The Psychological cost of Indebtedness in South Africa

Evidence from NIDS Wave 2 and 4.

Viwe Sakela
Student Number: SLVIW002

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Faculty of Commerce, University of Cape Town

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Abstract

The mechanisms that perpetuate over-indebtedness at individual level (or household) are still not well researched. Emerging literature on debt and mental health shows that being highly indebted is stressful and it leads to psychological problems. This paper explores the relationship between psychological well-being and debt in South Africa. We rely on Wave 2 and 4 of the National Income Dynamics Study (NIDS), a nationally representative household panel survey in South Africa. We have two indebtedness measures; Negative Asset Value and Financial Stress which are both constructed from the NIDS dataset. Negative asset value is based on the net worth of the respondent, whereas Financial Stress is based on household expenditure over income.

In the sample data, we observe that respondents have higher CES-D scores on average in Wave 4 than in Wave 2. As a result, the number of people who report depression is also higher in this wave. The proportion of the sample that is indebted increases between Wave 2 and 4,with more household reporting financial stress in wave 4.

In the empirical analysis, we firstly use cross-sectional data to estimate a probit model between debt and depression, while controlling for socioeconomic variables on the individual and the household they belong to. The results suggest that indebtedness is positively associated with depression. Debt and depression tend to be endogenous since poor mental health can lead to indebtedness.To deal with the endogeneity that exists between debt and depression, we estimate a recursive bivariate probit with the cross-sectional data. We find that the negative asset value is still positively associated with depression, but financial stress is not. Due to the inconsistency of results when using cross-sectional data, we shift to panel data. A fixed effects logit model is estimated to look at the changes in debt and changes in depression. The results show that both debt variables are significant determinants of the onset of depression. Lastly, in the fixed effects logit model, we swap out the debt variables with debt types to look at the changes in debt types and changes in the depression outcome. A personal loan from a bank, a loan from Mashonisa and Hire purchase debt are the significant determinants of changes depression.

Chapter 1: Introduction

A significant number of South African consumers owe the bulk of their monthly salaries to creditors (Debt Rescue, 2017). Some consumers owe as much as 75% of their monthly pay to creditors, while almost 60% of the population is struggling to meet their monthly payment for their home loans and credit card payments (Debt Rescue, 2017). High levels of debt have a negative effect on mental health (Marmot, Ryff, Bumpass, Shipley & Marks, 1997; Roberts, Golding & Towel, 1998; Brown, Price & Taylor, 2005). This is even worse for consumers living in poverty since the constant shortage of money combined with the dangerous living situations which exist in most poor communities contribute to higher stress levels (Mullainathan, 2013).

In 2014 South Africa had a population of 54 million people with approximately 37.8 million (70%) of them being above the age of 15 years (Stats SA, 2014). In December 2016, the country had 24.31 million credit-active customers, which is more than 40% of the population (National Credit Regulators (NCR), 2016)[1]. Credit-active consumers are obligated to pay credit providers and service providers; these obligations result in transactional entries on the consumers' credit records at the credit bureaus. More than 50% of the credit-active customers have impaired accounts, meaning that they are in arrears in paying their accounts. In other words, they are overly indebted[2] (NCR, 2016). Of the 12.7 million with impaired accounts, 12.3% were 1-2 months in arrears, 21.8% 3+ months in arrears, 11.8% were adversely listed and 6.6% had judgments and administrative orders against them. Only 47.6% had credit accounts that were up to date on their monthly payments (NCR, 2016). Adversely listed customers are those who have credit accounts that have been written off.

With a high real interest rate and a weak economy, levels of indebtedness in the country are growing across all income groups. The 2016 Gauteng City-Region Observatory Quality of Life Survey Report showed that about 40% of Gauteng residents had some form of debt against their names or households, which is a 10% increase since 2013 (Writer, 2015). Households who earned high incomes were mostly in debt due to asset investments. There was a substantial increase in the debt of lower-income groups between 2013 and 2015.

Given the high and rising levels of indebtedness in South Africa, it is highly likely that there are societal effects of this behaviour. Yet there is only a handful of South African- specific studies on the social and psychological impact of household indebtedness (Keese and Schmitz, 2012; Berger, Collins and Cuesta, 2013; Clayton, Liñares-Zegarra and Wilson, 2015). This study sets out to fill this critical gap in our knowledge.

This paper aims to investigate the dynamics between debt and depression in South Africa. Drawing on current literature, the analysis in this paper focuses on how indebtedness affects psychological well-being. The paper has three main chapters. Chapter 2 has a literature review of the studies on debt and depression. It includes literature on debt and mental health in South Africa. In Chapter 3, we look into the theoretical foundations of studying household debt. In Chapter 4, we give details about debt levels in the country using data from the National Income Dynamics Study (NIDS), a nationally representative survey. In Chapter 5, we use cross-sectional data and panel data to model

[1] The NCR is a national agency under the South African Department of Trade and Industry. It was created with the intention to promote responsible credit granting and use, and prohibits unfair credit-marketing practices. It provides debt reorganisation in cases of over-indebtedness, and has information about registered creditors and their debtors.

[2] Overly indebted customers are those who are in arrears for at least 3 months (Writer, 2015).

the relationship between debt and depression. We bring some of the main empirical findings up to date and extend this literature by exploiting recent waves of data from NIDS.

Chapter 2: Literature Review

2.1 Debt and Depression

It is well known that mental health problems are related to deprivation, health, poverty, inequality and other socio-economic determinants of health (Drentrea & Reynolds, 2012; Lund, 2010; Bruce, Takeuchi & Leaf, 1991). Economic crises are therefore times of risk to the mental well-being of the population and the affected people and their families. Mental health is an indivisible part of public health and significantly affects countries and their human, social and economic capital. Positive mental health is a state of well-being in which the individual realizes their abilities and can cope with the normal stresses of life, work productively and contribute to the community. Mental capital is important for the healthy functioning of families, communities and society.

The relationship between economic stress and distress has been well reported in studies using an individual level of analysis (e.g. DeVaney & Lytton, 1995). For example, household heads with outstanding non-mortgage credit debt have been found to report worse mental health, especially if such debt is high (Brown, Taylor & Price, 2005). Adults who live in poverty have a risk of depression twice as high as those who do not (Lund, 2010; Bruce, Takeuchi & Leaf, 1991). Nevertheless, not everyone living in poverty suffers from depression and not everyone with outstanding non-mortgage credit debt suffers from distress.

Hatcher (1994) showed that patients in debt were more likely to harm themselves and with greater suicidal intent, and after the episode were more likely to report symptoms of depression and hopelessness. He used a descriptive survey of financial difficulties in a consecutive series of patients who deliberately poisoned themselves. Information was available on 147 of these patients, of whom 54 (37%) had problem debts. Psychiatrists were more likely to diagnose mental illness in those with debt. Nettleton and Burrows (1998) later found that the onset of mortgage indebtedness appeared to be associated with deteriorating mental health. Those experiencing difficulties in repaying their debts were more likely to have some sort of minor mental disorder than those without such difficulties (Hintikka, 2007).

More attention has been focused on the topic since the 1990. Maciejewski et al. (2000) show that self-reported financial stress is a significant factor undermining the self-efficacy (i.e. appropriate behavioural responses) of individuals with a prior history of depression. Ferrie et al. (2003) examined gradients of morbidity, including measures of depression, across socio-economic groups (SEGs), and found that differences in self-reported financial insecurity across SEGs were a major determinant of differences in the incidence of depression. Using credit card data from the United States of America (USA) Drentea and Lavrakas (2000) conclude that high credit card debt-to-income ratios and arrears and defaults are associated with greater anxiety, especially among older respondents.

Using the British Household Panel Survey, Wildman and Jones (2005) showed that scaled self-reported financial status and year-on-year past and expected changes in financial status are associated with differences in self-reported health, incidence of longstanding illness and depression. Using the same data set Brown et al. (2005) argued that household psychological well-being is adversely affected by large values of unsecured debt.

Drentea and Lavrakas (2000) have suggested that debt “may be a more sensitive barometer of financial well-being than income” because it represents accumulated hardships over time. While this observation reinforces the likely importance of debt as a socio-economic indicator, it also points to the potential confounding that arises from longitudinal accumulation of debt. Personal financial debt may result from acute life events such as job loss, divorce, or medical emergencies, which may themselves be psychosocial stressors or health determinants. Accounting for prior psychosocial, socio-economic and health conditions is therefore critical for understanding the relationship between financial debt and health. Reading and Reynolds (2001) investigated maternal depression among women with young children. Using self-reported worries about debt on a categorical scale to proxy for the financial position of the household and controlling for other variables, they established a positive link between the extent of self-reported debt concerns and a scaled depression score.

Generally, financial stress was found to be higher in families with more children, with more income units and dependents and with an older head of the household, as well as among families from ethnic minorities (Lytton & DeVaney, 1995). This was especially the case when families were reliant on government pensions and benefits. Financial stress was found to be lower in families with higher disposable incomes and housing values.

In the United Kingdom (UK) during the 2007 economic crisis people with increasing debt showed an increase in the risk of mental illnesses (Jenkins et al., 2008); the more debt that people had, the worse their mental health. Odds ratios (ORs) were used to measure the risk of mental illnesses in people with increasing debt. An OR is a measure of association between an exposure and an outcome (Wooldridge, 2016); it represents the odds that an outcome will occur given a particular exposure, compared to the odds it occurring in the absence of that exposure. The OR risk was adjusted for income and sociodemographic variables such as age, ethnicity, marital status, household size, household tenure, education, employment status, urban or rural area and region.

Lenton and Mosley (2008) found that both psychological and physical health were affected by debt. Two intermediating variables influence the linkages: a high-interest debt repayment structure and worry exacerbate debt problems and influence health-seeking behaviour. Jessop, Herberts and Solomon (2005) confirmed that financial concern is a significant linear predictor of mental and physical health; the increased financial concern was consistently associated with worse health. Being seriously behind on any debt repayment and particular sources of debt were key correlates for all common types of mental disorders, both as a whole and when analysed by separate diagnostic criteria categories.

Bridges and Disney (2010) studied a large random sample of women and children in Britain to investigate the relationship between financial indebtedness and psychological well-being. They found a positive association between subjective measures of financial well-being and psychological well-being; individuals differed in their psychological response to objective household financial situations. Persons who failed to pay their mortgage or whose house was repossessed reported a particularly high prevalence of mental and physical health impairment (Cannuscio et al., 2012). They experienced poorer health relative to homeowners with no housing strain for every measure examined, including the number of days in the past month during which mental health was impaired. Other measures included self-rated health, psychological distress, the number of days in the past month during which physical health was impaired and physical symptoms. McLaughlin et al. (2012) also found foreclosure to be associated with an increased rate of symptoms pertaining to major depression and generalized anxiety disorder.

Drentrea and Reynolds (2012) examined the impact of indebtedness on depressive symptomatology, anxiety, and anger. They used data from a two-wave panel study of adults in Miami-Dade County in the USA. Controlling for education, income, occupational status, wealth and debt the results showed that indebtedness was common and was associated with more symptoms of depression, anxiety, and anger. They found that depressive symptomatology was weakly associated with other aspects of socio-economic status (SES). In fact, debtor status was more consistently associated with mental health than any other single traditional indicator of SES. The debtors mostly feared never being able to pay off their debt.

Keese and Schmitz (2012) analysed the association between household indebtedness and different health outcomes using data from the German Socio-Economic Panel from 1999 to 2009. Controlling for unobserved heterogeneity they applied fixed-effects methods and used a subsample of constantly employed individuals plus lagged debt variables to reduce problems of reverse causality. They used different measures of household indebtedness, such as the percentage share of household income spent on consumer credit and home loan repayments (indicating the severity of household indebtedness) and a binary variable of relative over-indebtedness (indicating a precarious debt situation). All debt measures were strongly correlated with health satisfaction, mental health, and obesity. After controlling for unobserved heterogeneity the relationship between debt and physical and mental health stayed significant.

Berger, Collins and Cuesta (2013) used data from waves 1 (1987-1989) and 2 (1992-1994) of the National Survey of Families and Households in the USA. They applied a series of standard ordinary least squares (OLS) regressions and OLS regressions with individual-specific fixed effects to estimate associations of particular types and levels of debt with adult depressive symptoms. Results suggested that household debt is positively associated with greater depressive symptoms, especially among people aged between 51 and 64 years with minimal education. However, they found that the association was driven by short-term (unsecured) debt. There was little evidence of associations of mid- or long-term debt with depressive symptoms. The link between short-term debt and depression was generally robust for alternative specifications of their models, including whether debt was defined in absolute or relative terms. In contrast, Clayton, Liñares-Zegarra and Wilson (2015) found that long-term unsecured debt and mortgage debt were associated with poorer health (including mental health) outcomes. Using aggregate data on household debt and aggregate health outcomes across 17 European countries between 1995 and 2012, they estimated an instrumental variable model (Generalised Method of Moments) to address possible reverse causality concerns. Their results showed that both short- and medium-term debt had a positive effect on health outcomes, that aggregate household debt affected health outcomes, and that this varied by the maturity of debt.

Sweet et al. (2013) investigated the associations of multiple indices of financial debt with psychological and general health outcomes among 8400 young adult respondents from the National Longitudinal Study of Adolescent Health. They reported that high financial debt relative to available assets is associated with higher perceived stress and depression, worse self-reported general health, and higher diastolic blood pressure. These associations remained significant when controlling for prior SES, psychological and physical health, and other demographic factors.

Most recently Turunen and Hiilamo (2014) assessed 33 peer-reviewed studies which demonstrated serious health effects related to indebtedness. Their conclusion was that individuals with unmet loan payments had suicidal ideation and suffered from depression more often than those without such financial problems. Unpaid financial obligations were also related to poorer subjective health and health-related behaviour. Debt counselling and other programmes to mitigate debt-related stress are needed to alleviate the adverse effects of indebtedness on health.

In summary, literature confirms that indebtedness strongly affects psychological well-being (Bridges & Disney, 2010; Brown, Taylor & Price, 2005; Drentea & Reynolds, 2012; Jenkins et al., 2008; McLaughlin et al., 2011; Meltzer et al., 2011; Pollack & Lynch, 2009; Reading & Reynolds, 2001). Indebtedness has negative mental health consequences for various reasons, possibly including the perception of not being able to get out of debt or the potential shame and anxiety resulting from defaulting on loans or declaring personal bankruptcy. Carrying heavy debt loads and being called by collectors are considered stressful for most people (Engelbrecht, 2014). Short-term debt may have an adverse influence on psychological well-being, particularly for those who are less educated or are approaching retirement age. Excessive debt is in part harmful to psychological well-being because it wears away at one's mental health.

2.2 South African Literature on Debt and Depression

In many South African communities, depression was historically thought to be rare or non-existent (Hamad, Fernald, Karlan & Zinman, 2008). There is growing recognition that mental health is an important public health issue in South Africa. Latest reviews of contribution to the disease burden in the country rank neuropsychiatric conditions third, after human immunodeficiency virus/acquired immune deficiency syndrome (HIV/AIDS) and other infectious diseases (Lund et al., 2011). The first major epidemiological study with a representative sample of South African adults revealed that 16.5% suffered from a common mental disorder (depression, anxiety or substance use disorder) in the previous year. A review of existing studies concluded that about 17% of children and adolescents in the Western Cape suffer from a mental disorder. These studies reported no evidence of differences in the prevalence of mental disorders between socially defined racial groups or cultural groups. South African students of differing African origin ethnicities have been shown to have similar depression scores (Hamad et al., 2008).

Studies have demonstrated that depression prevalence in South Africa is at or above average level relative to other developing countries, particularly among vulnerable subgroups such as women and individuals of low SES (Baron, Davies & Lund, 2017). Prevalence ranges of mental disorders in the country are difficult to report because studies examine different psychiatric conditions and use different measurement techniques, even when studying the same conditions (). In a developed countries, poor mental health has been found to be independently associated with female gender, low educational attainment, poor health, unemployment, low income and lack of a stable marriage (Bruce, Takeuchi & Leaf, 1991; Goldsmith, 1997).

Research that focuses on mental health in South Africa is not extensive, a situation that is similar to that in other low- to middle-income countries. Moreover, the prevalence of mental illness remains underestimated and mental health services remain chronically under-resourced (Lund et al., 2011). Under-resourcing of mental health is not unique to South Africa. While studies in developing countries are fewer in number they generally produce similar findings, with increased depression or emotional stress associated with lower educational attainment, greater poverty, worse health, lack of a stable marriage and employment in an informal rather than a formal job. Developing countries tend to focus more attention on conditions that threaten the population size, including infectious diseases and conditions surrounding maternal and child health. The compromise on which health sectors to focus on comes from a lack of funds and health resources relative to the population in need. Most of the relevant South African literature links socio-economic circumstances with mental health, but currently there is limited literature that unpacks the relationship between debt and mental health.

A study on major depression in South Africa by Tomlinson et al. (2009) showed that females were more likely to have a lifetime or a 12-month depression episode than males. The prevalence of depression was also higher among people with lower levels of education than those with higher levels of education. The number of people who reported depression increased with age. Similarly, Peltzer and Phaswana-Mafuya (2013) found that the overall prevalence of symptom-based depression in the past 12 months among adults above the age of 50 was 4%. Applying multivariable regression analysis, they used a national sample of older South Africans who participated in the Study of Global Ageing and Adult Health (SAGE, wave 1) in 2008. Results showed that functional disability, lack of quality of life and chronic conditions (angina, asthma, arthritis, and nocturnal sleep problems) were associated with reported depression symptoms in the past 12 months.

Children of women who suffer from untreated mental disorders are more likely to suffer from mental health issues themselves, and thus a secondary cost to children is incurred if mothers are not treated (Eyal & Burns, 2018). Adherence to HIV and other important medications is lower for the mentally ill. Poor mental health in mothers has been associated with poor infant nutrition, stunting, diarrhoeal disease, low vaccination rates, and limited breastfeeding (Lund, 2012; Berger, Collins & Cuesta, 2013), and thus treatment may have a great impact on infant development. Left untreated, poverty and mental health interact in a vicious cycle that continues throughout a person's life (Lund, 2012). Those suffering from mental illness are less likely to be able to take care of themselves and others, implying knock-on effects on physical health.

Although these analyses suggest correlations between mental illness and various demographic or socio-economic characteristics, there is a gap in the research when it comes to rigorous and multivariate analyses examining the risk factors and social context surrounding depression in sub-Saharan Africa. To address this critical research gap the analysis reported here will use a more rigorous methodology to obtain a better understanding of depression and debt in the South African context.

2.4 The South African Context

2.4.1 Poverty

More than 50% of the population of South Africa live in poverty (Stats SA, 2017). Depression is highly likely in a country that is poverty stricken, given the daily financial limitations and violence in poor communities (Lund et al, 2011). Poverty, unemployment and residential instability create neighbourhoods with fewer resources, lack of social connection, an unsafe environment, and poor transport and service delivery (Tomita & Burns, 2013). Poor individuals and families experience more chronic or uncontrollable life events than the general population (Ennis, Hobfol & Schroder, 2000). Consequently individuals among lower SEGs report higher incidences of smoking, drinking, obesity and poor diet.

Social causation theory posits that the poor develop psychological and physical health problems as a result of living with poverty-related hardship. Indeed, the SES health gradient is strongest for diseases with sensitivity to stress, such as heart disease, diabetes, metabolic disorders, and psychological disorders (Warren, 2009). Studies comparing social causation of psychological disorders with alternative models such as social selection generally find strong support for the social causation of psychological disorders such as depression and anxiety (Wadsworth & Achenbach, 2005). Poverty is chronic and toxic, taxing mental and physical resources and ultimately resulting in higher mortality rates for those living in poverty (Bruce, Takeuchi & Leaf, 1991; Lund et al., 2011). Children and adolescents in low-income communities are predicted to experience anxiety at the age of 15 (Eyal & Burns, 2014). Furthermore, increases in income or emergence out of poverty have been linked to declines in psychological problems (Stoop, Zizzamia & Leibbrandt, 2019).

Poverty's damage occurs at multiple levels. Poor families are exposed to more dangerous and deteriorating neighbourhoods, more crowded and noisier homes, more conflict and instability in the family, and more polluted air and water (Evans, 2004; Lund et al., 2011). These multiple risks affect children and adults, leading to an array of psychological and physical morbidity (Evans, 2004). Siefer, et al. (2000) showed that community-level stressors, including high poverty rates, low levels of education, high unemployment rates, and high residential mobility in the community, are chronic and affect all members of a given community. Similarly, Munster et al (2009) examined SES, neighbourhood disadvantage and poverty-related stress as predictors of a wide range of psychological problems, including anxiety, depression, aggression, relationship problems, physical problems and trouble with the law. The analyses showed that poverty-related stress was directly linked to depression symptoms. The study found that lower levels of neighbourhood education, higher levels neighbourhood poverty and more residential mobility are toxic for the mental health of poor families. The psychological stress takes a toll on children, adolescents and adults alike. Lower levels of income predicted more anxiety and depression and worsened social problems across time. Thus, income and neighbourhoods are key conduits for the transmission of risk for psychological problems.

2.4.2 Inequality

Inequality in South Africa is inherently complex and goes back to the 1800s when climate change caused migration within the country (Hino, Leibbrandt, Machema, Shifa & Soudien, 2018). People were migrating in search of food and pastures, which led to contestations between different ethnic groups. However, when the European settlers arrived in the country in quest of agricultural land and mineral resources they forcefully removed natives from their land and communities. The colonial administration designed and implemented policies that benefitted the development and wealth of whites, whereas black, coloured and Indian persons were deprived of the same opportunities. Apartheid was based on the idea that the people of South Africa were divided into clear racial groups, with whites as the superior racial group. Each racial group had a separate social, cultural and economic existence and was forced to develop and live separately (Hino et al., 2018). Inequality in South Africa is geographically entrenched, and the areas that were designated for blacks are still the poorest, with high population densities.

South Africa’s landscape is made up of three distinct geographic areas: rural, urban formal and urban informal (World Bank, 2014). Many research papers only take note of rural and urban areas as the two distinct geographical groupings, and so townships are categorised as part of the urban areas. Two-thirds of South Africans live in urban areas (Phakathi, 2013) and nearly 60% of these are unemployed (World Bank, 2014). Townships surround areas of high economic activity. Most people move from rural areas to informal settlements and townships in urban areas in search of employment (Phakathi, 2013).

Informal settlements and townships report the highest number of crimes in the country. Areas with daily experiences of crime, noise and drug use lower the psychological well-being of the population because of the distressing environment (Ross, 2000). Individuals in neighbourhoods with a large proportion of poor and mother-only households have higher depression levels than those who live in less disadvantaged neighbourhoods (Ross, 2000). Spatial inequality is directly linked to income inequality. Vertical inequality is defined as the distribution pattern of income among individuals in the country, and includes aggregate measures such as the Gini coefficient (Hino et al., 2018). South Africa has one of the highest Gini coefficients in the world. Evidence suggests that such aggregate measures of vertical inequality are not strongly correlated with social tension. Rather, it is horizontal inequality and polarisation (disparities in the level of well-being) between competing identity groups which correlates more closely with social conflicts (Stewart et al., 2010).

Inequality affects mental health through two mechanisms. Firstly, inequality causes direct stress due to social comparisons where the poorer individuals develop feelings of failure, resentment, shame and social defeat when compared to the rich (Burns, 2015). Secondly, inequality destroys networks of relationships between racial groups, leaving individuals from the poorer sections vulnerable to psychosocial stressors (Burns, 2015). The inverse relationship between income inequality and social capital is correlated with depression of the poorer population in low- to middle-income countries.

2.4.3 Unemployment

Employment is one of the factors used to describe the economic and social situation of a country. The South African unemployment rate has been increasing since 2008, particularly among the youth aged between 15 and 24 years (Stats SA, 2016). The official unemployment rate measures the proportion of the labour force that is unemployed and is still searching for jobs, and in quarter 2of 2015 it was 26.7 % (Stats SA, 2016). In order to be considered unemployed based on the official South African unemployment definition, three criteria must be met simultaneously: a person must be completely without work, currently available for work, and taking active steps to find work. The expanded definition excludes the requirement to have taken steps to find work, meaning that discouraged workers are included. The expanded unemployment rate was 36.3% because it included discouraged workers (Stats SA, 2016). Discouraged work seekers are persons who want to work but did not try to find work or start a business because they believed that there were no jobs available in their geographical area, or were unable to find jobs requiring their skills, or had lost hope of finding any kind of work (Stats SA, 2016). Existing research argues that the high unemployment rate in South Africa is a result of structural constraints and a skills mismatch between labour suppliers and those who demand labour (Perold, Cloete & Papier, 2012).

Several studies have demonstrated that unemployment can result in mental health deterioration because unemployed individuals are stripped of certain functions of employment, including time structure, social contact, a collective purpose, status, activity, goals, physical security, and a valued social position (Kawachi & Wamala, 2006). Unemployment is usually discussed as a cause of financial strain and distress (Livingstone & Lunt, 1992; McKee-Ryan et al., 2005; Mossakowski, 2009; Lloyd & Leibbrandt; Kingdon & Knight, 2006). Simultaneously, it has been suggested that acute and chronic stressors follow the unemployed because reduction in economic resources can be stressful for the unemployed individual and their family; moreover, such stressors have been found to relate to changes in physiological regulation, which leads to poor health. Stable employment, a secure income and social capital predict good mental health (Goldsmith, 1997). Social capital is the quality of social relationships within communities, including a sense of belonging and norms of cooperation and trust.

The stress-vulnerability model suggests that high-risk lifestyle behaviours – such as growth in unhealthy eating habits, smoking and alcohol use – are related to health status deterioration accompanying unemployment (Jesspo, Herbets & Solomon, 2010; Kawachi & Wamala, 2006). Adopting a negative health behaviour after a job loss is perceived as a method of coping with the stress of being stripped of a social role and social networks (Kawachi & Wamala, 2006). In the European region relatively high frequencies of common mental disorders are associated with poor education and unemployment. Suicide is more common in areas of high socio-economic deprivation and unemployment. Alcohol consumption plays a significant role in increasing suicide, especially among men (Hintika et al, 2007).

The deprivation model and the vitamin model – which are primarily concerned with the psychosocial consequences of unemployment – suggest that unemployment severely frustrates the human desire for agency and self-directedness (Dooley, Catalano & Wilson, 1994; Simmons, 2008). Selenko and Batinic (2011) measured the subjective economic stress of heavily indebted persons, and specifically its relationship with distress. They analysed three kinds of moderators: (a) the individual's employment situation, (b) the latent benefits the individual has access to, and (c) the individual's self-efficacy beliefs. The first factor they propose as a moderator of the relationship between perceived financial strain and mental health is the person's employment situation. Employment has positive effects on health, and may also have a moderating effect on the relationship between perceived financial strain and mental health. Those with financial difficulties are restricted in their roles as consumers and normal citizens. They are more likely to suffer from social exclusion as it is difficult to purchase the items needed to participate in ordinary social activities (Simmons, 2008). They found that the feeling of being a part of a collective purpose lowered the effect of financial strain on mental health.

Employment might be one of the few social institutions to which people under serious financial strain have access and it thereby buffers the negative relationship between financial strain and mental health (Jahoda, 1992). Similarly, unemployment might strengthen the negative relationship between financial strain and well-being. Given a situation of serious objective and subjective economic stress, unemployment might amplify the negative relationship between perceived financial strain and distress. If people who are under serious financial strain become unemployed, they are no longer able to cope with this strain through work and earning an income. Therefore an important way of handling the financially adverse situation is beyond their control. The feeling of having no control has been related to an increase in depressive symptoms (Dooley et al., 2000).

In summary, the levels of unemployment; poverty and inequality in South Africa are significantly high. Literature has linked these factors to reduced psychological well-being. As we try to isolate the relationship between debt and depression, it is important to keep in mind the socioeconomic dynamics of the country and to control for them in the lives of those whose psychological well-being we are attempting to assess.

Chapter 3: South African Household Debt

Household debt in South Africa has grown significantly relative to income over the past twenty years (Engelbrecht, 2009). Financial debt is a major problem for poor households in developing countries including South Africa. In many developing countries, there has been a rapid increase in the availability of microfinance which has been associated with a widespread of over-indebtedness. The literature above has shown that indebtedness in poor households often co-exists with social exclusion and a high incidence of poverty. In this chapter, we explore the dynamics of indebtedness in South Africa to fuel the design of our econometric model evaluating debt and depression. The aim of this chapter is to gain an understanding of what the South African household dynamics are regarding indebtedness. Debt needs to be understood in order to accurately model its impacts on psychological well-being. Although we mainly follow Bridges and Disney(2010) in our modelling of debt and depression, it is important to contextualise the econometric model to accurately account for South African dynamics.

3.1 Background on Consumer Debt

People use credit to pay for different things, including retail goods, school or medical fees, or to buy cars on instalment plans. A good credit record is measured by the ability to maintain agreed monthly payments. Failure to make a payment or making a payment less than the required amount increases the debt. The interest penalty on unpaid debt is high, and it can make debt a problem if not repaid over a long period. Consumers sometimes dishonour debt commitments out of neglect or due to unfortunate circumstances (such as job loss, health problems, or divorce). The recurrent consumption needs or unforeseen events might lead many individuals or households into positions where either their debts are too big relative to their incomes, or they are no longer able to meet their repayment obligations when due without substantially hurting their family or personal well-being (i.e. they are over-indebted).

Since the mid-1990s, the level of consumer indebtedness in South Africa has grown substantially. Policies which have played a significant role in increased consumer credit are the Usury Act Exemption Notices of 1992 and 1999, which are often criticized for exacerbating reckless credit practices and abuses (Goodwin-Groan & Kelly-Louw, 2006). The Usury Act Exemption Notices allowed micro-lenders to charge unlimited fees for small loans, which resulted in the exponential growth of the micro-lending industry coupled with extreme interest rates, inflated credit prices, and excessive consumer indebtedness (Hawkins, 2003). Post-apartheid, legislative changes in the micro-lending market in the early 1990s prioritized consumers who were not strategically prioritised by large institutions, including low- and middle-income earners. The previously excluded consumers were offered new credit products from a wide range of suppliers (financial retailers and others), including term-loans, revolving credit facilities, short-term cash loans, educational credit, non-mortgage housing finance backed by pension funds, and 'save-to-borrow' products that allow first-time credit access for previously excluded consumers.

Since then the level of consumer debt has grown in terms of the number of people using debt and the amount of credit owed. The socio-economic transformation policies of the post-apartheid government partially account for the increased use of credit. Initiatives such as black economic empowerment (BEE) raised the amount of wealth available in households and increased the ability to borrow (Hurwitz & Luiz, 2007). However, the growth in credit consumption in South Africa exceeds growth in incomes. The result has been dramatic increases in debt owed in numerous credit types. The National Credit Regulator (2009) showed that growth in debt owed on instalment payments to retailers rose by over 350% between 1994 and 2002, while debt on professional services rose by about 125%. Debt on cheques and credit cards grew by over 100%, as did debt on electricity, water and other services (NCR, 2009). The micro-lending market continues to grow, as does the size and term of loans. According to statistics from the Micro-Finance Regulatory Council year-on-year disbursements grew from R15.6 billion in February 2004 to R20.6 billion in February 2005, an increase of 32%.

The combination of increased availability of credit and ability to borrow resulted in substantial increases in private consumption relative to income, especially for new entrants into the job market (who often had little knowledge of credit dynamics and incurred high fees) (James, 2012). As a result of the growth in the credit sector, many working-class employees have multiple retail accounts, personal loans, payday loans and loans taken to repay other loans (DebtBusters, 2018). All this is leading many workers into a spiralling, inescapable debt trap. Household finances became ever more fragile and private saving rates declined as more and more personal income was being committed to debt servicing (Livingstone & Lunt, 1992; Prinsloo, 2002).

Indebtedness has spiralled out of control for many households. Stats SA (2008) showed that by November 2006, about 75 000 consumer debt default judgments were issued every month and nearly 4 million South Africans had been blacklisted by credit bureaux. Du Plessis (2007) notes that even though interest rates increased marginally during this period, many South African consumers were paying as much as 360% annual interest on short-term loans.

To protect consumers from drowning in debt, the government (in 2006) enacted the National Credit Act 34 of 2005 (hereafter, the NCA) to address reckless credit policies. The NCA set out new parameters for the granting of credit, with the main objective being the prevention of consumer over-indebtedness (Goodwin-Groen & Kelly-Louw, 2006; Roestoff, Haupt, Coetzee & Erasmus, 2009; Van Heerden & Boraine, 2009). Even with the new credit policies in place, indebtedness among South African households is still on the rise.

3.2 Theory of Indebtedness

3.2.1 Measuring Indebtedness

The narrowest meaning of getting into debt is 'spending money that you do not have', which takes place either voluntarily or involuntarily. Some households or individuals are forced to borrow because of factors beyond their control, while others borrow to increase private consumption because they have access to credit. Getting into debt is a function of both urgent need and creditworthiness. There are also social and cultural pressures that drive some people to borrow, especially in the case of conspicuous goods. For example, since the end of apartheid, the number of lower income households who are beneficiaries of social welfare has increased (Budlender & Woolard, 2006)The increase in disposable income results in these households being more credit worthy to incur debt (Gous, 2008). Consumers earning less than R3500 per month, most of whom are welfare recipients, represent 24% of credit active customers in South Africa (Watson, 2008).While there is a growing concern about consumer over-indebtedness around the world, there is less agreement on how it should be measured or defined. The current understanding of the problem is based largely on the level of borrowing or the extent of arrears, using indicators that take into account either the gross stock of household debt, net household liabilities, and/or the capacity to service the debt (Betti, Dourmashkin, Rossi & Yin, 2007). There are two broad approaches found in literature; subjective and objective (Getter, 2003; Niemi-Kiesiläinen & Henrikson, 2005; Betti et al., 2007; Anderloni & Vandone, 2008).

The objective measures use information on the economic situation of a household or individual to measure its relative financial burden, with reference to a defined threshold considered to be the critical level of indebtedness. This approach uses ratios to measure debt, which include the total debt-to-income ratio, debt-to-assets , repayment-to-income, default and arrears, net wealth, expenditure to income and the number of loans (Chichaibelu & Waibel, 2018). It is based on observable indicators, and gives insight on the consumers' current or future capacity to satisfy financial obligations. It is a good indicator of consumers' immediate financial burden (Anderloni & Vandone, 2008). These measures can be used individually or together. The limitation with objective measures is that they can underestimate the burden of indebtedness as they fail to capture the sacrifices that households make to service their debts (Schicks, 2014).

The subjective model of indebtedness relates to the consumer's own perception of their capacity to pay their due financial obligations without threatening the resources needed for subsistence. It poses that individuals (and households) are better positioned to judge their own levels of financial pressure. The difference is that consumers in the subjective model are expected to report if they are able to repay their debt when due without altering their financial position. The subjective criterion encompasses debt problems that may not otherwise be recognised (Niemi-Kiesiläinen & Henrikson, 2005). Schicks (2014) considers a household's struggle and sacrifice related to debt repayment, including reducing spending on food, taking children out of school, working additional jobs and increasing work hours. However, subjective debt measures can be inconsistent as they depend on the borrower's attitude and degree of financial literacy (Chichaibelu & Waibel, 2018).

Some analysts use a combination of subjective and objective indicators as each measure of debt captures a different aspect of the problem. Both debt measures used in this study from the NIDS dataset are objective indebtedness measures.

3.2.2 Drivers of Indebtedness

There are a number of theories which infer why people get into debt. Most literature references the irrationality of human beings or their inability to see the value of saving for their future (Richins & Dawson, 1992; Santos & Fernandes, 2011; Roazzi, 2011). This section gives a brief summary of the life cycle theory which has been used in literature to explain behaviours that lead to being overly indebted. It then uncovers the framework behind the most relevant theory about debt and behaviour, which is the relative income hypothesis.

Economic literature suggests two distinctive factors which influence indebtedness: irrational behaviours (poor judgement or myopic behaviour) and unavoidable circumstances. Some people get over-committed as they attempt to keep up with the cost of living, which can occur simultaneously with unexpected events. Others, in an attempt to maintain or aspire to a certain standard of living, make spending mistakes. Poor judgement entails credit provision practices and consumption behaviours (Niemi-Kiesiläinen & Henrikson, 2005). Myopic behaviour occurs when a consumer over-commits their finances, or when there is a lack of 'transparency' from credit providers about their credit terms (e.g. Disney et al., 2008; Peterson, 2008; Anderloni & Vandone, 2010).

Sociology models concentrate less on irrationally, and suggest that over-indebtedness occurs mostly as a result of household situational factors (Getter, 2003; Disney et al., 2008; Keese, 2009). Unexpected shocks affect individuals or communities and can trigger a decline in individual or family well-being, which may force them to borrow more in order to get through a bad situation or renders them incapable of repaying their current financial obligations; indebtedness then accumulates to unmanageable levels (Draut & Silva, 2003; Dickerson, 2008; Lupica, 2009). Therefore individuals can be overly indebted regardless of income level.

In practice it is difficult to judge whether the debt problems have been the result of reckless behaviour or a desperate attempt to make ends meet, as there is a definite causality between desperation and poor judgement. Also, in many cases consumers might be living on the edge with huge debts, to the degree that the occurrence of a shock might just push them over that edge (Disney et al., 2008).

3.2.2.1 The Life-Cycle Theory

The demand for debt is a function of the household's underlying plan for consumption and its deviation from income and expenditure (Bryant, 1990; Ludvigson, 1999; Bertola & Hochguertel, 2007). The core assumption of this model is that consumer behaviour is characterised as the maximization of expected lifetime utility subject to a budget constraint and on the available information (Gourinchas & Parker, 2002; Deaton, 2005; Bertola & Hochguertel, 2007). Consumers try to maximise utility from lifetime consumption by altering their consumption patterns to their needs at different stages of the life-cycle independent of income by building up assets (saving) and running down assets (borrowing). For economists, this approach is attractive because it meshes well with the traditional notions of economic rationality.

Because the life-cycle theory does not allow for any miscalculation or imprecise assessment of vital information (Bryant, 1990), consumers are prone to suboptimal consumption decisions. The idea of optimising consumers has been criticised on the grounds that consumers are rationally bounded (Barros, 2010; Camerer, 1998; World Bank, 2015). Graham and Isaac (2000) find that the behaviour of even highly educated consumers deviates radically from the neoclassical predictions. Consumers are inherently impatient and they use rules of thumbs when making decisions. This alters the behaviour needed to follow the saving pattern that would be required to solve the optimisation problem presented by the life-cycle point of view (Graham & Isaac, 2000). In addition, uncertainties regarding future income means that a positive demand for credit should be expected when current income and liquid assets fall short of consumption wishes, and the opposite should be expected to hold true (Shefrin & Thaler, 1988; Thaler, 1994; Graham & Isaac, 2002).

3.2.2.2 Relative Income Hypothesis

Duesenberry's (1949) "relative income" hypothesis suggests that lagged consumption explains current consumption, irrespective of income, assets and interest rates. This hypothesis sits on two premises: firstly, each household obtains utility from its consumption relative to the average consumption levels of other households; and secondly, there is a ratchet effect where consumers get used to a consumption standard and when income drops unexpectedly they take some time to adjust to the lower level of income.

The relative consumption hypothesis reconciles cross-sectional evidence for a low marginal propensity to consume with that for a high average propensity in aggregate time series. If there are lags in the perception of the average consumption levels of others, the individual’s level of consumption will match the perception they hold about their neighbours. When this perception changes, the consumption also changes. The hypothesis attributes this behaviour to habit persistence (Graham & Isaac, 2002).

Similar to the life-cycle theory, there are two versions of habit formation that are common in the literature: rational and myopic. When habits are rational consumers are aware that their current and future behaviour may have direct implications for future marginal rates of substitution (Shefrin & Thaler, 1988). If habits are myopic, past consumption influences current rates of substitution but consumers are unaware that current consumption may do likewise in future. They are thus constantly being surprised, even if they forecast their budget constraints accurately. The marginal rates of substitution for current consumption are independent of consumption patterns in earlier periods. Habits are a particular kind of breach of in intertemporal separability and are usually considered to be myopic (Stone & Rowe, 1958).

Consumers might borrow without regard to the costs or possible consequences thereof, and their borrowing might exceed their capacity to repay on time (Anderloni & Vandone, 2010). Other consumers might borrow within their means, but unfortunate events that might follow (e.g. job loss, health problems, or divorce) and erode their capacity to continue servicing their financial obligations (Prinsloo, 2002).

3.2.3 Theoretical Relevance in the South African Context

The above-mentioned theories cannot be used blindly when in unpacking the dynamics of household debt in South Africa. South Africa is a unique country where people in different income groups experience very different realities. The relative income hypothesis might partly explain how people who have means to save tend behave when they consider their environment, but its applicability on the poor is limited.

Schoombee(2000) and Mashigo (2006) find that unemployment and poverty are the greatest cause of survival debt. Since the majority of the country lives in poverty, some consumers will take on an unreasonable amount of debt (either knowingly or otherwise) to feed their families and later find themselves financially overstretched and unable to repay (Bertaut et al., 2009; Zhu, 2011). Poor households in South Africa are estimated to be spending between 50% and 80% of their income on food (Muller, 2008). The middle class along with the poor have felt the most pressure with the recent price hikes in electricity, fuel and food prices. The poor have subsequently become poorer, while the middle class has filled the financial gap with debt since they have access to credit markets. Food prices have risen exponentially over the past decade, and food for low-income households accounts for a much greater part of their budget (Van Rooyen, 2008). This explains why most of the loans to poor households in South Africa are spent on basic necessities (Black Sash, 2000). The debt behaviour of the poor is further characterised by informal borrowing from relatives, neighbours, friends, credit at the local store and credit from informal sellers of goods (Collins, 2007). Whenever there is a need for money or basic necessities, most people in these communities turn to those closest for help, who expect them to return the favour some time in the future (Mashigo, 2006). However, a significant proportion of low-income borrowers in South Africa borrow from micro-lenders, as their income is too low to meet basic expenses for survival (Schoombee, 2000). The poor usually have low educational attainment, which is associated with low financial literacy, making them vulnerable to borrowing from high-interest sources (Hurwitz & Luiz, 2007; Gathergood, 2012).

While we do suggest that the relative income hypothesis is not always relevant, we shy away from implying that it is completely inapplicable. The propensity toward indebtedness may be influenced by behavioural factors, such as values toward money, materialism, risk perception, and risk behaviour. People who classify money as a form of power and status tend to maintain a high level of consumption, which may lead to indebtedness. This scenario also encompasses materialism. Poverty is not bullet-proof from making financial decisions out of social and cultural pressures. For example, Banerjee and Duflo (2011) found that in African communities funerals can influence social status. Funerals are a strong contributor towards the indebtedness of the poor.

People who have high levels of materialism have, as a consequence, high levels of propensity toward indebtedness. Individuals with high risk perception tend to have lower levels of indebtedness because their aversion prevents unplanned expenses. Regarding this behavior, people who risk loving are more willing to be in debt. Katona (1975) and Flores & Vieira (2014) postulate that individuals with higher income tend to have a higher propensity toward indebtedness, followed by those with a lower salary range. In addition to income, it is observed that there are significant differences in the level of indebtedness according to age, gender, marital status, education, religion, religious principles, occupation, credit card use, dependence on credit, and expenses.

The relative income hypothesis may depict a more accurate picture about the behaviour of [a portion of] the new middle class in South Africa. This income group is known for using credit cards, store accounts and hire-purchase agreements to acquire goods for building social status (James, 2013). The South African middle class tends to have enough to eat but not enough to live the ideal lifestyle portrayed on social networks. 'Black Tax' for the black middle class means that the individual's monthly income is split between their own household (with immediate family) and another household where there are relatives or parents (Ngwadla, 2018). The financial burden of maintaining two or more households has been associated with increased use of debt.

The percentage of total credit-active consumers that are classified as impaired or in default rose from 43.89% in March 2018 to 45.45% in June 2018 (Experien, 2018). Reports of South Africans being over-indebted continue to reverberate in news headlines and academic as well as political rhetoric. For instance, an article on Fin24 (2018) recently stated how single women in South Africa seem to be struggling with their debt more than their single male counterparts. This finding was based on statistics reported by DebtBusters (a debt counselling and consolidation firm). Single women under debt counselling had more unsecured debt (71%) than single men (55%) under such counselling. The unsecured debt was often used to obtain cash to try to make ends meet. Non-consumer debt originates when households borrow for the purpose of creating or running a business, buying a house, land and other real estate (mortgages), or for home improvements. Most non-consumer debt is 'secured debt' (backed by collateral), either by the asset it was used to purchase or by another valuable asset. For example, a mortgage loan is secured by the home it helped purchase and a business loan may be secured by the business itself or by the business owner's home.

Sanlam (2017) showed that 73% of professional middle-class South Africans were distressed about their financial well-being, with more than 50% of credit-active members being three months or more in arrears with their debt repayments. The most significant sources of financial stress identified by the Sanlam survey were short-term debt obligations (car, credit card and personal loans), not being able to save for the future, or unanticipated emergencies. Some of the middle class have resorted to buying food with credit cards or borrowed money.

The household debt dynamics of South Africa seem to paint as similar picture as other developing countries such as Morocco, Pakistan, Ghana and India (Chen et al., 2010; Lascelles & Mendelson, 2012). Research on over-indebtedness in these countries has shown that poor households often borrow from high-interest bearing sources. In India, debt defaults have been related to suicides (Chen et al.,2010) which confirms the relationship that exists between debt and depression. Households acquire debt while trying to cover necessities, but social and cultural factors also play a significant role.

In view of the South African social context of debt, we expect indebtedness to be highly concentrated among the poor and the vulnerable middle-income class households. However, the high-income group might also be indebted if they have a strong desire to spend as suggested by Katona (1975). We also expect to see a relationship between demographic factors and debt as South African women and the black population group show more vulnerability to debt other groups.

Chapter 4: Data and Measures

4.1 Data

In this study, to estimate the level of indebtedness and the risk of developing depression given financial indebtedness we use panel data from the National Income Dynamics Study (NIDS) implemented by the Southern Africa Labour and Development Research Unit at the University of Cape Town (Brophy et al., 2018). At time of writing there were four waves of data available, each spaced approximately two years apart, with the first wave in 2008 covering more than 28 000 individuals and 7500 households. Wave 5 is latest wave, added in 2017. As mentioned above, our study is an adapted application of the methodology of Bridges and Disney (2010). It begins by using waves of NIDS data as cross-sections in order to profile..

Bridges and Disney (2010) examine the effect of household financial indebtedness on psychological well-being using a large household panel survey (the UK Families and Children Survey) of families in Britain collected between 1999 and 2005. The UK Families and Children Survey (FACS) was originally designed to collect information on household characteristics, health status and the economic and financial position of a sample of low-income families with children. The main aim of FACS is to examine the effectiveness of the then new government work incentive measures. The FACS survey like NIDS asks questions about aggregate household debt, ownership of specific assets and the use of particular credit instruments. The NIDS dataset is similar to the FACS survey in that it is also a national panel study in South Africa. It examines the livelihoods of individuals and households overtime, providing information on poverty and well-being; household composition and structure; labour market participation and economic activity; health, psychological well-being and education amongst other themes. NIDS is an initiative by the government to track and understand the shifting faces of poverty. The NIDS dataset allows us to explore most of the variables listed in the literature.

NIDS is South Africa's first national panel study covering five waves of data. We limit the focus of this study between wave 2 and wave 4, wave 3 is excluded because does not have the debt measures we are using. Wave 2 has 9128 households and 34 086 individuals surveyed and Wave 4 surveyed 11 898 households and 42 348 individuals (SALDRU, 2016). Wave 2 took place in two phases, and respondents in phase 2 were asked fewer questions that those in phase 1. This increases the number of missing values in the data on some of the variables. However, based on the scale of the survey we expect the estimates to be representative of the South African population. Our focus is on debt dynamics, and thus individuals need to be tracked successfully over at least two waves. To correct for attrition on each wave, we apply cross-sectional weights.The sample used in this study for regression analysis is restricted to individuals and households who were successfully interviewed in both wave 2 and wave 4. A household is successfully re-interviewed when all the members belonging to the house registered in wave 1 are interviewed in other waves, unless they have passed away or refuse to continue participating in the survey.

Panel weights are applied to for correct attrition in the panel study (Brophy et al.,2018). We use these panel weights when we are doing panel analysis of the two waves. Of the 26 775 sample members who were successfully interviewed in 2008, 15 673 were re-interviewed in all four subsequent waves; thus the attrition rate for the balanced panel is 41.47%. There is a high success rate for interviewing respondents who were missed in one wave in the subsequent wave. Attrition between waves is therefore lower, ranging between 9% and 21%.

4.2 Measures

4. 2.1 Depression

The depression outcome was assessed using the Kessler Psychological Distress Scale 10 item (K10) of the Centre for Epidemiologic Studies Depression (CES-D) Scale. This scale was developed for use in epidemiological studies to identify people in the general population who are experiencing non-specific psychological distress (Bruce, Takeuchi & Leaf, 1991). The K10 scale is widely used as a self-report scale to screen for depression (Burns, 2014). NIDS includes this 10-item version of the CES-D scale, which probes the frequency of various feelings including depression, loneliness, fear, hopelessness and happiness. The depression variable was created using information from the emotional health section of the Adult questionnaire.

The CES-D 10 scale has questions about how often the study participants experienced symptoms of depression in the past week. The scale asks about the respondent's mood over the past week on a 4-point (0-3) scale. Responses to these questions were coded in a Likert format, where '0' was '*Rarely or none of the time*' (<1 day), and '3' was '*Almost all or all of the time*' (5-7 days). The depression outcome was assessed as a sum of scores of the 10 items. The final score ranges from 0 to 30. A score of twelve or above indicates the presence of mild to significant depression (Eyal & Burns, 2017; Baron, Davies & Lund, 2017). The K10 scale is widely used in the literature for depression in developing countries.

A problem within this field of study is a lack of commonality in the measures used to assess emotional health. Life satisfaction, depression, anxiety and self-perceived health are some of the options available to researchers to measure psychological health. The majority of mental health-screening instruments, including CES-D 10, are created in developed countries, where individuals face a widely different set of challenges to those living in lower-income countries, and the cultures are not similar. The translation of CES-D 10 questions into other languages may also lose something of essence relative to the original questions. The idioms used to describe depression in different languages and cultures are important (Eyal & Burns, 2018). A recent study tested the reliability and validity of the CES-D 10 in Zulu, Xhosa and Afrikaans populations in South Africa and concluded that it is a valid screening tool for depression (Baron, Davies & Lund, 2017).

In South Africa the CES-D 10 score is widely used and has been verified for use as an initial screening tool. The score has been found to be consistent both internally and in repeated testing in other countries and in South Africa. The internal reliability using Cronbach's alpha for the CES-D in South Africa was 75%. Cronbach's alpha is a measure of internal consistency for a psychometric scale, where a value above 70% indicates reliability. The scale is also consistent when compared to shorter and longer versions of the same questionnaire. One advantage of the CES-D 10 scale is its ability to successfully ask questions about mental health without explicitly mentioning the names of any psychiatric conditions. This mitigates the effect of high levels of stigma on data quality. African communities tend to have higher levels of stigma associated with psychiatric illnesses. On the NIDS data the rate of response for CES-D 10 are high.

4.2.2 Debt Measures

4.2.2.1. Negative Asset Value

NIDS collects data on personal debt in Section G of the Adult questionnaire. Questions G11-G21 ask each adult whether they hold loans from a variety of sources, vehicle finance, a credit card, a store card or a hire purchase agreement. An individual who answered yes to any of Section G questions is considered to be positively indebted (Nyawurata & Leibbrandt, 2009). To understand the individual's perception of what their finances currently look like, we consider their response to the question:

"Suppose you (and your household members living here) were to sell off all your major possessions (including your home), turn all of your investments into cash and pay-off all your debt - would you have something left over, break-even or be in debt?"

The non-response to these questions are low, with possession of debt questions having approximately 88% and 90% response rates for wave 2 and wave 4 respectively. Table 1 shows the non-response rates on the types of debt the respondents hold. Low non-response rates allow for an accurate representation of the possession of debt by many individuals; however, there may be a bias in the level of debt that is estimated from the data if there is a high non-response rate for outstanding balance of debt and monthly debt payments among those who said they do have debt (Nyawurata & Leibbrandt, 2009). Non-response regarding what would happen if they sold their share of household possessions was high, with the bulk of such non-responses being 'Don't Know' – indicating that participants may have had difficulty in calculating the exact net balance of their assets and debts. Wave 2 non-response on this question is 52.22%, which declines significantly to 30.22% in wave 4.

Table 1: Non-Response Rates for Debt Variables

Variable	**Variable Label**	**Non-response for possession of this type of debt**	
		Wave 2 (%)	Wave 4 (%)
G11	Bond	11.96	10.14
G12	Bank Loan	12.09	10.03
G13	Microlender	11.94	10.01
G14	Mashonisa	11.90	10.00
G15	Student loan (Bank)	11.88	10.03
G16	Student Loan (Other)	12.00	10.40
G17	Vehicle Loan	12.06	10.12
G18	Credit Card	12.00	10.03
G19	Store Card	11.98	10.01
G20	Hire Purchase	11.98	10.03
G21	Family Loan	11.93	9.92
G22	Friend Loan	11.95	10.06
G23	Employer Loan	11.99	9.99

Nyawurata and Leibbrandt (2009) found that age is a significant determinant of the 'Don't know' response. In terms of race there was a significant difference only between African and Coloured respondents, with the latter having a higher probability of such non-response. Interestingly, the probability of non-response on the balance increased with the associated income quintile and with the highest education attained. This may have been a result of individuals in higher income segments having more complex financial instrument facilities and thus struggling to recall the exact amount outstanding in a specific category of debt.

As in any panel study, sample attrition is a concern. Despite using weights throughout the analysis that partly mitigate the sample bias caused by non-random attrition, there is reason to believe that the presented model may be biased due to some individuals exiting the panel. First, attrition is generally highest among the wealthy households, which is a cause of concern because the high-income households have the highest level of debt due to mortgages and other debts associated with acquiring assets. Zizzamia and Leibbrandt (2016) found that controlling for observable characteristics, the unobservable factors governing panel attrition are not significantly correlated with the unobservable variables affecting poverty transitions. Therefore, we are confident that our results are not affected to any important degree by attrition as we later balance the panel for depression and indebtedness. Besides, NIDS follows individuals and not households. This means that individuals that belong to a particular household in wave 2 will not necessarily belong to the same household in subsequent waves. Nevertheless our analysis works on the assumption that household resources in wave 2 are relevant in determining indebtedness in wave 4, adding a limited set of controls for changes in household composition.

4.2.2.2 Financial Stress

We construct another measure of debt called Financial Stress using the household monthly expenditure variable. We compare the size of monthly expenditure to monthly income (household monthly expenditure/household monthly income) to determine which households spend more than they have. The construction of this variable is based on the loose definition of debt; expenditure exceeding income (Ssebagala, 2016).

The NIDS questionnaire design focuses on the last 30 days prior to the interview in the measurement of income and expenditure, with a few exceptions in the individual level data. Reporting on the activities that happened in the last 30 days reduces recall bias and gives a good snapshot of the welfare of the household over the past month. NIDS has two sources of income data. There is a one-shot question from the household questionnaire which asks for the total amount of household income after-tax. The second source is at individual, where the responded reports on their income from different sources including employment, government, rental and etc. Total household income is calculated by aggregating across the questions (i.e. using both sources of income). Expenditure data is collected at household level. The total monthly household expenditure variable is derived using three expenditure variables (total monthly food expenditure, total monthly non-food expenditure & rent per month). Imputations are used to correct for item non-response (by responding household) for specific expenditure items, which allows a construction of a complete household expenditure aggregate.

Both, Negative Asset Value and Financial Stress are used in the empirical model in Chapter 5.

4.2.3 Demographic Characteristics

Based on the above review of literature on the triggers of depression universally and in South Africa, the independent variables discussed below are relevant controls in investigating the likelihood of depression and the level of indebtedness. The inclusion of socio-economic and demographic characteristics follows existing literature by on determinants of debt (Disney & Bridges, 2010; Brown et al., 2014, Disney et al., 2008, Schicks, 2014).

Age, Gender

Age is an important determinant for acquiring debt. (Bridges & Disney, 2004; Drentea & Lavrakas, 2000; Lea, Webley, & Levine, 1993; Livingstone & Lunt, 1992) find that a younger age increased the risk of indebtedness. Another influence factor on indebtedness is gender. Some researchers find that women have a stronger debt repayment performance which is associated with lower risk of being indebted(Chant, 2013). South African debt reports show that women report more debt than males (DebtBuster, 2017; Du Plessis, 2007). Moreover, women are inherently more susceptible to depression than men genetically (Albert, 2015).

We expect to see significant differences between genders, although we cannot determine the direction of differences as literature is inconsistent.

Household Size, Number of children, Number of unemployed

The number of children; elders; and unemployed individuals all contribute to the sources and distribution of income in the household. Reading and Reynolds (2001) investigated maternal depression among women with young children and found a positive link. Having children in a household can also provide income through social grants. In South Africa, the two most important social assistant programmes are the state Old Age Pension and Child Support Grant. These unconditional cash transfer programmes are linked to reduced poverty and vulnerability, and have been shown to increase educational outcomes in South African households (Budlender & Woolard, 2006). Livingstone and Lunt (1992) find that having more children reduced the risk of indebtedness.

We expect that a higher number of unemployed people in a household will increase the risk of depression, while more children are likely to reduce this risk particularly if they are social welfare recipients. A big household dependant on a single or small income source is also likely to increase the risk of depression (Lytton & deVaney, 1995).

Education and Employment, Income Class

In South Africa, education is a strong determinant of employment which is strongly associated with positive mental health outcomes (Goldsmith, 2007). The effect of education on the probability of being depressed maybe be positive or negative. As stated in the literature review, South Africa has a high unemployment rate which has been shown to deteriorate mental health (Kawachi & Wamala, 2006). Moreover, job searching can displace household income through travel fares to [and from] areas of high economic activity and can lead to indebtedness (Wittinberg, 2002).

We use expenditure as a measure of economic welfare rather than income, as suggested by Zizzamia and Leibbrandt (2016). Expenditure is measured per month at household level and covers food and non-food expenditure. We believe that is it a good proxy for resources available to individuals to use. Since our analysis of depression is at individual level, we assume that expenditure is divided equally within the household, which does not necessarily hold in all contexts (Zizzamia, Schotte & Leibbrandt, 2018).

Geography Type and Race

For historical and cultural reasons the extent of indebtedness and the nature of debt is uneven across racial groups. For many South Africans location is partly determined by race (a signal of wealth and income) because of the country’s history, and partly by job search. South African neighbourhoods are profoundly affected by urbanisation. A study by the City of Cape Town (2006) investigated the reasons for migration in the Western Cape province. They found that 65% of the migrants were young (under 30), lived in informal dwellings (57.4%) and were mainly unemployed (51.0%). Because of the perceived better circumstances, these young migrants remained in the province and started families. Informal settlements (which are classified as urban areas) are densely populated with high crime rates, and are positively associated with mental distress (Siefer et al., 2000).

The effects of urbanisation on depression are inevitable given that those who migrate are most likely to end up in informal dwellings that are poverty-stricken. Geographical location is intrinsic to spatial inequality: it affects both mental health and aspirations that can lead to debt.

Health

Debt and the stress surrounding debt have been found to be negatively associated with physical health (Drentea & Lavrakas, 2000; Munster, Ruger, Ochsmann, Letzel & Toschke, 2009; Nettleton & Burrows, 1998). Psychosocial factors, including stress and depression, impact health and a substantial body of work has investigated this pathway. The experience of stress is known to lead to short- and long-term physiological changes that play crucial roles in several disease processes, particularly those involving the metabolic and cardiovascular systems (McEwen, 2015). Stress can also impact health indirectly by influencing health behaviours, including diet, physical activity, and substance use (Case, 2004). Therefore, considering the evidence that debt has psychological consequences, it is possible that it could also impact other health outcomes through psychosocial pathways. Ill-health is also related to debt problems, although the cause and effect are ambiguous.

The health variable used asks the individuals to rate their health between 1 and 5, 1 being 'Excellent' and 5 being 'Poor'. For analysis purposes, we manipulate this variable to have three outcomes instead of the original five. We group those who consider their health as Excellent and Very good together under 'Very good', those who believe their health as Good and Fair under 'Fair', while those who thought of their health as Poor remain ungrouped.

Negative Events

The life cycle model which we briefly described in Chapter 3 notes that unexpected negative adverse shocks can push households into debt (Betti et al., 2007). Similarly, these adverse shocks are associated with an increase in the likelihood of depression. This combination can result in over-indebtedness (Phillips, Carrol & Der, 2015). NIDS collects data on the negative events experienced by households between the waves, and they range from death in the family to destruction of household property. We construct the Shock variable to equal 1 when the household has experienced any kind of negative event since they were last interviewed, else 0.

4.3 Descriptive Analysis of Depression, Debt and Relevant Variables

We start our analysis with some simple descriptive statistics for waves 2 and 4 of the sample data (Table 2). The statistics describe the characteristics of the original sample in wave 2 (2010) and wave 4 (2016), weighted for sample attrition. The sample size in wave 2 is 22 696, whereas in wave 4 is 24 861 individuals. Table 2 provides a descriptive analysis of the pooled sample of Wave 2 and 4, as well as the descriptive information of the group reporting depression. In Wave 2, 5 806 individuals report depression. The number of depressed individuals increases to 8385 in Wave 4.

4.3.1 Depression

We find that 29,96% of the respondents in wave 2 report depression (with a CES-D score above 12). The level of reported depression increases to 38,54% in wave 4. The average CES-D score increases from 8,96 in wave 2 to 10,44 in wave 4. The average CES-D score among the depressed in both waves is 15. The increase on the average CES-D score confirms that the level of depression in wave 4 is indeed higher for the general population. The rise in depression can be associated with several factors that affected the country in 2015, such as an increase in crime rate, fuel prices and unemployment (Lekgetho, 2015).

4.3.2 Demographics

The vast majority of the respondents are women, and consequently, most households have female household heads (79% in both waves). The predominant racial group is Africans at 82%, followed by Coloured, White and Indian, as expected based on the census (Stats SA, 2011). Both samples have more lone individuals/parents than couples with the 'Never Married' averaging above 50% in both waves, and both samples (Full Sample and Depressed Sample). On average each household has 3,19 children in wave 2, which decreases slightly to 2,97 in wave 4, although this may be an age effect. The older children may not have been available for interviewing because they are in educational institutions or moved out in search of jobs and to start their own families. The number of people unemployed in household averages 6 across the scope of our analysis.

Statistics from DebtBusters (2018) show that single women (defined as unmarried or married out of community of property) in South Africa are hit more by debt than their male counterparts. South Africa has a high rate of absent fathers, leaving the burden of raising children to women. Over 60% of children younger than 18 are raised without their biological fathers even though these fathers are alive (Stats SA, 2017).

The average age is 35. In both wave 2 and 4 the majority of the population has less than 12 years of education (Grade 12) at 72% for both waves. Majority of the sample in the data was not economically active at 53,47% in Wave 2 and 48,02% in Wave 4. In the depressed sample, the proportions are quite similar. Employment increases between waves from 30,88% in Wave 2 of the full sample to 38,46%. Similarly, with the depressed sample; the number of people employed increased from 27% in Wave 2 to 40% in Wave 4.

Above 60% of the pooled sample consider their health to be ‘Very good’. This suggests that people are highly optimistic about their health, and are most likely to overstate how good their health is. The individuals who report poor health (below 5%) may have indicated so because they were feeling extremely ill. We regressed poor health against the sicknesses the respondents had experienced in the last 30 days and going to consult a health worker. We found that people who are most likely to rate their health as Poor had experienced (in the last 30 days) cough with blood, tight chest, chest pain, headache, backache, pain/arthritis, pain in the abdomen, pain while urinating, weakness, severe weight loss, or memory loss. The regression output is attached in the appendix (Table A).

Table 2:Descriptive Analysis of Individuals in the NIDS sample Wave 2 and 4

Variables	Full Sample				Depression==1			
	Wave 2		Wave 4		Wave 2		Wave 4	
	Mean		Mean		Mean		Mean	
Age	34,8		35,5		34,42		35,28	
CES-D Score	8,96		10,44		15,28		15,00	
HH Income per month	11191,34		12115,06		9418,31		13312,72	
HH Expenditure per month	8472,78		7839,31		7728,23		9112,61	
Household Size	7,54		6,95		8,70		7,51	
No. of children(age<18)	3,19		2,97		3,56		3,19	
No. of unemployed	6,79		5,87		7,91		6,22	
	N	%	N	%	N	%	N	%
Gender								
Female	10893,26	56,24	14038,02	56,53	3119,32	56,29	4793,47	57,17
Male	8476,73	43,76	10 794	43,47	2422,68	43,71	3 592	42,83
Race								
African	15890,94	82,01	20285,67	81,68	4876,02	87,94	6812,86	81,25
White	1312,36	6,77	2312,68	9,31	129,36	2,33	471,02	5,62
Asian/Indian	508,37	2,62	647,99	2,61	203,47	3,67	186,79	2,23
Coloured	1665,22	8,59	1589,65	6,4	336,06	6,06	914,31	10,9
Marital Status								
Married/Living Together	4496,54	31,8	5765,43	35,83	1110,95	27,42	1835,16	34,43
Separated/Widowed/Divorced	1011,06	7,15	1635,16	10,16	281,19	6,94	561,86	10,54
Never Married	8631,4	61,05	8688,41	54,00	2659,86	65,64	2932,97	55,03
Education								
No Matric	14022,4	72,63	17745,74	71,82	4227,04	76,72	5996,12	71,87
Matric Completed	3367,65	17,44	3887,39	15,73	813,24	14,7	1351,73	16,2
Tertiary	1916,95	9,93	3075,86	12,45	490,72	8,87	995,17	11,93
Employment Status								
Not Economically Active	9345,09	53,47	11322,46	46,7	2989,12	58,4	3730,83	45,4
Unemployed	2671,36	15,36	3597,55	14,83	735,83	14,38	1181,92	14,38
Employed	5369,54	30,88	9324,99	38,46	1393,04	27,22	3302,26	40,22
Health								
Poor	566,34	3,04	746,87	3,07	247,61	4,6	332,88	4,04
Fair	4906,36	26,3	8431,3	34,68	3491,97	64,92	4904,09	59,5
Very Good	13180,29	70,66	15131,83	62,25	1639,42	30,48	3005,03	36,46

Notes: Table Continues to next page

	Full Sample				Depressed Sample			
	Wave 2		**Wave 4**		**Wave 2**		**Wave 4**	
	N	**%**	**N**	**%**	**N**	**%**	**N**	**%**
Is Household Head? No	14069,51	72,61	17095,89	68,84	4079,34	73,56	5988,10	71,41
Yes	5307,49	27,39	7740,11	31,16	1465,96	26,44	2396,89	28,59
<u>Household Characteristics</u>								
Income Group								
Poor	14851,94	76,65	17562,12	70,72	4691,52	84,61	5789,3	69,04
Vulnerable Class	2064,33	10,65	4007,52	16,14	454,36	8,19	1514,04	18,04
Middle Class	1826,07	9,42	2575,54	10,37	284,02	5,12	897,33	10,7
Elite	634,65	3,28	688,83	2,77	115,1	2,08	184,33	2,2
Geography Type								
Rural Traditional	7779,27	40,45	9575,46	38,55	2289,76	41,67	2487,77	29,67
Urban	10520,76	54,71	14222,54	57,27	2798,04	50,92	5613,13	66,94
Rural Farms	929,96	4,84	1037,99	4,18	407,19	7,41	284,09	3,39
Negative Event or Shock								
No Shock/Negative Event	14392,74	74,28	21817,88	87,85	3940,38	71,06	7337,48	87,51
Experienced Shock	4984,26	25,72	3018,12	12,15	1604,68	28,94	1047,52	12,49
<u>Financial Variables</u>								
Debt Measures								
Negative Asset Value	1131,34	5,84	2081,77	8,38	483,96	8,73	1066,64	12,72
Asset Value≥0	18245,65	94,16	22754,23	91,62	5061,04	91,28	7318,36	87,28
Financial Stress								
Yes: HH Expenditure > Income	5631,09	29,06	5071,92	20,42	1633,04	29,45	1821,67	21,73
No: HH Expenditure ≤ Income	13745,09	70,94	19764,08	79,58	3911,96	70,55	6563,33	78,27
N	**22 696**		**24861**		**5 806**		**8385**	

4.3.3 Financial Variables

About 5,84% of the respondents reported they would be indebted in wave 2 if they sold all their assets and paid their liabilities, compared to 8,38% in Wave 4. With the depressed sample, we see that the number of respondents who report indebtedness increases from 8,34% (full sample, wave 4) to 12,7%. Wave 2 shows a similar increase between the whole and depressed sample. Approximately 70% of the sample households spend less than what they earn per month, with about 50% dedicating less than 75% of their monthly income to monthly expenditure. However, close to 30% of households in Wave 2 (20,42% in Wave 4) spend more than they earn.

We further look at the proportion under each type of debt. Table 3 gives the proportions of the people who confirmed having debt. The proportion of households in debt between wave 2 and 4 increases. The growth rate in the use of store cards between wave 2 and wave 4 is more than 100%. About 18.24% of the sample had store cards. We also notice that the number of people with bank loans is higher in wave 4. These findings confirm the report from Debt Counsellors (2018) where a significant number of the people receiving debt counselling were found to hold numerous store account cards as well as personal loans from the bank. The number of people who have debt from the Mashonisa in wave 4 is twice the number in wave 2. More and more people are consulting informal lenders to obtain credit.

Table 3:Debt Proportions in Wave 2 and 4

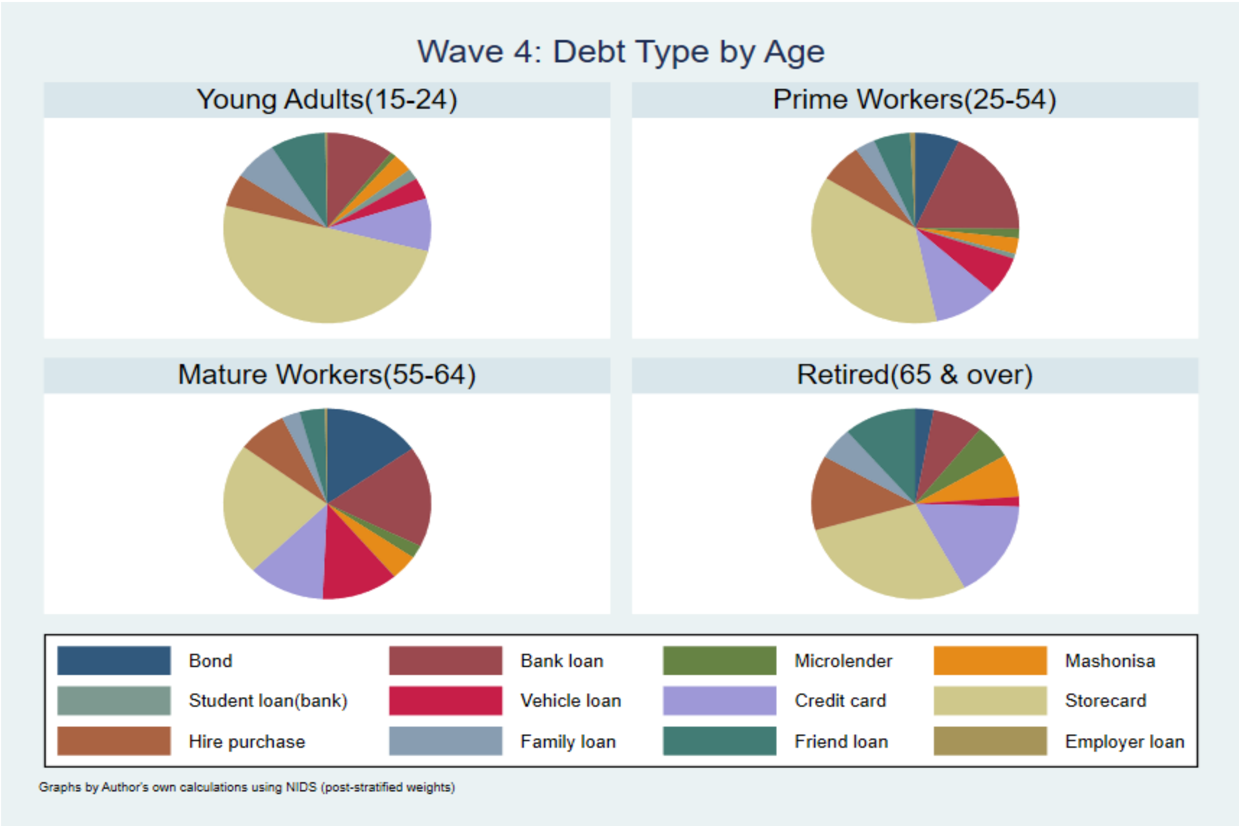
Types of Debt (if Yes)	Wave 2		Wave 4	
	N	*%*	*N*	*%*
Bond	669	3.98	817	3.6
Bank Loan	578	3.44	1995	8.78
Microlender	79	0.47	198	0.87
Mashonisa	149	0.89	349	1.54
Student loan (Bank)	58	0.35	97	0.43
Student Loan (Other)	43	0.26	78	0.34
Vehicle Loan	408	2.43	786	3.46
Credit Card	708	4.21	1223	5.38
Store Card	1452	8.63	4179	18.39
Hire Purchase	316	1.88	777	3.42
Family Loan	123	0.74	404	1.78
Friend Loan	150	0.89	698	3.07
Employer Loan	36	0.22	76	0.34

The number of debts a household has difficulty repaying tend to be of more concern to respondents than the actual value of any arrears (Disney & Bridges, 2016). The data used in this paper does not ask respondents about being in arrears but do ask about the remaining balance of debt. The response rate on the questions about debt balances are very low, reinforcing that people are more concerned about what they can pay now than the actual value of arrears.

4.4 The South African Debt Profile with NIDS Wave 4

In this section, we profile household debt to get a better understanding of the level of indebtedness in our sample. We further examine whether the predictions from the relative income hypothesis are present in the NIDS data. We only use wave 4. The figures below present the debts across various covariates including age, gender, and income class.

Figure 1: Debt Types by Age

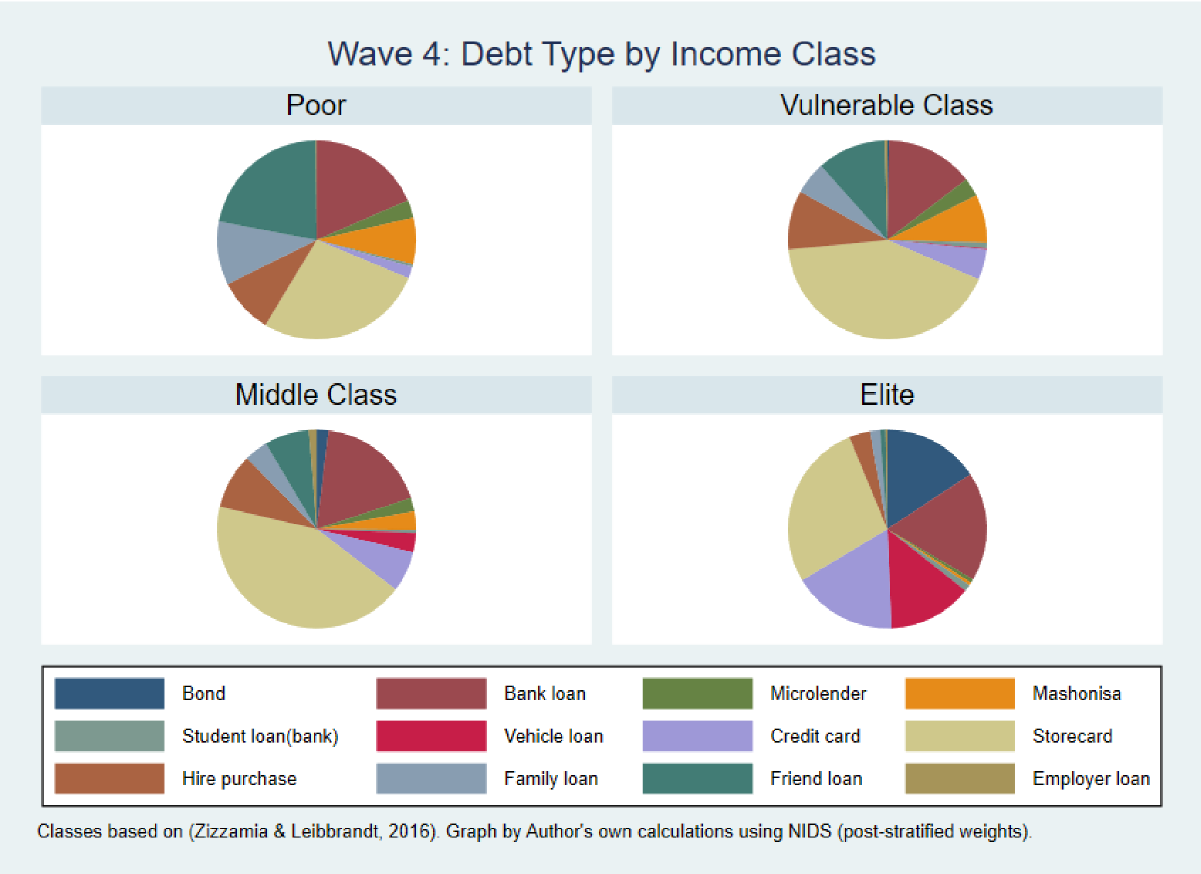


The dominant debt category throughout the age groups are storecards (Figure 1). It appears that the young adults acquire more store accounts that the other age groups. The older people are, the more they use credit cards. One of the reasons why young adults might have more storecards than any other form of debt is because store account credit is easily accessible compared to credit cards which have strict income requirements. The income requirement for store accounts tends to be low, and we can assume that people aged between 18 and 24 years do not have high income, since they are new in the workforce. New entrants into the job market tend to have little knowledge about credit dynamics (Barba & Pivertti, 2008). Storecards provide access to borrowing which is explicitly tied to the purchase of small-ticket items (with low or no second-hand value) such as clothing.

Prime workers and mature workers have high proportions of bonds, vehicle loans and bank loans, which speaks to their life stages where they are working towards building stable home environments. Bank loans are not usually linked to a specific purchase or asset and they usually do not have collateral. For these loans a specified amount is extended at a specified interest rate with specified maturity and a prescribed repayment plan; the size of the loan is often dependent on assessment of the repayment capacity. The amounts involved may range from very small (with a maturity of just weeks) to substantial with a maturity of a few years.

It is a social norm to have your 'own home' (even if it is a rental) when a person joins the working class. By the age of 60, most people have paid up their bonds or bankloan debt to reduce financial strains while retired; hence the proportion of bonds in the retired group is small. The proportion of informal lending sources increases with age. Informal debt results from borrowing from relatives, friends, or Mashonisa or microlenders. There are no institutionalised terms of payment or interest rates, except those mutually agreed to between the lender and borrower. Individuals in their old age, especially these who worked elementary jobs, are mostly likely to experience increasing household financial burdens when they stop working (Worthington, 2006).

Figure 2: Type of Debt by Income Group



All households in every income group have a large proportion of storecard debt, making up the biggest debt for the vulnerable class and middle-class groups (Figure 2). Following storecard debt are bank loans for all the income groups. It is surprising to see that people in the lower income class have access to bank loans. This shows that the financial industry in South Africa has become more inclusive over time. However, there is still a significant number of people in the poor and vulnerable class depending on their friends and family to access credit. The proportions of Mashonisa and hire purchase debt are higher for the poor, vulnerable class and middle class. The elite have the more credit cards, vehicle loans and bonds than the other income classes. Females have more debt in the bracket R0 to R5000 than male counterparts. This confirms the findings in literature about women acquiring more debt to make ends meet. At the same time, the proportion of males with debt in the same bracket is above 50%, which suggests that it is not just females borrowing to survive. Figure 3 shows that both males and females have high unsecured debt (storecards, credit cards and bank loans). Total debt by gender confirms that debt behaviour by males and females is very similar (Figure 4).

Figure 3: Debt type by gender

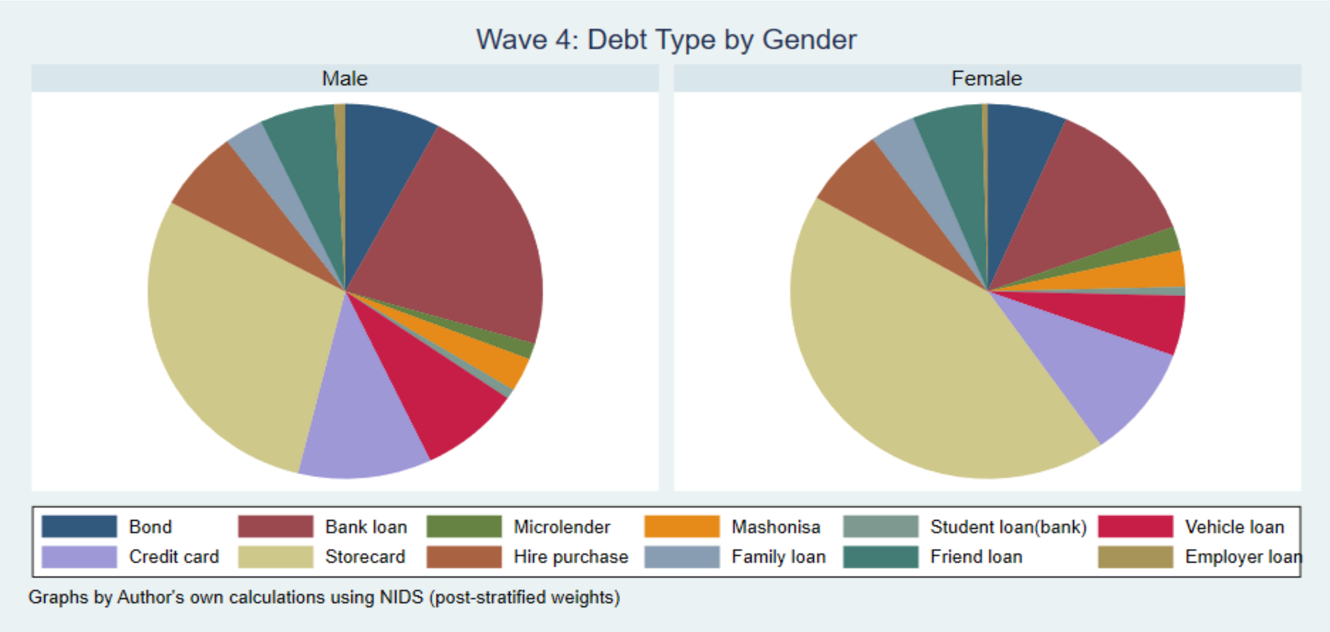
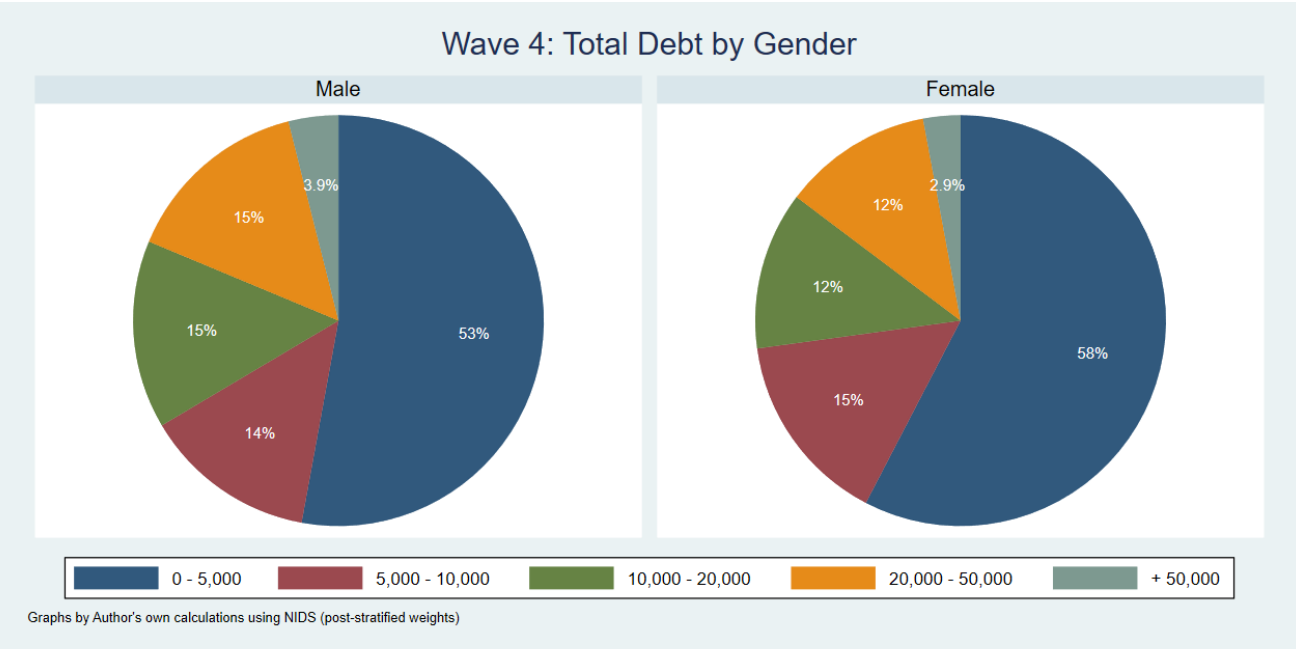
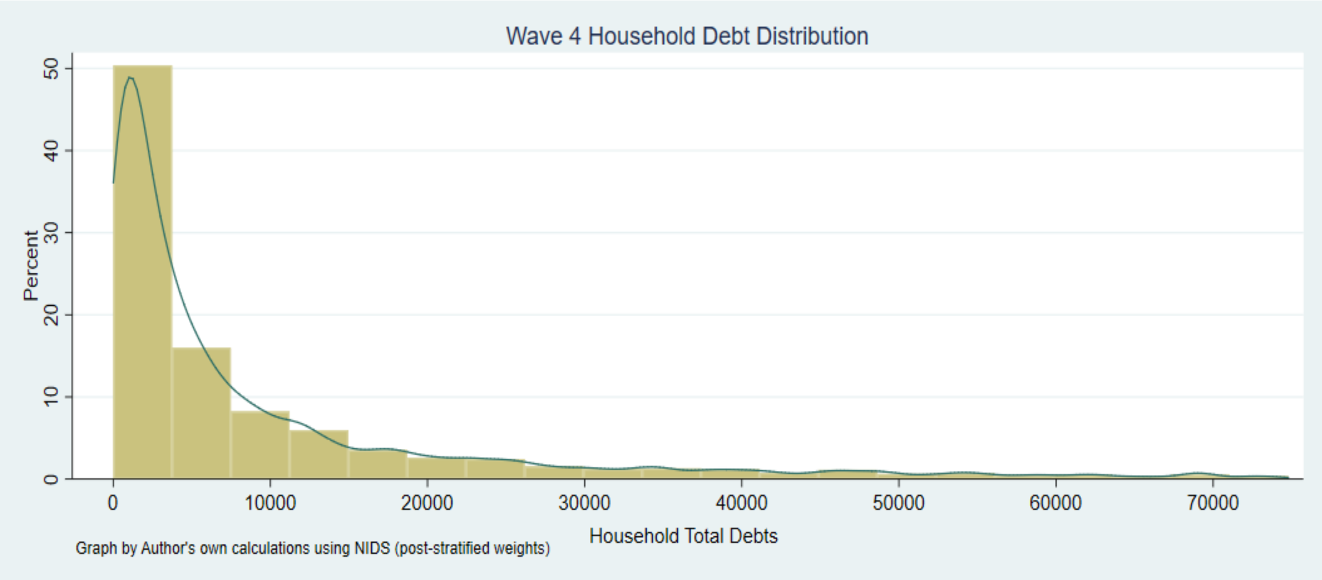


Figure 4: Total Debt by Gender



The distribution of debt (Figure 5) in South Africa is concentrated in the lower bracket, with the majority of the population owing less than R10 000. Given that more than 50% of the country's population is living in poverty, these numbers are not surprising.

Figure 5: Total debt distribution



Chapter 5: Modelling Debt and Depression

The consumer debt situation in South Africa is very clear. Unsecured debt among the population is common across all income groups and age categories. In this chapter we unpack the extent to which consumer indebtedness in the country affects reported depression in South Africa using NIDS datasets from waves 2 and 4. Literature reviewed earlier established a strong link between high levels of debt and mental illness (for example, Roberts et al., 1999; Brown, Price & Taylor, 2005). The first task is to confirm that for this NIDS sample there is indeed a relationship between reported depression and self-reported measures of financial difficulties.

As explained earlier, with the NIDS data, we have two debt measures (1) Negative Asset Value (2) Financial Stress where household expenses exceed income. The data collected by NIDS allows us to analyse the correlation between indebtedness and reported depression. In our analysis, both debt measures are binary, as is the depression variable. The negative asset value takes the value 1 if the responded expects to be indebted if they sold all their assets and resolved liabilities, and 0 otherwise. The financial stress variable takes the value of 1 if the household has higher expenditure than income and is poor; otherwise 0. Since the measures of debt are correlated and substitutes, we control for them in separate model specifications.

Therefore, from the econometric point of view, we are interested in explaining the impact of debt and other socioeconomic factors on a CES-D score indicating depression. Such binary outcome variables are the simplest case of a discrete choice situation and can for example be analysed using a probit model, including in panel data analysis. Our empirical models broadly replicate (Bridges and Disney, 2010), while using the NIDS dataset rather than the FACS data.

Bridges and Disney (2010) use three steps to empirically model the relationship between debt and depression. They start by estimating the impact of indebtedness on depression using a univariate probit. This estimation does not deal with endogeneity and, therefore, they use the recursive bivariate probit approach to address potential endogeneity between covariates. Lastly, they use their panel data to look at the impact of a change in indebtedness on the change in depression and a fixed effects approach to difference out person-specific effects that may affect the outcome of debt and depression. The control variables in all three of their models include household demographics, health, education, employment status and measures of financial well-being. In this chapter, we follow the same three steps as Bridges and Disney (2010). We first run a probit model for Wave 2 and 4. We then move on to a Recursive Bivariate probit to mitigate the endogeneity which exists between debt and depression. Lastly, a panel regression model (using Wave 2 and 4) with fixed effects is used to characterise the dynamics of debt and depression overtime.

The socioeconomic variables in our model include controls for individual and household demographics such as age, gender, population group, marital status, education, employment status, and health. The household variables controlled for are the number of people unemployed, the number of children (age<18) and elderly (age>60) in the household, as well as the type of geography that the household is located in. Adding the number of unemployed and type of geography augments the controls used by Bridges and Disney (2010) but makes sense in the South African context.

5.1 The Maximum Likelihood of Depression: Univariate Probit

Our first model uses a probit framework to model depression and debt in a given period. This model estimates the probability of reported depression given a set of explanatory variables, including debt. The probit models are usually estimated using a maximum likelihood approach. We examine whether the correlation between reported depression and debt can be shown to be significant within a set of alternative measures of a household's circumstances in explaining psychological well-being. We perform these cross-sectional regressions on waves 2 and 4 NIDS datasets, respectively.

In a probit framework (Greene, 2013), the expression for the probability of reporting depression can be written as:

$$\Pr(y = 1|\boldsymbol{x}) = \varphi(\beta' x) \qquad (1)$$

Pr is the probability that the respondent reported a CES-D score equal or above 12 and thus they can be identified as depressed, β is a vector of coefficients, and x represents a set of regressors that were motivated earlier as the drivers of depression, such as socioeconomic characteristics, and also a dummy variable indicating whether or not they reported debt. Equation (2) is a detailed illustration of how the probit model in (1) is specified for our analysis. We model the probability that an individual is depressed ($d = 1$) using a latent variable model:

$$d_i^* = \alpha + \beta' X_i + \delta' HH_h + \gamma F + v \qquad (2)$$

Where d_i^* is the unobserved propensity of being depressed for individual (i), X_i is a vector of socioeconomic variables of the individual, HH_h is a vector of household variables, F is a measure of debt and v is a random error that is standard normally distributed. Standard errors are clustered by province and wave. The indexes *i* represents individuals, *h* households. Since the measures of debt are correlated, we control for them in separate model specifications.

We report marginal effects instead of coefficients. Marginal effects can be described as the change in outcome as a function of the change in the independent variable (depression) holding all other variables in the model constant at some value (Wooldridge, 2016). The marginal effects can be calculated for each individual observation or for any specific vector of the regressors. In this study, the marginal effects are calculated for the sample means. The marginal effects for categorial variables show how conditional probability changes as the categorical variable changes from 0 to 1, after controlling in some way for the other variable in the model.

The purpose of this model is to establish multivariate (conditional) correlation. The results do not establish causality, mainly because of underlying endogeneity in the variables, especially debt, which is dealt with in section 5.2. Table 4 examines the degree of conditional correlation between indebtedness and depression using NIDS Wave 2 & 4 data as two cross-sectional data sets.

Table 4: The maximum likelihood of depression given debt with NIDS (Marginal Effects).

	Wave 2		Wave 4	
	(1)	(2)	(3)	(4)
Depression	**Negative Asset Value**	**Financial Stress**	**Negative Asset Value**	**Financial Stress**
Age (Young Adults: 16-24)				
Prime Workers (25-34)	0.030	0.029	-0.015	-0.015
	(0.019)	(0.019)	(0.018)	(0.018)
Mature Workers (55-64)	0.051	0.050	-0.051	-0.052
	(0.040)	(0.040)	(0.036)	(0.036)
Retired (65 & Over)	0.050	0.050	-0.007	-0.006
	(0.059)	(0.060)	(0.053)	(0.054)
Gender (Female=1, Male=0)	-0.015	-0.015	0.015	0.012
	(0.013)	(0.013)	(0.012)	(0.012)
Marriage (Married/Live Together=0)				
Separated/Widowed/Divorced	0.031	0.029	0.034	0.036
	(0.024)	(0.024)	(0.022)	(0.023)
Never Married	0.034**	0.036**	0.001	-0.000
	(0.016)	(0.016)	(0.016)	(0.016)
Population Group *(Black)*				
Coloured	-0.094***	-0.094***	-0.015	-0.009
	(0.020)	(0.020)	(0.020)	(0.020)
Asian/Indian	0.067	0.074	-0.080	-0.082
	(0.049)	(0.050)	(0.050)	(0.051)
White	-0.156***	-0.159***	-0.113***	-0.108***
	(0.034)	(0.033)	(0.033)	(0.034)
Education *(Matric)*				
No Matric	0.012	0.013	-0.007	-0.010
	(0.018)	(0.018)	(0.017)	(0.017)
Tertiary Education	0.056**	0.057**	-0.025	-0.024
	(0.027)	(0.028)	(0.024)	(0.024)
Employment Status*(Employed)*				
Unemployed	-0.035*	-0.038*	-0.039**	-0.048***
	(0.019)	(0.020)	(0.018)	(0.018)
Not Economically Active	0.022	0.019	-0.042***	-0.048***
	(0.017)	(0.017)	(0.016)	(0.016)
Health *(Very Good)*				
Fair	0.063***	0.064***	0.039***	0.039***
	(0.014)	(0.015)	(0.013)	(0.013)
Poor	0.163***	0.162***	0.141***	0.147***
	(0.035)	(0.036)	(0.036)	(0.037)
Household Head (No=0)				
Yes	0.028*	0.032*	-0.032**	-0.032**
	(0.016)	(0.016)	(0.015)	(0.015)
<u>Household Characteristics</u>				
Income Class *(Elite)*				
Middle Class	-0.126***	-0.138***	0.034	0.044
	(0.049)	(0.051)	(0.047)	(0.046)
Vulnerable Class	-0.083*	-0.100*	0.033	0.049
	(0.050)	(0.052)	(0.048)	(0.047)
Poor	-0.036	-0.053	-0.045	-0.025
	(0.052)	(0.054)	(0.048)	(0.048)

Continuation from Table 4				
Depression	(1) Negative Asset Value	(2) Financial Stress	(3) Negative Asset Value	(4) Financial Stress
Household Size (1-3)				
4-5	0.021	0.025	0.055***	0.061***
	(0.016)	(0.016)	(0.016)	(0.016)
6-8	0.092***	0.098***	0.060***	0.072***
	(0.020)	(0.019)	(0.020)	(0.020)
9 or more	0.053*	0.065**	0.122***	0.143***
	(0.029)	(0.028)	(0.030)	(0.030)
No. of children (age<18)	-0.009**	-0.010***	0.001	0.000
	(0.004)	(0.004)	(0.004)	(0.004)
No. unemployed	0.012***	0.013***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
Geotype *(Traditional)*				
Urban	0.065***	0.066***	0.179***	0.188***
	(0.014)	(0.014)	(0.013)	(0.013)
Farms	0.195***	0.190***	0.062**	0.065**
	(0.023)	(0.023)	(0.026)	(0.026)
Negative Event (No=0)				
Yes	0.056***	0.064***	0.003	0.003
	(0.014)	(0.014)	(0.016)	(0.016)
Negative Asset Value	0.124***		0.153***	
	(0.030)		(0.022)	
Financial Stress		-0.002		0.043***
		(0.013)		(0.014)
Observations	17,204	17,204	24,123	24,123
Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors reported in parentheses. The dependent variable is Depression. Post-stratified weights were applied.				

In both Wave 2 and 4, the negative asset value is a statistically significant (at 1% level) correlate of depression. Conditional on the controls, a negative asset value relative to positive asset value (or break even point) is associated with an increased likelihood of depression by 12,4 percentage points in Wave 2 and 15,3 percentage points in Wave 4. The Financial stress variable is positively correlated with depression but is only statistically significant in Wave 4. Similar to the negative asset value, expenses above income relative to surplus income after expenses (or income=expenses) increased the likelihood of depression by 4,3 percentage points in Wave 4, conditional on the controls.

As with the rise in indebtedness between the waves, we also observe increased average CES-D score in Wave 4 from Wave 2, implying that, in general, more respondents experienced depression in Wave 4 (than in Wave 2). There is no clear explanation of what may have raised reported depression and indebtedness in this wave, particularly because the employment rate increased between the waves for the full sample and the depressed sample, as noted earlier. Like most studies in the topic of debt and depression (Bridges & Disney, 2010; Brown, Taylor & Price, 2005; Drentea & Reynolds, 2012; Jenkins et al., 2008, we also find that indebtedness strongly affects the depression outcome.

In the rest of this univariate probit section, we discuss the controls to understand their relationship with the debt and depression variables. We discuss these controls in more detail now so that we do not dwell on them in later models. Throughout the chapter discussions focus on the sign of the coefficient and significance level. We only consider a variable to be statistically significant at 5% or 1% level.

In Wave 2, the 'Never Married' compared to respondents in relationships (Married or Living together) showed a higher likelihood of depression for both debt variables at 5% significance level. Since the majority of the sample 'Never Married' and are females, we can postulate that most women (in the sample) are household heads. According to Statistics South Africa (2011), the proportion of female-headed households in the low-income category surpassed that of male-headed households in 2011. The presence of female-headed household is an increasingly significant feature of South African households since the colonial and apartheid system (Hall, 2017). During apartheid, young men would be forced to go work in mines and farms, leaving their families behind and headship to women and children. Since then, South Africa has had a legacy of female-headed households. Most studies find increased indebtedness among single adult households, where there is high dependence on a single income (Bridges & Disney,2004; Canner & Luckett, 1991; Del-Rı´o & Young, 2005; Lea et al., 1993; Webley & Nyhus, 2001). Furthermore, research has shown that female-headed households tend to be disadvantaged regarding access to land, labour, and credit (World Bank, 2001; World Bank, 2011; Chant, 2013). Additionally, they may be discriminated against by cultural and social norms (World Bank, 2011). It is possible that the individuals who never married are at a higher risk of depression due to the financial and social constraints they experience.

We expected gender to be statistically significant as some researchers suggests that there is a significant relationship between gender and depression, and indebtedness although it is ambiguous about the direction of causality (Engelbrecht, 2009; Mersland, 2011). Similarly, the analysis by DebtRescue (2017) suggests that women in South Africa are more affected by indebtedness than men, especially if they are the household head (Bridges & Disney,2004). Some research reveals that women are more risk averse when conducting financing decisions (Almenberg and Dreber, 2015; Jianakoplos and Bernasek, 1998; Powell and Ansic, 1997). For example, Almenberg et al.(2018) finds that women feel less comfortable with debt compared to men. Some studies suggest that debt increases the vulnerability of female debtors, especially those borrowing from microlenders who use unorthodox debt collection methods (Engelbrecht, 2009; Mersland, 2011; Garikipati, 2008). It is surprising that gender was not statistically significant.

Race has a negative effect on depression. Being Black relative to other races increased the likelihood of depression. For example, being white reduced the likelihood of depression by at least 10 percentage points, whereas being Coloured reduced it by 9,4 percentage points (only in wave 2).

Unexpectedly, lower levels of educational attainment have no significant effect on likelihood of depression. Instead, we find that individuals with tertiary education compared to those with Matric only had a higher likelihood of depression by approximately 5 percentage points (in Wave 2). In contrast, Tomlinson et al. (2009) found that the prevalence of depression was higher among groups with lower levels of education than higher levels of education. Individuals experiencing unemployment or were economically inactive had a lower likelihood of depression relative their employed counterparts. Common literature opposes this finding, most research has shown that unemployment is associated with an increase reported depression, suicide or alcohol abuse (Jesspo, Herbets & Solomon, 2010; Kawachi & Wamala, 2006; Hintika et al, 2007).

On the household characteristics, we notice that the higher number of people unemployed in the household the higher the likelihood of depression. Conversely, the number of children in the household reduced the likelihood of depression. Livingstone and Lunt (1992) found that having children made the parents more risk averse when it came to debt, which then reduced their likelihood of depression triggered by financial constraints. We also find that a bigger household size compared to one with 1-3 members results in the higher likelihood of depression.

Being a household head increases the likelihood of depression by 2,4 percentage points in wave 2 if the responded reported a negative asset value, and 3,5 percentage points where financial stress is reported. In wave 4, being a household head reduced the likelihood of depression.

We find that the income class is not a consistent predictor [in terms of significance] of depression between the waves. Moreover, all the income classes relative to elite were negatively correlated with depression, contrasting what literature suggests (Chant, 2013; Damia´n, 2003; Klasen, Lechtenfeld, & Povel, 2015; Duflo, 2012). This literature includes South African-based studies which show that poverty is linked to declining mental health (Lund et al.,2011; Stoop, Zizzamia & Leibbrandt, 2019).

We find that poor health for both debt variables and waves increases the likelihood of depression by atleast 14 percentage points relative to 'Very Good' health. Rating health as 'Fair' instead of 'Very Good' raised the likelihood of depression by 6,3 percentage points in wave 2 and 3,9 percentage points in wave 4. Our health outcome is similar to Sweet et al. (2013) who found that poor self-reported general health is associated with depression and debt. In the same way, experiencing a negative event increased the likelihood of depression by at least 5 percentage points in wave 2 (but not in wave 4).

The people who live in urban areas and farms were more likely to report depression in both waves for both debt variables than those living in traditional areas. For instance, living in an urban area in wave 2 compared to a traditional area increased the probability of depression by 6,5 percentage points when controlling for a negative asset value, and 6,6 percentage points when controlling for financial stress. The increase in depression can possibly explained by the effects of migration on household dynamics, and thus psychological and financial-well being. There are more women are migrating to urban centres for work in South Africa. The migration is changing household structures and composition in urban and rural areas. Chant (2013) notes that female headship is relatively higher in urban areas than traditional rural due to women's access to independent housing and higher salaries compared to rural areas. At the same time, rural households continue to carry a large burden of care for the dependents of those working (or attempting to join) in the urban labour force (Hall, 2017).

5.2 Dealing with Endogeneity

The binary probit model which was used to assess the effect of socioeconomic variables on the probability of the individual reporting depression is vulnerable to bias, since reporting indebtedness is endogenous and simultaneously determined by the depression variable. Also, there is a potential bias in the probit estimates, due to the likelihood of unobserved characteristics that explain both indebtedness and reported depression (Disney & Bridges, 2010; Disney, 2008).

Some respondents may report both financial problems and psychological problems, irrespective of environmental and socio-economic circumstances. A personal history or family history of ill-health including depression are likely to induce adverse economic outcomes, such as loss of employment (thus income), which may induce financial problems. Past psychological problems may also cause individuals to be less able to cope with adverse financial shocks. Therefore, financial well-being may not be strictly exogenous where there is a history of adverse psychological events (Roberts, Golding, & Towell, 1998; Stradling, 2001; Brown et al., 2005) in order to control this effect, a simultaneous bivariate probit model was used.

5.2.1 Modelling the Impact of Indebtedness on Depression: Recursive Bivariate Probit

We run a recursive bivariate probit (Maddala, 1983; Bridges & Disney, 2010) to address the potential of endogeneity by simultaneously estimating the relationship between indebtedness and reported depression. Bivariate probit models (Wooldridge, 2016) are used when there is an a priori reason to expect a dependant binary variable to be simultaneously determined with a dichotomous regressor. Since indebtedness is endogenously and simultaneously determined by the depression variable, this is a specific case of a recursive model of simultaneous equations (Maddala,1983 and Greene,2003). The outcome variables (depression, indebtedness) are both dichotomous and are jointly modelled allowing for a correlation between the error terms of the two equations. The indebtedness outcome variable is endogenous and also appears as an explanatory variable in the equation for the depression (hence the term 'recursive'). A recursive biprobit is increasingly being used when dealing with endogeneity, for example (Farlie, 2005; Filippini et al., 2018; Buchmueller et al., 2004). A recursive bivariate is structured as follows:

Depression Equation:

$$d_i^* = \beta'_1 X_1 + \gamma F + v_1, \qquad d_i = 1 \; if \; d_i^* > 0 \quad and \qquad d_i = 0 \; otherwise \qquad (3)$$

Indebtedness Equation:

$$F_i^* = \beta'_2 X_2 + v_2, \qquad F_i = 1 \; if \; F_i^* > 0 \quad and \qquad F_i = 0 \; otherwise \qquad (4)$$

Where γ is the coefficient on the binary indebtedness outcome variable from equation (3) appearing in the depression equation (4). F_i^* is the unobserved propensity that individual *(i)* reports indebtedness and d_i^* is the depression status as defined before in the previous model. $X_1 \; and \; X_2$ are vectors of individual and household characteristics, and they are defined as before in the previous model. Depression is not included in the regressors used for indebtedness equation. For simpler interpretation, we convert the categorial variables (Race, Marriage, Education, Employment, Health, and Geography) to binary variables. Wilde (2000) argues that the parameters of the first equation can be identified if the same regressors appear in both equations provided there is sufficient variation in the data. But it is better if variation can be achieved by providing each equation at least one varying independent variable. To ensure variation, we add a new regressor in equation 4, called Household Compare. We used the NIDS variable that asks respondents where they would classify their income relative to their neighbours and it ranges from 'Well above average' to 'Well below average'. The responses are then converted into binary so that Household Compare is equal to 1 if the respondents perceive their average income as lower than neighbours, 0 otherwise. This variable is based on the Relative Income Hypothesis which suggests that indebtedness may come from subjective wealth assessment and social comparison (Cynamon & Fazzari, 2008; Stewart et al., 2010). Households that compare themselves with wealthier households in their social circle and perceive their own social standing to be lower tend to overspend relative to their levels of income and thus borrow more in an attempt to catch up with their peers (Cynamon & Fazzari, 2008; Lea et al., 1995; Livingstone & Lunt, 1992). Household Compare is not included in equation (3).

The error terms (v_1, v_2) are identically distributed as bivariate normal with zero mean, unit variance and a correlation coefficient (ρ). Greene (1997) shows that the probabilities that enter the likelihood function are of the form:

$$\Pr[d_i = 1, F_i = 1] = \varphi(\beta'_1 X_1 + \gamma, \beta'_2 X_2, \rho)$$

$$\Pr[d_i = 0, F_i = 1] = \varphi(-\beta'_1 X_1 - \gamma, \beta'_2 X_2, -\rho)$$

$$\Pr[d_i = 1, F_i = 0] = \varphi(\beta'_1 X_1, -\beta'_2 X_2, -\rho)$$

$$\Pr[d_i = 0, F_i = 0] = \varphi(-\beta'_1 X_1, -\beta'_2 X_2, \rho)$$

The recursive bivariate probit model was estimated using the negative asset value as the measure of debt since it was statistically significant in both Waves in the univariate probit estimation. Tables 5 presents the results of the recursive bivariate probit model for Wave 2 and 4, Table 6 gives a summary of the marginal effects from estimating the recursive model. After we estimate the parameters we have to consider the marginal effects of the covariates in the conditional distribution (Filippini et al, 2018). As in the case of the univariate probit, marginal effects are more informative than coefficients, because they inform us how the outcome variable will change when an explanatory variable changes, holding other explanatory variables fixed at some value. These models give us insights into the factors that influence indebtedness and depression.

The correlation coefficient (rho in table 5) between the two error terms is statistically significant for the Wave 2 and 4 of the recursive bivariate probit. Due to the significance of the correlation coefficient, it is clear that our recursive model provides more reliable estimation than the univariate probit model. However, it also means that there is still some element of endogeneity between debt and depression after controlling for socioeconomic variables in this wave (Filippini et al., 2018). In this situation Fillippini et al. (2018) cautions that one cannot claim that a causal relationship from debt to depression has been estimated. We observe a positive and significant effect of the negative asset value for both Wave 2 and 4. This means that a negative asset value compared to assets greater or equal to liabilities increases the likelihood of depression. In contrast, the financial stress variable has a negative and significant effect suggesting that indebtedness from overspending does not increases the likelihood of depression, rather it reduces it.

The estimated coefficients for the controls are similar to the probit model estimated earlier. Race still has a positive and significant effect on depression, which means that being black increases the likelihood of depression. Marriage (being a couple) also has no significant effect on depression but has a positive effect on financial stress in Wave 4. The overall effect of being the household head is still ambiguous since the sign of the coefficient changes between debt controls and waves.

Health has a positive and significant effect on depression and the debt variables, which means that poor health increases the likelihood of indebtedness as well as the likelihood of depression. In Wave 2 , income class is significant and positively related to depression. However, in wave 4, it is negatively correlated to depression. These results are similar to the probit model estimated above where it seems that there are unobserved differences between wave 2 and 4. The number of children have a significant and negative effect on depression but a positive effect on financial stress in both waves. Earlier, we found similar results between depression and the number of children in a household. Geography type has a positive effect on depression in both waves. Lastly, the household income comparison has a significant and positive effect of financial stress in Wave 2.

We also notice a positive and significant effect of experiencing a negative event on depression, and on the net asset value and financial stress in wave 2. Gonzalez (2008) found that unexpected adverse shocks played a major role in household over-indebtedness in the financial crisis of experienced by Bolivia between 1999 and 2002. Likewise, Schicks (2014) found that unexpected shocks significantly increased the likelihood of over-indebtedness of micro-borrowers in Ghana.

In Table 6 (marginal effects of the recursive biprobit), we notice that a negative asset value increases the likelihood of depression by only 0,7 percentage points in Wave 2 while it increases the likelihood of depression by 1,8 percentage points in Wave 4. As mentioned above, the financial stress variable shows a negative correlation with depression. In Wave 2, financial stress reduces the likelihood of depression by 6,8 percentage points meanwhile it reduces it by 4,8 percentage points in Wave 4. Unemployment increases the likelihood of depression by 8,1 percentage points in Wave 2 when expenditure exceeds income, and by 3,3 percentage points in Wave 4. Poverty reduces the likelihood of depression by 14,5 percentage points in wave 2 when expenditure exceeds income, and by 12,6 percentage points in wave 4. The number of unemployed individuals in the household increase the likelihood of depression by 1,2 percentage points in Wave 2 (1,5 percentage points, Wave 4) when household expenditure exceeds income.

Contrary to our first probit model, a higher the number of children in the household increase the likelihood of depression when household expenditure exceeds income (1,6 percentage points in Wave 2 and by 2,9 percentage points in Wave 4). What is also different is that age no longer has an insignificant effect on depression. Age has a negative effect on indebtedness, meaning that as individuals get older; there is a lower likelihood that they will report indebtedness. This is likely to be since younger people are more willing to take risk and older people try and get out of debt before retirement (Livingstone & Lunt, 1992).

Summarising the most important findings: we observe a positive and significant effect of negative asset value on the likelihood of reporting depression in both wave 2 and 4. Focusing on the negative asset value outcome, we can safely say the results of this estimate support the hypothesis that individuals with higher levels of debt are more likely to fall into depression. However, we find a negative and significant effect of financial stress on depression which is counterintuitive and is mismatched with our expectation. Some of the controls like employment status and education were quite contradictory to theory. One of the disadvantages of using cross-sectional data is that variables can be inconsistent across waves. By combining data into 2 dimensions, panel data gives more variation and it reduces collinearity as it allows us to observe variables over time (Williams, 2018). Fortunately, NIDS is a panel survey and can be used to directly estimate the dynamics between debt and depression.

Table 5: Maximum likelihood estimates of recursive bivariate probit (Depression and Indebtedness, Wave 2 & 4)

	Wave 2 (N=15 438)				*Wave 4 (N=22 246)*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model	**Depression**	**Negative Asset Value**	**Depression**	**Financial Stress**	**Depression**	**Negative Asset Value**	**Depression**	**Financial Stress**
Age	0.002	-0.008***	-0.004***	-0.007***	0.001	-0.003	-0.001	-0.006***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Gender (Female=1)	-0.021	0.001	-0.005	0.007	0.051	-0.085*	0.044	0.071*
	(0.037)	(0.061)	(0.034)	(0.039)	(0.034)	(0.051)	(0.035)	(0.037)
Race (Black=1, 0=Otherwise)	0.211***	-0.193***	0.192***	0.063	0.121**	-0.103	0.105**	0.029
	(0.059)	(0.070)	(0.051)	(0.054)	(0.053)	(0.069)	(0.053)	(0.056)
Marriage (Couple=1, 0=Otherwise)	-0.058	0.009	-0.020	0.031	-0.036	0.075	-0.010	0.095**
	(0.043)	(0.062)	(0.038)	(0.042)	(0.038)	(0.060)	(0.039)	(0.041)
Education (Matric=1, 0=Otherwise)	0.082	0.108	0.057	-0.034	0.022	-0.078	0.005	-0.022
	(0.052)	(0.082)	(0.046)	(0.052)	(0.047)	(0.068)	(0.048)	(0.049)
Employment (Unemployed=1, 0=Otherwise)	0.017	-0.129*	0.179***	0.327***	-0.050	-0.075	-0.027	0.276***
	(0.046)	(0.073)	(0.044)	(0.049)	(0.037)	(0.057)	(0.049)	(0.042)
Health (Good=1, 0=Otherwise)	0.428***	-0.159	0.343***	0.110	0.334***	0.252*	0.423***	-0.060
	(0.096)	(0.117)	(0.083)	(0.094)	(0.102)	(0.151)	(0.103)	(0.120)
Household Head (Yes=1)	-0.056	0.142*	0.136***	0.235***	-0.092**	0.039	-0.052	0.137***
	(0.046)	(0.081)	(0.045)	(0.050)	(0.041)	(0.058)	(0.047)	(0.045)
Household Characteristics								
Income Class (Poor=1, 0=Otherwise)	0.217***	-0.118*	-0.246***	-0.605***	-0.128***	-0.094	-0.289***	-0.823***
	(0.049)	(0.066)	(0.042)	(0.047)	(0.043)	(0.058)	(0.095)	(0.045)
Household Size	0.010	0.123***	-0.034	-0.113***	0.049***	0.061***	0.031	-0.263***
	(0.017)	(0.019)	(0.022)	(0.026)	(0.014)	(0.018)	(0.028)	(0.020)
No. of children (age<18)	-0.033	-0.153***	-0.004	0.073***	-0.036**	-0.044*	-0.014	0.242***
	(0.020)	(0.021)	(0.022)	(0.027)	(0.016)	(0.026)	(0.028)	(0.023)
No. unemployed	0.021**	-0.007	0.038***	0.047***	0.007	0.017	0.025**	0.104***
	(0.009)	(0.010)	(0.010)	(0.012)	(0.009)	(0.010)	(0.012)	(0.010)
Geography type (Urban=1, 0=Otherwise)	0.082*	0.064	0.002	-0.125***	0.361***	0.462***	0.476***	0.047
	(0.042)	(0.071)	(0.038)	(0.041)	(0.038)	(0.058)	(0.042)	(0.040)
Negative Event (Yes=1)	0.016	0.469***	0.177***	0.148***	-0.010	0.113	0.029	0.108**
	(0.040)	(0.067)	(0.035)	(0.039)	(0.043)	(0.069)	(0.046)	(0.048)
Household Compare (Below Avg=1, 0=Otherwise)		-0.038		0.039		0.209***		0.020
		(0.056)		(0.026)		(0.048)		(0.053)
Negative Asset Value (Yes=1)	2.145***				1.694***			
	(0.092)				(0.118)			
Financial Stress (Yes=1)			-1.457***				-0.615*	
			(0.026)				(0.342)	
Constant	-1.440***	-1.425***	-1.942***	0.611***	-0.718***	-2.010***	0.188	0.901***
	(0.144)	(0.281)	(0.201)	(0.146)	(0.126)	(0.187)	(0.276)	(0.140)
Rho	-1.459***		1.956*		-0.823***		0.516**	
	(0.170)		(1.094)		(0.103)		(0.208)	

Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors reported in parentheses. Post-stratified weights were applied.

Table 6: Maximum likelihood estimates of recursive bivariate probit (Marginal Effects)

	Wave 2 (N=15 438)		*Wave 4 (N=22 246)*	
	(1)	(2)	(3)	(4)
Depression	Negative Asset Value	Financial Stress	Negative Asset Value	Financial Stress
Age	-0.000***	-0.002***	-0.000	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Gender	-0.000	0.001	-0.001	0.012**
	(0.000)	(0.010)	(0.001)	(0.006)
Race	-0.001	0.023*	-0.001	0.012
	(0.001)	(0.014)	(0.001)	(0.009)
Marriage	-0.000	0.006	0.001	0.011
	(0.000)	(0.010)	(0.001)	(0.007)
Education	0.001*	-0.005	-0.001	-0.002
	(0.001)	(0.013)	(0.001)	(0.008)
Employment	-0.001*	0.081***	-0.002*	0.033***
	(0.001)	(0.013)	(0.001)	(0.010)
Health	0.000	0.040*	0.009**	0.025
	(0.001)	(0.023)	(0.003)	(0.019)
Household Head	0.001	0.058***	-0.000	0.013
	(0.001)	(0.013)	(0.001)	(0.008)
Household Characteristics				
Income Class	-0.000	-0.145***	-0.003***	-0.126***
	(0.001)	(0.011)	(0.001)	(0.018)
Household Size	0.001***	-0.027***	0.002***	-0.031***
	(0.000)	(0.007)	(0.000)	(0.007)
No. of children (age<18)	-0.001***	0.016**	-0.001**	0.029***
	(0.000)	(0.007)	(0.001)	(0.007)
No. unemployed	0.000	0.012***	0.000**	0.015***
	(0.000)	(0.003)	(0.000)	(0.003)
Geography type	0.001	-0.027***	0.013***	0.043***
	(0.001)	(0.010)	(0.003)	(0.006)
Negative Event	0.004***	0.041***	0.002	0.016**
	(0.001)	(0.010)	(0.001)	(0.008)
Household Compare	-0.000	0.009	0.004***	0.003
	(0.000)	(0.006)	(0.001)	(0.006)
Negative Asset Value	0.007***		0.018***	
	(0.001)		(0.003)	
Financial Stress		-0.068***		-0.048**
		(0.003)		(0.024)

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors reported in parentheses. Post-stratified weights were applied.*

5.3 Dynamics of Debt and Depression

The results outlined on the recursive bivariate model show that there are still unobserved effects between reported depression and indebtedness in both waves since all correlation coefficients of the error terms were statistically significant. The models we have estimated so far measure the relationship between debt and depression cross-sectionally. Panel data is more suited than cross-sectional data for studying the dynamics of change or transition behaviour (Torres-Reyna, 2007). Fixed effects are commonly used to reduce selection bias in the estimation of causal effects in observational data by eliminating large portions of variation thought to contain confounding factors (Mummolo & Peterson, 2017).

In this section, we continue to follow Disney and Bridges (2010) and exploit the panel aspect of the NIDS data to examine the dynamics of depression and indebtedness. By using a fixed-effects approach we hope to difference out individual-specific, time-invariant effects that may cause individuals to respond in a particular way to general questions (Wooldridge, 2010). Individuals who report financial difficulties may be inherently depressed. Alternatively, having a history of economic instability may affect an individual's mental status due to fear of future financial problems. Individual fixed effects eliminate all the between-individual variation, producing an estimate of a variable’s average effect within individuals over time.

Firstly, we look at the number of individuals who transition between the waves on reporting indebtedness and depression. The fixed effects estimation relies on these transitions and so it is important to see that there are sufficient transitions to estimation an average effect (Torres-Reyna, 2007). In Table 7, we observe a low degree of persistence in reported depression between waves 2 and 4 with 1411 individuals reporting depression in both waves. About 2745 of the individuals who reported depression in wave 2 are no longer depressed in wave 4, and 3931 of the people who did not report depression in wave 2 are depressed in wave 4. Fixed effects estimate the impact of a change in financial status on the change in depression status[3]. We assume that the change in status is simultaneous to a shock occurring. Coming to the debt measures, 5681 respondents reported a change in negative asset value status between Wave 2 and 4. Similarly, 1500 respondents reported a change in financial stress between Wave 2 and 4.

[3] An alternative is to control for unobserved person specific effects using random effects. Although Disney and Bridges (2010) do not perform these specification tests on their paper, we run Hausman’s Specification Test to confirm that fixed-effects specification is appropriate for the individual-specific changes in our model. We fit a random-effects model (keeping all controls the same as fixed effects model) as a fully efficient specification of the individual effects under the assumption that they are random and follow normal distribution. The results indicate that there may be a systematic difference in the coefficients, and we should prefer the fixed-effects ("within") model rather than include the random-effects ("between") model. We can reject the null hypothesis that the individual-level effects are adequately modelled by a random effects model.

Table 7: Transition matrix of debt and depression between Wave 2 and 4

Wave 2	**Wave 4**	
	Depressed	**Not Depressed**
Depressed	1411	2745
Not Depressed	3931	8072
	Negative Asset Value	**Asset Value ≥0**
Negative Asset Value	1116	3251
Asset Value ≥0	2430	9362
	Financial Stress	**Income≥ Expenses**
Financial Stress (Income ≤ Expenses)	66	927
Income ≥ Expenses	573	14593
Note: Author's own calculations using the unweighted balanced panel for waves 2 and 4.		

Given the transition across the waves, we model the probability of being depressed in *t* (NIDS wave 4) given the household and individual characteristics observed in the base year *t-1* (NIDS wave 2). The probability that an individual is depressed ($d_{it} = 1$) becomes

$$d_{it}^{*} = \beta' X_{it-1} + \delta' HH_{ht-1} + \gamma F_{t-1} + \theta_i + \varepsilon_{it} \qquad (5)$$

Where θ_i captures time-invariant individual-specific effects, and ε_{it} is independently distributed over (i). If we assume that ε_{it} has a logistic distribution, then the above model can be estimated by conditional maximum likelihood; conditioning the model on the number of individual transitions results in the conditional likelihood function being free of the fixed-effect parameter, θ_i. So, a contribution to the likelihood function only arises from those individuals who exhibit a change in status (in this instance, into or out of depression).

Both debt measures are significant and positive determinants of the onset of depression. A change from a positive asset value to negative asset value is positively associated with depression. Similarly, a change from a state of surplus in income after expenses to expenses exceeding income (i.e. Financial Stress) increases the probability of depression .These findings match what literature suggests as mentioned numerous times in this paper unlike the recursive bivariate probit which showed that financial stress is negatively related to depression. Also, the magnitude of the effects (of negative asset value and financial stress on depression) are larger, implying that moving into indebtedness has a strong influence on moving into depression.

Also different from the other models is that age is a positive and significant determinant of change in depression, whereas in the recursive probit it was negatively associated to the level of depression. Another key driver for the onset of depression is an individual's health status; a current ill-health shock is associated with an increase in the probability of reported depression as the literature had suggested. The association between income class and depression remains negative, as it was in our previous models. This means that people of lower-income classes experience a lower probability of falling into depression, whereas individuals from their higher-income classes experience an increased risk of depression. Some research shows that the ‘highly successful’ are prone to depression because of the extreme competition and feelings of failure if they compare themselves to counterparts of similar status (Walton, 2015). A threat to assets, if they are associated with social status, will cause deterioration in mental health. This is particularly true for people who habitually measure their self-worth by whoever seems to be more successful than they are – a recipe for constant depression-inducing envy (Stewart et al., 2010).

The number of people unemployed in the household is a strong determinant of change in depression status. The individual’s level of education and employment status are not important determinants of change in depression. In the univariate probit model, educational attainment and employment status of the individual were negatively correlated to depression but did not consistently show statistical significance.

Table 8: Fixed effects estimates of the probability of depression given debt – coefficients estimates

Variables	(1) **Negative Asset Value**	(2) **Financial Stress**
Age	0.0657***	0.0705***
	(0.00719)	(0.00722)
Marriage (Couple=1, 0=Otherwise)	-0.0335	-0.0345
	(0.0803)	(0.0803)
Education *(Matric==1, 0=Otherwise)*	0.0952	0.0996
	(0.0829)	(0.0828)
Employment Status*(Employed==1, 0=Otherwise)*	0.0300	0.0564
	(0.0557)	(0.0560)
Health *(Good/Fair=1, 0=Otherwise)*	0.357***	0.359***
	(0.117)	(0.117)
Health (t-1)	-0.105	-0.104
	(0.113)	(0.112)
Household Head(Yes=1, 0=No)	0.0566	0.0572
	(0.0539)	(0.0540)
Household Characteristics		
Income Class *(Poor=1, 0=Otherwise)*	-0.215***	-0.179***
	(0.0613)	(0.0624)
Household Size	0.0514**	0.0655***
	(0.0220)	(0.0221)
No. of children (age<18)	-0.0346	-0.0474*
	(0.0278)	(0.0278)
No. unemployed	0.0589***	0.0562***
	(0.0102)	(0.0103)
Negative Event (Yes=1, No=0)	0.213***	0.206***
	(0.0734)	(0.0735)
Negative event (t-1)	-0.0785	-0.0767
	(0.0733)	(0.0733)
Geotype *(Urban=1, 0=Otherwise)*	-0.0369	-0.0262
	(0.106)	(0.106)
Negative Asset Value	0.376***	
	(0.103)	
Negative Asset Value (t-1)	0.00562	
	(0.106)	
Financial Stress		0.127**
		(0.0606)
Financial Stress (t-1)		-0.0334
		(0.0579)
Observations	10,852	10,852
Number of pid	5,426	5,426
*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors reported in parentheses.*		

5.4 The Impact of Indebtedness on Depression: Debt Types

We further investigated how different types of debt acquired by the individual contribute to their mental health (controlling for demographic characteristics) using the Fixed Effects model in Equation (5). We keep the exogenous variables the same as in fixed effects model, but instead of controlling for the negative asset value or financial stress, we control for debt types. Each debt type is equal to 1 if the individual has that type of loan, otherwise 0.

Table 9 shows the probability of depression when controlling for debt types and individual-household characteristics. The estimates of the household and individual characteristics remain as they were in the previous model in their direction of correlation and significance levels. There is negligible differences in the magnitude of coefficients.

We find that debt from Mashonisa has the strongest effect on change in depression. When an individual gets a loan from a Mashonisa, their probability of depression increases by 40,3 percentage points compared to when they did not have the loan. People tend borrow from a Mashonisa when they are highly desperate for subsistence and have run out of any other possible options for financial relief (Ssebagala, 2016). Secondly, borrowing from Mashonisa involves high interest that has to be paid back, and potential harm (usually confiscation of bank card or home furniture or threats of violence) if the money is not paid back on time (Du Plessis, 2007). The amount of pressure that an individual experiences by virtue of borrowing from a Mashonisa compared to other lending structures is one possible explanation as to why the probability of depression increases (Ssebagala, 2014). Furthermore, the financial industry is not inclusive to the poor who do not have a stable source of income, which makes them vulnerable to financial sources like Mashonisa, since those are the only institutions they can access credit from (James, 2012).

Another debt type associated with the on-set of depression is a personal loan(s) from a bank. Hire purchase debt is the only significant debt type that is negatively associated with change in depression. Buying on hire purchase decreases the probability of depression. There is not a clear explanation of why this type of loan has a negative effect. Other debt types have a positive association with depression even if not significant.

Table 9: Fixed effects estimates of the probability of depression given debt types– coefficients estimates

	Depression
Age	0.0552***
	(0.00768)
Marriage (Couple=1, 0=Otherwise)	-0.0588
	(0.0837)
***Education* (Matric==1, 0=Otherwise)**	0.0626
	(0.0901)
***Employment Status*(Employed==1, 0=Otherwise)**	0.0464
	(0.0587)
***Health* (Good/Fair=1, 0=Otherwise)**	0.390***
	(0.130)
Health (t-1)	-0.0972
	(0.122)
Household Head(Yes=1, 0=No)	-0.0730
	(0.0579)
Household Characteristics	
***Income Class* (Poor=1, 0=Otherwise)**	-0.181***
	(0.0646)
Household Size	0.0605***
	(0.0234)
No. of children (age<18)	-0.0459
	(0.0293)
No. unemployed	0.0471***
	(0.0110)
Negative Event (Yes=1, No=0)	0.212***
	(0.0772)
Negative event (t-1)	-0.0365
	(0.0772)
***Geotype* (Urban=1, 0=Otherwise)**	0.0353
	(0.110)
Debt Types	
Bond	-0.00291
	(0.247)
Bank Loan	0.350***
	(0.118)
Microlender	0.152
	(0.268)
Mashonisa	0.403**
	(0.176)
Student Loan (Bank)	0.322
	(0.518)
Vehicle Loan	0.174
	(0.215)
Credit Card	0.192
	(0.176)
Hire Purchase	-0.321***
	(0.119)
Family Loan	0.120
	(0.197)
Friend Loan	0.0397
	(0.139)
Employer Loan	0.148
	(0.356)
Observations	9,656
Number of pid	4,828

*Notes: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors reported in parentheses*

5.5 Summary and Conclusion

We investigate the relationship between psychological well-being and indebtedness in South Africa. Using data from waves 2 and 4 of the NIDS, we measure debt with Negative Asset Value and Financial Stress, where household expenditure exceeds income. The negative asset value and Financial Stress variable are used as alternatives in all the models. For both objective debt measures, we document a significant and positive effect of indebtedness on depression. Our analysis resonates with findings from the recent economic literature on debt and depression, particularly Bridges and Disney (2010).

We followed the three-step model used by Bridges and Disney (2010). We first used a probit model to estimate the maximum likelihood of depression given debt while controlling for socioeconomic variables at the individual and household level. The results from the probit approach suggest that those who reported a negative asset value or financial stress were more likely to be depressed on average, relative to those who did not. Both Negative Asset Value and Financial Stress were statistically significant determinants of depression at 1% level. We found that health and the number of unemployed individuals in the household were the variables that consistently raised the likelihood of depression for the respondents.

In the literature review, we had established that there is a simultaneous link between economic and psychological circumstances due to unobserved characteristics that explain both indebtedness and depression. We attempted to address the potential endogeneity between depression and indebtedness by estimating a recursive bivariate probit. The correlation efficient from estimating this recursive bivariate probit model came out statistically significant which meant that although indebtedness has a positive effect on depression, there are unobserved characteristics that still affect the causality links. The recursive bivariate probit model is the best cross-sectional alternative to a simple probit model for estimating and understanding the relationship between debt and depression at cross-sectional level. This is because it assesses and addresses endogeneity.

We then move on to exploit the panel aspect of the data to examine the dynamics of depression and indebtedness. Cross-sectional models do not directly examine the extent to which changes in time can trigger episodes of depression. We, therefore, applied fixed effects to control for time-invariant individual characteristics that are correlated with depression. Using fixed-effects limited our data sample to participants whose depression status changes between waves 2 and 4. Our panel results showed that both changes in the negative asset value and financial stress when used as substitutes are statistically significant predictors of change in depression. The key drivers to the on-set of depression were deteriorating health, an increase in household size, an increase in the number of household members who are unemployed, as well as having experienced a negative event since being interviewed by NIDS. With regards to debt types, a loan from Mashonisa or a personal loan from a bank can trigger the onset of depression. In contrast, higher purchase debt is negatively associated with depression.

The evidence from our results and other literature suggests that there needs to be an increase in the attention given to the relationship between debt and psychological well-being. Further research into the topic could investigate how levels of indebtedness affect psychological well-being. Most of the existing is based on developed countries, particularly the United Kingdom and the USA. This calls for more research on African countries and other developing countries. It is important from a policy perspective to understand the extent to which development interventions can prevent the most vulnerable from entering the cycle of over-indebtedness. Government and the private sector should collaborate in supporting and protecting consumers from being overly indebted. Moreover, the support must include mental health resources.

Appendix

Table A

This table was constructed using Wave 4 NIDS data from the adult questionnaire, where the responded is asked to report on their health status 30 days prior to the interview.

Table 10: Maximum likelihood estimates of Poor Health

	Poor Health
Tight Chest	0.126
	(0.0928)
Chest Pain	0.318***
	(0.0787)
Body Ache	0.141
	(0.107)
Headache	0.137
	(0.104)
Back Ache	0.179*
	(0.107)
Joint pain/arthritis	0.236***
	(0.0896)
Weakness	0.143*
	(0.0868)
Pain in Lower Abdomen	-1.152**
	(0.489)
Painful Urination	0.100
	(0.158)
Severe Weight-loss	0.189
	(0.200)
Memory Loss	0.192**
	(0.0891)
Consultant someone (In the last 30 days)	
1-5months ago	1.218***
	(0.255)
6-12 months ago	1.223***
	(0.331)
More than 1 and less than 2yrs ago	2.751***
	(0.374)
2-4 years ago	3.000***
	(0.293)
5-10 years ago	1.240*
	(0.750)
More than 10 years ago	3.286***
	(1.089)
Never	3.103***
	(0.639)
Constant	1.297*
	(0.701)
Observations	13,667

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*
Source: Author's own calculations using NIDS (post-stratified weights)

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