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Socio-economic determinants of the gender gap in mental health in South Africa

Amanda Thabisile Mbokazi

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School of Accounting, Economics and Finance

Supervisor: Dr. Claire Vermaak

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Supervisor's acknowledgement of dissertation submitted for examination

Student name: Amanda Thabisile Mbokazi

Student number: 215008004

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Abstract

A large body of theoretical and empirical epidemiological literature investigating the relation between gender and depression find that depression is more prevalent among women than men. However, this research is mainly done in developed countries such as the US. These studies suggest that women are found to be more likely than men to experience depression. For developing countries, South Africa in particular, empirical studies investigating the gender gap in depression in South Africa are very limited. Thus, a research gap examining this relationship exists. Using data from all five waves of the National Income

Dynamics Study (NIDS), this study aims to investigate the gender gap in depression among South Africans and to identify social and economic factors that may explain why the gender gap occurs, given the high levels of inequalities between men and women in South Africa.

This study used descriptive statistics to show characteristics of the chosen sample (individuals of ages 15 and above, with at least one reported depression score), by their gender and birth year cohort. Hierarchical linear models are used to determine the age trajectory in mental health for women and men in South Africa, the magnitude of the gender gap in depression in South Africa and how it differs across different birth cohorts, and in addition, to determine the extent at which gender differences in social and household roles, and in labour market roles, explain the gender gap in mental health.

This study found that women experience more depressive symptoms than men. Thus, confirming the existence of a gender gap in depression in South Africa. In addition, the study found that gender differences in variables such decision-making power in the household, employment status and childcare responsibilities explained the differences in the depression scores between men and women.

Keywords: mental health; gender gap; multilevel models

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Chapter 1: Introduction

Mental health is a key component of overall health. A lack of mental health therefore hampers individuals' quality of life and well-being, as well as their ability to participate fully in their desired social and economic roles (Frank and McGuire, 2000). The costs of mental disorders on individuals in both developed and developing countries have risen dramatically in recent years. Between 2005 and 2015, the estimated number of persons suffering with depression globally grew by 18.4 percent, from approximately 179 million to 322 million people. While more recent evidence of world depression estimates is limited, the World Health Organization's Global Health Estimates Report (2017) predicted that depression would affect 4.4 percent of the worldwide population by 2015. Mental illnesses (especially depression) are widespread in both developed and developing countries (Kessler et al., 2009). However, not all groups are equally affected. Gender differences in depression are among the most common disparities in epidemiological research (Weissman and Klerman, 1977; Kessler et al., 1994; Salk et al., 2016; Platt et al., 2020). Depression is more prevalent among women than men, where 5.1 percent of the global population of women is estimated to suffer from depression compared to 3.6 percent of men (World Health Organization, 2017). It is critical to examine and understand the gender gap in depression, but little detailed research exists on the nature of this gap in developing countries. Therefore, this dissertation aims to investigate the gender gap in depression among South Africans and to identify social and economic factors that may explain why the gender gap occurs.

Women across each of the different World Health Organization country regions (African, Eastern Mediterranean, region of the Americas, South-East Asia, European and the Western Pacific) are generally more susceptible to suffering from depression compared to men (World Health Organization, 2017). In the African region, women are estimated to have a depression prevalence rate of approximately 5.7 percent, compared to 4.6 percent of men. A gender gap is also observed in developed parts of the world, such as the European region where the depression rate among women is approximately 5.2 percent whilst 3.4 percent of men are said to suffer from depression.

Despite common prevalence rates of mental illnesses across countries and the similar finding that women generally have higher depression prevalence rates than men, low- to middle-income nations may be the most burdened by mental health problems. The World Bank (2003) indicates that 80 percent of people in low- and middle-income nations are likely to suffer from a mental condition at some point in their lives. In addition to higher depression rates among women in all regions when compared to men, the African region records the highest depression rate for women compared to other women from other regions (World Health Organization, 2017). This may be attributed to the lack of consistent funding, resources and mental health facilities in African countries. Furthermore, some studies have discovered that poor socio-economic conditions predispose individuals to mental health illnesses (Lorant at el., 2003; Reiss, 2013). As a result of socio-economic disadvantage or deprivation, mental health illnesses are more likely to arise.

In addition, sociocultural factors might also explain why women are more depressed than men (Hammarström et al., 2009). Structural gender inequalities, as well as cultural attitudes and standards, may contribute to depressive symptoms amongst women (Kessler et al., 2009). In some parts of the continent, cultures may expect women to be submissive to their male partners and in addition, society often expects women to be home-makers. In South Africa, the history of apartheid could additionally explain why women are more likely to experience depression than men. The apartheid regime was responsible for the systemic oppression and injustices experienced by black people in South Africa and gender inequality was linked to, but distinct from, racial inequality and oppression (Albertyn, 2011). While all women were disadvantaged by society during this period, black women were subjected to a set of gendered regulations and laws that favoured black men compared to them (Albertyn, 2011). In contrast, white women got numerous benefits as a result of their social standing and race, despite being marginalized in relation to white men.

Despite being democratic, South Africa remains a deeply patriarchal country due to economic, social, and cultural factors, with women perceived as inferior to men and hence need to be subordinate to men in both public and private life. As a result of societal inequalities that marginalize women and deny them access to resources, benefits, and opportunities enjoyed by men, women in South Africa are degraded to a lower status as compared to men (Albertyn, 2011). According to Mutyambizi et al (2019), subjective social status has a substantially larger impact to inequalities in depression symptoms for women than for men. Thus, women's perceptions of their position in the social hierarchy in South Africa contribute to inequalities in depression more so than men's.

A key finding of studies investigating the gender differences in mental health is that the gender gap in depression changes with age and across birth year cohorts (Mirowsky, 1996; Salk et al., 2017; Platt et al., 2020). As individuals age, they experience many changes in their physical development and well-being, economic circumstances, and social roles, all of which may affect their mental health. According to Mirowsky (1996), the gender difference in depression widens significantly with age. Another aspect of the gender gap in mental health that has been increasingly investigated is the birth year cohort effect on mental health (Abrams and Metha, 2019; Platt et al., 2020). According to these existing studies, the gender gap in depression is smaller when comparing more recent birth cohort to older cohorts.

The gender-mental health relationship has been greatly researched internationally. However, empirical studies investigating the gender gap in depression in South Africa are very limited. Although women have been shown to have poorer mental health than men at the cross-sectional level (Mutyambizi et al., 2019), no longitudinal research has yet estimated the size and trajectory of the gender gap with age, nor how socio-economic factors contribute to this gender difference. Thus, a research gap exists. The main objective of this study is therefore to explore the nature of the depression gender gap for adults in South Africa. The study uses the five existing waves of the nationally representative National Income Dynamics Study (NIDS) data to examine the average change in the gender depression gap across age and cohorts while also investigating the individual patterns of mental health across time. Given the multilevel structure of the longitudinal data being utilized, the hierarchical linear modelling approach is used for the analysis. The key questions this study seeks to answer are as follows:

- What is the age trajectory in mental health for women and men in South Africa?
- Is there evidence of a gender gap in mental health, and if so, how does the gender gap differ for individuals from different birth cohorts?

- To what extent do gender differences in social and household roles, and in labour market roles, explain the gender gap in mental health?

The remainder of this dissertation uses the following structure to address different aspects of the topic. Chapter 2 reviews both theoretical and empirical literature on gender differences in mental health to gain insight into the mechanisms that link gender with mental health, and the methods and findings of past research in this field. Chapter 3 discusses the NIDS data and the key variables utilised in this study and goes on to present descriptive statistics for the analysis sample. Chapter 4 outlines the regression method used in this study, and then presents and discusses the estimation results. Thereafter, Chapter 5 concludes.

Chapter 2: Literature review

The history of apartheid in South Africa and the country's continuing high levels of inequality make it an interesting context for the study of mental health. Existing research has established the existence of a gender gap in mental health in a variety of contexts, although research into this issue from developing countries is limited. This dissertation aims to contribute evidence from South Africa to this body of knowledge.

This chapter reviews both the theoretical and empirical research on the gender gap and the socio-economic factors that influence gender inequalities in mental health. Firstly, Section 2.1 examines the affective model, biomedical model, sociocultural model, and psychological model, which are all frequently employed as theoretical frameworks in understanding gender disparities in depression. Thereafter, Section 2.2 discusses existing empirical literature that investigates the gender gap in mental health. Throughout the discussion, the chapter particularly highlights empirical research that uses the same econometric analysis method as this study, namely the hierarchical linear modelling method. Section 2.2 is structured into studies that examine cross-national evidence, followed by individual-country longitudinal studies, and lastly the limited empirical evidence from South Africa related to mental health and gendered mental health disparities. Thereafter, the literature review chapter is concluded.

2.1 Theoretical models on gender depression gap

The gender gap in depression has a large body of theoretical research, and these studies serve as core conceptual frameworks for establishing and understanding the link between mental health and gender. Four of the most prominent models are explored in this study: the affective model, biological model, the sociocultural model, and the psychological model.

2.1.1 The affective model

The affective model explains the relationship between mental health and gender using an individual’s emotional reactivity to stressors and their temperament (marked by aversion toward novel situations, a proclivity towards becoming upset easily, and a high sensitivity to unpleasant stimuli). These are genetically based individual differences in emotional and attentional reactivity and self-regulation that emerge early in life and thereafter remain stable (Rothbart and Bates, 1998; Mezulis et al., 2011).

Individual disparities in emotional and attentional reactivity, according to the affective model of depression, may be an early temperamental risk factor for depressive disorders. A pattern of high negative affect and reactivity, high intensity of emotional reactions, low adaptability, and low approach is termed as negative affectivity or negative emotionality (Rothbart and Bates, 1998; Mezulis et al., 2011). Depression or depressive symptoms can be caused by a variety of factors, including negative emotionality.

According to Mezulis et al. (2011), negative emotionality may have a direct effect on depression, by causing someone to develop depressive symptoms over time. Secondly, an individual's negative emotions may lead to a negative cognitive style of thinking, making them vulnerable to depressive symptoms as a result of psychological susceptibility. As a result of negative emotionality and being mentally vulnerable, a person may become more reactive to stress (Rothbart and Bates, 1998; Mezulis et al., 2011). This model contends that when girls and women go through puberty, hormonal and social changes, as well as the transition through the adolescence stage into adulthood, they are exposed to increased stressors that exacerbate negative emotionality, resulting in depression. Consequently, women may be more likely experience depression than men.

2.1.2. The biomedical model

According to most epidemiological studies of mental illnesses, women are more likely than men to suffer from mental health disorders. The biomedical model argues that biological and hormonal factors explain why the depression prevalence rates are higher for women than men (Nolen-Hoeksema, 1987; Hammarström et al., 2009). The biological explanation for the gender gap is divided into two categories: women are more prone to depression when their hormone levels shift significantly, and gender disparities exist because women have a higher hereditary propensity to mental health illnesses such as depression.

According to the first form of the biomedical model, women are more vulnerable to depression during the premenstrual stage, the post-partum period, and menopause, all of which are characterized by significant changes in hormone levels, hormonal fluctuations in oestrogen, progesterone, and other hormones (Nolen-Hoeksema, 1987). In the second form, gender variations in depression are explained by gender-specific genes. It is thought that the hereditary or genetic defect that causes depression is linked to the chromosomes that determine an individual's gender (Nolen-Hoeksema, 1987; Hammarström et al., 2009).

2.1.3 The sociocultural model

Researchers employ the societal and cultural levels of analysis to further explain gender disparities in depression, using non-individual level elements that may contribute to the gender gap in depression. Societal factors are defined as the structural or systematic inequalities that exist in society between men and women, whereas cultural variables account for theories, attitudes, and standards (Kessler et al., 2009). The nature of these factors is likely to vary considerably across societies and across time.

Structural gender inequalities in society refer to income differences (such as the gender wage gap) and power differences between men and women (where women lack influence at home and at work and are subjugated to various roles in the household) (Kessler et al., 2009). Furthermore, the sociocultural explanatory model's societal factors propose that women are more likely than men to experience depressive symptoms as a result of life events and circumstances such as sexual and physical abuse, and in certain parts of the world, women are not given the same opportunities to attain education as men. Lastly, women are frequently under-represented in parliaments and other government leadership positions, and the resulting policies developed by male-dominated governments may discriminate against women or not be sensitive to women’s socio-economic needs, making women more prone to experiencing depressive symptoms compared to men (Hammarström et al., 2009; Hyde and Mezulis, 2020).

Religion, cultural institutions, and the media are a few examples of cultural influences that explain why women are more susceptible to depression than men. Traditional media such as television, film, and music have been shown to contain large amounts of sexual material, especially material that often sexually objectifies women (Hammarström et al., 2009). Furthermore, cultural difficulties such as dealing with extended family and the pressure to have numerous children within marriages are thought to be additional cultural issues that may have a negative impact on women's mental health (Hammarström et al., 2009; Hyde and Mezulis, 2020).

2.1.4 The psychological model

The last model discussed in this study on the relationship between mental health and gender is the psychological model, which explains this relationship using behavioural and cognitive factors classified into three categories: whether or not an individual has a pessimistic cognitive response style to life events, whether or not an individual has objectified body awareness, and rumination.

The negative cognitive component explains the prevalence of the gender gap by claiming that people with a negative cognitive style are more likely to become depressed when faced with challenging life conditions (Hyde et al., 2008). These people are thought to frequently form negative conclusions about causality, oneself, and the outcomes or effects of negative circumstances. However, the majority of research indicates that the gender gap in depression begins before the gender disparity in negative cognitive style, making the negative cognitive factor an unusual explanation for gender discrepancies in depression.

The objectified body-image awareness factor refers to unpleasant thoughts about one's physique that make one more vulnerable to depression. This aspect involves self-surveillance and body shaming, in which an individual examines and evaluates his or her own body and appearance in comparison to social norms, and the individual feels shame if he or she perceives that they do not meet these society ideals (Hyde et al., 2008). The body consciousness factor is thought to affect women more than men due to internalization of societal ideals and standards regarding the perfect body and beauty, as women are more likely to experience bodily changes throughout their lifetime (for example, during puberty and post-partum), making women more susceptible to experiencing depressive symptoms than men (Hyde et al., 2008; Hammarström et al., 2009).

Lastly, the psychological element of rumination refers to the behaviour of thinking about an individual’s negative feelings frequently and ineffectively. Rumination is divided into two parts: brooding and reflection. Brooding is defined as passive and repetitious thinking on one's mood, whereas reflection is characterized as adaptive and non-judgemental thought about one's mood (Hyde et al., 2008). According to theoretical literature, ruminating is associated with depression and is thought to predict depression because women ruminate more than males, resulting in gender differences in depression (Nolen-Hoeksema, 2000; Hammarström et al., 2009).

In summary, numerous theoretical models agree that gender disparities in depression are likely to exist, but they propose diverse explanations for why this is so. The next section of the chapter examines empirical quantitative studies to determine the extent to which these theoretical explanations are supported by empirical evidence.

2.2 Empirical studies on the gender depression gap

Gender disparities in mental health have been well documented in the literature (Weissman et al., 1993; Bebbington, 1998; Piccinelli and Wilkinson, 2000). Many studies are conducted in developed countries, where they investigate the association between gender and mental health and why gender discrepancies in mental health exist. In addition, some studies have shown that mental disorders are equally prevalent in both developed and developing countries (Kessler et al., 2009). Despite the common overall prevalence rates across countries, however, the prevalence rates are not similar for women and men. According to epidemiological research, the prevalence rates of several mental disorders differ significantly by gender, and women are continuously more likely than men to experience depressive symptoms or disorders (Weissman and Klerman, 1977; Kessler et al., 1994).

This section first discusses empirical studies that investigate the existence of a gender gap in depression across different nations, and the various cross-national socio-economic factors that influence gender disparities in mental health. The focus is on research that uses the same proposed econometric analysis method as this study, namely multilevel regression modelling, as discussed below. These studies illustrate differences in the mental health gender gap between developed and developing countries and between countries with high or low gender equality. The subsequent section discusses empirical studies conducted within various individual countries using longitudinal data. Finally, this study evaluates the few empirical studies that shed some light on gender differences in depression in South Africa.

As individuals age, they experience many changes in their physical development and well-being, economic circumstances, and social roles. For example, older individuals may become more vulnerable to different illnesses and events occurring at later stages of life such as chronic diseases, and income reductions as they age and leave the labour market, relying on pensions and government support. The discussion in Section 2.1 outlined how such changes may influence the mental health of women and men differently. Thus, when investigating the relationship between mental health and gender, it is crucial to track mental health throughout the stages of life in order to understand how individuals are affected by exposure to risk factors as they age, how these factors affect their mental health and lastly, how these factors differ in causing depression between men and women.

Thus, the multilevel modelling method of analysis is used in this study to examine gender differences in depression while controlling for the individual's age and birth cohort. Multilevel modelling is used to study the behaviour of a given phenomenon in the presence of nested data, and in this context is applied to longitudinal data with repeated measures. The advantage of using this method over traditional regression modelling is that multilevel modelling takes into account the existence of nested data structures, thus enabling the identification and analysis of individual heterogeneities, and differences between groups to which these individuals belong, over time (Raudenbush and Bryk, 2002). The method itself is discussed in more detail in Chapter 3, but the remainder of this chapter especially highlights empirical studies that use this method to explore the gender gap in depression, as they are the most relevant to the dissertation's research approach.

2.2.1 Cross-national studies

A large body of cross-national studies have used multilevel regression modelling to investigate the link between various socio-economic factors and the depression gap in mental health (Fischer and Manstead, 2000; Hopcroft and Bradley, 2007; Van de Velde et al., 2010). This research investigates the extent to which the gender depression gap differs across countries with different economic statuses and gender equity standings. According to epidemiological research, women are more likely than men to experience depressive symptoms in both developing and developed countries (Weissman et al., 1996). However, despite having similar prevalence rates of mental disorders, developing and developed countries do not necessarily have similar rates of gender differences in depression. Cultural factors play an important role, with gender differences in emotional reactions being larger in more individualistic nations, and smaller in more traditional countries (Fischer and Manstead, 2000).

Two studies explore differences in the gender depression gap between high and low gender equity societies and the role of socio-economic variables. Hopcroft and McLaughlin (2012) used the World Value Survey, a collection of national sample surveys across developed and developing countries that collect information and data on beliefs and values, subjective well-being, economic development, and gender equality among other various socio-economic factors in each country. The study included adults from 23 countries (such as Britain, China, India, Nigeria, and the United States), and measured depression as a binary score indicating whether a respondent had experienced symptoms of depression in the past week.

As a result of the hierarchical nature of the World Value Survey data due to individuals being nested within the different countries, this study used multilevel modelling which to estimate the prevalence of depressive symptoms across individuals and countries while controlling for various socio-economic factors. In agreement with Fischer and Manstead (2000), this study found that the gender gap in depression is wider in high gender equity countries compared to low gender equity societies. The wider gender gap in depression in gender-equal countries is attributed, in part, to differences in the effects of children on women's depressive symptoms. For women living in gender-equal societies, having or living with children increases feelings of despair, whereas the opposite is true for unemployed women in countries with low gender equality, while no difference is experienced by men (Hopcroft and McLaughlin, 2012).

Rather than using a global sample, Van de Velde et al. (2010) used data from 25 European countries (such as Belgium, France, and the United Kingdom). This study measured depression as a score calculated using the eight-item type of the Center for Epidemiologic Studies Depression Scale, based on the number and severity of the symptoms of depression respondents had experienced in the past week. To account for the clustered nature of the data, Van de Velde et al. (2010) used hierarchical linear modelling to estimate the prevalence rates of depressive symptoms across the individuals and the countries. Like most studies on the epidemiology of depression, Van de Velde et al. (2010) found that women reported significantly higher levels of depressive symptoms compared to men in most countries, but not in for Ireland, Finland and Slovakia. Both women and men have lower levels of depression when they hold a better socio-economic status. However, for women, the education level attained is substantially more predictive of depression when compared to men, perhaps due to women being paid less than men. As a result, women become socially and economically disadvantaged thus needing more education than men to improve the level of pay and socio-economic status (Van de Velde et al., 2010).

A key finding of these two papers is that children affect men's and women's mental health in different ways. In the European countries, taking care of others (children included) did not have a negative effect on the level of depressive symptoms experienced by women but it did for men (Van de Velde et al., 2010). In contrast, Hopcroft and McLaughlin (2012) found that taking care of others (specifically children) contributed significantly to depression for women in countries with high gender equality but did not for unemployed women in countries with low gender equality. However, taking care of children did not significantly impact the level of depression in men in either high or low gender equity countries (Hopcroft and McLaughlin, 2012). Van de Velde et al. (2010) found that living with a partner (married or cohabiting) acted as a shield against depression for both genders. However, Hopcroft and McLaughlin (2012) show that the role of marital status differs by context: for men and women in high gender equality countries, being married significantly reduces one's levels of depressive symptoms, but being married does not act as shield against depression for either gender in low gender equality countries.

2.2.2 Individual-country studies

While studies focusing on cross-national differences in the gender gap in mental health are enlightening about broad commonalities, these studies are insufficient for identifying extensive trends in the gender depression gap as they typically use cross-sectional data. Utilizing extensive longitudinal data offers an advantage by identifying any temporal variation in the gender depression gap due to social changes over a longer period of time. Longitudinal data also allow researchers to account for unobserved heterogeneity which may arise due to unmeasurable differences between individuals that are correlated with key variables of interest (Hsiao, 2014).

Longitudinal studies on depression and gender across the life-course using multilevel models have been conducted mainly for the US, as well as for several European countries. The research typically uses data collected in waves at intervals of one to three years. All studies estimate an age trajectory in mental health, while many also consider the role of the cohort in which the individual was born (such as Brault et al., 2012; Abrams and Mehta, 2019; Platt et al., 2020). The birth cohort effect captures the cumulative impacts of experiencing or being exposed to certain historical conditions from birth and onward and these impacts can be used to explain changes in the depression differences in mental health across time (Platt et al., 2020). Some studies focus on a specific life stage, such as adolescence (Baldwin and Hoffman, 2002; Salk et al., 2016) or older age (Abrams and Mehta, 2019; Ferrand et al., 2020), rather than the full life course. The discussion in this section focuses on research that analyses gender differences in mental health among adults of any age. The papers are discussed in some detail, due to their methodological relevance to the analysis conducted in this dissertation.

In a study that focused on disentangling age effects and birth cohort effects on the intensity of depressive symptoms, Brault et al. (2012) examined whether people had a higher intensity of depression as they aged and whether the most recent cohort had the highest depressive symptoms score. This study used longitudinal data for Belgium, with a sample of 7 000 adults aged between 25 and 74 years grouped into various birth cohorts (from 1918 to 1967). Depression is measured using the Health and Daily Living form depression scale where individuals report the frequency of occurrence for each of 13 depression symptoms within three months preceding the survey.

In order to determine the effects of age and birth cohort on the depressive score trajectory, the multilevel approach to growth curves (growth curve modelling) was used. This method allowed Brault et al. (2012) to estimate simultaneously how depression scores evolve over the life-course (as a function of age), and how certain variables affect the growth pattern of the gender gap. In line with other findings from studies of gender and mental health, Brault et al. (2012) found that women reported significantly higher levels of depressive symptoms compared to men. This study also found a linear and positive age effect on depression which suggests that the levels of depressive symptoms increase as people age. Depression increased with age in every birth year cohort, and a quadratic function was determined as the best functional form for the relationship between age and depression. Different magnitudes of growth in depressive symptoms were observed for different cohorts.

Platt et al., (2020) examine the change in the gender gap in depression across different birth cohorts in the US over time. This study utilizes data from the National Longitudinal Survey collected biennially, with adults grouped into various birth cohorts (ranging between 1957 until 1994). The dependent variable is a depression score which measures the number of depressive symptoms experienced in the past two weeks (using the 7-item version of the CESD symptom scale). The paper focuses on how gender roles, and their changes across birth cohorts, affect depression, using gender ratios in education, employment and housework as proxies.

Similarly to Brault et al. (2012), this study found that across all birth cohorts, women reported higher depression and had a higher prevalence rate of depressive symptoms, compared to men. In addition, both studies determined that the relationship between age and depression is non-linear, with this study finding that the best-fitting model included cubic age terms. According to Platt et al. (2020), the gender differences in depression decreased in more recent birth year cohorts thus, as people age, gender differences in mental health decrease. These results were in contrast to those found by Brault et al. (2012) in Belgium, where gender differences in depression increase across every birth cohort. The decrease in the depression gap over birth cohorts was largely attributed to women experiencing lower levels of depressive symptoms due to improvements in their socio-economic status relative to men (Platt et al., 2020), which agrees with the cross-national findings that a better socio-economic status reduced depressive symptoms (Van de Velde et al., 2010).

Another study that determined the aging and cohort effects is by Yang and Lee (2009) which examined the changes in several dimensions of overall health, including self-reported depressive symptoms as well as physical health, across different birth cohorts over time. This study utilized data from the Americans' Changing Lives Study, a nationally representative longitudinal survey, with individuals aged 25 years and older grouped into multiple birth cohorts (before the year 1905 to 1964). The 11-item version of the CESD symptom scale is used as a depression score. The hierarchical linear modelling approach was used to estimate simultaneously the intra-cohort age trajectories and the inter-cohort differences in age trajectories of health (indicated by depressive symptoms, disability and self-assessed quality of health).

According to this study, similarly to Brault et al. (2012), the best-fitting model for the relationship between age and health (depression included) contained quadratic age terms. In addition, both these studies found that in successive birth cohorts, there is a persistent and increasing depressive symptoms (Yang and Lee, 2009; Brault et al., 2012). This suggests that in every birth cohort, women had a higher prevalence rate of depressive symptoms, compared to men. In contrast to Brault et al. (2012) however, this study argues that as aging of individuals narrows and levels the gender gap in depression over the life course net of cohort effects. These results were in similar to those found by Platt et al. (2020) which found that gender differences in depression decrease across every birth cohort.

Two studies examine whether people experienced higher levels of depressive symptoms as they age into their older years. Abrams and Metha (2019) use data from the Health and Retirement Study, a longitudinal survey for older Americans (over the age of 51), collected in Wave 2 to Wave 12 from 1994 to 2014. They examine the differences in prevalence rates and age-related changes in depressive symptoms over time according to gender, race, education levels and birth cohort (between 1890 until 1959). Depression was measured using depressive symptoms through the 8-item version of the CESD symptom scale.

Consistent with the findings of existing studies, this study found that women report higher scores of depressive symptoms than men. According to Abrams and Metha (2019), the gender gap in depression was found to get narrower in mid-life compared to older cohorts. Thus, the gender disparities in mental health shrink in the later stages of life, as also found by Platt et al., 2020 in the study looking at the gender depression gap in the age cohorts ranging from 1957 to 1994. This reduction in the depression gap over time was partly attributed to the decline in universal health as people age and the decline in their social and economic statuses (Abrams and Metha, 2019). However, the study also argues that as people age, men become more susceptible to experiencing depressive symptoms thus explaining the shrinking depression gap. In addition, Abrams and Metha (2019) argue that the gender gap may also be attributable to the inability or unwillingness of men to talk about feelings of depression and sadness.

In another study that used data for older people, Ferrand et al. (2020) examined the changes in depressive symptoms among older French individuals over time and investigated the gender-related changes in the developmental trajectory of depressive symptoms using an ongoing longitudinal study for older French adults (using five waves, period from 2001 to 2011). A depression score measured depressive symptoms through the 15-item Geriatic Depression Scale, which measures specific experiences of geriatric depressive symptoms. Similar to all the studies reviewed above, this study used the multilevel modelling method to examine the changes in depression symptoms and the gender gap over time. This study found that a gender gap existed. This is consistent with the findings that even for older people, women report higher levels of depressive symptoms than men Abrams and Metha (2019). However, Ferrand et al. (2020) find that the gender gap in depression does not change as people age. This is in contrast to the findings that argue that the gender differences in depression either decrease or increase at later stages of life as found the previously reviewed studies.

These results show a range of commonalities in how the studies approach the investigation of the gender gap in depression, but a diversity of findings about how gender differences in depression change as people age. This diversity suggests that the social and economic context is important, as uncovered in the cross-national studies. Next, the empirical evidence from South Africa related to mental health and gendered mental health disparities is reviewed.

2.2.3 Evidence from South Africa

As shown by the various studies reviewed above, most individual-country empirical studies investigating the gender depression gap are conducted in developed countries. Collecting longitudinal data over an extensive period of time is costly, time consuming and logistically challenging. As a result, literature in developing nations investigating the relationship between gender and depression and the various socio-economic factors that drive this relationship is lacking.

In South Africa, there is a small but growing literature on the socio-economic correlates of depression, with most studies analysing cross-sectional or longitudinal data from NIDS. Two studies using multilevel analysis methods have investigated the relationship between neighbourhood social capital and depression (Tomita and Burns, 2013; Somefun and Fotso, 2020). Other research has explored various socio-economic factors that influence depression, including the role of negative household events (Burger et al, 2017), income and income inequality (Burns et al, 2017), and cash transfers (Eyal and Burns, 2019; Garman et al., 2022).

In a study that focuses on the relationship between socio-economic status and the risk of depression, Mungai and Bayat (2019) utilized data from the National Income Dynamics Study that investigates the livelihoods of people and households in South Africa. The study used data for individuals aged 18 years and above from four NIDS data waves (from 2008 to 2015). The dependent variable was indicated by the depression score measured using the 10-item version of the Centre for Epidemiological Studies Depression (CES-D) score, computed using respondents experience of certain depressive symptoms (ranging from rarely to all the time). Using descriptive statistics, the study found that the average depression score was higher for women than for men in 2008, and remained so by 2014/2015, although the magnitude of the gap decreased somewhat (Mungai and Bayat, 2019).

Only one existing paper for South Africa focuses specifically on the role of gender in influencing mental health outcomes. Mutyambizi et al. (2019) examine the effect of perceived social standing on gender inequalities in depressive symptoms using the nationally representative 2014 South African Social Attitudes Survey. Depressive symptoms were measured using the 8-item version of the CESD symptom scale, while subjective social status was the respondent’s self-reported ranking in the social hierarchy. Women had an average depression score of 7.72 (where the maximum potential value was 24), while men had a score of 7.04. Around 26 percent of the sampled population had depressive symptoms that may indicate clinical depression, with the prevalence of depression being higher for women than for men (Mutyambizi et al., 2019). This study found that social standing contributes more to the extent of inequality in depression for women than for men, after controlling for other socio-economic characteristics. This suggests that factors associated with social roles may be especially important for women's mental health.

The paper decomposes inequalities in mental health for each gender, but it does not estimate the size of the gender gap in a multivariate context. Therefore, whether the average gap persists after controlling for gender differences in socio-economic factors is unknown. In addition, the paper analyses cross-sectional data, and therefore it is unable to examine trajectories in mental health as people age, or to account for unobserved heterogeneity. This dissertation therefore aims to fill this research gap by exploring gender differences in depression across the life-course using longitudinal data.

2.3 Conclusion

Numerous studies have found that women experience more depressive symptoms than men. The theoretical models reviewed in this chapter focus on different arguments for why, in general, women are more susceptible to mental illnesses compared to men. The biomedical theory argues that women experience higher rates of depression than men due to genetics and hormones (Nolen-Hoeksema, 1987; Hammarström et al., 2009), whilst the affective and psychological models focus on gender differences in negative emotionality as well as behavioural and cognitive factors (Rothbart and Bates, 1998; Hyde et al., 2008). Finally, the sociocultural theory argues for the role of societal (including economic) and cultural factors that women are subjected to in their public and private lives to explain this relationship (Hammarström et al., 2009; Hyde and Mezulis, 2020).

The consensus from the empirical literature is that the gender gap in depression exists in a wide variety of contexts, including both developed and developing countries (Van de Velde et al., 2010; Brault et al., 2012; Mutyambizi et al., 2019). This finding is consistent whether researchers use cross-sectional or longitudinal data. In addition, some longitudinal studies show that the gender difference in depression shrinks as people age (Abrams and Metha, 2019; Platt et al., 2020). Studies in developed countries have found that education levels, social factors, and an individual's birth cohort are important in explaining the size of the gender gap. In South Africa, however, little is known concerning the gender gap in mental health. On average at a cross-sectional level, women have greater depression scores than men (Mutyambizi et al., 2019; Mungai & Bayat, 2019). However, no longitudinal research has estimated the size and trajectory of the gender gap with age, nor established the contribution of birth cohort membership or socio-economic factors to the gender gap in depression.

Thus, the lack of empirical analysis on the gender gap in depression within the South African context is a significant research gap, given the inequality between South African men and women in the workplace and in society, as illustrated by the gender wage gap and high rates of gender-based violence. Little is known about whether the gender gap increases or decreases as individuals age, or the role of changes over time in access to education or employment. Therefore, to better understand the relationship between gender and mental health, which has primarily been investigated in developed countries, the remainder of this dissertation explores the gender depression gap using longitudinal South African data.

Chapter 3: Data and descriptive statistics

The previous chapter highlighted that many studies have been conducted internationally to explore the existence and magnitude of the gender gap in mental health, and the trajectory of the gender gap as individual's age. As demonstrated in that chapter, both theory and empirical studies agree that gender differences in mental health do exist, in both developing and developed countries. However, little is known of this association between gender and mental health in South Africa and how the gender gap changes with age. In the South African context, the few cross-sectional studies that investigate the gender disparities in the prevalence of depression focus on the subjective social status of individuals and their mental health. Thus, this dissertation aims to determine what the gender gap is in South Africa, how it changes with age, and to examine the extent to which gender differences in social/household roles, and in labour market roles, explain the gender gap. In order to do so, the dissertation uses nationally representative longitudinal data. This chapter introduces these data, as well as the key measures that are then investigated econometrically in Chapter 4.

The remainder of this chapter is organized as follows. Section 3.1 outlines the data used for this chapter and Chapter 4. Next, Section 3.2 outlines the key variables and measures used for this empirical investigation. Section 3.3 presents and discusses the descriptive statistics for the analysis sample and key variables, and Section 3.4 concludes the chapter.

3.1 Data

The data used in this chapter are sourced from the five existing waves of the National Income Dynamics Study (NIDS) which examines the livelihood of people and households in South Africa. The NIDS is the first nationally representative household longitudinal study in South Africa, and it is carried out by the Southern Africa Labour and Development Research Unit at the University of Cape Town. The NIDS is used for this dissertation because it offers substantial information about individuals of various demographics, education levels, and labour market roles, among other things. This data is presented in a variety of themes, each of which records a respondent's response to each question. Key for this study, the questionnaire covers themes that directly address an individual's mental health. This is done in section K of the questionnaire, where respondents are asked ten questions regarding their emotional well-being over the previous week and are asked to rate the frequency with which they experienced these emotions on a scale of ‘rarely’ to ‘all the time’. As explained in Section 3.2, the answers to these questions are combined to construct a mental health score, which is used as the dependent variable in the empirical analysis.

The longitudinal nature of NIDS is key to the ability to carry out this research. The first proposed research question entails examining the age trajectory in mental health, before exploring the nature of the gender gap in the presence of this trajectory. Cross-sectional data would have allowed only the comparison of average mental health amongst individuals of a given age, whereas using panel data has the advantage of allowing the study to account for intra-individual changes in depression. Using panel data not only offers an advantage in establishing causal relationships between variables and within-individual change over time, but also helps account for unobserved heterogeneity which may arise due to unmeasurable differences between individuals that are correlated with key variables of interest.

The data utilized make up an unbalanced panel because, throughout the years that the NIDS data were collected, some respondents dropped out of the survey while others were added to the sample, resulting in a varied number of respondents being interviewed each year. Attrition is an expected limitation of longitudinal data analysis, since some individuals may appear in only a small number of waves, resulting in a sample that becomes less representative over time. Analysis methods that require the sample to be balanced typically exacerbate the representativeness problem by excluding further observations. However, the main analysis method used in Chapter 4, namely multilevel modelling, allows for the analysis of an unbalanced sample. The chosen sample to be used in this research is therefore limited only by the availability of data. The questions on emotional well-being are part of the adult questionnaire. Thus, individuals aged 15 and older who reported the information used to calculate the depression score are included in the sample. As a result, the purpose of this research is to examine mental health disparities between South African men and women aged 15 and upwards.

3.2 Measures

For this dissertation, a depression score is the measure of mental health and is derived from respondents' answers to ten questions. Eight of these questions were concerning negative emotions such as how frequently the respondent had been unusually bothered, had trouble focusing or felt depressed. Respondents' answers were assigned a value from zero (rarely or none of the time) to a maximum of three (all of the time). In contrast, two questions asked respondent about positive emotions, namely how frequently during the past week they felt hopeful and felt happy. Their responses were reverse coded so that the range corresponded with the questions concerning their negative emotions. Therefore, a zero is assigned when a respondent felt happy or felt hopeful all the time (no depressive symptoms) and three when the respondent rarely or never felt happy or hopeful. Thereafter, the scores to these ten questions were summed to generate a mental health score with a range from zero, meaning that the individual reports no depressive symptoms, to thirty, which is the highest depression level across all recorded dimensions. This measure of depression is known as the ten-item Center for Epidemiologic Studies Depression (CESD) score. Although this measure of depression is constructed using self-reported data, studies show that it correlates strongly with clinical psychological diagnoses and the measure has been used in multiple empirical studies both in South Africa and internationally (Andresen et al., 1994; Burger et al., 2017). In a number of South African populations, including Xhosa, Zulu, and Afrikaans-speaking people, the CES-D10 score has been shown to be reliable and valid in measuring and diagnosing clinically significant depressive symptoms (Baron et al, 2017).

The first key explanatory variable in this study will be an individual's gender. Gender is self-reported in NIDS and this dissertation defines the gender dummy variable as being 1 if the respondent indicates they are female and 0 if male. Comparisons between women and men are made to quantify the size of the gender gap in depression. A second key explanatory variable is the respondent's current age. This continuous variable, measured in years, is used to investigate whether mental health improves or deteriorates with increasing age.

The study also includes birth year cohorts as key explanatory variables in order to examine the age increment hypothesis which states that the gender differences in mental health rise in successively older age groups throughout one's lifetime (Mirowsky, 1996). Age and cohort effects, according to Yang and Lee (2009), are distinct. The former represents individual-specific aging processes which describe developmental changes over the course of a person's life, whereas the latter represents social (external) changes, which include the influence or impact of early life circumstances as well as cumulative on-going experiences and exposures to various biological and social risk factors for health over the course of a person's life. When analysing health trends over time, ignoring cohort effects implies that the rates at which health fluctuates with age are equal for all cohorts (Yang and Lee, 2009).

In this study, individuals are grouped into three birth cohorts where cohort 3 is those born up to the year 1959 (that is, the oldest cohort), cohort 2 is those born from 1960 until 1979 and cohort 1 is those born from 1980 onwards (the youngest cohort). Some type of cohort categorization is conventional in much demographic research and is validated by many studies that use similar cohort groups in order to examine how the gender gap in health varies across individuals born in different generations (Abrams and Mehta, 2019; Platt et al., 2020). Birth cohorts are commonly defined based on evenly spaced birth years (Yang and Lee, 2009; Platt et al., 2020) or based on historical events (Abrams and Mehta, 2019), although such definitions remain somewhat arbitrary. This dissertation uses a relatively small number of broad cohorts, to ensure a sufficient sample size in each gender-cohort-wave combination, as shown later in Table 3.1. Therefore, each cohort groups together individuals who may have had fairly different social expectations and experiences. In addition, Chapter 4 also includes some sensitivity analysis on cohort definitions.

To analyse the extent at which gender differences in social or household roles, and in economic roles, explain the gender gap in mental health, this dissertation includes three proxies that represent these roles. The social and household roles are a proxy for the systematic inequalities that exist in society between men and women and these are measured using two categories of factors, namely, child-care responsibilities and decision-making power in the household. Child-care is indicated by two variables indicating the number of children by age that the individual is responsible for, with these ages including children less than 7 years, and children between the ages of 7 and 15. These measures are defined based on who is identified as being responsible for each child in the household. They therefore account for the differing levels of engagement in childcare as reflected by the number and developmental stage of the children being cared for. Childcare responsibilities may raise the depression score through the effort required, or lower it through the rewards of raising children. Decision-making power in the household is indicated by the main and degree of joint decision-making power that the individual has. These measures indicate whether an individual is the main decision-maker or the joint decision-maker over any of the spheres of household decision-making**.**

The economic roles are a proxy for the labour market inequalities that exist in South Africa, and these are measured using the respondent's employment status. Employment status has four categories contrasting those that are non-searching unemployed (discouraged work seekers), strictly unemployed, and employed to those that are not economically active. Employment is typically associated with better mental health, through a range of economic and psychological mechanisms (Rantakeisa et al., 1999), but labour market access is highly gendered in South Africa.

In addition to the key explanatory variables discussed above, this study also includes control variables such race, marital status, education level, health status, household size, household income, and rural. Race is defined into four categories representing black Africans, Coloureds, Asian or Indian individuals, and whites. Marital status is indicated by a dummy variable contrasting the married to those who are not married. The highest level of education completed is categorized into four levels contrasting respondents with primary, secondary, and tertiary education with those with no education. Self-reported health status is represented by five categories contrasting individuals with very good, good, fair, and poor health statuses with those that have an excellent health status. To control for household effects, this study includes household size which indicates the total number of people living in the respondent's household. Household income is indicated by the total household income measured in South African Rands per month. Lastly, the type of area a respondent lives in is indicated by the rural dummy variable which is coded 1 for individuals living in the rural areas and 0 for those that live in urban areas.

3.3 Descriptive statistics

This section presents and discusses descriptive statistics for the sample of individuals who are 15 years and above, in order to show the nature of the data that are analysed in Chapter

4. In particular, this section highlights differences in mental health between different genders and birth year cohorts.

Table 3.1 below shows the frequencies and percentages of men and women in the various cohorts who are present in each wave. These data are presented unweighted, at the level of the sample, and show that there are more than one thousand observations of each gender, in each cohort-wave cell. The youngest birth cohort is the largest, in line with South Africa’s population distribution. This table shows that women increasingly dominate the sample across the birth year cohorts making up almost two-thirds of cohort 3, due to their greater longevity than men. The number of observations varies across waves for each cohort and gender. This may be attributed to individuals who exit from the sample entirely, or are left out in one wave and then return in the next wave, or individuals who join the NIDS sample. In addition, in cohort 1, young individuals who were already part of the NIDS sample are added to the analysis sample once they are 15 years old. As a result, the number of observations of each person differs. However, using multilevel modelling allows for the estimation of models when the number of observations per person differs, therefore any individual with at least one reported depression score is included in the sample.

Table 3.1: Sample size, by wave, cohort and gender

Cohort	Gender	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5	Total
Cohort 1	Male	2,307	3,172	3,718	5,273	5,665	20,135
(1980		44.34	46.37	44.72	45.82	44.67	45.20
onwards)	Female	2,896	3,669	4,596	6,235	7,017	24,413
		55.66	53.63	55.28	54.18	55.33	54.80
	Total	5,203	6,841	8,314	11,508	12,682	44,548
		100.00	100.00	100.00	100.00	100.00	100.00
Cohort 2	Male	2,044	1,941	2,069	2,375	2,279	10,708
(1960-		39.26	38.72	37.73	38.28	36.64	38.07
1979)	Female	3,162	3,072	3,414	3,830	3,941	17,419
		60.74	61.28	62.27	61.72	63.36	61.93
	Total	5,206	5,013	5,483	6,205	6,220	28,127
		100.00	100.00	100.00	100.00	100.00	100.00
Cohort 3	Male	1,559	1,377	1,348	1,357	1,362	7,003
(1959 or		35.60	35.45	33.57	32.98	33.87	34.31
earlier)	Female	2,820	2,507	2,667	2,757	2,659	13,410
		64.40	64.55	66.43	67.02	66.13	65.69
	Total	4,379	3,884	4,015	4,114	4,021	20,413
		100.00	100.00	100.00	100.00	100.00	100.00

Source: NIDS waves 1-5, own calculations

Notes: The data are unweighted. The sample includes all individuals aged 15 years and older who have a reported depression score in a given wave. Each cell shows the frequency of observations, with the percentage of observations in each gender, for the given wave and cohort, shown below.

The different number of observations per person is largely due to sample attrition which refers to a situation where there are missing data due to the fact that some respondents die, withdraw from the survey, or move away and are untraceable, thus causing loss of power due to the diminishing numbers of participants. In addition, some individuals join the sample. This concept of sample attrition is illustrated below in Table 3.2 that shows participation patterns of both men and women in the potential sample. This table shows that not all respondents participated in each and every wave and that some individuals joined as well as left the analysis sample. The prevalence of individuals joining the sample who were not observed in previous waves might be partly attributed to the fact that individuals who were NIDS sample members as children ‘age into’ the analysis sample once they are 15 years old.

Table 3.2: Participation pattern of the analysis sample

Pattern	Female		Male	
	Number	Percent	Number	Percent
11111	4077	19.61	1839	11.73
....1	3210	15.44	2369	15.12
...11	1849	8.89	1413	9.02
...1.	1442	6.93	1232	7.86
..111	1059	5.09	785	5.01
1....	1058	5.09	1032	6.58
.1111	1039	5.00	871	5.56
..1..	898	4.32	721	4.60
1.111	816	3.92	563	3.59
.1...	750	3.61	749	4.78
Other patterns	4596	22.10	4099	26.15
Observations	20794	100.00	15673	100.00

Source: NIDS waves 1-5, own calculations

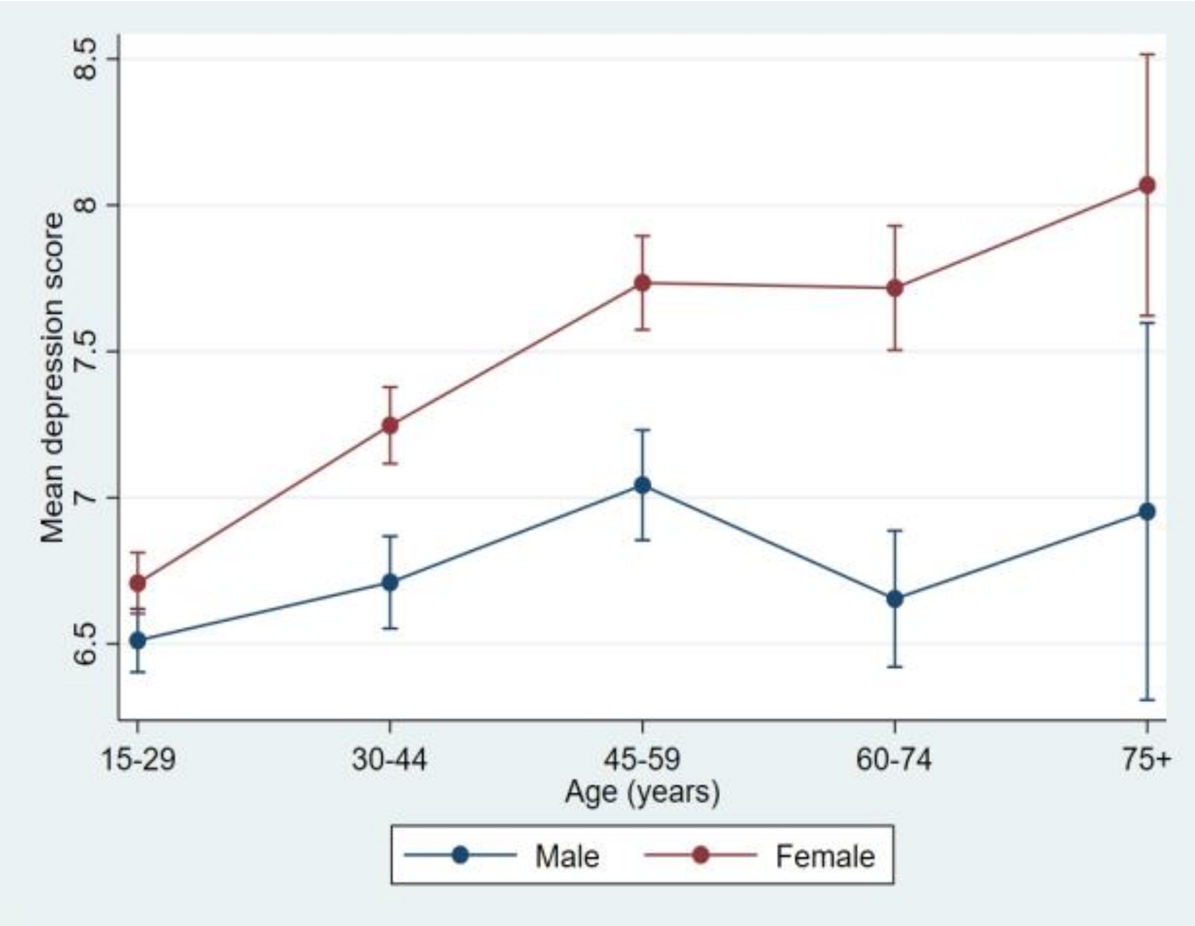
Notes: The data are unweighted. The sample includes all individuals who, in at least one wave, are aged 15 years or older and have a reported depression score. In the pattern, '1' represents a wave-observation where an individual was successfully interviewed, is aged 15 years and older, and has a reported depression score. '.' represents an individual who is not successfully interviewed, or is younger than 15, or does not have a reported depression score.

The most common pattern shown in this table for women (19.61 percent), and the second most common for men (11.73 percent), is for an individual to appear in all five waves. Around 15 percent of both women and men participated in the analysis in only the fifth wave, which is likely due to the top-up of the sample in this wave (Brophy et al, 2018). The participation patterns are similar by gender, suggesting that gender-differential attrition is not a likely driving factor for changes in the measured gender gap in depression scores.

For this study, the NIDS weights are used to make the sample results representative of the population and to adjust for any non-random attrition. Therefore, all subsequent results presented will be weighted. Further issues relating to attrition and weighting, as they affect the econometric analysis, are discussed in Chapter 4.

The remainder of this section explores the nature of the key variables analysed in the dissertation. Figure 3.1 shows the average age trajectory in depression, or the average 'growth' in depression over the life course. For both genders, the depression score rises into middle age, then stabilises or declines, before increasing sharply at older ages. This suggests that there is a cubic function in age. In addition, the figure shows that there is a gender gap in depression, whereby women report higher depression scores than men, and that this gap rises as individual's age. However, this figure does not show any differences across cohorts, which are summarised in the next table.

Figure 3.1 Mean depression score, by age and gender



Source: NIDS waves 1-5, own calculations
Notes: The data are weighted.

Table 3.3 below shows the characteristics of the chosen sample (individuals of ages 15 and above, with at least one reported depression score), by their gender and birth year cohort. The values displayed in the table represent the mean of each continuous variable, and the proportion of the given gender that belong to the named category, for the given cohort. The significance stars indicate differences between mean values for women and men within a given cohort, at different levels of significance. The results show that the mental health score average value differs according to gender in every cohort. In Cohort 1, women report approximately 6.7 depressive symptoms, whilst men in the same cohort have an average of 6.5 depressive symptoms. In the second cohort, women report an average of 7.5 depressive symptoms and their male counterparts record an average of 6.9. This pattern is also seen in Cohort 3 where women have a significantly larger average depression score compared to men in the same cohort. This shows that there is a significant difference in the depressive symptoms between women and men in every birth year cohort. Furthermore, the results show that mental health worsens, and the gender differences in mental health increase, across cohorts. In the first cohort the gender gap is 0.227, in the second cohort the difference is 0.604 and in the third cohort the gender gap is 0.92. These varying gaps are what Chapter 4 seeks to understand further.

Table 3.3 Mean characteristics, by gender and cohort

	Cohort 1		Cohort 2		Cohort 3	
	Female	Male	Female	Male	Female	Male
Depression score	6.708**	6.481	7.486***	6.882	7.846***	6.926
	(0.049)	(0.053)	(0.063)	(0.075)	(0.079)	(0.093)
Demographics						
Age	24.100*	23.888	42.053	42.020	64.373***	62.868
	(0.066)	(0.071)	(0.089)	(0.110)	(0.146)	(0.177)
Black	0.871	0.857	0.778	0.795	0.708	0.683
	(0.005)	(0.005)	(0.007)	(0.008)	(0.009)	(0.012)
Coloured	0.076	0.078	0.103	0.100	0.084	0.089
	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.006)
Asian/Indian	0.018	0.019	0.025	0.028	0.032	0.031
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)
White	0.035*	0.045	0.094*	0.077	0.176	0.197
	(0.003)	(0.004)	(0.005)	(0.006)	(0.008)	(0.011)
Gender roles						
No. of young children taken care of	0.500***	0.022	0.425***	0.043	0.200***	0.017
	(0.008)	(0.003)	(0.009)	(0.004)	(0.007)	(0.002)
No. of older children taken care of	0.258***	0.019	0.717***	0.102	0.409***	0.057
	(0.007)	(0.002)	(0.011)	(0.006)	(0.011)	(0.005)
Main decision maker	0.399***	0.326	0.779	0.766	0.808**	0.836
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.008)
Joint decision making	0.263***	0.150	0.396***	0.326	0.310*	0.342
	(0.005)	(0.005)	(0.007)	(0.008)	(0.008)	(0.011)
Not economically active	0.480***	0.387	0.287***	0.141	0.751***	0.543

	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.011)
Unemployed-discouraged	0.028***	0.020	0.034***	0.016	0.017	0.015
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Unemployed-strict	0.186***	0.145	0.136***	0.098	0.018***	0.038
	(0.004)	(0.004)	(0.005)	(0.005)	(0.002)	(0.004)
Employed	0.306***	0.448	0.543***	0.745	0.214***	0.404
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.011)
Household characteristics						
Household income (R '000s)	7.969	8.190	9.832	10.202	9.827	10.371
	(0.203)	(0.189)	(0.277)	(0.336)	(0.764)	(0.523)
Household size	5.598***	4.826	4.884***	3.668	4.604***	4.063
	(0.039)	(0.039)	(0.036)	(0.043)	(0.046)	(0.058)
Rural	0.394	0.390	0.362***	0.301	0.437***	0.389
	(0.005)	(0.006)	(0.006)	(0.007)	(0.008)	(0.010)
Individual characteristics						
No education	0.004***	0.007	0.054	0.051	0.273***	0.182
	(0.000)	(0.001)	(0.002)	(0.003)	(0.006)	(0.007)
Primary	0.057***	0.086	0.188	0.202	0.320	0.305
	(0.002)	(0.003)	(0.005)	(0.007)	(0.007)	(0.009)
Secondary	0.789	0.781	0.562	0.572	0.301***	0.390
	(0.005)	(0.005)	(0.007)	(0.009)	(0.008)	(0.011)
Tertiary	0.150***	0.126	0.196*	0.175	0.106	0.123
	(0.004)	(0.005)	(0.006)	(0.007)	(0.006)	(0.009)
Excellent health	0.407***	0.463	0.280***	0.330	0.111***	0.169
	(0.006)	(0.006)	(0.006)	(0.008)	(0.005)	(0.009)
Very good health	0.324*	0.308	0.284	0.302	0.201**	0.238
	(0.005)	(0.006)	(0.006)	(0.008)	(0.007)	(0.010)
Good health	0.223***	0.198	0.289***	0.252	0.347	0.339
	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)	(0.011)
Fair health	0.036***	0.023	0.104**	0.085	0.239***	0.183
	(0.002)	(0.002)	(0.004)	(0.005)	(0.007)	(0.008)
Poor health	0.010	0.008	0.043***	0.030	0.102***	0.071
	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)	(0.005)
Married	0.114***	0.058	0.444**	0.480	0.380***	0.693
	(0.004)	(0.004)	(0.007)	(0.009)	(0.008)	(0.010)
Sample	17582	15289	13425	8329	10990	5712

Population	37928876	35583376	29115594	22932498	17819204	11724231

Source: NIDS waves 1-5, own calculations

Notes: All estimates are weighted. Standard errors in parentheses. Significance levels are shown as * p<0.05, ** p<0.01, *** p<0.001. They test whether the mean value for women differs from the mean for men, within the same birth cohort.

Individuals are approximately 24 years old on average in cohort 1, 42 in cohort 2 and in their early 60s in cohort 3. Women are significantly older than men, on average, in the youngest and oldest cohorts. The results show that approximately 85 percent of women in cohort 1 are black African, 7.64 percent are Coloured, 1.77 percent are Asian or Indian, and 3.52 percent are white. Older cohorts have a smaller share of black African individuals, and a larger share of each other race group. There are no significant gender differences in the racial composition of any cohort, except that cohort 1 has a slightly larger share of white men and women, and the reverse is true for cohort 2.

According to Table 3.3, women take care of significantly more young children than men in every cohort. This is also true for the number of older children taken care of by the respondent. This shows that women are more likely to take care of children in the household compared to men regardless of their birth year cohort. More than 80 percent of individuals in the oldest cohort are a main decision-maker in their household, while the same is true of less than 40 percent of cohort 1 individuals. Women are more likely than men to be a main decision-maker in the two younger cohorts, but less likely in the oldest cohort. In addition, there is a smaller share of individuals who are joint decision-makers in their households, but with the same gender pattern across cohorts.

Employment status varies considerably by cohort and gender. Almost half of women in cohort 1 are not economically active, compared to 28.7 and 75.1 percent in cohort 2 and 3, respectively. The results suggest that women in all cohorts are significantly more likely than men to be economically inactive. Women are more likely than men to be unemployed, for both categories of unemployment and across all cohorts. In cohort 1, 30.6 percent of women are employed while approximately 54.3 and 21.4 percent of women are employed in the second and third cohort, respectively. Across all three cohorts, men are significantly more likely than women to be employed. Women live in households with lower average incomes and more household members than men, in every cohort, suggesting that they are economically more vulnerable than men. A greater share of women than men in the second and third cohort live in rural areas. Among the individual characteristics, the results indicate the significant expansion of access to education in South Africa over time.

Among the individual characteristics, the results indicate the significant expansion of access to education in South Africa over time. In cohort 3, more than a quarter of women and 18 percent of men have no schooling, but the same is true of less than one percent of individuals in the youngest cohort. In general, men have higher levels of education than women only in the oldest cohort. Women are significantly more likely than men to have tertiary education in cohorts 1 and 2. However, a smaller share of cohort 1 compared to cohort 2 have tertiary education, since many individuals in the youngest cohort may be ongoing with their studies.

Table 3.3 clearly illustrates the deterioration of health with age. More than 40 percent of women report having excellent health in cohort 1, but only 11.1 percent in cohort 3. Within each cohort, men report better health than women. Men are around five percentage points more likely to report excellent health than women, in each cohort. Individuals in cohort 3 are disproportionately likely to report having fair or poor health status relative to cohort 1 and 2. Lastly, the results show that a much greater proportion of women than men in cohort 1 are married. On average, 11.4 percent of women in cohort 1 are married compared to 5.84 percent of men. There is a small marriage gap in favour of men in cohort 2, but a very large difference in cohort 3, where almost 70 percent of men but less than 40 percent of women are married.

Therefore, Table 3.3 illustrates the existence of a range of cohort-level gender differences in factors that may affect mental health. In general, women have more childcare responsibilities, less access to the labour market, live in households with lower incomes and more members, and report worse health than men. All of these factors may contribute to the observed gender gap in mental health. The table also illustrates that there is considerable variation in many of these factors across the birth cohorts. For example, individuals in cohort 3 have worse self-reported health than the other cohorts, which may negatively affect their mental health. However, age effects and cohort effects cannot be disentangled in descriptive statistics. It is not possible to distinguish the age deterioration in health from the long-term impact of the limited apartheid-era access to healthcare during this cohort's younger years. The regression analysis conducted in Chapter 4 will therefore be used to assess the relative roles of age and cohort membership in influencing the gender gap in mental health.

3.4 Conclusion

This chapter introduced the empirical analysis conducted in the dissertation, by outlining the dataset used for the analysis and presenting summary statistics for the analysis sample. Five waves of the longitudinal NIDS data are analysed, allowing for the investigation of both inter- and intra-individual variation in mental health. The mental health (dependent) variable is measured using the depression score of the respondents is the measure of mental health (using a ten-item CESD score) and the key explanatory variables include gender, age and birth cohort. In addition, a range of other control variables are also defined.

Table 3.1 represented the frequencies and percentages of men and women in the various cohorts who are present in each wave, indicating that women are increasingly dominant in the sample across the birth year cohorts. Table 3.2 illustrated the participation patterns in the analysis sample, indicating that although individuals both join and leave the analysis sample across the waves, appearance and attrition patterns are similar for men compared to women. Figure 3.1 illustrated both the age trajectory and gender gap in mental health. Women report more depressive symptoms than men at each age, but for both genders there is a non-linear increase in depression with age. Finally, Table 3.3 presented the characteristics of the chosen sample (made up of individuals aged 15 and above, with at least one reported depression score), by their gender and birth year cohort. The table suggests that there are significant differences in the average level of depressive symptoms between women and men in every birth cohort. Furthermore, the table suggested that the gender differences in mental health increase across cohorts.

The descriptive statistics in Section 3.3 thus indicate that the gender gap in mental health exists in the South African context and that it increases across the specified cohorts in this study. In addition, there are a range of cohort-level gender differences in socio-economic factors that may affect mental health. However, while descriptive statistics help in describing the mean characteristics or features of the dataset, they are unable to disentangle the roles of different factors. Therefore, the next chapter conducts the regression analysis to aid in understanding the independent roles of age, birth cohort, gender roles, and other household and individual characteristics, in influencing the level of depression and size of the mental health gap between women and men.

Chapter 4: Methodology and results

As outlined in Chapter 3, all five of the NIDS waves are used in the analysis, because one of the purposes of this study is to examine the average change in the gender depression gap across cohorts over time while also investigating the individual patterns of mental health across time. As a result, the data used in this study follows people over time, resulting in many measurements on the same person. This approach provides enhanced statistical power in detecting effects of interest in a given group of respondents, as well as enabling the analysis of change in the outcome over time, allowing for more comprehensive modelling of human behaviour than an analysis of cross-sectional data (Bryk and Raudenbush, 1992). However, an appropriate econometric method must be identified in order to use this panel data to understand between-individual and within-individual changes in mental health across time.

The remainder of this chapter is structured as follows: Section 4.1 outlines the methodology used for the econometric analysis, namely multilevel or hierarchical modelling. Section 4.2 presents the results of the application of this method, using a range of model specifications, while 4.3 conducts sensitivity analysis for the key specifications. Section 4.4 summarises the key findings and discusses their meaning, before Section 4.5 concludes.

4.1 Methodology

The main objective of this empirical investigation is to determine the age trajectory of development of depressive symptoms and the gender gaps in mental health trajectories for different birth cohorts over time. As a result, the responses of individuals over time (repeated measurements) may be correlated with each other such that the repeated measures can be thought of as being clustered or nested within those individuals thus resulting in the data used having a hierarchical or multilevel structure. Thus using ordinary one-level regression methods may be erroneous (Goldstein, 1991). In addition, a traditional fixed effects panel estimation is not appropriate here, since all three of the key variables of interest are either time-invariant (gender and birth cohort) or change at a constant rate (age). Fixed effects regression would be unable to estimate the parameters on such variables. To achieve the study objective, the multilevel modelling estimation method is therefore used in this chapter. This is the standard econometric approach in the literature that explores age trajectories in health over the life course, which is widely used for the analysis of gender gaps as well as other issues in health (Hopcroft and McLaughlin, 2012; Yang and Lee, 2009; Ferrand et al., 2020; Platt et al., 2020).

4.1.1 Multilevel modelling

Multilevel modelling is an analytical approach ideal for data that has layered sources of variability—that is, units observed at a lower or micro level (in this case, repeated longitudinal measurements) nested within units at a higher or macro level (for example, individuals). Unlike traditional regression methods, multilevel models take into account the multilevel structure of the data. For clustered data, these models provide accurate parameter estimates and standard errors. Another significant benefit of this approach is that different intercepts can be estimated for different levels, and the research can explore how the introduction of additional explanatory and control variables affects these intercept estimates.

Unlike the fixed effects estimating method, which treats higher level effects as nuisance parameters that must be dealt with so that desirable properties of the fixed part parameters are obtained, making it impossible to measure these effects, the multilevel modelling approach permits these effects to be simulated. Multilevel models with growth effects can be used to model individual differences in 'development' with age or time. This is the typical application of multilevel modelling to longitudinal data, with the resulting models known as growth-curve models (Rabe-Hesketh and Skrondal, 2021). The repeated measures are considered as outcomes that are dependent on some time metric in the growth curve approach (such as wave or age). The estimated model not only generates an estimated mean curve, but it also predicts individual curve variation as a function of the growth factors. Individuals may have a different number of measurement occasions or observations compared to others, for example, due to attrition (Ferrand et al., 2020). The estimated growth trajectory can vary due to covariates measured at the level of the individual or the occasion, as well as randomly (Rabe-Hesketh and Skrondal, 2021). This concept provides for a wide range of curves for different individuals and it also allows for data to be analysed in any form, long or wide.

Panel data comprise repeated Level 1 measurements (occasions) that are nested in individuals at Level 2. Time-varying covariates are measured at the first level, whereas time-invariant characteristics, such as gender, are measured at the second. A key element of these models is that they allow for flexibility in the shape of the growth trajectory, for example by including a polynomial function. The remainder of this section outlines a simple growth curve model in general terms, with random intercept and random slope, based on Rabe-Hesketh and Skrondal (2021). The application of the model to the NIDS depression score data is described in Section 4.1.2.

The Level 1 equation is given by:

$$\boldsymbol{y_{ij}} = \boldsymbol{\beta_{0j}} + \boldsymbol{\beta_{1j}}\, \boldsymbol{t_{ij}} + \boldsymbol{\beta_2 t_{ij}^2} + \cdots + \boldsymbol{e_{ij}} \qquad (\mathbf{4.1})$$

Individuals are denoted by the letter *j*, while repeated measures are denoted by the letter *i*. The outcome variable is represented by $\boldsymbol{y_{ij}}$, while $\boldsymbol{t_{ij}}$ represents time or age. The ellipsis represents the possible inclusion of further polynomial terms. The coefficients $\boldsymbol{\beta_{0j}}$ and $\boldsymbol{\beta_{1j}}$ are the random intercept and random slope, which are individual-specific parameters. They are described by the Level 2 equations:

$$\begin{aligned} \boldsymbol{\beta_{0j}} &= \boldsymbol{\gamma_{00}} + \boldsymbol{\gamma_{00} x_j} + \boldsymbol{u_{0j}} \\ \boldsymbol{\beta_{1j}} &= \boldsymbol{\gamma_{10}} + \boldsymbol{u_{1j}} \end{aligned} \qquad (\mathbf{4.2})$$

Here, $\boldsymbol{x_j}$ represents an individual-level (time invariant) covariate. The above Level 2 equations are substituted into the Level 1 equation to form the reduced form model that is represented by the main equation below, with the substitutions for the random coefficients shown in curly brackets:

$$\begin{aligned} \boldsymbol{y_{ij}} &= \{\boldsymbol{\gamma_{00}} + \boldsymbol{\gamma_{00} x_j} + \boldsymbol{u_{0j}}\} + \{\boldsymbol{\gamma_{10}} + \boldsymbol{u_{1j}}\}\boldsymbol{t_{ij}} + \boldsymbol{\beta_2 t_{ij}^2} + \cdots + \boldsymbol{e_{ij}} \\ &= \underbrace{\boldsymbol{\gamma_{00}} + \boldsymbol{\gamma_{00} x_j} + \boldsymbol{\gamma_{10} t_{ij}} + \boldsymbol{\beta_2 t_{ij}^2} + \cdots}_{\boldsymbol{fixed}} + \underbrace{(\boldsymbol{u_{0j}} + \boldsymbol{u_{1j} t_{1ij}} + \boldsymbol{e_{ij}})}_{\boldsymbol{random}} \end{aligned} \qquad (\mathbf{4.3})$$

In the reduced form model, the fixed part contains parameters $\boldsymbol{\gamma}$ and $\boldsymbol{\beta_2}$ that do not vary across individuals and are typically referred to as fixed effects parameters.

The random part (shown in brackets above) includes:

$\boldsymbol{u_{0j}}$ and $\boldsymbol{u_{1j}}$, the random effects (individual-specific) parameters, and

$\boldsymbol{e_{ij}}$, the Level 1 residual for the i^{th} measurement of individual j, which allows the outcomes to vary from the polynomial trajectory given by the rest of equation 4.3. The variance of the individual-specific intercept and slope, as well as the variance in the Level 1 residual, are estimated along with the fixed effects parameters.

Given that some explanatory variables in this study are measured on a ratio scale, which means that these variables have a 'true zero' value which has no substantive meaning and is not a relevant point at which to make an interpretation. Therefore, centering variables involves rescaling continuous explanatory variables so that the results become more interpretable and more meaningful (Dalal and Zickar, 2012).

The Level 1 model (4.1) contains only covariates that are measured at Level 1, that is, those that vary over time for the individual. Control variables, in addition to the growth dimension, can be added to the model at this level. Although it is possible to specify a model where the parameters on the higher-order terms in the polynomial, such as $\boldsymbol{\beta_2}$, are also individual-specific, this is seldom done in practice. Time-invariant characteristics, such as $\boldsymbol{x_j}$, can be included only at Level 2, while cross-level interactions can be introduced by adding time-invariant characteristics into the random slope equation of model (4.2) (Rabe-Hesketh and Skrondal, 2021).

Multilevel models are typically estimated using maximum likelihood. In Stata, this is carried out using the command `mixed`. The fit of the models can be assessed and compared using likelihood ratio chi-squared tests, as well as information criteria such as the Bayesian information criterion (BIC).

4.1.2 The analysis strategy

As described in the previous chapter, the dependent variable in this dissertation is a depression score based on the Centre for Epidemiologic Studies Short Depression Scale (CES-D 10), which is a numerical variable that assesses each individual's mental health on a scale of zero to thirty. The econometric analysis involves growth-curve modelling of the depression score measurements taken on the respondents over time, to estimate the size of the gender gap while controlling for the age trajectory in mental health. No previous studies have estimated age trajectories in depression in South Africa, and therefore the analysis is structured as a series of unfolding model specifications to explore the role of each addition group of factors. These factors are chosen on the basis of international literature on age trajectories and gender gaps in mental health, as well as the existing South African literature on the correlates of the depression score.

Following Platt et al (2020), the first objective of this analysis is to determine the model fit of the age polynomial, that is, the shape of the age trajectory in depression. The depression score ($\boldsymbol{y_{ij}}$) of the j^{th} respondent recorded at the i^{th} measurement is modelled as shown below at Level 1:

$$\boldsymbol{depression_{ij} = \beta_{0j} + \beta_{1j}\, age_{ij} + \beta_2\, age_{ij}^2 + \beta_3\, age_{ij}^3 + \beta_4\, age_{ij}^4 + e_{ij}}$$

and at Level 2:

$$\boldsymbol{\beta_{0j} = \alpha_{00} + u_{0j}}$$

$$\boldsymbol{\beta_{1j} = \alpha_{10} + u_{1j}}$$

Substituting these two (Level 2) equations into the Level 1 equation produces the reduced form growth-curve model equation is:

$$\boldsymbol{depression_{ij} = \alpha_{00} + \alpha_{10} age_{ij} + \beta_2\, age_{ij}^2 + \beta_3\, age_{ij}^3 + \beta_4\, age_{ij}^4 + \left(u_{0j} + u_{1j} age_{ij} + e_{ij}\right)} \qquad \boldsymbol{(4.4)}$$

where the first five terms are fixed-effects that capture the average model, and the last three terms ($\boldsymbol{u_{0b}}$, $\boldsymbol{u_{1j} * age_{ij}}$ and $\boldsymbol{e_{ij}}$) are random-effects that capture the variation between individuals' regression models and the average model, as well as the variation between individual observations and the regression model within each person. Model 4.4 is utilized to account for the age trajectory in mental health. The aim is to determine whether allowing for the linear, squared, cubed, and fourth power effects significantly improves the model fit, and therefore each term in the polynomial will be added sequentially. Figure 3.1

indicated that a cubic function is likely to be the best approximation of the trajectory, but the model fit will be investigated up to a fourth power age polynomial.

Following this estimation, all subsequent models will take into account the identified polynomial relationship between age and the depression score, and add to it the other socio-economic factors that influence mental health. The following equations indicate the general form of the regression models to be estimated, which will include key variables of interest in the specifications sequentially in order to evaluate their relationships with mental health. The sequence in which the variables are introduced follows similar strategies adopted by Platt et al (2020), Yang and Lee (2009) and Baldwin and Hoffman (2002).

The key variables of interest, beyond age, are gender ($\boldsymbol{F_j}$ representing a dummy variable for female) and birth cohort ($\boldsymbol{C_j}$). Both are time-invariant and are therefore included in the model at Level 2. The expanded model at Level 1 is given by:

$$\boldsymbol{depression_{ij} = \beta_{0j} + \beta_{1j}\, age_{ij} + (poly) + \delta_1 X_{ij} + e_{ij}}$$

while the Level 2 equations are:

$$\boldsymbol{\beta_{0j} = \alpha_{00} + \alpha_{01}F_j + \alpha_{02}C_j + \alpha_{03}F_J C_j + \alpha_{04}Z_{1j} + u_{0j}}$$
$$\boldsymbol{\beta_{1j} = \alpha_{10} + \alpha_{11}Z_{2j} + u_{1j}}$$

The reduced form model is:

$$\boldsymbol{depression_{ij} = \alpha_{00} + \underbrace{\alpha_{01}F_j + \alpha_{02}C_j + \alpha_{03}F_J * C_j}_{gender\ gap\ and\ cohort\ effects} + \underbrace{\alpha_{10}age_{ij} + (poly)}_{age\ trajectory}}$$
$$\boldsymbol{+ \underbrace{\alpha_{04}Z_{1j}}_{time-inv.} + \underbrace{\alpha_{11}Z_{2j}age_{ij}}_{cross-level} + \underbrace{\delta_1 X_{ij}}_{time-vary.} + \underbrace{\left(u_{0j} + u_{1j}age_{ij} + e_{ij}\right)}_{random\ effects} \qquad (4.5)}$$

All models include the age trajectory, consisting of $\boldsymbol{age_{ij}}$ as well as whichever further polynomial terms are determined by the estimation of equation 4.4, shown here simply as $(\boldsymbol{poly})$. The first set of unfolding model specifications based on equation 4.5 estimates the gender gap and cohort effects. These models allow for variation in the gender gap across cohorts, but initially without including other controls. The second set of specifications adds additional time-invariant demographic variables, $\boldsymbol{Z_{1j}}$, namely race category dummy variables, as well as cross-level interactions between age and a vector of time-invariant demographic characteristics, $\boldsymbol{Z_{2j}}$ (gender and race).

Two further sets of specifications explore the role of a vector of time-varying factors, $\boldsymbol{X_{ij}}$. The third set of models adds variables that act as proxies for gendered social and economic roles. These include the measures for childcare responsibilities and decision-making power in the household, as described in Chapter 3, as well as employment status. These are included to determine the extent at which roles within the household and access to the labour market impact an individual's mental health, and affect the estimates of the gender gap across cohorts. Finally, further sets of time-varying control variables are added, measured at both the level of the household and the individual.

The fixed-effects in equation 4.5 therefore include both Level 1 and the Level 2 variables. Finally, the random effects part of all the models is specified as it was in equation 4.4. Many variables that could potentially have influences that vary across individuals, that is, they could be part of the random component of the model, are therefore constrained in this study to be non-random. Growth-curve models can typically include half as many random coefficients as the number of waves of data (Bryk and Raudenbush, 1992), and models that exceed this number can usually not be estimated. Nonetheless, some sensitivity analysis is conducted at the end of the estimation section to explore the possible inclusion of further characteristics in the random slope equation.

4.1.3 Further estimation details

Throughout these models the gender dummy variable is included as one of the key variables. Thus, the separate models are not estimated by gender as one of the main aims of this investigation is to estimate the magnitude of the gender gap in mental health, as well as determine how it varies when controlling for different socio-economic variables. Consequently, this means that the effects of most variables on mental health are constrained as being the same for women and men.

Continuous variables in this study are centred using their mean values in the first wave, thus the variables represent deviations from their baseline values. For example, the age variable is centred so that the intercept variance is interpreted as the between-individual variance in depression scores at the baseline age of 39 years. This is done to make the regression constant more meaningful and the interpretation of parameter estimates easier (as they have realistic numerical meaning within the analysis sample).

Complex sample designs frequently include unequal selection probabilities. In the typical multilevel modelling, failing to account for this component of the design can result in biased parameter estimates (Carle, 2009). While the conventional multilevel modelling method can accurately estimate parameters and standard errors in clustered data resulting from equal probability sampling, when used in samples with unequal likelihood of selection, this standard method can lead to biased results. Furthermore, Carle (2009) suggests that design weights be included in the likelihood function to solve this problem because design weights taken into account the unequal selection probabilities in the data. However, appropriately design weights in the probability function while estimating multilevel models necessitates rescaling the weights (StataCorp, 2021). Carle (2009) recommends rescaling the weights to sum to the cluster size when the main interest is in obtaining unbiased point estimates, but rescaling to the effective cluster size when analysing the residual variance between clusters.

The weight in this study is constructed using the value of the NIDS post-stratified weight in wave 1 (which accounts for non-response and calibrates to the population totals) and the value of the panel weight in succeeding waves (which also corrects for bias resulting from non-random attrition between wave 1 and a subsequent wave) (Brophy et al, 2018). These weights, measured at Level 1, are then scaled so that they sum to the cluster size, as also implemented for the NIDS data by Somefun and Fotso (2020). However, even when using these weights, it is possible for non-random attrition to bias the results, for example, if those with worse mental health are more likely to attrit than their healthier counterparts even after accounting for general NIDS sample attrition. This issue is somewhat mitigated by the fact that multilevel models are able to include individuals in the sample in any wave in which they provide data, rather than requiring several observations per person, or adjacent observations, or a balanced sample. Nonetheless, it is acknowledged as potential a limitation of the study.

4.2 Results

All specifications of the multilevel models include a polynomial in age, in order to account for the age trajectory in mental health. Table 4.1 below explores the specification of this polynomial, by including age terms raised to sequentially higher powers. The empirical fit and significance of the age polynomial is evaluated in each specification. The first model includes only the centred age variable, and shows that an individual of mean baseline age (39 years) has a predicted depression score of 7.073, and that this score rises on average by 0.03 for each year that they age, assuming a linear relationship. The random effects variance part of the models shows the extent to which there is individual-level variation around these average fixed effects. Within individuals over time, there is more random variation in the intercept (variance = 2.15) than in the slope (variance of age coefficient = 0.00057) in this specification. However, the between-individual variation (that is, the residual variance) is by far the largest part of the random variation.

Table 4.1: Selection of the age polynomial specification

	Linear	Quadratic	Cubic	Quartic
Fixed effects parameters				
Age in years (centred)	0.031***	0.034***	0.028***	0.023***
	(0.001)	(0.001)	(0.002)	(0.003)
Age squared		-0.000***	-0.001***	-0.001***
		(0.000)	(0.000)	(0.000)
Age cubed			0.000***	0.000***
			(0.000)	(0.000)
Age fourth power				-0.000
				(0.000)
Constant	7.073***	7.164***	7.229***	7.218***
	(0.019)	(0.028)	(0.030)	(0.031)
Random effects variance				
Variance (Age)	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Variance (Intercept)	2.151***	2.137***	2.145***	2.147***
	(0.099)	(0.099)	(0.098)	(0.098)
Variance (Residual)	17.260***	17.259***	17.259***	17.259***
	(0.130)	(0.130)	(0.130)	(0.130)
Observations	72058	72058	72058	72058
BIC	417664	417650	417636	417644
Log-likelihood	-208804	-208791	-208779	-208777
Chi-squared		25.646	25.074	3.502

p-value	0.000	0.000	0.061

Source: NIDS waves 1-5, own calculations

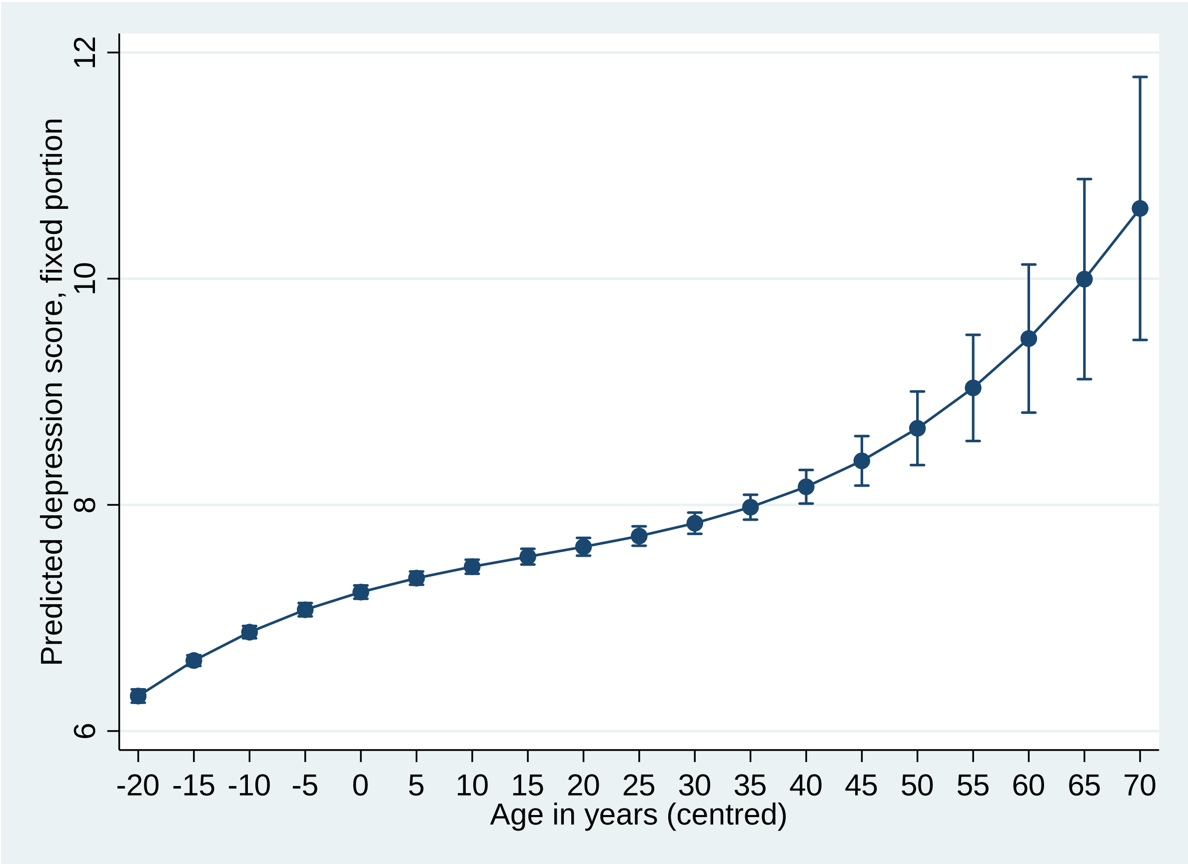
Notes: Estimates are weighted. Standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The further columns of results show the models when age is included additionally in its squared, cubed and fourth exponential power. Likelihood ratio tests are conducted between each adjacent set of specifications, with the likelihood ratio (LR) chi-square test statistic and its associated probability value shown at the bottom of the table. The squared age estimated coefficient is extremely small in magnitude but is statistically significant at all levels of significance. In addition, the p-value associated with the chi-square test statistic (which is 25.646) is also less than 0.05. Thus, the linear specification is improved statistically by estimating the relationship between mental health and age as a quadratic. Similarly, a cubic function is an improvement relative to the quadratic specification. The p-value of the estimated coefficient of age cubed shows that the age cubed variable is statistically significance at all levels. The cubic model has a p-value of 0.000 that is associated with the likelihood ratio test statistic (equal to 25.074). Thus, according to the likelihood ratio test, the cubic model is statistically significant relative to the quadratic model. For both the age squared and age cubed variables, the likelihood ratio test and the individual coefficient's significance test produce the same results, that these variables are significant despite their small magnitude coefficients. Thus, adding these variables as explanatory variables improves the statistical power of the model to explain age trajectories in mental health.

The estimated coefficient of age raised to its fourth exponential is statistically insignificant at the 5 percent level. This model is also found not to be a statistically significant improvement over the cubic model at the 5 percent significance level as the likelihood test p-value is 0.061. Thus, the coefficient significance test and model likelihood ratio test concur that adding the fourth power of age jointly with the cubic function does not result in any significant statistical improvement of that particular model. Therefore, this variable is not included in any further model specifications of this study.

The graphical representation of the specification of the cubic function in age is shown in Figure 4.1 below which shows an increasing non-linear age trajectory in mental health. This suggests that the predicted depression score of an individual rises as they age. The non-linear shape is clear in the visual representation, even though the magnitudes of the coefficient estimates for age squared and cubed in the tabulated results are very small.

<u>Figure 4.1: Graphical representation of the cubic function in age</u>



Source: NIDS waves 1-5, own calculations

Note: The figure displays 95% confidence intervals for the predictions.

All the subsequent models allow for this cubic relationship between age and the depression score, and they investigate the further role of other factors in influencing mental health. Table 4.2 shows the estimates when the key variables of interest, namely gender and birth cohort, are included. The variables and their interactions are included sequentially to discuss their effects and choose the preferred format of specification, following the method of Platt et al (2020). The first model specification (Model 1) adds the gender dummy variable to the age cubic function. The results show that females, on average after controlling for the age trajectory, experience 0.503 more depressive symptoms when compared to males, ceteris paribus. Therefore, the baseline estimate of the gender gap in depression, without controlling for any factors other than age, is approximately half of a unit. In Models 2 and 3, which add controls for the individual's birth cohort to the regressions, women continue to experience approximately 0.5 more depressive symptoms than men.

In Model 2, the birth cohort is included as a numerical variable, assuming a constant linear change in mental health from one birth cohort to the next. Each older birth cohort has on average 0.822 more depressive symptoms than the one before it. In contrast, Model 3 estimates the birth cohort relationship using dummy variables, with the youngest cohort as the reference category. The second and third cohort coefficients in Model 3 indicate that on average, the depression scores for individuals in the birth cohort 2 (1960-1979) and 3 (1959 and earlier) are predicted to be 0.694 and 1.726 units higher than people in the youngest cohort (1980 or later). When calculating the difference in mental health (measured as number of depressive symptoms) between cohort 2 and 1 (difference is 0.694) and between cohort 3 and 2 (difference is equal to 1.032), the difference suggests that the cohort effect on mental health is not linear.

<u>Table 4.2: Multilevel models of depression: gender and cohort effects</u>

	Model 1	Model 2	Model 3	Model 4	Model 5
Age in years (centred)	0.026***	-0.017***	-0.018***	-0.017***	-0.018***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Age squared	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age cubed	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female (ref=male)	0.503***	0.501***	0.502***	0.060	0.309***
	(0.038)	(0.038)	(0.038)	(0.088)	(0.050)
Cohort (continuous)		0.822***		0.670***	
		(0.070)		(0.075)	
Cohort 2 (ref=1)			0.694***		0.521***
			(0.079)		(0.095)
Cohort 3 (ref=1)			1.726***		1.434***
			(0.146)		(0.157)
Cohort*female				0.257***	
				(0.049)	
Cohort 2*female					0.299***
					(0.091)
Cohort 3*female					0.495***
					(0.102)

Constant	6.931***	5.495***	6.390***	5.754***	6.500***
	(0.038)	(0.129)	(0.067)	(0.136)	(0.070)
Variance (Age)	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Variance (Intercept)	2.093***	2.152***	2.145***	2.141***	2.135***
	(0.097)	(0.098)	(0.098)	(0.098)	(0.098)
Variance (Residual)	17.259***	17.174***	17.173***	17.175***	17.174***
	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)
Observations	72058	72058	72058	72058	72058
BIC	417477	417336	417338	417320	417332
Log-likelihood	-208694	-208618	-208613	-208604	-208599

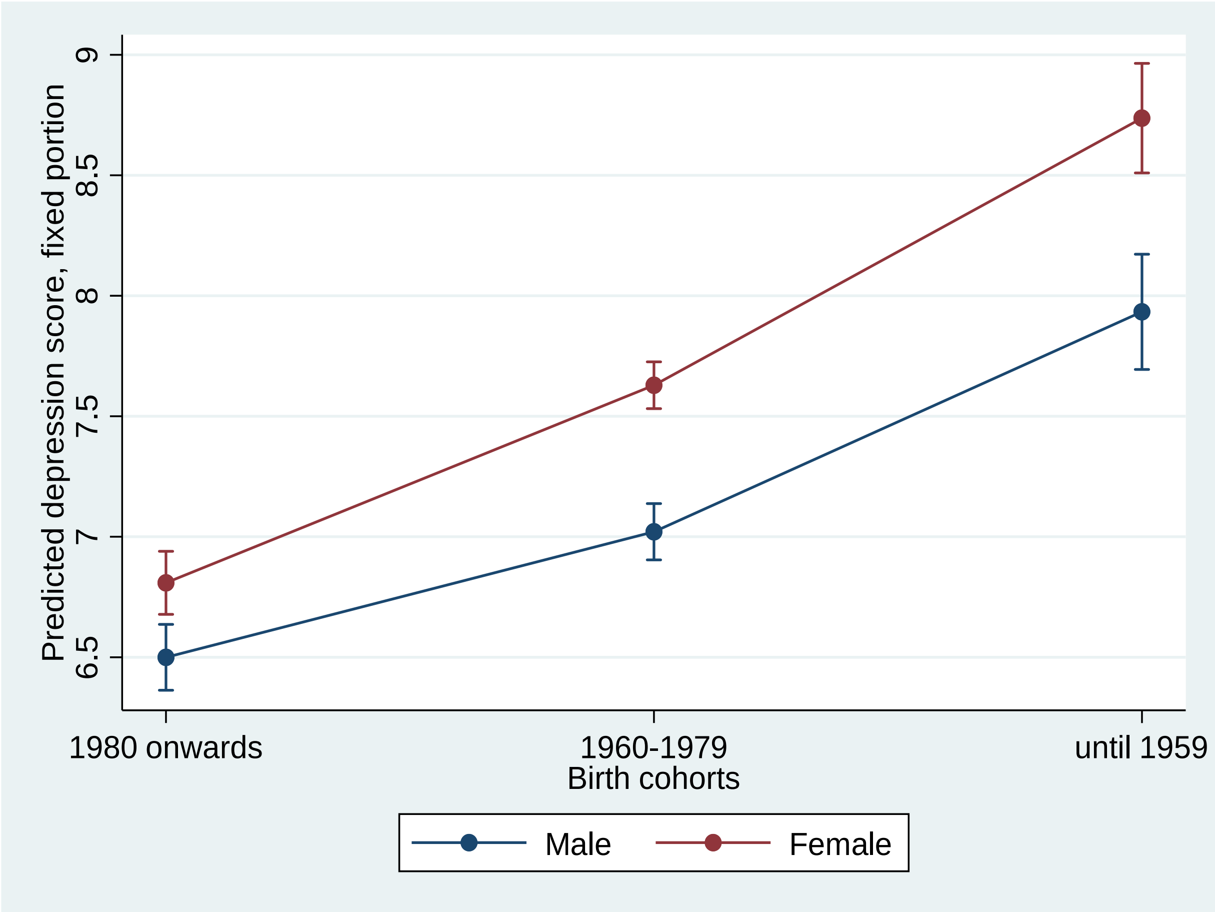
Source: NIDS waves 1-5, own calculations

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Models 4 and 5 add interactions between gender and cohort, with the latter in numerical and dummy variable form respectively. In the Model 4 specification, the female dummy variable coefficient is much reduced in magnitude and statistically insignificant. This indicates that, on average, the mental health score of a female individual is not significantly higher than the average depression score reported by a male individual once the cohort interaction is allowed for, that is, that the gender gap in mental health is observed only across cohorts. Among men, each subsequent cohort has a 0.670 unit higher depression score, while the score increases by 0.257 across each cohort for women. Finally, Model 5 again relaxes the assumption of a linear cohort effect, while now also allowing for a gender-cohort interaction. The gender coefficient of 0.309 therefore represents the gender gap in the youngest birth cohort. The gender-cohort interactions represent the difference in the gender gap in each older cohort, and show that the gender gap increases by 0.299 units for cohort 2 and by 0.495 units for cohort 3 relative to this youngest cohort. Among men, the depression score is 0.521 higher for those born in cohort 2, and 1.434 higher for those born in the oldest cohort compared to the youngest. These estimates indicate that when comparing the mental health among men, there is a much bigger mental health difference between cohorts 2 and 3 than the mental health difference between cohorts 1 and 2. This non-linear cohort effect is also observed among women, where the gender gap in the depression score rises by 0.299 between cohorts 1 and 2 and by a further 0.196 (0.495-0.299) between cohorts 2 and 3. Due to these non-linear effects, all model specifications from now onwards will include dummy variables for the second and third cohorts, as well as their interactions with gender.

The results of the full specification in Model 5 therefore show that the youngest cohort (first cohort and is the base cohort) has an average gender gap in mental health of 0.309. The estimated coefficient of the second cohort interaction with the gender dummy variable (female) is 0.299, which indicates that the gender gap in mental health increases by 0.299 in the second cohort relative to the first cohort. Finally, the estimated coefficient of the interaction between the third cohort and the female dummy suggests that the gender difference in depressive symptoms or mental health increases by 0.495 in the third cohort relative to the first cohort. The predicted depression score by gender and cohort, as estimated in Model 5, is displayed in Figure 4.2 below. The difference between the predicted score for women and men is the gender gap in depression for each cohort.

Figure 4.2: Graphical representation of the gender gap across cohorts



Source: NIDS waves 1-5, own calculations

Notes: The figure displays 95% confidence intervals for the predictions, based on Model 5. The estimates are shown at the mean baseline age (centred age = zero).

The next set of estimates in Table 4.3 expands the models further to incorporate another key demographic characteristic that may be related to the depression score, namely the individual's race group, and to account for potential age interactions. The dummy variables for race are included to compare the mental well-being of individuals from different ethnicities, given the high rate of racial inequalities in the country. Model 6 adds race category dummies to the final specification from the previous table, with black African as the reference group. The results show that, when controlling for race, the gender gap in mental health for the youngest cohort is 0.309 which is identical to Model 5. Compared to that model, which did not control for race, the cohort differences in mental health estimated here are slightly larger for men, while the additional increases in the depression score by cohort for women are slightly smaller. This suggests that there are some racial differences in how mental health varies across gender and birth cohort, but these effects are small. On average, Coloured, Asian/Indian and White individuals in South Africa all have much lower depression scores than black African individuals. Coloured and Asian/Indian individuals have average depression scores that are approximately 1.6 units smaller than the mental health scores of black Africans while white individuals have mental health scores that are 2.510 smaller than black African individuals. Model 6's log likelihood and BIC values indicate that controlling for racial differences in depression substantially improves the model specification, and therefore race is included in all subsequent models.

Table 4.3: Demographic characteristics

	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11
Age in years (centred)	-0.010*	-0.016*	-0.007	-0.007	-0.006	-0.003
	(0.004)	(0.007)	(0.004)	(0.004)	(0.004)	(0.005)
Age squared	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age cubed	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female (ref=male)	0.309***	0.243	0.309***	0.308***	0.308***	0.227
	(0.049)	(0.125)	(0.049)	(0.049)	(0.049)	(0.125)
Cohort 2 (ref=1)	0.573***	0.574***	0.559***	0.572***	0.564***	0.502***
	(0.092)	(0.117)	(0.092)	(0.092)	(0.092)	(0.114)
Cohort 3 (ref=1)	1.491***	1.521***	1.486***	1.499***	1.495***	1.306***
	(0.152)	(0.222)	(0.152)	(0.152)	(0.152)	(0.203)
Cohort2*Female	0.267**	0.294	0.266**	0.265**	0.264**	0.372*
	(0.087)	(0.155)	(0.087)	(0.087)	(0.087)	(0.150)
Cohort3*Female	0.382***	0.363	0.367***	0.376***	0.375***	0.686**
	(0.097)	(0.287)	(0.097)	(0.097)	(0.097)	(0.249)
Coloured	-1.620***	-1.621***	-1.619***	-1.723***	-1.709***	-1.710***
	(0.055)	(0.055)	(0.055)	(0.078)	(0.086)	(0.086)
Asian or Indian	-1.600***	-1.601***	-1.589***	-1.717***	-2.094***	-2.094***
	(0.176)	(0.176)	(0.176)	(0.252)	(0.278)	(0.277)
White	-2.510***	-2.514***	-2.302***	-2.550***	-2.342***	-2.341***
	(0.105)	(0.105)	(0.119)	(0.142)	(0.178)	(0.178)
Female*Age		0.008				-0.007
		(0.009)				(0.006)
Female*Age squared		0.000				-0.000
		(0.000)				(0.000)
Female*Age cubed		-0.000*				
		(0.000)				
Coloured*Age			-0.006*	-0.010**	-0.011*	-0.011*
			(0.003)	(0.003)	(0.006)	(0.006)
Asian/Indian*Age			-0.007	-0.011	0.038*	0.039*

			(0.010)	(0.011)	(0.019)	(0.019)
White*Age			-0.020***	-0.042***	-0.052***	-0.052***
			(0.006)	(0.008)	(0.010)	(0.010)
Coloured*Age squared				0.000*	0.000	0.000
				(0.000)	(0.000)	(0.000)
Asian/Indian*Age squared				0.000	0.003**	0.003**
				(0.001)	(0.001)	(0.001)
White*Age squared				0.001***	0.000	0.000
				(0.000)	(0.001)	(0.001)
Coloured*Age cubed					0.000	0.000
					(0.000)	(0.000)
Asian/Indian*Age cubed					-0.000***	-0.000***
					(0.000)	(0.000)
White*Age cubed					0.000	0.000
					(0.000)	(0.000)
Constant	6.845***	6.871***	6.850***	6.872***	6.875***	6.921***
	(0.069)	(0.095)	(0.069)	(0.069)	(0.069)	(0.095)
Variance (Age)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Variance (Intercept)	1.638***	1.645***	1.627***	1.632***	1.628***	1.632***
	(0.090)	(0.091)	(0.090)	(0.090)	(0.090)	(0.090)
Variance (Residual)	17.178***	17.178***	17.179***	17.177***	17.176***	17.175***
	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)
Observations	72058	72058	72058	72058	72058	72058
BIC	415855	415879	415872	415885	415903	415923
Log-likelihood	-207844	-207839	-207835	-207825	-207817	-207816

Source: NIDS waves 1-5, own calculations

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

When the female-age interaction is added to the Model 7 specification (removing the race dummies) the second and third cohort and female dummy interaction variables become statistically insignificant suggesting that there is no significant increase in the gender gap in the second or third cohort relative to the first. Despite this, the female dummy variable remains significance in this model indicating that the gender gap in depression for the youngest cohort is 0.322 and does not significantly change in the following cohorts. The gender gap in depression increases by 0.013 from Model 6 to Model 7.

Model 7 adds interactions between gender and the cubic age function, while Models 8 to 10 add interactions between race and each part of the cubic age function. Finally, Model 11 includes full set of age interactions with both gender and race. These models therefore allow for the possibility that the age trajectory in depression differs between men and women, and across race groups.

Only a small number of the age-interaction coefficients are statistically significant in these models. When age is interacted with gender in Model 7 and Model 11, the age cubed coefficient is significantly smaller for women than for men. The gender gap in depression is not significantly different from zero for any of the cohorts in either model. However, adding gender-age interactions to the models substantially increases the standard errors of many of the other coefficients due to collinearity. This may explain why the cohort gender gaps, which are of similar magnitude to the other model specifications, are insignificant here. The BIC statistics indicate that Models 7 and 11 both perform worse than Model 6.

Models 8 to 10 include age interactions with race instead of with gender. Again, only a limited number of the age-interaction coefficients are statistically significant. They suggest that the linear component of the age trajectory may differ for white individuals, and the curvature for Asian/Indian individuals, relative to black Africans. Across these specifications, the gender gap in the youngest cohort, as well as the size of the change in the gender gap to the two older cohorts, remain both statistically significant and similar in magnitude to Model 6 which omitted the age interactions.

Table 4.3 illustrates that the magnitude of the gender gap in depression is robust to the way in which the age trajectories in mental health are specified. The BIC statistics indicate that each additional set of age-race interactions worsens the fit of the model. Therefore, the race dummy variables are retained in all further models, but interactions between age and other characteristics are omitted.

Platt et al. (2020) do not include any age interactions while Ferrand et al. (2020) find no significant age interaction with gender but a significant linear interaction with two non-demographic factors. In addition, Yang and Lee (2009) find no significant age interaction with race, but significant linear interactions with cohort and gender while Baldwin and Hoffman (2002) find a significant linear interaction of age with gender only in one specification and find no significant interactions with non-demographic factors. Therefore, both the existing literature and the results in this chapter suggest that the extent to which age trajectories differ across other characteristics is context specific.

Table 4.4 explores the extent to which roles within the household and access to the labour market, which Chapter 3 showed to be highly gendered, may explain the gender gap in mental health. Model 12 accounts for childcare responsibilities by including the number of young children (under the age of seven) and the number of older children (aged seven to 15) for whom the individual is responsible, to determine how taking care of children within a household affects an individual's mental health. The results show insignificant coefficients for both of the childcare variables, which indicates that there is no significant difference in the average depression scores of individuals related to their care responsibilities for young or older children. However, the lack of a significant relationship between childcare responsibilities and the depression score is robust to alternative ways that the existence and extent of these duties can be measured using the NIDS data. It is not possible to determine the time that individuals spend on childcare using these data, and therefore it remains possible that childcare duties influence mental health in ways that cannot be measured.

The inclusion of the childcare variables does not change the magnitude of the estimated gender gap to any notable extent in any of the cohorts. Therefore, gender and cohort differences in childcare responsibilities do not explain the gender gap in mental health in South Africa.

Table 4.4: Proxies for gendered social and economic roles

	Model 12	Model 13	Model 14	Model 15
Age in years (centred)	-0.010*	-0.001	-0.009*	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Age squared	-0.001***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Age cubed	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Female(ref=male)	0.294***	0.384***	0.211***	0.276***
	(0.052)	(0.049)	(0.049)	(0.052)
Cohort 2(ref=1)	0.576***	0.529***	0.512***	0.483***
	(0.092)	(0.091)	(0.091)	(0.091)
Cohort 3(ref=1)	1.486***	1.444***	1.373***	1.343***

	(0.152)	(0.151)	(0.151)	(0.150)
Cohort2*Female	0.266**	0.234**	0.235**	0.205*
	(0.089)	(0.087)	(0.087)	(0.088)
Cohort3*Female	0.389***	0.283**	0.377***	0.288**
	(0.098)	(0.097)	(0.097)	(0.097)
Coloured	-1.619***	-1.610***	-1.556***	-1.543***
	(0.055)	(0.055)	(0.055)	(0.055)
Asian or Indian	-1.596***	-1.566***	-1.576***	-1.534***
	(0.176)	(0.174)	(0.175)	(0.173)
White	-2.505***	-2.449***	-2.365***	-2.306***
	(0.105)	(0.105)	(0.105)	(0.105)
Number of young children (<7) being cared for	0.029			0.012
	(0.034)			(0.034)
Number of older children (7-15) being cared for	0.008			0.004
	(0.030)			(0.030)
Makes main decisions in household		-0.313***		-0.213***
		(0.043)		(0.044)
Makes joint decisions in household		-0.541***		-0.531***
		(0.040)		(0.040)
Unemployed-discouraged			-0.124	-0.154
			(0.102)	(0.102)
Unemployed-strict			-0.275***	-0.281***
			(0.059)	(0.059)
Employed			-0.746***	-0.725***
			(0.045)	(0.046)
Constant	6.839***	7.276***	7.472***	7.799***
	(0.069)	(0.079)	(0.079)	(0.087)
Variance (Age)	0.000***	0.000***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Variance (Intercept)	1.639***	1.588***	1.515***	1.474***
	(0.090)	(0.090)	(0.089)	(0.089)
Variance (Residual)	17.178***	17.160***	17.162***	17.145***
	(0.130)	(0.130)	(0.131)	(0.130)
Observations	72058	72058	71766	71766
BIC	415876	415660	413859	413711
Log-likelihood	-207843	-207735	-206829	-206733

Source: NIDS waves 1-5, own calculations

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Model 13 includes the locus of control variables, namely whether individuals are the household's main decision-maker about any of the five domains of day-to-day or larger decisions, and whether they are a joint or second decision-maker over any of the domains, in order to determine the effect that decision-making power within a household has on an individual's mental health. The results show negative and significant effects for both variables, with a slightly larger magnitude of effect for joint decision-making power. Having some degree of decision-making power in the household is therefore beneficial for mental health. Relative to Model 6 that omitted these variables, the gender gap in depression in the youngest cohort (represented by the estimated coefficient of the female dummy variable) increases by almost a quarter to 0.384. In contrast, the increase in the depression gap in in the next two birth cohorts is smaller, especially in the third cohort relative to the first where the increase declines from 0.382 to 0.283. Overall, the gender depression gap remains significant and rises across the three cohorts when controlling for decision-making power.

Model 14 includes employment status dummy variables, with the reference category being individuals who are not economically active. The results show that the inclusion of this factor substantially changes the gender gap estimates. For the youngest cohort the gender gap in mental health is 0.211, which approximately is two thirds of the size it was in Model 6 before controlling for employment status. The estimated coefficient of the interaction between the second cohort and the female gender dummy variable is 0.235 and thus, the gender gap increases by 0.235 in the second cohort relative to the first birth year cohort. This increase in the gender gap in mental health from the first cohort to the second is approximately 90 percent of its previous size in Model 6. Finally, the gender gap in depressive symptoms increases by 0.377 in the third cohort relative to the first birth year cohort, which is approximately the same size as the previous estimate.

Chapter 3 showed that women are less likely to be employed, and more likely to be unemployed, than men. Controlling for employment status explains a substantial part of the gender gap in mental health for the youngest cohort, but explains less of the gap for older birth cohorts. This suggests that employment may be a more important determinant of mental health for younger cohorts. Therefore, part of why women in the most recent birth cohort have depression scores that are higher than men is because their lower access to employment negatively affects their mental health to a greater extent than it does for older cohorts.

The results show a negative but statistically insignificant difference between the average depression scores of unemployed (discouraged) individuals and those that are not economically active. In contrast, individuals who are part of the labour force according to the strict definition have significantly lower depression scores than the completely economically inactive. On average, strictly unemployed individuals have depression scores that are 0.275 lesser than the mental health scores of individuals that are not economically active. The largest benefit is derived from being employed, where the mental health scores of employed individuals are, on average, 0.746 lower than the scores of individuals that are economically inactive. Therefore, of the proxies for gendered roles considered here, employment status has the largest influence on both an individual's average depression score and on the size of the gender gap. Part of the mental health benefit of being employed is likely to operate through income, which is one of the factors considered in the last table in this section.

Finally, Model 15 includes all of the proxies for gendered social roles. Their coefficients have identical significance and similar, though typically slightly smaller, magnitudes to when each group of proxies was included sequentially. On aggregate, individuals report lower depression scores when they have decision-making power in the household, as well as when they are engaged actively with the labour market, especially when they are employed. Childcare responsibilities do not affect the average depression score. When accounting for these proxies for gendered social and economic roles, the magnitude of the gender gap in mental health is reduced, and the extent by which the gender gap rises in older cohorts is also reduced. However, a significant gender gap persists across all cohorts.

Table 4.5 adds two sets of further control variables to the final model specification from the previous table and explores the extent to which household and individual-level factors, may explain the gender gap in mental health. Model 16 adds household-level variables such as household income and size to the final model specification from the previous table. The results show that depression scores are typically significantly lower when household income is higher (although the relationship is U-shaped), when the household is larger, and when the household lives in a rural area. Controlling for house-hold characteristics improves the fit of the model, and decreases the estimated racial depression gaps for Asian/Indian and white individuals relative to black Africans. However, controlling for house-hold characteristics does not change the magnitude or significance of the estimate of the gender gap in the depression score.

Table 4.5: Household and individual-level factors

	Model 16	Model 17	Model 18
Age in years (centred)	0.003	-0.006	-0.003
	(0.004)	(0.004)	(0.004)
Age squared	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)
Age cubed	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Female(ref=male)	0.276***	0.238***	0.238***
	(0.052)	(0.052)	(0.052)
Cohort 2(ref=1)	0.425***	0.412***	0.367***
	(0.090)	(0.089)	(0.089)
Cohort 3(ref=1)	1.186***	1.101***	0.979***
	(0.150)	(0.145)	(0.145)
Cohort2*Female	0.201*	0.122	0.123
	(0.087)	(0.085)	(0.084)
Cohort3*Female	0.278**	0.006	0.012
	(0.096)	(0.094)	(0.094)
Coloured	-1.550***	-1.513***	-1.521***
	(0.057)	(0.053)	(0.056)
Asian or Indian	-1.273***	-1.288***	-1.103***
	(0.174)	(0.164)	(0.166)
White	-1.940***	-1.781***	-1.530***
	(0.119)	(0.101)	(0.112)
Unemployed-discouraged	-0.182	-0.150	-0.169
	(0.102)	(0.100)	(0.100)
Unemployed-strict	-0.304***	-0.196***	-0.214***
	(0.059)	(0.058)	(0.059)
Employed	-0.675***	-0.562***	-0.529***
	(0.047)	(0.045)	(0.046)
Number of young children (<7) being cared for	0.032	0.052	0.071*
	(0.035)	(0.034)	(0.034)
Number of older children (7-15) being cared for	0.024	0.027	0.045
	(0.031)	(0.029)	(0.030)
Makes main decisions in household	-0.294***	-0.157***	-0.233***
	(0.046)	(0.043)	(0.045)
Makes joint decisions in household	-0.521***	-0.369***	-0.373***
	(0.040)	(0.041)	(0.041)
Household income (R '000s)	-0.024***		-0.019***

	(0.003)		(0.003)
Household income squared	0.000***		0.000***
	(0.000)		(0.000)
Household size (centred)	-0.015*		-0.016**
	(0.006)		(0.006)
Rural (ref=urban)	-0.133***		-0.114**
	(0.040)		(0.039)
Primary		0.319***	0.235***
		(0.061)	(0.062)
Secondary		-0.019	-0.099
		(0.056)	(0.057)
Tertiary		-0.239**	-0.287***
		(0.078)	(0.078)
Very good health		0.256***	0.257***
		(0.042)	(0.042)
Good health		0.682***	0.674***
		(0.046)	(0.046)
Fair health		1.716***	1.695***
		(0.071)	(0.071)
Poor health		3.517***	3.483***
		(0.110)	(0.110)
Married		-0.652***	-0.595***
		(0.048)	(0.048)
Constant	7.962***	7.312***	7.507***
	(0.091)	(0.101)	(0.105)
Variance (Age)	0.001***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Variance (Intercept)	1.388***	1.126	1.088
	(0.088)	(0.080)	(0.080)
Variance (Residual)	17.149***	16.846***	16.841***
	(0.130)	(0.127)	(0.127)
Observations	71682	71556	71472
BIC	413033	410203	409614
Log-likelihood	-206371	-204934	-204617

Source: NIDS waves 1-5, own calculations

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Model 17 removes the household-level factors and includes the individual-level characteristics such as education, health and marriage status in order to determine the effect that an individual’s obtained education level, health and marriage status has on his or her mental health. The results show that the depression scores are significantly lower at each higher level of completed education. Thus, the more educated an individual is, the smaller their depression scores. When controlling for education, the racial depression gaps and the relationship between labour market participation and depression are reduced but remain significant. Individuals with worse self-reported health have higher depression scores. On average, individuals with poor self-reported health have depression scores that are 3.517 more than the mental health scores of individuals that report having excellent health. In addition, health has a very large magnitude of relationship with depression. Married individuals report significantly lower depressive symptoms compared to those who are not married. The differences in mental health across race and employment status are much reduced when controlling for other individual characteristics, but again remain significant.

Finally, Model 18 includes all of the household and individual-level characteristics. The results show that including the individual characteristics substantially improves the model fit, and including them alongside the household characteristics improves the fit further. In the full specification this model, being responsible for the care of a greater number of young children increases the depression score significantly at a 5 percent level, whereas in previous models the coefficient was positive but not significant.

When including individual factors either alone or with household characteristics, the gender depression gap in the youngest cohort is slightly reduced, to 0.25, but remains significant at better than a 0.1 percent level. For men, older cohorts have significantly higher depression scores than the youngest cohort. The gender-cohort interactions are however no longer significantly different from zero. Therefore, for women, there is no additional significant increase in the gender gap in older cohorts, beyond that experienced by men, when controlling for the full set of individual characteristics.

Given that the individual characteristics make a big difference to the gender gap, an additional regression was performed in order to determine which of the individual factors plays a role in doing what. As a result, introducing the individual characteristics one factor at a time, in Appendix Table A1, reveals that the decline in the estimated depression gaps by race can be attributed mainly to controlling for education, while the decline in the magnitude of the relationship between depression and employment status can be attributed to controlling for the individual’s health status. Finally, the lack of any significant difference in the gender gap by age cohort in Models 17 and 18 is driven by the inclusion of marital status. Being married lowers the depression score, and men are more likely than women to be married in the older cohorts, especially in cohort 3. Therefore, the larger depression gaps in the older cohorts are explained by low marriage rates of women in those cohorts.

4.3 Sensitivity analysis

The models in this chapter have demonstrated that depression scores differ across birth cohorts. In particular, a consistent finding is that an individual born in an earlier cohort has significantly worse mental health than someone from a later cohort. However, the birth cohorts were defined in a somewhat arbitrary manner, as outlined in Chapter 3. Therefore, a concern is that the findings presented in this chapter may be predicated on how the cohorts were defined. Appendix Table A2 shows the key model specifications from this chapter, re-estimated using a narrower definition of cohorts in which six cohorts are defined using birth intervals of ten years. The results show the same patterns in terms of the gender gap and inter-cohort depression as the models presented in detail in this chapter: women have higher depression scores than men, earlier birth cohorts have higher depression scores than more recent cohorts, and the gender gap in depression widens significantly across cohorts only when the full set of household and individual controls is not included. Therefore, the results do not appear to be sensitive to the definition of birth cohorts. However, further research may explore whether birth cohorts of unequal length, defined on the basis of significant political or socio-economic events rather than on decades, may further the understanding of depression scores.

The discussion of the models has focused on the estimates of the fixed effects parameters, since the dissertation's research questions relate to these parameters. However, the results obtained may be sensitive to the specification of the random effects variance component of the model, which is explored briefly in the second aspect of the sensitivity analysis. In Model 18 of Table 4.5, the between-individual variance in depression scores is 1.087 at the mean baseline age and increases by 0.0004 per year that an individual ages. Two other specifications of the variance component of this model were estimated to assess sensitivity. Allowing for the random effects variance to have a non-linear relationship with age showed that the between-individual variance in depression scores increased at an increasing rate with age, but that the coefficient on the quadratic term was extremely small. Alternatively, allowing for gender differences in the variance, along with a linear relationship with age, showed that the between-individual variance in depression scores is larger for women than for men. The estimation of the model did not converge when allowing for an unstructured variance-covariance matrix between age and gender, that is, when relaxing the assumption of independence in the variance components. However, in both of the estimated cases, both the magnitudes and significance of the fixed parameter estimates were robust to these different specifications of the random effects component of the model.

4.4 Summary and discussion

The results presented in Table 4.1 indicated the way forward in terms of the fit and significance of the various age polynomial terms. These results showed that depression scores follow a cubic trajectory with age. All subsequent models therefore include this cubic function. The results of the models, as they relate to the estimates of the gender gap in depression, are summarised in Table 4.6 below.

Table 4.6: Summary of estimated gender and cohort effects for selected models

	Table 2 Model 5	Table 3 Model 6	Table 4 Model 15	Table 5 Model 18
Female	0.309^{***}	0.309^{***}	0.276^{***}	0.238^{***}
	(0.050)	(0.049)	(0.052)	(0.052)
Cohort 2 (ref=1)	0.521^{***}	0.573^{***}	0.483^{***}	0.367^{***}
	(0.095)	(0.092)	(0.091)	(0.089)
Cohort 1 (ref=1)	1.434^{***}	1.491^{***}	1.343^{***}	0.979^{***}
	(0.157)	(0.152)	(0.150)	(0.145)
Cohort2*female	0.299^{***}	0.267^{**}	0.205^{*}	0.123
	(0.091)	(0.087)	(0.088)	(0.084)
Cohort3*female	0.495^{***}	0.382^{***}	0.288^{**}	0.012
	(0.102)	(0.097)	(0.097)	(0.094)
Age cubic function	Yes	Yes	Yes	Yes
Race	No	Yes	Yes	Yes
Gender roles	No	No	Yes	Yes
Household and individual characteristics	No	No	No	Yes
Observations	72058	72058	71766	71472
BIC	417332	415855	413711	409614
Log-likelihood	-208599	-207844	-206733	-204617

Source: NIDS waves 1-5, own calculations

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results presented in Table 4.2 showed that, after accounting for the age trajectory, women experience more depressive symptoms on average relative to men, and that depression scores for individuals in the birth year cohorts 2 (1960-1979) and 3 (1959 or earlier) are higher than the scores of people in the youngest cohort. Lastly, according to the Model 5 results, the gender gap in depression in the youngest cohort is 0.309 which increases by 0.299 to the second cohort, and by 0.495 in the third cohort relative to the first cohort. In Table 4.3, the results indicated that Coloured, Asian/Indian and White individuals have smaller depression scores than black Africans which one can expect due to the high levels of racial inequalities in the country. Model 6 estimated the gender gap for the youngest cohort to be of the same magnitude as the previous model, but the further increases in the gap to the two older cohorts were somewhat smaller.

Variables measuring an individual's gendered social and economic roles were included in Table 4.4. Doing so slightly decreased the estimated gender depression gap in the youngest cohort, and also decreased the additional gender gap in the second and third cohorts relative to the first cohort. Therefore, some of the difference in depression scores between men and women, across all birth years is explained by controlling for individuals' roles in the labour market and in their households. Both unemployed (strictly) and employed individuals have significantly lower depression scores than individuals who are economically inactive. Controlling for employment status mainly influences the estimated gender gap in the youngest cohort. This suggests that, among women born from 1980 onwards, the mental health effect of their limited labour market access explains part of their depression gap. Thus, as sociocultural standards and norms change over time, gender expectations also change and as a result, the social and economic roles of women in society also change.

Surprisingly, there are no significant differences in the average depression scores of individuals who are responsible for childcare in this model, although responsibility for young children raises the depression score in Model 18, and such responsibilities do not explain the gender gap. Lastly those with decision-making power in their household have lower depression scores than those without such power. Controlling for these roles raises the estimate of the gender gap in the youngest cohort, but explains some of the additional gap between the youngest and oldest cohort.

Finally, Table 4.5 controlled for additional observable characteristics of the household and the individual which other literature has shown may be determinants of mental health. Although the results showed that whether the household lives in an urban or rural area, the number of people living in the household, and its income can all impact the level of an individual's depression score, controlling for these factors did not change the magnitude or significance of the estimated gender gap. This is in contrast with the suggestion of the sociocultural model that households in traditional or rural areas, who still follow cultural norms that place women as subordinates to men, explains the gender gap in depression as women are expected to have more depression symptoms due to lack of power. At the individual level, higher levels of education, better health, and being married all significantly decreased the depression score. The full model specification, Model 18, showed that a gender depression gap, of magnitude 0.252, persists in the youngest cohort even after controlling for all included characteristics. However, although depression scores are significantly higher in the older cohorts, the gender gap is not significantly larger in the second or third cohort relative to the first. This result can be explained by the role of marital status. Men in the older cohorts are more likely than women to be currently married, and marriage is associated with a lower depression score. Larger depression gaps in the older cohorts are therefore explained by women's low marriage rates, which can be attributed to women outliving men.

Change affects every aspect of life including social, economic, and cultural. As societal and cultural standards and norms change, people adjust to these. As these standards and norms change, people are open to different circumstances and opportunities than previously. Over time, people start placing more value to different social and cultural factors and roles. Thus, as society becomes less traditional in terms of the social and economic role of a woman (as a home-maker, bearing childcare responsibilities, and a subordinate to the provider), women seek more educational and labour market opportunities. Changing gender expectations, for example, may explain why women in younger cohorts could be focused more their labour market activities than older cohorts. Despite accounting for these sociocultural factors, much of the gender gap in depression remains unexplained. The remaining gender gap may be explained by various unmeasured elements from the affective, biomedical, and psychological theories that could not be assessed with the study data.

4.5 Conclusion

This chapter presented the empirical estimation of the relationship between gender and mental health for South African individuals, using data from five waves of NIDS. Through these results and analysis of the regression models, one can conclude that as an individual ages their depression score increases, although in a non-linear manner. Even after controlling for factors measuring an individual's social and economic roles, as well as other household-level and individual-level characteristics, women experience significantly more depressive symptoms than men, thus providing evidence of a persistent gender gap in mental health in South Africa, which has also been observed in multiple other contexts. In most of the estimated models, the gender depression gap was larger in the second and third birth cohorts relative to the first (youngest) cohort, suggesting gender differences in expectations, opportunities, and experiences between birth cohorts. However, in the final model, while depression scores were significantly higher in each older birth cohort, the size of the gender gap in depression was statistically constant across cohorts, at approximately 0.25 units on the depression score.

Pertaining to the effects of other socio-economic variables on an individual's mental health, Coloured, Asian/Indian and White individuals have lower depression scores than black Africans. Given the political history of South Africa and the persistent racial inequalities in the country, one can expect that those that are marginalised will suffer more in terms of mental health. In addition, being in poorer health or unmarried places an individual at risk of having a higher depression score compared to those with better health or who are married, while household income provides some protection against depressive symptoms. Finally, social and economic roles that are traditionally highly gendered also influence mental health: individuals have lower depression scores when they are active in the labour market, are responsible for fewer young children, and have decision-making power in their household. However, even after accounting for these factors, much of the gender gap in depression remains unexplained.

Chapter 5: Conclusion

Poorer mental health among women than among men has been observed across a wide variety of contexts (Weissman and Klerman, 1977; Kessler et al., 1994; Salk et al., 2016; Platt et al., 2020). However, although a gender gap in depression exists in developing countries (World Health Organization, 2017), little detailed research has investigated its nature or determinants. The overall objective of this study was therefore to explore the nature of the depression gender gap in South Africa through determining the age trajectory in mental health for women and men, and investigating the existence of a gender gap in mental health and how it differs for individuals from different birth cohorts. In addition, this study set out to determine the extent to which gender differences in social and household roles, and in labour market roles, explained the gender gap in mental health. The lack of in-depth empirical analysis on the gender gap in depression within the South Africa context is a significant research gap, given the gender inequality in South African that is caused by the marginalization of women in society. This study achieved its objective through answering key research questions throughout the previous chapters.

In Chapter 2, both theoretical and empirical literature on the gender gap and the socio-economic factors that influence gender inequalities in mental health were reviewed. There are four theoretical frameworks that are the most prominent in understanding why gender disparities in depression occur. According to the affective model of depression, individual disparities in emotional and attentional reactivity may be an early temperamental risk factor for depressive disorders (Mezulis et al., 2011). The biomedical model argues that biological and hormonal factors explain why the depression prevalence rates are higher for women than men (Hammarström et al., 2009). The sociocultural model indicated that systematic inequalities, standards, and theories that exist in society, explain why the depression prevalence rates are higher for women than men (Kessler et al., 2009). Lastly, the psychological model argued that the gender gap in mental health is due to behavioural and cognitive factors (Hyde et al., 2008; Hammarström et al., 2009).

Empirical literature on the gender gap in mental health was then reviewed, focusing particularly on studies that use the hierarchical linear modelling method to explore the gender gap in depression, because this method is used in this dissertation. These included studies examining the cross-national evidence, individual-country longitudinal studies conducted in developed countries, and the limited empirical evidence from the South African context. Cross-national studies show consistent evidence of a gender gap in depression, although the extent of the gap varies according to factors such as socio-economic circumstances and levels of gender equity (Weissman et al., 1996; Van de Velde et al., 2010; Hopcroft and McLaughlin, 2012). The single-country longitudinal studies control for the age trajectory of depression, and find that the gender gap in mental health typically narrows in the later stages of life (Yang and Lee, 2009; Ferrand et al., 2020) although the gap is larger among cohorts that were born earlier than those born more recently (Platt et al., 2020). Lastly, empirical studies examining the role of gender in influencing mental health outcomes for South Africa were very limited. The prevalence of depression was higher for women than for men (Mungai and Bayat, 2019) and perceived social standing played a greater role in explaining inequalities in depression for women than for men (Mutyambizi et al., 2019). However, these studies did not explore any longitudinal changes in the gender gap as individuals age.

Chapter 3 outlined the data and key variables used in this study. This study used the adult data from five waves of NIDS, and constructed an individual's depression score as a measure of his or her mental health, following the Center for Epidemiologic Studies Depression scale method. Other key variables include the individual's birth cohort and measures of social and economic roles. This chapter presented and discussed the descriptive statistics for the analysis sample and key variables in order to show the nature of the data utilised in this study. Using descriptive statistics, the study found that women had significantly more depressive symptoms compared to men in every birth year cohort. The results also suggested that the differences in depression between men and women worsened in older cohorts, indicating that the gender differences in mental health are greater for individuals who were born earlier. In addition, the results illustrated the existence of a range of cohort-level gender differences in factors that may affect mental health.

Thereafter, Chapter 4 of this study presented the econometric investigation of the research questions. It provided an in-depth discussion of the growth-curve application of hierarchical linear modelling, the regression analysis method utilised in this chapter. This method, which is standard in this research area, enables the estimation of trajectories in mental health using longitudinal data, allowing for the role of individual-level and occasion-level factors as well as random effects (Rabe-Hesketh and Skrondal, 2021). The estimation part of this chapter presented five sets of regression results. The first table examined the age trajectory of mental health in order to answer the first research question. It found that the depression score increased non-linearly with each year an individual aged, and that the relationship between age and the depression score is cubic in nature.

The second set of models explored the roles of gender and birth cohorts, which were the focus of the dissertation's second research question. The results showed that women experience more depressive symptoms than men. Depressive symptoms increased in a non-linear manner across birth cohorts, with the second and third birth year cohorts experiencing significantly more depressive symptoms than the youngest cohort. In addition, the gender gap increased for cohort 2 and cohort 3 relative to the youngest cohort. The gender-cohort interactions were used to represent the difference in the gender gap in each older cohort. The results showed that the gender gap increased by 0.299 units between cohort 1 and 2 and by 0.495 units between cohort 1 and 3. In addition, between cohort 2 and 3, the gender gap increased by 0.196 (0.495-0.299). This indicated that the cohort effect was non-linear since the magnitudes of these gaps are not equal. The third set of results expanded the previous models further to incorporate the individual's race group and potential age interactions. The results suggested that there were some racial differences in how mental health varied across gender and birth cohort, but age interaction effects were found to be small.

The fourth set of models explored research question three, namely the extent to which roles within the household and access to the labour market explained gender differences in mental health. When childcare responsibility variables were controlled for, the gender gap in depression became significant and the magnitude of the coefficient of the gender dummy variable increased. Thus, childcare responsibilities partly explained the difference in depression scores between men and women in South Africa. The gender depression gap remained significant and increasing across the three cohorts when controlling for decision-making power. Thus, although having some degree of decision-making power in the household is beneficial for mental health, lower decision-making power among some women and among younger cohorts accounts for a small share of the difference in depression scores between men and women. Employment status significantly influenced an individual's level of depression, and employment was a more important determinant of mental health for the younger cohorts compared to older cohorts. Summarised, the results showed that individuals that have some decision-making power in the household and who are actively engaged in the labour market, especially when they are employed, are more likely to report lower depression scores. Surprisingly however, the results suggested that childcare responsibilities do not affect the average depression score.

The last set of results in this chapter found that controlling for household characteristics, such as income and household size, improved the fit of the model, and decreased the estimated racial depression gaps for Asian or Indian and white individuals relative to black Africans. However, this did not change the magnitude or significance of the estimate of the gender gap in the depression score. Among the individual characteristics, the results indicated that individuals who reported worse health statuses were more likely to record higher depression scores. Individuals who have completed higher levels of education and those that are married reported lower depression scores. There are lower marriage rates among women than men in older birth year cohorts. Since men in the older cohorts are more likely than women to be currently married, and marriage is associated with a lower depression score, these low marriage rates by women therefore explained the larger depression gaps in the older cohorts, as a result of women outliving men.

In summary, this study found a non-linearly increasing age trajectory in depression scores for adults in South Africa. In all model specifications, women experience more depressive symptoms than men in every birth year cohort, thus the study confirms the existence of a gender gap in depression in South Africa. It was found that each older birth cohort had more depressive symptoms than the one before it, even after controlling for age. It suggests that the social and economic circumstances experienced by each generation influence their mental health. Although causal links cannot be identified in this study, individuals who lived more of their lives during apartheid have worse mental health than those born more recently.

The study also found that gender differences in variables such decision-making power in the household, employment status and childcare responsibilities explained the differences in the depression scores between men and women. Thus, people who have a say in the decisions taken in the household, and those that are employed, are likely to be less distressed. In addition, gender differences in variables such as education level, marital status and health status explain the gender gap in depression because individuals with lower levels of education, who are not married and who report worse health have significantly higher levels of depressive symptoms. Therefore, to address the gender disparities in mental health, women should be given opportunities to advance themselves, for example, by ensuring equal job opportunities between women and men, equal wages and greater education opportunities for women.

Given that this study aims to determine how the gender gap in depression scores changes over time as people age, it is important to note that this study was conducted using pre-Covid-19 data and thus does not account for the psychological ramifications of the Coronavirus and the national lock-down implemented by the government on the respondents. While this study and other South African literature written before the Coronavirus have long established that women experience more depressive symptoms than men, emerging mental health research suggests that some of these accepted and long-held relationships, particularly between mental health and gender, have changed during the pandemic. According to recent research on psychological health during the Coronavirus pandemic, health and financial problems were both prompted and exacerbated, which potentially increased the chances of a detrimental mental health effect for South Africans (Oyenubi and Kollamparambil, 2020).

As a result of South Africa's high levels of inequality, Oyenubi and Kollamparambil (2020; 2022) discovered that individuals of different socio-economic positions went through the government-imposed lock-down in different ways. As evidenced by pre-Coronavirus studies, including this dissertation, the prevalence of depressive symptoms is typically higher among women compared to men. Surprisingly however, during the Covid-19 pandemic, no significant difference in the prevalence of depressive symptoms between men and women was discovered (Oyenubi and Kollamparambil, 2020). This indicates that the gender gap in depression has narrowed which is attributed to the increase in depressive symptoms among men, which could partly be caused by the psychological implications of the Coronavirus and the national lock-down, which left many people mentally distressed and unemployed (Hunt et al, 2021; Posel et al, 2021).

This dissertation is the first detailed investigation of the factors explaining the gender gap in depression in South Africa and therefore the study chose to focus mainly on a core set of variables. Although the models included a large number of factors, other potential variables were omitted in the interests of parsimony. In addition, while the models explored gender differences in mental health by cohort, they did not allow for gender heterogeneity in how other factors related to mental health. The richness of the NIDS data means that many other possible influences on mental health could potentially be explored in future research. Further research could also expand the multilevel models to explore in greater detail the between-individual variation in mental health, through expanding the random-effects variance component of the model.

Although this study identified a number of factors that influence mental health, approximately half of the gender gap in depression could not be explained by these observable factors. This research focused on the role of socio-economic influences, and therefore unmeasured affective, biomedical, and psychological elements may explain the remaining gap. In addition, the proxies used to measure gendered socio-economic roles are somewhat crude, due to the limitations of the data. These variables are not able to capture fully the range of choices available to women and men, and how these have changed over time. Such issues, and how they relate to the mental health of women and men, may perhaps be explored better by sociological research.

References

Abrams, L.R. and Mehta, N.K., 2019. Changes in depressive symptoms over age among older Americans: differences by gender, race/ethnicity, education, and birth cohort. *SSM-population health*, *7*, pp.100399.

Albertyn, C., 2011. Law, gender and inequality in South Africa. *Oxford Development Studies*, *39*(02), pp.139-162.

Andresen, E.M., Malmgren, J.A., Carter, W.B. and Patrick, D.L., 1994. Screening for depression in well older adults: Evaluation of a short form of the CES-D. *American journal of preventive medicine*, *10*(2), pp.77-84.

Baldwin, S.A. and Hoffmann, J.P., 2002. The dynamics of self-esteem: A growth-curve analysis. *Journal of youth and adolescence*, *31*(2), pp.101-113.

Baron, E.C., Davies, T. and Lund, C., 2017. Validation of the 10-item centre for epidemiological studies depression scale (CES-D-10) in Zulu, Xhosa and Afrikaans populations in South Africa. *BMC psychiatry*, *17*(1), pp.1-14.

Bebbington, P.E., 1998. Sex and depression. *Psychological medicine*, *28*(1), pp.1-8.

Brault, M.C., Meuleman, B. and Bracke, P., 2012. Depressive symptoms in the Belgian population: disentangling age and cohort effects. *Social Psychiatry and Psychiatric Epidemiology*, *47*(6), pp.903-915.

Brophy, T., Branson, N., Daniels, R.C., Leibbrandt, M., Mlatsheni, C. and Woolard, I. 2018. National Income Dynamics Study Panel User Manual. Release 2018. Version 1. Cape Town: Southern Africa Labour and Development Research Unit.

Bryk, A.S. and Raudenbush, S.W., 1992. *Hierarchical linear models: Applications and data analysis methods*. Sage Publications, Inc.

Burger, R., Posel, D. and Von Fintel, M. 2017. Relationship between negative household events and depressive symptoms: Evidence from South African longitudinal data. *Journal of Affective Disorders*, 218, 170-175.

Burns, J.K., Tomita, A. and Lund, C., 2017. Income inequality widens the existing income-related disparity in depression risk in post-apartheid South Africa: Evidence from a nationally representative panel study. *Health & place*, *45*, pp.10-16.

Carle, A.C., 2009. Fitting multilevel models in complex survey data with design weights: Recommendations. *BMC medical research methodology*, *9*(1), pp.1-13.

Dalal, D.K. and Zickar, M.J., 2012. Some common myths about centering predictor variables in moderated multiple regression and polynomial regression. *Organizational Research Methods*, *15*(3), pp.339-362.

Eyal, K. and Burns, J., 2019. The parent trap: cash transfers and the intergenerational transmission of depressive symptoms in South Africa. *World Development*, *117*, pp.211-229.

Ferrand, C., Martinent, G., Bailly, N., Giraudeau, C., Pothier, K. and Agli, O., 2020. Change of depressive symptoms in a French nine-year longitudinal study of aging: Gender differences and relationships between social support, health status and depressive symptoms. *Archives of Gerontology and Geriatrics*, *89*, p.104059.

Fischer, A.H. and Manstead, A.S. 2000. *The relation between gender and emotion in different cultures.* In: Fischer, A.H. (ed.) *Gender and Emotion: Social Psychological Perspectives*, Studies in Emotion and Social Interaction. Cambridge University Press, pp. 71-94.

Frank, R.G., & McGuire, T.G. 2000. Economics and mental health. In Culyer, A.J., Newhouse, J.P., Pauly, M.V., McGuire, T.G., & Barros, P.P. (Eds.). *Handbook of health economics*. Elsevier.

Garman, E.C., Eyal, K., Avendano, M., Evans-Lacko, S. and Lund, C., 2022. Cash transfers and the mental health of young people: Evidence from South Africa's child support grant. *Social Science & Medicine*, *292*, p.114631.

Goldstein, H., 1991. Multilevel modelling of survey data. *Journal of the Royal Statistical Society. Series D (The Statistician)*, *40*(2), pp.235-244.

Hammarström, A., Lehti, A., Danielsson, U., Bengs, C. and Johansson, E.E., 2009. Gender-related explanatory models of depression: A critical evaluation of medical articles. *Public health*, *123*(10), pp.689-693.

Hesketh, S.R. and Skrondal, A., 2021. *Multilevel and longitudinal modelling using Stata*. STATA press.

Hopcroft, R.L. and Bradley, D.B., 2007. The sex difference in depression across 29 countries. *Social Forces*, *85*(4), pp.1483-1507.

Hopcroft, R.L. and McLaughlin, J., 2012. Why is the sex gap in feelings of depression wider in high gender equity countries? The effect of children on the psychological well-being of men and women. *Social Science Research*, *41*(3), pp.501-513.

Hsiao, C., 2014. *Analysis of panel data* (No. 54). Cambridge university press.

Hunt, X., Breet, E., Stein, D., and Tomlinson, M. 2021. Hunger as a driver of depressive symptoms: Optimising responses to mental health aspects of the COVID-19 pandemic. *SAMJ: South African Medical Journal* 111.7 (2021): pp.604-605.

Hyde, J.S. and Mezulis, A.H., 2020. Gender differences in depression: biological, affective, cognitive, and sociocultural factors. *Harvard review of psychiatry*, *28*(1), pp.4-13.

Hyde, J.S., Mezulis, A.H. and Abramson, L.Y., 2008. The ABCs of depression: integrating affective, biological, and cognitive models to explain the emergence of the gender difference in depression. *Psychological review*, *115*(2), p.291.

Kessler, R.C., Aguilar-Gaxiola, S., Alonso, J., Chatterji, S., Lee, S., Ormel, J., Üstün, T.B. and Wang, P.S., 2009. The global burden of mental disorders: an update from the WHO World Mental Health (WMH) surveys. *Epidemiology and Psychiatric Sciences*, *18*(1), pp.23-33.

Kessler, R.C., McGonagle, K.A., Zhao, S., Nelson, C.B., Hughes, M., Eshleman, S., Wittchen, H.U. and Kendler, K.S., 1994. Lifetime and 12-month prevalence of DSM-III-R psychiatric disorders in the United States: results from the National Comorbidity Survey. *Archives of general psychiatry*, *51*(1), pp.8-19.

Lorant, V., Deliège, D., Eaton, W., Robert, A., Philippot, P. and Ansseau, M., 2003. Socioeconomic inequalities in depression: a meta-analysis. *American journal of epidemiology*, *157*(2), pp.98-112.

Mezulis, A. H., Hyde, J. S., Simonson, J., & Charbonneau, A. M. 2011. Integrating affective, biological, and cognitive vulnerability models to explain the gender difference in depression: The ABC Model and its implications for intervention. In T. J. Strauman, P. R. Costanzo, & J. Garber (Eds.), Depression in adolescent girls: Science and prevention (pp. 64–96). The Guilford Press

Mirowsky, J., 1996. Age and the gender gap in depression. *Journal of health and social behavior*, pp.362-380.

Mungai, K. and Bayat, A., 2019. An overview of trends in depressive symptoms in South Africa. *South African journal of psychology*, *49*(4), pp.518-535.

Mutyambizi, C., Booysen, F., Stornes, P. and Eikemo, T.A., 2019. Subjective social status and inequalities in depressive symptoms: a gender-specific decomposition analysis for South Africa. *International journal for equity in health*, *18*(1), pp.1-13.

Nolen-Hoeksema, S., 1987. Sex differences in unipolar depression: evidence and theory. *Psychological bulletin*, *101*(2), p.259.

Nolen-Hoeksema, S., 2000. The role of rumination in depressive disorders and mixed anxiety/depressive symptoms. *Journal of abnormal psychology*, *109*(3), p.504.

Oyenubi A, and Kollamparambil U. 2020., COVID-19 and Depressive symptoms in South Africa. National Income Dynamics Study (NIDS)–Coronavirus Rapid Mobile Survey Wave 2 Report No. 2020 Sep 30;12.

Oyenubi, A., and Kollamparambil, U., 2022. Does Socioeconomic status mediate the relationship between income loss and depression scores? Evidence from South Africa. *Current Psychology*, pp.1-12.

Piccinelli, M. and Wilkinson, G., 2000. Gender differences in depression: Critical review. *The British Journal of Psychiatry*, *177*(6), pp.486-492.

Platt, J.M., Bates, L.M., Jager, J., McLaughlin, K.A. and Keyes, K.M., 2020. Changes in the depression gender gap from 1992 to 2014: Cohort effects and mediation by gendered social position. *Social Science & Medicine*, *258*, p.113088.

Posel, D., Oyenubi, A. and Kollamparambil, U., 2021. Job loss and mental health during the COVID-19 lockdown: Evidence from South Africa. *PloS one*, *16*(3), p.e0249352.

Rabe-Hesketh, S. and Skrondal, A., 2021. *Multilevel and longitudinal modeling using Stata*, Fourth Edition. Stata Press.

Rantakeisa, U., Starrin, B., and Hagquist, C. 1999. Financial hardship and shame: A tentative model to understand the social and health effects of unemployment. *British Journal of Social Work*, 29, 877 – 901.

Raudenbush, S.W. and Bryk, A.S., 2002. *Hierarchical linear models: Applications and data analysis methods* (Vol. 1), Sage, pp. 31-57.

Reiss, F., 2013. Socioeconomic inequalities and mental health problems in children and adolescents: a systematic review. *Social science & medicine*, *90*, pp.24-31.

Rothbart, M.K., and Bates J.E., 1998. Temperament. In: Damon W, Eisenberg N, editors. *Handbook of child psychology: Vol. 3. Social, emotional, and personality development.* 5. New York: Wiley; 1998. pp. 105–176.

Salk, R.H., Hyde, J.S. and Abramson, L.Y., 2017. Gender differences in depression in representative national samples: Meta-analyses of diagnoses and symptoms. *Psychological bulletin*, *143*(8), p.783.

Salk, R.H., Petersen, J.L., Abramson, L.Y. and Hyde, J.S., 2016. The contemporary face of gender differences and similarities in depression throughout adolescence: Development and chronicity. *Journal of affective disorders*, *205*, pp.28-35.

Somefun, O.D. and Fotso, A.S., 2020. The effect of family and neighbourhood social capital on youth mental health in South Africa. *Journal of Adolescence*, *83*, pp.22-26.

StataCorp, 2021. *Stata multilevel mixed-effects reference manual, Release 17*. Stata Press.

Tomita, A. and Burns, J.K., 2013. A multilevel analysis of association between neighborhood social capital and depression: evidence from the first South African National Income Dynamics Study. *Journal of affective disorders*, *144*(1-2), pp.101-105.

Van de Velde, S., Bracke, P. and Levecque, K., 2010. Gender differences in depression in 23 European countries. Cross-national variation in the gender gap in depression. *Social science & medicine*, *71*(2), pp.305-313.

Weissman, M.M. and Klerman, G.L., 1977. Sex differences and the epidemiology of depression. *Archives of general psychiatry*, *34*(1), pp.98-111.

Weissman, M.M., Bland, R., Joyce, P.R., Newman, S., Wells, J.E. and Wittchen, H.U., 1993. Sex differences in rates of depression: cross-national perspectives. *Journal of affective disorders*, *29*(2-3), pp.77-84.

Weissman, M.M., Bland, R.C., Canino, G.J., Faravelli, C., Greenwald, S., Hwu, H.G., Joyce, P.R., Karam, E.G., Lee, C.K., Lellouch, J. and Lepine, J.P., 1996. Cross-national epidemiology of major depression and bipolar disorder. *Jama*, *276*(4), pp.293-299.

World Bank, 2002. *World development report 2003: Sustainable development in a dynamic world: Transforming institutions, growth, and quality of life*. The World Bank.

World Health Organization. *World Health Statistics 2017.* Geneva, Switzerland: 2017.

Yang, Y. and Lee, L.C., 2009. Sex and race disparities in health: Cohort variations in life course patterns. *Social Forces*, *87*(4), pp.2093-2124.

Appendices

Table A1

	Model A1_1	Model A1_2	Model A1_3
Age in years (centred)	-0.011*	-0.011*	0.006
	(0.004)	(0.004)	(0.004)
Age squared	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)
Age cubed	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Female (ref=male)	0.341***	0.221***	0.275***
	(0.052)	(0.052)	(0.052)
Cohort2 (ref=1)	0.363***	0.355***	0.595***
	(0.090)	(0.088)	(0.091)
Cohort3 (ref=1)	1.154***	0.981***	1.532***
	(0.149)	(0.145)	(0.149)
Cohort 2*Female	0.173*	0.193*	0.141
	(0.087)	(0.085)	(0.087)
Cohort 3*Female	0.197*	0.227*	0.050
	(0.096)	(0.094)	(0.097)
Coloured	-1.534***	-1.541***	-1.492***
	(0.055)	(0.053)	(0.055)
Asian or Indian	-1.286***	-1.491***	-1.335***
	(0.174)	(0.166)	(0.170)
White	-1.735***	-2.031***	-2.135***
	(0.108)	(0.100)	(0.105)
Unemployed-discouraged	-0.192	-0.125	-0.168
	(0.102)	(0.100)	(0.102)
Unemployed-strict	-0.227***	-0.188**	-0.304***
	(0.059)	(0.058)	(0.059)
Employed	-0.615***	-0.589***	-0.720***
	(0.046)	(0.045)	(0.046)
Number of young children (<7) being cared for	-0.008	0.036	0.037
	(0.034)	(0.034)	(0.034)
Number of older children (7-15) being cared for	-0.029	0.015	0.026
	(0.030)	(0.029)	(0.030)
Makes main decisions in household	-0.173***	-0.188***	-0.187***
	(0.044)	(0.043)	(0.044)

Makes joint decisions in household	-0.511***	-0.505***	-0.383***
	(0.040)	(0.040)	(0.041)
Primary	-0.297***		
	(0.075)		
Secondary	-0.964***		
	(0.076)		
Tertiary	-1.583***		
	(0.092)		
Very good health		0.272***	
		(0.042)	
Good health		0.711***	
		(0.046)	
Fair health		1.770***	
		(0.071)	
Poor health		3.595***	
		(0.110)	
Married			-0.749***
			(0.049)
Constant	8.631***	7.222***	7.900***
	(0.109)	(0.090)	(0.087)
Variance (Age)	0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)
Variance (Intercept)	1.332***	1.210**	1.387***
	(0.087)	(0.082)	(0.087)
Variance (Residual)	17.125***	16.844***	17.160***
	(0.130)	(0.127)	(0.130)
Observations	71621	71671	71651
BIC	412492	411078	412826
Log-likelihood	-206106	-205394	-206285

Source: NIDS waves 1-5, own calculations

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2

	Alternate Model 5	Alternate Model 6	Alternate Model 15	Alternate Model 18
Age in years (centred)	-0.080***	-0.073***	-0.064***	-0.052***
	(0.006)	(0.006)	(0.006)	(0.006)
Age squared	-0.001***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Age cubed	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Female (ref=male)	0.231***	0.249***	0.229***	0.226***
	(0.068)	(0.067)	(0.068)	(0.068)
Cohort 2	0.760***	0.754***	0.723***	0.639***
	(0.087)	(0.085)	(0.086)	(0.084)
Cohort 3	1.478***	1.515***	1.395***	1.149***
	(0.128)	(0.125)	(0.125)	(0.123)
Cohort 4	2.480***	2.587***	2.423***	1.863***
	(0.168)	(0.165)	(0.164)	(0.162)
Cohort 5	3.576***	3.660***	3.465***	2.600***
	(0.212)	(0.206)	(0.207)	(0.203)
Cohort 6	4.524***	4.672***	4.402***	3.223***
	(0.259)	(0.252)	(0.253)	(0.247)
Cohort 2*female	0.118	0.082	0.055	0.043
	(0.101)	(0.099)	(0.099)	(0.098)
Cohort 3*female	0.204	0.197	0.131	0.071
	(0.120)	(0.116)	(0.118)	(0.114)
Cohort 4*female	0.554***	0.454***	0.377**	0.250*
	(0.133)	(0.129)	(0.128)	(0.123)
Cohort 5*female	0.517***	0.428**	0.301*	0.007
	(0.141)	(0.134)	(0.133)	(0.128)
Cohort 6*female	0.650***	0.474***	0.391**	0.048
	(0.145)	(0.138)	(0.139)	(0.133)
Coloured		-1.612***	-1.532***	-1.529***
		(0.055)	(0.055)	(0.056)
Asian or Indian		-1.619***	-1.552***	-1.056***
		(0.176)	(0.174)	(0.168)
White		-2.545***	-2.341***	-1.436***
		(0.105)	(0.105)	(0.111)
Unemployed-discouraged			-0.293**	-0.283**
			(0.102)	(0.100)
Unemployed-strict			-0.303***	-0.210***

			(0.059)	(0.058)
Employed			-0.735***	-0.512***
			(0.046)	(0.046)
Number of young children (<7) being cared for			0.005	0.065
			(0.034)	(0.034)
Number of older children (7-15) being cared for			-0.000	0.033
			(0.030)	(0.030)
Makes main decisions in household			-0.161***	-0.187***
			(0.044)	(0.045)
Makes joint decisions in household			-0.501***	-0.353***
			(0.040)	(0.041)
Primary				-0.194**
				(0.072)
Secondary				-0.611***
				(0.074)
Tertiary				-1.007***
				(0.094)
Very good health				0.259***
				(0.042)
Good health				0.661***
				(0.046)
Fair health				1.636***
				(0.071)
Poor health				3.369***
				(0.110)
Married				-0.577***
				(0.049)
Household income (R '000s)				-0.014***
				(0.003)
Household income squared				0.000***
				(0.000)
Household size (centred)				-0.020***
				(0.006)
Rural				-0.168***
				(0.039)
Constant	5.281***	5.618***	6.586***	7.009***
	(0.112)	(0.111)	(0.126)	(0.148)
Variance (Age)	0.001***	0.000***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)

Variance (Intercept)	2.132***	1.652***	1.489***	1.090
	(0.097)	(0.090)	(0.089)	(0.080)
Variance (Residual)	17.078***	17.069***	17.042***	16.762***
	(0.129)	(0.130)	(0.130)	(0.127)
Observations	72058	72058	71766	71327
BIC	417046	415556	413445	408537
Log-likelihood	-208422	-207660	-206566	-204045

Source: NIDS waves 1-5, own calculations

Notes: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The birth years for the cohorts are: cohort 1 = 1990 onwards, cohort 2 = 1980-1989, cohort 3 = 1970-1979, cohort 4 = 1960-1969, cohort 5 = 1950-1959, and cohort 6 = 1949 or earlier.