 (0.138)	-0.001 (0.185)	-0.026 (0.189)	-0.354* (0.200)	0.014 (0.209)
A*No. of children younger than 7	-0.102** (0.041)	0.002 (0.031)	0.039 (0.051)	-0.061* (0.036)	0.028 (0.049)	-0.027 (0.041)	-0.033 (0.056)	0.004 (0.045)
Cut 1	-2.629*** (0.273)	-1.576*** (0.224)	-2.309*** (0.276)	-2.288*** (0.236)	-2.101*** (0.235)	-1.840*** (0.179)	-1.989*** (0.234)	-1.905*** (0.178)
Cut 2	-1.837*** (0.274)	-0.722*** (0.227)	-1.446*** (0.273)	-1.471*** (0.233)	-1.027*** (0.234)	-0.786*** (0.179)	-0.913*** (0.233)	-0.852*** (0.178)
Cut 3	-1.060*** (0.276)	0.046 (0.229)	-0.576** (0.274)	-0.613*** (0.232)	-0.194 (0.234)	0.068 (0.178)	-0.079 (0.232)	0.002 (0.177)
Observations	5,042	7,838	4,614	6,819	5,032	7,629	5,032	7,629
Log likelihood	-6276	-9723	-5460	-8434	-6164	-9537	-6158	-9539

Source: Own calculations using NIDS Waves 1 to 4 (2008; 2010-12; 2012; 2014-15).

Notes: Coefficients from ordered probit regression models with attrition dummy variables (A) and interaction terms (A*variable) are presented. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in are shown in parentheses.

Table 4.11 BGLW test for attrition bias on ordered probit models with perceived inequality

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	W1-2	W1-2		W2-3		W3-2		W3-4
Four-level SRH	Men	Women	W2-3	Men	Women	W3-2	Men	Women
Perceived inequality	-0.524 (0.569)	-1.109** (0.565)	-1.310** (0.569)	-0.962* (0.584)	-0.066 (0.304)	0.045 (0.235)	-0.273 (0.295)	0.104 (0.231)
District average non-rent income (R10,000s)	0.642** (0.284)	0.350 (0.300)	0.408 (0.395)	0.664* (0.368)	0.238 (0.291)	0.524** (0.239)	0.101 (0.280)	0.317 (0.235)
Non-rent PC HH income(R10,000s)	0.213** (0.089)	0.307*** (0.106)	0.147* (0.077)	0.080 (0.138)	0.130 (0.092)	0.096 (0.108)	0.143 (0.089)	0.085 (0.105)
Non-rent PC HH income (R10,000s) squared	-0.012 (0.009)	-0.041*** (0.015)	-0.008* (0.004)	0.048 (0.050)	0.009 (0.019)	-0.014 (0.035)	-0.002 (0.017)	-0.021 (0.036)
Age	-0.053*** (0.007)	-0.037*** (0.005)	-0.028*** (0.006)	-0.036*** (0.005)	-0.025*** (0.006)	-0.026*** (0.004)	-0.026*** (0.006)	-0.027*** (0.004)
Age squared/100	0.026*** (0.007)	0.011** (0.005)	0.002 (0.007)	0.011** (0.005)	-0.002 (0.006)	0.002 (0.004)	0.000 (0.006)	0.004 (0.004)
Race								
Coloured	-0.010 (0.067)	0.168*** (0.059)	-0.015 (0.066)	0.152** (0.066)	-0.011 (0.052)	0.010 (0.042)	-0.040 (0.050)	-0.008 (0.041)
Indian/ Asian	-0.592*** (0.079)	-0.359*** (0.120)	0.145 (0.212)	0.198 (0.165)	-0.383** (0.156)	-0.152 (0.129)	-0.301* (0.162)	-0.178 (0.127)
White	-0.159 (0.114)	0.116 (0.113)	0.227** (0.111)	0.271** (0.116)	-0.185* (0.111)	0.089 (0.095)	-0.176* (0.103)	-0.009 (0.090)

Table 4.11 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Four-level SRH	W1-2 Men	W1-2 Women	W2-3 Men	W2-3 Women	W3-2 Men	W3-2 Women	W3-4 Men	W3-4 Women
Marital status								
Married	0.190*** (0.054)	0.120*** (0.036)	0.160*** (0.057)	0.070* (0.040)	0.194*** (0.050)	0.108*** (0.034)	0.168*** (0.049)	0.120*** (0.034)
Div/sep/widowed	0.025 (0.100)	0.044 (0.053)	-0.021 (0.109)	-0.003 (0.053)	0.091 (0.090)	0.049 (0.046)	0.094 (0.091)	0.048 (0.046)
Education								
Primary	0.237*** (0.053)	0.293*** (0.042)	0.241*** (0.051)	0.164*** (0.042)	0.218*** (0.048)	0.198*** (0.037)	0.216*** (0.048)	0.220*** (0.037)
Secondary	0.434*** (0.064)	0.593*** (0.053)	0.407*** (0.060)	0.400*** (0.055)	0.398*** (0.059)	0.410*** (0.047)	0.424*** (0.058)	0.435*** (0.046)
Tertiary	0.790*** (0.157)	0.764*** (0.133)	0.274** (0.130)	0.425*** (0.106)	0.623*** (0.133)	0.346*** (0.110)	0.515*** (0.134)	0.426*** (0.108)
Geo type								
Traditional	0.056 (0.059)	0.160*** (0.058)	0.075 (0.058)	0.202*** (0.053)	-0.009 (0.043)	0.008 (0.034)	-0.018 (0.042)	-0.023 (0.034)
Farms	0.114 (0.073)	0.069 (0.066)	-0.058 (0.058)	-0.143** (0.067)	0.168** (0.065)	0.049 (0.058)	0.209*** (0.064)	0.051 (0.057)
No. of children younger than 7	-0.013 (0.020)	0.012 (0.015)	0.010 (0.020)	0.006 (0.013)	-0.032* (0.018)	0.010 (0.012)	-0.027 (0.018)	0.005 (0.012)
A (attrition dummy variable)	-0.325 (0.502)	-0.396 (0.471)	-0.244 (0.845)	-0.940 (0.710)	0.818 (0.611)	-0.089 (0.545)	0.062 (0.667)	0.305 (0.587)
A*Perceived inequality	-0.075 (0.760)	0.550 (0.772)	0.393 (1.212)	1.051 (0.993)	-1.471* (0.787)	0.054 (0.722)	-0.089 (0.928)	-0.757 (0.813)

Table 4.11 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		W1-2		W2-3		W3-2		W3-4
Four-level SRH	W1-2 Men	Women	W2-3 Men	Women	W3-2 Men	Women	W3-4 Men	Women
A*District avg income	0.039 (0.351)	0.102 (0.364)	-1.127 (0.798)	0.972 (0.768)	-0.395 (0.695)	-1.310* (0.676)	0.204 (0.848)	0.279 (0.747)
A*PC HH income	0.240* (0.143)	-0.109 (0.172)	0.007 (0.170)	0.492 (0.301)	0.009 (0.225)	0.149 (0.306)	-0.042 (0.293)	0.287 (0.321)
A*PC HH income squared	-0.027 (0.019)	0.005 (0.046)	-0.006 (0.013)	-0.210 (0.136)	-0.032 (0.045)	-0.010 (0.115)	0.016 (0.068)	-0.031 (0.097)
A*Age	0.016 (0.013)	0.004 (0.010)	0.003 (0.016)	-0.001 (0.012)	0.005 (0.017)	0.004 (0.013)	0.004 (0.015)	-0.002 (0.013)
A*Age squared	-0.017 (0.013)	-0.003 (0.010)	-0.001 (0.016)	0.002 (0.012)	-0.001 (0.018)	-0.004 (0.014)	-0.007 (0.015)	-0.000 (0.012)
A*Coloured	-0.092 (0.102)	-0.023 (0.099)	-0.003 (0.143)	-0.193 (0.122)	-0.162 (0.122)	-0.065 (0.112)	-0.036 (0.143)	0.043 (0.127)
A*Indian/Asian	0.495*** (0.175)	0.427*** (0.148)	-0.663 (0.447)	-0.338 (0.345)	0.514 (0.383)	-0.365 (0.303)	0.199 (0.343)	-0.125 (0.334)
A*White	0.088 (0.158)	0.150 (0.125)	-0.140 (0.196)	-0.078 (0.190)	0.099 (0.206)	-0.265 (0.188)	0.082 (0.238)	0.124 (0.205)
A*Married	-0.034 (0.089)	-0.150* (0.078)	-0.098 (0.129)	-0.004 (0.103)	-0.286** (0.122)	0.016 (0.100)	-0.171 (0.138)	-0.147 (0.113)
A*Div/Sep/Wid	-0.037 (0.161)	-0.110 (0.112)	-0.107 (0.235)	0.204 (0.158)	-0.185 (0.235)	-0.040 (0.149)	-0.207 (0.226)	-0.018 (0.144)

Table 4.11 (continued)

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	W1-2 Men	W1-2 Women	W2-3 Men	W2-3 Women	W3-2 Men	W3-2 Women	W3-4 Men	W3-4 Women
Four-level SRH								
A*Primary educ	0.078 (0.094)	0.123 (0.093)	0.067 (0.125)	-0.030 (0.115)	-0.025 (0.132)	0.315*** (0.121)	-0.001 (0.136)	0.105 (0.121)
A*Secondary educ	-0.098 (0.114)	0.021 (0.108)	0.094 (0.148)	-0.023 (0.136)	-0.002 (0.154)	0.349** (0.144)	-0.256 (0.173)	0.168 (0.151)
A*Tertiary educ	-0.263 (0.238)	0.188 (0.244)	0.248 (0.336)	0.160 (0.270)	-0.069 (0.332)	0.446* (0.253)	0.397 (0.335)	0.048 (0.264)
A*Traditional geo type	-0.015 (0.093)	-0.045 (0.088)	-0.106 (0.116)	0.076 (0.109)	0.029 (0.124)	-0.283** (0.113)	0.072 (0.134)	-0.025 (0.113)
A*Farms geo type	-0.046 (0.104)	-0.018 (0.101)	-0.011 (0.155)	0.251* (0.134)	0.031 (0.184)	-0.009 (0.188)	-0.412** (0.199)	-0.034 (0.206)
A*No. of children younger than 7	-0.075* (0.044)	0.029 (0.030)	0.044 (0.047)	-0.068** (0.034)	0.029 (0.049)	-0.043 (0.041)	-0.017 (0.054)	0.009 (0.045)
Cut 1	-2.433*** (0.350)	-2.156*** (0.323)	-2.845*** (0.393)	-2.599*** (0.389)	-2.090*** (0.231)	-1.828*** (0.180)	-2.234*** (0.227)	-1.825*** (0.179)
Cut 2	-1.647*** (0.348)	-1.314*** (0.322)	-1.976*** (0.392)	-1.764*** (0.388)	-1.009*** (0.229)	-0.778*** (0.180)	-1.152*** (0.226)	-0.774*** (0.178)
Cut 3	-0.886** (0.349)	-0.564* (0.323)	-1.141*** (0.390)	-0.942** (0.388)	-0.181 (0.229)	0.073 (0.180)	-0.325 (0.226)	0.076 (0.178)
Observations	5,394	8,365	5,131	7,574	5,099	7,717	5,099	7,717
Log likelihood	-6757	-10435	-6126	-9431	-6247	-9664	-6247	-9665

Source: Own calculations using NIDS Waves 1 to 4 (2008; 2010-12; 2012; 2014-15).

Notes: Coefficients from ordered probit regression models with attrition dummy variables (A) and interaction terms (A*variable) are presented. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors in are shown in parentheses.

Chapter 5

Conclusion

5.1. Significance

The shift towards a more people-centred and multidimensional concept of well-being in development and welfare research in the last two decades places increasing importance on the measurement of a broader range of indicators (Kanbur *et al.*, 2019; Stiglitz *et al.*, 2009). In addition to the traditional, money-metric ones, indicators based on perceptions have attracted increasing attention from researchers and policymakers alike. However, in order to make the broader well-being ideas useful for policymaking, it is crucial to understand the degree to which the different dimensions complement or contradict each other.

This thesis examined the measurement of health in the first two empirical studies (Chapter 2 and Chapter 3), focusing on the reliability of self-rated health (SRH) as a health indicator in the diverse South African context. The third empirical study (Chapter 4) then analysed the relationship between health (specifically SRH) and several dimensions of material well-being, such as income, measured rank, and measured inequality (in relation to other households in the same district); in addition, it interrogated whether perceived rank and perceived inequality had a stronger link with health than money-metric measures. In order to test whether these relationships are distinct by gender, separate analyses were undertaken for women and men throughout the thesis.

5.2. Overview

The thesis utilised the first four waves of a nationally representative panel survey, the National Income Dynamics Study (NIDS), conducted over the period 2008 – 2014. The NIDS data are particularly suitable because extensive information on health, demographic, and socioeconomic indicators is available. The NIDS adult questionnaire contains a section dedicated to health, including health-related and health-seeking behaviours, and a section that relates specifically to mental health; in addition to extensive batteries of questions about individual and household income and expenditure. Further, the panel nature of the dataset allows for the use of estimation methods, which control for unobserved individual characteristics, which can be drivers of endogeneity in the relationship between health and aspects of material well-being.

The measurement of health presents both conceptual and empirical challenges. The key measure used in the thesis, SRH, draws on a single question, eliciting an individual's instantaneous and subjective assessment: "How would you describe your health at present? Would you say it is excellent, very good, good, fair, or poor?". Given the subjective nature of SRH, an ongoing debate about the reliability of this measure surrounds its widespread use in social and medical sciences research (Jürges, 2007; Kerkhofs & Lindeboom, 1995; Lindeboom & van Doorslaer, 2004). Further, the gender differences, rooted in intrinsic biological, psychosocial, structural, and behavioural factors, have received little attention in social sciences research (Denton *et al.*, 2004; Denton & Walters, 1999).

Chapter 2 outlined the benefits and drawbacks associated with the use of SRH, and focussed specifically on the main weakness of SRH, seen to be its purely subjective nature. The analysis examined the variations in reporting styles, which derive from this subjectivity. Reporting styles are based on individuals' internal concepts of health, which are steeped in their worldview, culture, and access to resources (Huisman & Deeg, 2010; Jylhä, 2009; Ziebarth, 2010).

Treating "true health" as an underlying but not directly measurable latent variable, the analysis in Chapter 2 applied Kerkhofs and Lindeboom's (1995) theoretical and empirical framework. Employing an iterative procedure for panel data, developed by Pfarr *et al.* (2010), SRH was benchmarked against a number of other health indicators, both self-reported and measured, which are often considered to be more objective. This procedure distinguished individual characteristics that are associated with uniform shifts in all the ordered categories of SRH (referred to as index shifts), from those associated with respondents' switching more readily in favour of, or away from, only some of the categories (referred to as cut-point shifts), with the latter being more distorting and more difficult to control for in empirical models.

The results for both men and women revealed differences in reporting styles, but mostly in the form of index shifts. Gender differences were found to exist with regard to household disposable income (proxied by household expenditure per capita) and location type. Men from poorer households tended to report being in worse health than those who were better-off, across all SRH categories, while for women, household expenditure per capita was linked to a cut-point shift. For both men and women, living in traditional areas (formerly known as "homelands") was related to cut-point shifts, but the pattern of these differed by gender.

Chapter 2 added to the relatively scarce evidence regarding reporting heterogeneity in SRH from developing countries and specifically from a context as diverse as South Africa. Compared to previous South African research exploring heterogeneous reporting patterns (Boyce & Harris, 2011; Charasse-Pouélé & Fournier, 2006; Jelsma & Ferguson, 2004; Rossouw *et al.*, 2018), this study used nationally-representative data, it considered a greater number of possible drivers of reporting behaviour, and it treated the reporting patterns as distinct by gender, hence the results reflected within-gender reporting heterogeneity. Chapter 2 established that individuals' own ratings of health are not directly comparable. Hence, caution is warranted when using SRH in cross-sectional analysis (Sen, 2002). Nevertheless, "self-rated health is a unique, valuable indicator of human health status. Its origins lie in a process where information from the individual's body and mind is received, selected, reviewed and summarized" (Jylhä, 2009: 314). Hence, SRH is likely to be an internally consistent and reliable health measure in studies that utilise panel data.

Chapter 3 explored the internal consistency and credibility of SRH in more detail. The predictive power of SRH for mortality, even after other health indicators, as well as demographic and socioeconomic characteristics, are taken into account, is the strongest argument for its credibility and usefulness in empirical research (Benyamini & Idler, 1999; DeSalvo *et al.*, 2006; Idler & Benyamini, 1997). The specific focus of the second empirical study was whether less-than-good SRH is an independent predictor of mortality over a two-year and a six-year horizon.

When controlling only for age, the results pointed to a significant association with the odds of death in two years' time for both men and women who reported their SRH as "fair" or "poor" at baseline (NIDS Wave 1), with a stronger link for men. This association persisted for men, even after other self-reported and directly measured indicators were included, in addition to controls for individual and household characteristics. For women, the link between SRH and mortality weakened considerably when self-reported indicators were taken into account, and disappeared when measured indicators were added. Over a six-year horizon, SRH retained its ability to predict mortality only for men who considered their health to be "poor" at baseline, even after all controls were applied, but the association was insignificant for women. Hence, in line with many international studies, for men, SRH captures mostly aspects of physical health that are directly related to mortality and that are not contained in other health indicators, whether self-reported or

measured. For women, SRH is a broader, all-encompassing measure, which overarches physical, psychological, and behavioural aspects of health.

The analysis of this relationship based on NIDS data provided insights into the nature of SRH in a developing country context, without restricting its attention to an elderly subpopulation, as in previous international and South African studies (Benyamini & Idler, 1999; Idler & Benyamini, 1997; Rossouw *et al.*, 2018). In addition, the gender-specific nature of SRH and its predictive capacity for mortality is evident through the shorter- and longer-term follow-up periods studied. The first two empirical studies in the thesis laid a foundation for the third study by providing evidence for SRH as a reliable and credible indicator for each individual over time, as part of an enduring self-concept (Bailis *et al.*, 2003; Jylhä, 2009; Jylhä, 2010; Mora *et al.*, 2008). Further, SRH was shown to comprise different aspects of health for men and women (Benyamini *et al.*, 1999; Benyamini *et al.*, 2000).

The third empirical study, Chapter 4, utilised the earlier chapters' finding to investigate the relationship between SRH, on the one hand, and the level of income, relative income (rank), and inequality, on the other. Further, the study tested whether measured or perceived indicators of rank and inequality had a stronger association with health. Perceived rank was based on a question in NIDS, which prompted respondents to position their household on a five-step income ladder, compared to others in their village or neighbourhood. Perceived inequality was assessed indirectly using Cowell and Flachaire's (2017) metric designed for ordered categorical data, which was applied to the perceived rank variable. All empirical models included controls for demographic and socioeconomic characteristics and took unobserved individual heterogeneity into account.

As in the preceding chapters, the findings were mostly gender-distinct, except there was little evidence that absolute income (adjusted for household size) was related to health for all individuals. For men, measured rank was positively associated with health only for those in the highest-earning households, but perceived rank had a stronger and negative relationship to health for men who thought their households' incomes were below the highest two rungs on the income ladder, compared to those in their immediate vicinity. Neither measured inequality (proxied by the Gini coefficient at district level), nor perceived inequality was linked to men's health.

For women, there was no evidence of a significant relationship between measured rank and health; however, perceived rank had a graded association with worse health for all who thought their households could not be described as “much above average income”. Contrary to expectations, a higher Gini coefficient was associated with better health, a finding which may reflect the availability of better infrastructure and service provision, as well as easier access to resources (possibly including government grants, free services, and better employment opportunities), in more unequal districts. In contrast, and as was the case with men, perceived inequality had a negative relationship to women’s health.

Chapter 4 contributed to the debate about the relationships between health and material aspects of well-being by providing evidence from a country whose position among the world’s most unequal societies has persisted, despite a wide social safety net, since the transition to democracy in 1994 (Leibbrandt *et al.*, 2010; Sulla *et al.*, 2022). To the extent that inequality is negatively associated with health, then it is perceptions of inequality or perceived rank that matter, rather than money-metric measures. The empirical results highlighted the complex nature of these relationships and the role that perception-based indicators could play in understanding the mechanisms at work. In addition, the gender plays a strong role in these relationships – an aspect that had been obscured in the few previous South African studies (Alaba & Chola, 2013; Ataguba *et al.*, 2011; McIntyre & Gilson, 2002).

5.3. Limitations

The empirical analysis is subject to several limitations. Despite the richness of the survey instrument, the health section in the NIDS questionnaire does not include a standardised scale; therefore, in order to identify patterns of reporting heterogeneity in Chapter 2, SRH was benchmarked against a number of health indicators, instead of a single benchmark, as in most similar studies (Etilé & Milcent, 2006; Pfarr *et al.*, 2012; Schneider *et al.*, 2012). Mortality is treated primarily as a cause of attrition in NIDS and hence, the measure used in Chapter 3 could not differentiate between natural and non-natural causes, whereas analysing mortality from natural causes only would have been preferable. The first two empirical studies also excluded Indian/Asian respondents because of small sample sizes across the time dimension of the panel.

The most important limitation in Chapter 4 is that reverse causality cannot be addressed with the method used. That is, it is not possible to differentiate whether money-metric or perceived SES

and inequality influence health, or whether health states lead to certain types of material outcomes, or whether certain health states colour perceptions about rank and economic disparities.

5.4. Future research

The theme that connects all three empirical studies relates to the value of indicators, based on perceptions. Caution regarding their comparability across individuals is undoubtedly warranted; however, in analyses tracking individuals over time, perception-based indicators are likely to be reliable and complementary to more established indicators, filling the gaps that evade direct measurement. The thesis raises several questions, which can be explored in future research. These include: How are perceptions about material well-being formed? What factors are associated with the largest gaps between perceived and measured rank and inequality? Why are perceived indicators valuable, in general, and how can they be utilised better, both in research and in policymaking?

The empirical evidence presented in Chapter 4 revealed that perceived rank and inequality had a stronger link with health than their monetary-based counterparts did. A possible reason is that measured rank and inequality may be a better reflection of inequality of outcome, while perceived rank and inequality may be more closely tied to inequality of opportunity. This is another avenue for future research.

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