Quantifying household deleveraging following the 2007 South African financial cycle peak

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Abstract

Many countries experienced a credit and housing boom over the period 2003 - 2007. This was followed by a burst in the US housing bubble, which contributed to the deep global economic and financial crisis which began in 2007. Consequently households found themselves in highly leveraged positions, and as a result, sought to restore the health of their balance sheets by following a process of deleveraging, particularly in the mortgage market. The global financial crisis raised important questions about the timing of the South African financial cycle, its characteristics, and how it impacted the real economy. Some suggest that it is the post-crisis debt overhang that has been a drag on consumption and thus economic growth.

We date the South African financial cycle turning points and determine stylised facts about the South African financial cycle, as well as the behaviour of household debt over the cycles. We evaluate mortgage, vehicle and other consumer debt at the macroeconomic level, as well as their respective ratios to income. South Africa entered the current financial downward phase in May 2007, and as of December 2017 has not reached a trough or lower turning point. In general we find that South African financial cycles last 17.3 years, around 3 times longer than business cycles (5.8 years). We find that on average financial cycle contractions (10.3 years) last longer than expansions (7.0 years) showing that deleveraging is a long process.

However, as information regarding the distribution of debt across the income groups gets masked at the aggregate level, we use the National Income Dynamic Study (NIDS) to determine who deleverages and in which debt categories most of the deleveraging occurs following the current financial cycle peak in May 2007. We create a panel from the NIDS data by following household representatives that were the main or joint decision maker on expenses in the household (different from other studies where the household head is usually followed). We also use multiple imputations by chained equations (MICE) with predictive mean matching to impute point values for bracket responses for debt and income variables, as well as for those who reported that they have debt, but did not provide a value. By imputing the individual debt variables for those who responded that they were debt participants, we increased the total number of observations for all debt types by 43.8% in Wave 1, 35.4% in Wave 2, 26.3% in Wave 3 and 13.4% in Wave 4. We also increased the household income response rate from 75% to 81% in Wave 1, 84% to 94% in Wave 2, 90% to 97% in Wave 3 and 95% to 98% in Wave 4. Our debt categories in the micro data include information on informal debt, which we refer to as other debt. We therefore have four categories: mortgage, vehicle, consumer and other debt.

Lastly, we estimate the probability of deleveraging, while controlling for individual, household, and financial characteristics. We show that deleveraging after the recent financial cycle peak is mostly driven by married households in urban areas and those who are in the highest income quintile. We further show that employment, although a major factor in obtaining debt, is not a major driver of deleveraging. This suggests that even as the economy starts to recover, and employment opportunities are created, this will likely not translate into significant deleveraging. This implies that having a job, in itself, does not necessary provide adequate means for households to deleverage in South Africa. By assessing which characteristics assist deleveraging, policy makers can determine in which debt categories an uptake in credit will likely resume, and consequently, consumption expenditure and an economic recovery.

Although growth rates in mortgage, vehicle and other consumer debt have decelerated, debt to income levels across all these debt types remain high, compared to the latest pre-financial cycle peak. This suggests that consumers are still in a more vulnerable state than in the period leading up to the May 2007 financial cycle peak. As such any major negative income shocks, either caused by external factors, domestic economic or political conditions, could prolong the financial cycle downward phase. This could halt any consumer-led recovery and the renewed uptake of credit. A further important policy conclusion is that it is mostly those with the financial resources (i.e. higher income earners) to deleverage that do so and mainly in the form of mortgage and consumer debt. This suggests that it is only a small section of the economy that is able to deleverage. Disconcertingly, this means that indebted households in the lower income quintiles are most severely impacted and are unlikely to deleverage.

If it were not for the blessings and support from my Lord, Jesus Christ, this study would not have been possible. I would like to thank my supervisor, Prof. Koch, and my co-supervisor, Dr. Clance, for their commitment and dedication. I appreciate that you were available at all times, even on weekends to assist me and answer my many questions. One of the many things I have learnt from you is that research is an expedition. If you set out to find the right answer, you will surely be disappointed.

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I, Adel Bosch, declare that this thesis titled, "Quantifying household deleveraging following the 2007 South African financial cycle peak" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed: ABosch

Date: 09/05/2019

Notes and list of abbreviations

Notes

For our race classification we follow the naming convention used by the National Income Dynamic Study survey when refering to racial groups in capital letters, i.e. African, Coloured, Indian/Asian and White.

List of abbreviations

BB	Bry and Boschan
CPI	Consumer Price Index
HP	Hodrick-Prescott
JSE	Johannesburg Stock Exchange
MAR	Missing at Random
MCAR	Missing Completely at Random
MI	Multiple Imputations
MICE	Multivariate Imputation by Chained Equation
NCR	National Credit Regulator
NIDS	National Income Dynamics Study
NMAR	Not Missing at Random
OLS	Ordinary Least Squares
PAT	Phase Average Trend
PMM	Predictive Mean Matching
SARB	South African Reserve Bank
SD	Standard Deviation
US	United States

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Chapter 1

Introduction

In the aftermath of the global financial crisis of 2007/08, households in many countries across the globe sought to repair their balance sheets by following a process of deleveraging. This was particularly evident in the mortgage market as many households were left highly leveraged following the bursting of the house price bubble. This rebalancing created a cause of concern for economic policy makers, as the repayment of these high debt levels, and the high levels themselves, possibly resulted in households holding back consumption (Dynan, 2012a), consequently decreasing economic growth. Many countries experienced a credit and housing boom over the 2003 - 2007 period, followed by the bursting of a housing and asset bubble, which resulted in a severe credit crunch and deep global economic and financial crisis, similar to that seen during the great depression (Claessens et al., 2012). In the wake of the deep and widespread global financial crisis, understanding and characterising the financial cycle and the impact on the economy took centre stage in the global research arena (see Reinhart and Rogoff (2009), Claessens et al. (2011, 2012) and Borio et al. (2001, 2010); Borio (2014); Borio et al. (2017)). For economic policy makers (especially monetary policy) it became crucial to understand the causes of the financial cycle, whether and where households have deleveraged, and the impact that this had on the real economy in order to determine appropriate interest rate responses.

This thesis dates the turning points, and analyses the behaviour of the South African financial cycle, with a focus on the recent financial cycle peak. Apart from the work of Boshoff (2005), Boshoff (2010), Thompson et al. (2015a)[1] and Farrell and Kemp (2018), policy makers have very little information regarding the timing of the South African financial cycle, its characteristics, and how it impacted the real economy, outside of well documented business cycle theory. Furthermore,

[1] Also see work on forecasting and nonlinearities in financial condition indices by Thompson et al. (2015b), Balcilar et al. (2016b) and Balcilar et al. (2018).

this thesis examines deleveraging behaviour among South African households, following the recent peak in the South African financial cycle. Knowing the extent of deleveraging, especially in which debt types (mortgages, vehicle or consumer credit), enables policy makers to firstly understand the impact that interest rates have on highly leveraged individuals in the different debt markets, and secondly, the impact that deleveraging has on consumption and economic growth. This is especially relevant in inflation targeting countries such as South Africa, where monetary policy is the main tool for managing inflation whilst simultaneously ensuring sustained economic growth.

Policy makers, in these unusual circumstances, are faced with difficult policy decisions, which warrant a deeper understanding of household's reactions to financial crisis. According to Dynan (2012b) it is not unreasonable to believe that these shocks will result in heterogeneous household responses which should be brought to the attention of policy makers. Although our findings at an aggregate level prove to be useful, this study will not be complete without a deeper understanding of household's behaviour at a microeconomic level. Not only do different households hold different types of debt, but they differ in how leveraged they are with respect to income, their household structure and their employment status. By assessing which characteristics assist deleveraging we can determine in which markets an uptake in credit will likely resume, and consequently, consumption expenditure and the economic recovery. This information is instrumental for monetary policy makers, as they will be able to pre-empt possible inflation risks associated with a pickup in credit demand, consumption, and economic growth. It will also allow policy makers to make appropriate monetary policy decisions, in a situation where the debt overhang has held back consumption for such an extended period, that the economic recovery failed to gain any meaningful momentum. This is the case for South Africa, even 10 years after the financial cycle peak has been reached.

Unfortunately, most global financial crisis literature finds that monetary policy is a blunt tool to deal with a house price bubble and increasing debt levels (André, 2016). Although, according to Mian and Sufi (2010), monetary policy did play an important role in containing house price growth during the build-up of the financial crisis, it unintentionally causes a slowdown in the real economy. As interest rates start to rise, domestic demand weakens, which results in job losses and a deceleration in the inflation rate. Under the conditions of an asset bubble bust, this situation gets exacerbated by other factors, such as wealth losses (as house prices fall sharply), a loss of income and less access to credit and/or tighter lending criteria by banks (Pistaferri, 2016; Dynan and Edelberg, 2013).

Typical post war recessions were triggered by monetary policy makers attempting to contain inflation (Borio et al., 2014) which was mostly linked to the business cycle, for which monetary policy is an effective tool. It was believed to be so effective, that after a sustained period of economic growth, Lucas (2003) and Bernanke (2012) advocated that the business cycle had been tamed and that a great moderation was underway, especially in terms of a decrease in volatility (Blanchard et al., 2001). But, after the financial crisis (which advanced economies refer to as the great recession), it became clear that economic cycles were still alive and well, and cycle theory gained renewed interest (Granados, 2012). Evidence suggested that the amplitude, length and potential disruptive force of the financial cycle were closely related to the financial, and also possibly, monetary regimes in place (e.g. Lowe and Borio, 2002; Drehmann et al., 2012). In fact, a recent study by Borio et al. (2018) suggests that there is a changing nature in the business cycle; where policy tightening has previously played a role in triggering recessions, research around financial cycles as a recession trigger has gained importance.

In order to contextualise the recent global financial crisis, we need to go back to 1999, and the securitisation of sub-prime mortgage loans in the US market (see Ellis, 2010). Sub-prime mortgage loans provided funding to poorer US families, and these riskier loans were packaged with higher rated instruments and sold as collateralised debt obligations to investors. The US housing market peaked in 2006, but increasing interest rates and falling house prices led banks to become reluctant to take on debt from other banks, as they were unsure of the quality of each others' debtor books. Exacerbated by rising food and fuel prices and higher debt obligations, the US economy experienced a significant economic slowdown, which spread to other countries in a synchronized way, causing a global economic slowdown.

After the financial crisis, many policy makers were searching for clarity regarding the timing and impact of household deleveraging on the economy, especially with regards to the uptake of new credit and an anticipated increase in consumption and economic growth, as this has a direct bearing on inflation and, hence, monetary policy. The 2007/08 global financial crisis, and the subsequent peak in the financial cycle in South Africa, resulted in a large part of the population being over-leveraged, especially in the South African mortgage market.

It is important to note that South Africa was already experiencing a slowdown in consumption growth in 2007 (SARB, 2011), and that the lack of demand from international markets for commodities, the fall in commodity prices and subsequent job losses, only intensified South Africa's economic downturn over this period. Domestically, after several years of exceptional house and asset price growth, households drew on their mortgage credit (in the form of access or flexi bonds), believing that house and asset price growth would continue to outgrow their mortgage debt. The resulting sharp increase in household debt-to-income ratios left little room for households to manoeuvre. The common factor in both the international and South African economy, is the long period of expansion, which contributed to a credit and asset price boom, followed by a subsequent bust and the start of the 2007/08 global financial crisis. As property prices started to fall in South Africa, and the slowdown gained momentum, South Africans were left with falling house and asset prices and over-leveraged household balance sheets.

Since the 2007/08 financial crisis, international literature has advanced our understanding of the impact of asset prices and financial markets on the real economy and business cycles. We establish to what extent South African households have deleveraged following the South African financial cycle peak. No stylised behaviour of household debt and financial variables over the South African financial cycle exists. Thompson et al. (2015a) estimates a financial conditions index, and shows its performance in leading actual business cycle slowdowns in the South African economy, while Farrell and Kemp (2018), using credit extended, house prices and equity prices, determine the financial cycle, however, they do not provide any official dates. Therefore, to determine the extent to which households in South Africa have deleveraged over the financial cycle from a macroeconomic perspective, we are guided by international literature, such as Drehmann et al. (2012) and Claessens et al. (2011, 2012), who formulated methods of dating the financial cycle in the US and other developed and emerging economies. We determine turning point dates for the South African financial cycle.

As we have significant information regarding the official dating procedure followed by the South African Reserve Bank (SARB) to date business cycle phases, and based on the recent financial cycle work of Farrell and Kemp (2018), we use this methodology as a foundation for dating the financial cycle turning points for the South African economy. We use the Hodrick and Prescott (1997) (HP) filter, with a λ value that most closely resembles the Phase Average Trend (PAT) filter that is used in traditional business cycle dating procedures and by the SARB.

Another consideration in dating the financial cycle is that the HP filter needs to be adapted for financial cycles (as opposed to business cycles). The Basel Committee on Banking Supervision (2010) suggests that, based on results from Drehmann et al. (2010), the financial cycle is four times longer than the business cycle, therefore a higher λ value should be used. Other studies that apply this methodology include Gerdrup et al. (2013), Alessi and Detken (2009a), Claessens et al. (2011, 2012), Drehmann et al. (2012) and Hiebert et al. (2014).

From aggregate economic data we establish important trends and drivers of the financial cycle and how household debt developed over this period. Unfortunately at an aggregate level, especially in a high income-inequality country like South Africa, information on the distribution of debt and the ability of households to repay loans, which depends on the distribution of income, could also be masked. This led us to explore micro data following the financial cycle peak, which we determine to be May 2007 (see chapter 2), to investigate the properties of households who deleveraged versus those who did not.

Micro-data based studies analysing household debt have gained prominence in recent years (Mian and Sufi, 2010; Mian et al., 2013; Dynan, 2012a; McCarthy and McQuinn, 2017b). We utilise the National Income Dynamics Study (NIDS) panel data, as it contains detailed questions on individual and household debt. NIDS is a longitudinal data set designed to be representative of South African households. Individuals are tracked from wave to wave, even if they relocate. We use the first four rounds (waves) of the survey, which were conducted over the period 2008, 2010/2011, 2012, and 2014/2015.

Typical to most household surveys, the incidence of missing data and non-response were high on sensitive questions such as income, assets, and debt in the NIDS data. In an attempt to gather information in the case of non-response, interviewers often provide alternative options, such as bracket responses. Bracket responses provide a useful supplement to point value responses, as they attempt to lower the non-response rate and provide some broad information. NIDS interviewers tried to lower non-response rates by determining if the household had assets or debt. Binary responses (e.g., yes, we have debt), when combined with additional survey data, can be used to impute missing values (e.g., the amount of debt we have). We therefore considered different options to use this additional information, gathered by interviewers, such as bracket responses or other elicitation techniques, to impute point or value estimates.

Evidence suggests that we benefit by making use of multivariate imputation by chained equation (MICE), which is a useful method for dealing with missing data[2]. Importantly, MICE provides for bounds, which allows for the imputation of a point value from a bracket response. Our variables of interest relate to household debt and deleveraging. We find that there are many who responded that they have debt, but did not provide a point value. We used this information to impute a point value for those who said that they had debt to extend the panel dataset to include as much information as possible on income and household debt across the waves.

A concern for policy-makers involves the timing of deleveraging and the uptake of new credit, which is a necessary condition for consumption and growth. Without sufficient deleveraging, households will not be able to create financial space for the increased demand that is necessary for the next growth cycle. Cooper and Dynan (2016) suggest that the weak recovery in the US consumer market was in part due to wealth losses, weak income growth, limited credit extension and a more negative outlook for future income. Although there are many benefits in having a longitudinal panel, unfortunately, NIDS has been designed to only follow individuals which make it nearly impossible to follow households across waves. We therefore had to develop a unique

[2] MICE is also referred to as a 'fully conditional specification' or 'sequential regression multiple imputation' in the literature.

household identifier to follow households across waves.

The analysis of deleveraging and the impact of the financial crisis at a household level is motivated by potential heterogeneous responses to shocks across different groups of the population. According to Dynan (2012b) and Cooper and Dynan (2016), households react in different ways when facing economic challenges. We rely on micro data for a better understanding of household debt and deleveraging dynamics. As debt is usually associated with a household, we aim to follow households, and therefore select a household member who is the main or joint decision maker in the household, and attach household information to this household member to allow us to control for both individual and household characteristics. This is different from the traditional method of following only the household head across the different waves.

This thesis exploits the NIDS panel structure to determine the drivers and impact of household deleveraging after the South African financial cycle peak. A benefit of the timing of the NIDS study is that the NIDS data, more or less, coincides with the start of the financial downswing in 2007. As a developing economy with high income-inequality, both income and debt are unevenly distributed among South African households, which further support the rationale of using household level data for our analysis. Dynan and Edelberg (2013), using micro panel data, showed that US households have not made much progress in terms of debt reduction and that households may take years to reduce their debt to pre-crisis levels. Similar to Dynan and Edelberg (2013), Baker (2014) suggests that the decrease in consumption may not purely be due to higher debt levels or liquidity constraints, but might be because highly indebted households hold back consumption so that they can attain what they perceive to be a more controllable debt level. McCarthy and McQuinn (2017a), using an Irish data set, also show that when controlling for wealth effects, deleveraging has a negative and statistically significant impact on consumption, although the effect was economically small.

Lastly, we follow McCarthy and McQuinn (2017a) by estimating a probit function to determine who deleveraged between Wave 1 and subsequent waves in the NIDS data. We control for household and individual characteristics in our first stage. We then introduce financial controls in stages. In our second equation we vary our income restriction to control for income quintiles instead of income levels. We include additional controls for our various debt outstanding to income ratios to account for high leveraged households. Lastly, we control for liquidity (mortgage repayment to income ratio).

To summarise our results, we date the most recent financial cycle peak in South Africa as May 2007 using the methodology described in chapter 2. Previous financial cycle peaks were in April 1974 and January 1984. The average length of the financial cycle in South Africa of 17.3

years. Financial cycles in South Africa are therefore around 3 times longer than business cycles. We find that on average financial cycle contractions (10.3 years) last longer than expansions (7.0 years).

We show that mortgage debt as a percentage of income was a large driver of the build-up of debt, peaking at 52.5% in March 2008. Since then, households have managed to bring this ratio down to 34.4% by December 2017. Our results show a clear build-up of debt in the lead-up to the 2007/08 financial crisis, and a slow and difficult deleveraging process, that is continuing. We proceed by using imputations from chapter 3 to create various household debt outstanding variables, which we use in chapter 4. In chapter 4 we show that high income households hold different debt types compared to lower income households. We also find that mortgage debt is held primarily by high income households. Similar to findings from McCarthy and McQuinn (2017a) we see that it is the ability to repay (financial resources) rather than the amount of indebtedness that drives deleveraging. We also find that deleveraging after the recent financial cycle peak is mostly driven by married households in urban areas and those who are in the highest income quintile. We identified that even if deleveraging seemed to have happened at an aggregate level, it is mostly the higher income households with mortgage and consumer credit that seem to have deleveraged. As a final robustness test, we include separate interactions between income and each of our debt-to-income variables, which confirms our initial results.

CHAPTER 2

Determining the 2007 South African Financial cycle peak and evaluating household deleveraging following the turning point

2.1 Introduction

The 2007/08 global financial crisis raised important questions about the behaviour of financial cycles and the length of time it takes households to deleverage from the cycle peak, especially when the cycle is largely driven by an asset bubble. When an asset price bubble bursts, asset prices fall sharply, making it harder for households to sell off assets (usually not by choice) or to use them as collateral. Interest rates may fall rapidly in an attempt to support the economy, succeeding in lowering general debt burdens, but that may not fully describe households financial health. In the literature, the link between deleveraging and economic activity has not received much attention (see Dynan, 2012a), although Brown et al. (2011), and Bricker et al. (2011) examine balance sheet adjustment while households deleverage.

Monetary policy makers are particularly interested in when the new credit cycle will start and how long before imbalances work through the economy. Typical post war recessions, according to Borio (2014) are triggered by monetary policy attempts to contain inflation. However, when a financial boom originates in an environment of low and stable inflation it becomes what Koo (2013) refers to as a 'balance sheet' recession, where companies seek to repay excessive debts instead of seeking profit. Before such a financial cycle recession the preceding boom is much longer, because inflation is contained in the eyes of policy makers, which allows asset prices to continue to inflate, resulting in a much larger debt overhang in the aftermath.

Reinhart and Rogoff (2009) show that financial cycle recessions are deeper and followed by weaker recoveries, while Borio et al. (2014) suggests that policy makers in these situations have little room for policy manoeuvring. Their challenge is to prevent a stock problem from turning into a flow problem, where income, output and expenditures are impacted in the long run; they have few policy options in a situation where capital and financial institutions are constrained. In twenty-four advanced economies, since the 1960s, Bech et al. (2014) find that monetary policy is relatively ineffective in a balance sheet recession and its subsequent recovery. Evidence also suggests that the amplitude, length and potential disruptive force of the financial cycle are closely related to the financial, and possibly also, monetary regimes in place (e.g. Lowe and Borio, 2002; Drehmann et al., 2012).

Many countries experienced a credit and housing boom over the 2003 - 2007 period. After the housing and asset bubbles burst, there was a severe credit crunch, resulting in a deep global economic and financial crisis, similar to that seen during the great depression (Claessens et al., 2012). For households that made decisions based on overvalued housing stock, deleveraging and an uncomfortable unwinding of imbalances was the order of the day. Those imbalances need to work their way out of the system, before positive momentum can build towards the next upward phase. For policy makers the end of the deleveraging process is critical, as it has a direct bearing on consumption, growth, inflation, and the start of the new credit cycle, and hence, the coordination of monetary policy.

The build-up of the global financial crisis started in 1999 in the US sub-prime market as a result of the securitisation of sub-prime mortgage loans (see Ellis, 2010)[3]. The US housing market peaked in 2006, but increasing interest rates exerted pressure on the market, house prices fell and many struggled to repay their loans. Since sub-prime mortgage loans were a large component of portfolios, banks became reluctant to take on debt from other banks; they were unsure of the quality of each others' debtor books. Exacerbated by rising food and fuel prices, higher debt obligations and the credit crunch, the US economy experienced a significant economic slowdown, which quickly spread to other countries triggering a synchronized global economic slowdown (which advanced economies refer to as the great recession) (Baxter, 2009; Miranda, 2017).

South Africa was already experiencing a slowdown in consumption growth in 2007 (SARB, 2011), so the lack of demand from international markets for commodities, the fall in commodity prices and subsequent job losses intensified South Africa's economic downturn over this period. Domestically, after several years of exceptional house and asset price growth, households drew on their mortgage credit (in the form of access or flexi bonds), believing that house and asset

[3] Sub-prime mortgage loans provided funding to poorer US families, and these riskier loans were packaged with higher rated instruments and sold as collateralised debt obligations to investors.

price growth would continue to outgrow their mortgage debt. The resulting sharp increase in household debt-to-income ratios left little room for households to manoeuvre. As property prices started to fall and the slowdown gained momentum, South Africans were left with falling house and asset prices, and over-leveraged household balance sheets.

The common factor in both the international and South African economies since the start of the 2007/08 global financial crisis is the long period of expansion, a credit and asset price boom and a subsequent bust. Since the global financial crisis, international literature has advanced our understanding of the impact of asset prices and financial markets on the real economy and business cycles. These financial drivers (excessive growth in house prices, credit extension and asset prices - an asset bubble) manifest in what is commonly referred to as the financial cycle (Adarov, 2018). Most empirical research on the financial cycle focuses on developed economies or groups of emerging market economies (see Borio, 2014; Borio et al., 2017; Claessens et al., 2011, 2012; Drehmann et al., 2012; Schularick and Taylor, 2012; Aikman et al., 2015; Gonzalez et al., 2015)[4], while empirical findings from South Africa are focussed mainly on characterising the financial cycle (Boshoff, 2005, 2010; Kabundi and Mbelu, 2017; Farrell and Kemp, 2018). What is missing for South Africa, is an analysis of the aftermath of the global financial crisis, when policy making and its timing is most crucial. Although we give an overview of policy and economic conditions prevailing over the financial cycle downward phases, a full analysis of credit supply conditions falls outside of the scope of this study.

The growing numbers of studies on the measurement and properties of international financial cycles find that they display vastly different properties than business cycles, which have received more attention[5]. The financial cycle is usually measured by three key financial variables, credit, equity and house prices (e.g. Kindleberger and Aliber, 2005; Minsky, 1992; Claessens et al., 2011, 2012)[6]. This is not an exhaustive list, and it is easy to imagine other financial measures to be included. Drehmann et al. (2012) and Borio et al. (1994) also consider the ratio of credit-to-GDP and an index of aggregate asset prices, which combines residential property, commercial property

[4]Borio et al. (2017) looks at the US, while Borio (2014) and Drehmann et al. (2012) look at 7 developed countries. Claessens et al. (2011) analyses 21 advanced economies and Claessens et al. (2012) divide 44 countries into 21 advanced countries and 23 emerging market economies. Schularick and Taylor (2012) and Aikman et al. (2015) look at 14 developed economies, while Gonzalez et al. (2015) groups South Africa together with 27 other countries.

[5]Burns and Mitchell (1946) originally proposed the business cycle definition that has supported decades of research on the business cycle.

[6]It is also possible to focus on only one variable such as credit and date the credit cycle - although not covered in this thesis, Borio and Drehmann (2009), Borio (2014), Alessi and Detken (2009b) and Drehmann et al. (2012) find that the ratio of credit-to-GDP and especially property prices make for likely leading indicators of financial crisis. Drehmann and Juselius (2014) also find that together with the credit-to-GDP ratio, the debt-service ratio also makes for a promising early warning indicator (see Aikman et al., 2015; Schularick and Taylor, 2012; Jorda et al., 2011; Dell'ariccia et al., 2012). A recent paper by Borio et al. (2018) highlights that the predictive capabilities of the financial cycle for recession risk outperforms the generally used interest rate spread. Their finding suggest that financial cycle proxies, especially the debt-service ratio, could benefit policymakers and forecasters in a meaningful way when looking for early recession warning signs.

and equity prices.

This chapter considers the extent to which South African households have deleveraged, emphasising the most recent 2007/08 global financial crisis. We set out to determine three things. First, whether credit extension to households and their debt-to-income ratios have returned to pre-financial cycle peak levels. Second, to address the first, we identify the peaks and troughs of the SA financial cycle. Third, we compare and contrast the deleveraging process in the current cycle to the experience from previous financial cycles we are able to date.

This chapter uncovers a clear debt build-up in the lead-up to the 2007/08 global financial crisis, preceding a slow and difficult deleveraging process that continues. We identify the peaks and troughs for the South African financial cycle, finding that the overall length of the financial cycle in South Africa is 17.3 years - very close to 17.1 years found for South Africa in a cross country study by Gonzalez et al. (2015). The financial cycle duration is much longer than the 5.8 year average business cycle[7]. Financial cycles in South Africa are therefore around 3 times longer than business cycles. Contrary to Hiebert et al. (2018), we find that, on average, financial cycle contractions (10.3 years) last longer than expansions (7.0 years), possibly because deleveraging is a longer process. We further show that deleveraging is not the same for every financial cycle. In the current financial cycle, it has mainly happened in the mortgage debt sector.

Lastly, on average, we find that during financial crises in South Africa, real house prices fall by 30% and real stock prices fall by 28%. Total growth in real domestic credit extended by all monetary institutions slows to about 31% on average over a downward phase (compared to 64% during an upward phase in the financial cycle). In the recent financial cycle downward phase, real house prices only fell by 15%, about half of the average. Similarly, stock prices fell by 20%, also not as much as the average over all financial downswings. The mortgage debt-to-income ratio was 10.7 percentage points higher than the average over all of the downward phases, as mortgage credit grew at a much faster pace than income over this period. Vehicle debt-to-income was also 5.2 percentage points above the average, while other consumer credit registered 6.2 percentage points above the average over all downward phases.

2.2 Establishing the financial cycle for South Africa

In order to determine if behaviour after the cycle peak has differed from previous cycles, we need to date the financial cycle, which tend to be long. Dating long cycles is more challenging than dating short cycles (Kamada and Nasu, 2011). We follow the approach of Farrell and

[7] The average duration of business cycle downturns in South Africa is 2.4 years, and for upturns 3.4 years.

Kemp (2018) to date the financial cycle using credit extension, house prices and equity prices[8]. The selection of these variables is largely based on the work of Drehmann et al. (2012) and Claessens et al. (2011, 2012). Although other variables can be included to determine the financial cycle, this depends on the availability of historical time series spanning at least a few long cycles[9].

Although long cycle theory dates back to the work of Schumpeter (1939), who gave status to the long cycles of Kondratieff (1922, 1925, 1926, 1928), more recent empirical work (Drehmann et al., 2010; Einarsson et al., 2015; Gonzalez et al., 2015; Farrell and Kemp, 2018) show that the financial cycle is about four times longer than the business cycle.

Similar to the official dating procedure followed by the South African Reserve Bank (SARB) to date business cycle phases, and based on recent financial cycle work (Farrell and Kemp, 2018), we take a conservative approach. We apply Bry and Boschan's (1971) dating algorithm adapted for financial cycles, as suggested by Drehmann et al. (2012). However, where Farrell and Kemp (2018) make use of the popular Christiano and Fitzgerald (2003) trend filter to determine the financial cycle, we use the Hodrick and Prescott (1997) filter with a λ value that most closely resembles the phase average trend (PAT) filter that is used in traditional business cycle dating procedures and by the SARB[10].

2.2.1 Data

We use monthly data, similar to the official methodology of the SARB for dating business cycle turning points. We include a composite monthly house price index, total domestic credit extension sourced from the SARB and equity prices from the Johannesburg Stock Exchange (JSE). All three series have been seasonally adjusted and deflated using the headline Consumer Price Index (CPI). We use these three series over the period 1966 to 2017 to compute a composite financial index for South Africa. Our house price index differs from Farrell and Kemp (2018) in that it includes data from more banks. The three variables used to determine the financial cycle are *house prices*, *equity prices* and *domestic credit extended*. We discuss each variable separately.

[8]Other work includes Boshoff (2005, 2010) who base their cycle on frequency-based filters, while Kabundi and Mbelu (2017) and Thompson et al. (2015a) estimate a financial conditions index for South Africa. Thompson et al. (2015b) showed that the forecasting ability of their constructed financial conditions index can possibly be used as an early warning indicator for macroeconomic instability, while Balcilar et al. (2016b) points to the importance of allowing for nonlinear effects when forecasting. Balcilar et al. (2018) show that it is not only the size of the financial shock that matters, but how the policy response accounts for the nonlinearities in the South African economy and subsequent policy reaction.

[9]See Einarsson et al. (2016) and Borio et al. (2001, 2010).

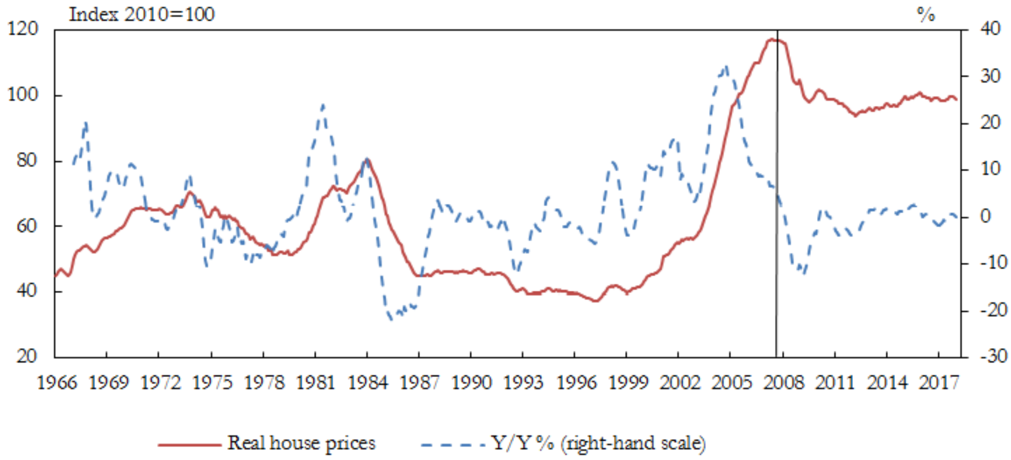
[10]See Zarnowitz and Ozyildirim (2006) for the translation of the PAT to the HP filter. Also see Ravn and Uhlig (2002), Lowe and Borio (2002) and Goodhart and Hofmann (2008) for using HP filters to detrend financial variables.

2.2.1.1 House price index

House price data in South Africa are sourced mainly from Absa, one of South Africas largest commercial banks. Homeownership in South Africa during the 1970s and 1980s was largely funded by building societies and not, as they are today, by commercial banks (Luüs, 2005). In 1990, the largest of these building societies, United Building Society, merged with other banks to form Absa.

The Absa house price index is often used in research on house prices in South Africa[11], as it has a long history and is available on a monthly basis. However, Absa stopped publishing the index in December 2016[12]. From 2000, First National Bank (FNB) and Standard Bank began to publically disseminate their house price data. Boonzaaier (2018) developed a weighted composite house price indicator, using indices produced by South African commercial banks, which have large mortgage books, including Absa, FNB and Standard Bank. Between 1966 and 2000 only Absa data is used, and from 2000 to 2001 a weighted index of Absa and Standard Bank is incorporated. From 2001 to 2017, the index is a weighted composite of all three banks. See Boonzaaier (2018) for the methodology (see figure 2.1 for the series). Luüs (2005) identified a house price bubble in the early 1980's based on house price growth. We identify two additional periods that are similar to Luüs (2005), where peak year-on-year growth is immediately followed by contractions in house prices (mid-1970's and from the 2000's).

Figure 2.1: Composite real house price index



Source: Boonzaaier (2018)

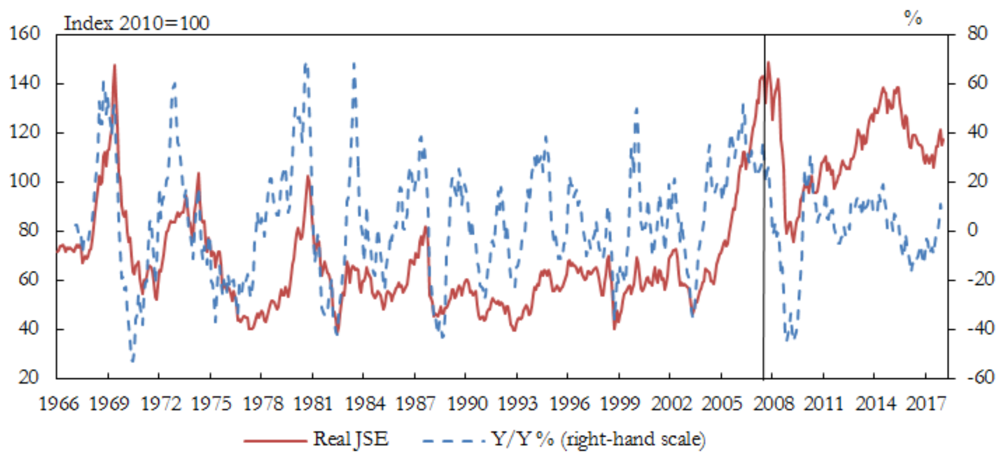
[11]Also see Simo-Kengne et al. (2014), Aye et al. (2014) and Patterson and Steenkamp (2017) for research on South African house prices and macro shocks.

[12]Boonzaaier (2018) draws attention to two big drawbacks in the Absa methodology. One is that the arithmetic mean is not ideal for a series that is likely skewed in its distribution and likely contains outliers. Boonzaaier (2018) also highlights that the unconventional stratification process together with the likelihood that the use of headline CPI for adjusting the bands can result in a series that may not be a true representation of house price movements in South Africa.

2.2.1.2 Equity prices

We include equity prices in the form of an index of all shares traded on the JSE (figure 2.2). Claessens et al. (2011) find that equity cycles are often not as correlated with business cycles as credit and house prices. This is also true in South Africa and one of a few reasons why the JSE share prices were dropped from the suite of indicators included in the SARB's composite leading business cycle indicator (see SARB, 2015). We also observe more cycles in equity prices than in house prices and credit extension, while the series is also more volatile. Balcilar et al. (2016a) show that there is a correlation between the probability that a bubble will burst in the JSE all share index and the relative size of the bubble. They identify 10 past episodes of possible bubbles in the JSE all share index.

Figure 2.2: JSE index



Source: SARB

2.2.1.3 Credit extended

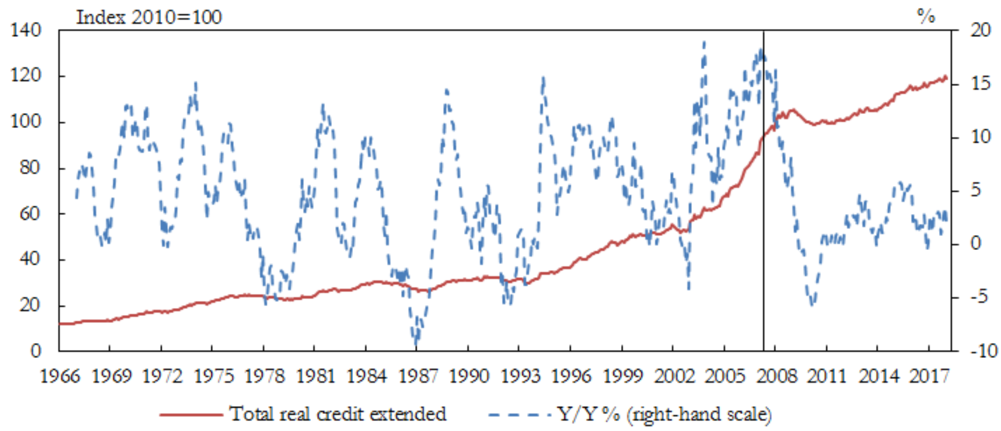
We also use total domestic credit extension by monetary institutions as a measure for credit extension (figure 2.3). The data includes mortgage debt, vehicle debt and all other consumer credit extended by South African registered banks to the domestic private sector, excluding bills (acceptances, commercial paper, similar acknowledgements of debt) and investments. The data has been deflated and seasonally adjusted.

2.2.2 Methodology

We use a similar approach to the SARB's composite indicator methodology for constructing a composite financial cycle indicator for South Africa[13]. The approach is based on the indicator

[13]See Venter (2019a) for the full chronology of business cycle dating in South Africa.

Figure 2.3: Real credit extended to private sector by all monetary institutions



Source: SARB

approach which was first developed in the 1930s by the National Bureau of Economic Research (NBER), under the supervision of Burns and Mitchell (The Conference Board, 2001; Moore, 1983). Later the production of the indicators was done by the U.S. Department of Commerce and in December 1995 the responsibility was given to the Conference Board[14]. We include the real house price index, the real JSE index and total real credit extended, all in levels. We construct our composite index based on The Conference Board (2001) methodology:

We calculate the symmetrical month-to-month percentage changes, $r_{i,t}$ for each component series $Y_{i,t}$ where $i = 1 \dots 3$

$$r_{i,t} = 200 * (Y_{i,t} - Y_{i,t-1})/(Y_{i,t} + Y_{i,t-1})$$

Next we calculate the standardized monthly changes, $c_{i,t}$ for each component series:

$$c_{i,t} = r_{i,t}/SD_i, \text{ where}$$

SD_i = the standard deviation of $r_{i,t}$ over the specified standardization period[15].

We then calculate the average standardized sum of contributions (SS_t) by adding $c_{i,t}$ across all the components for each month:

[14] The OECD started publishing leading indicators in 1987 (Mongardini and Saadi-Sedik, 2003). Although there are slight differences in the methodologies of dating classical or growth cycles, the indicator approach is broadly followed by all three of these institutions.

[15] The standardization period should cover a number of complete financial cycles, i.e. an equal amount of upward and downward phases.

$$SS_t = \sum_{i=1}^{n} \frac{c_{i,t}}{N}$$

and compile preliminary levels of the composite index using the standardized sum of contributions (SS_t) and the symmetrical percentage change formula. Start with an initial value $I_t = 100$, then

$$I_{t+1} = I_t * (200 + SS_{t+1})/(200 - SS_{t+1}), \text{ for all values of } t.$$

Lastly, we rebase the index to average 100 in base year, which is 2010 in our case.

Different weights may be assigned to component series to reflect their importance in the cycle (Brunet, 2000). Weights can be selected to give more importance to statistically reliable data or data with a broader coverage. Alternatives could include using models such as principal component analysis (PCA) or factor analysis (Nardo et al., 2008). We found that PCA suggested that each variable contributed almost equally to the total variation in our composite financial index[16]. Although confirming our equal weighting, these methods could bias the index over the full cycle as the timing relationship of the different indicators are not always the same and in some periods one indicator may dominate the cycle more than another.

Most composite indicators rely on equal weighting where all variables are weighted the same, and therefore their weights are implicitly equal (in other words they are not, unweighted) (Nardo et al., 2008). Since 2004, the SARB also follows this weighting methodology for business cycle indicators (Venter, 2019b). We therefore also allow each indicator to add equal value to the index.

In dating the reference financial cycle, most researchers start with Burns and Mitchell (1946), although Zarnowitz (1992) formalised the approach, while Laidler (1999) and Besomi (2006) have extended it to apply to financial cycle analysis. The SARB makes use of growth cycle analysis to determine reference turning points in the business cycle, which should not be confused with classical cycle methodology. Growth cycle analysis examines the deviation of an indicator from its long-term trend to determine if it is accelerating or decelerating above or below the trend. In the development of growth cycles, long-term moving averages were initially used as a trend approximation (Mintz, 1969, 1972). The phase-average trend (PAT) provides the best results for determining growth cycle turning points (Boschan and Ebanks, 1978; Klein and Moore, 1985). Zarnowitz and Ozyildirim (2006) show that instead of an iterative PAT process, the Hodrick-Prescott (HP) filter could be used.

[16]The author would like to thank a reviewer who suggested we test the contributions of each variable to the total. Each variable contributed around 1/3 to the total variation.

Different detrending techniques have been used to establish financial cycles, none of them are without drawbacks. Other options include band-pass filters, such as the Christiano and Fitzgerald (2003)[17] or the Baxter and King (1999) filter; however, the HP filter remains a popular choice, when detrending a series[18]. Although many follow the Hodrick and Prescott (1997) standard value of λ, 1 600 for quarterly data, Zarnowitz and Ozyildirim (2006) suggest that λ should be chosen to minimise the difference between the PAT and the HP –for growth cycles with monthly data, 108 000 is more appropriate. Einarsson et al. (2015), Stremmel (2015), Gonzalez et al. (2015) and Drehmann and Juselius (2014) follow Ravn and Uhlig (2002) to convert λ between monthly, quarterly and annual series; however, each conversion formula starts from the 1600 quarterly data default proposed by Hodrick and Prescott (1997)[19].

To adapt the HP filter for financial cycles, the Basel Committee on Banking Supervision (2010) suggest following Drehmann et al. (2010), as the financial cycle is four times longer than the business cycle[20]. Therefore, a higher λ value of 400 000 for quarterly data ($\approx 4^4 * 1600$) should be used. Since we are using monthly data, our starting point is 108 000, as proposed by Zarnowitz and Ozyildirim (2006) for monthly data. We apply the Drehmann et al. (2010) conversion for the longer length of the financial cycle. Thus, for financial cycles the λ for monthly frequency data is 27 648 000 ($\approx 4^4 * 108000$)[21]. The trend result is shown in figure 2.4.

[17] See Drehmann et al. (2012); Einarsson et al. (2015, 2016); Aikman et al. (2015); Hiebert et al. (2015); Strohsal et al. (2017) for examples of these.

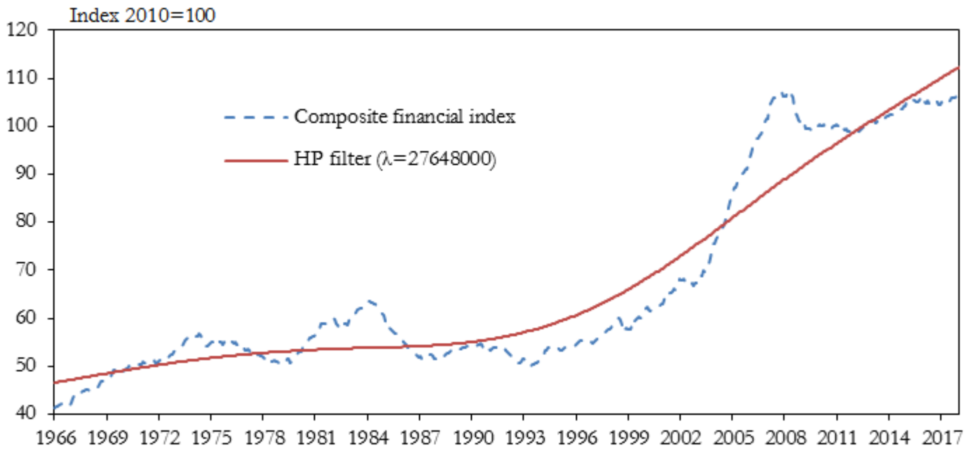
[18] Hamilton (2018) proposes an alternative to the HP filter. The author would like to thank a reviewer for suggesting that we test the HP procedure against the Hamilton (2018) regression. We applied this methodology (adjusted for the financial cycle length). As used by Schüler (2018), based on the Basel III recommendation (see Hamilton (2018)), we used (for monthly data) a 5-year regression period. We therefore take h=60 and p=12 for monthly frequency to get to the Hamilton cycle (Hamilton, 2018). Our turning points remained the same (see A.2.1 for a graphical comparison).

[19] $\lambda_{quarterly}$=1600; λ_{annual}=1600/4^4=6.25 and $\lambda_{monthly}$=$1600 * 3^4$=129600.

[20] Other studies that apply this methodology include Gerdrup et al. (2013), Alessi and Detken (2009a), Claessens et al. (2011, 2012), Drehmann et al. (2012) and Hiebert et al. (2014).

[21] We find that the HP filter provides robust turning points at these large λ values. We also tested a λ of 352 proposed by du Toit (2008) (7 299 072 when converted to financial cycles) and the turning points remain unchanged. A very small λ will result in many additional short cycles.

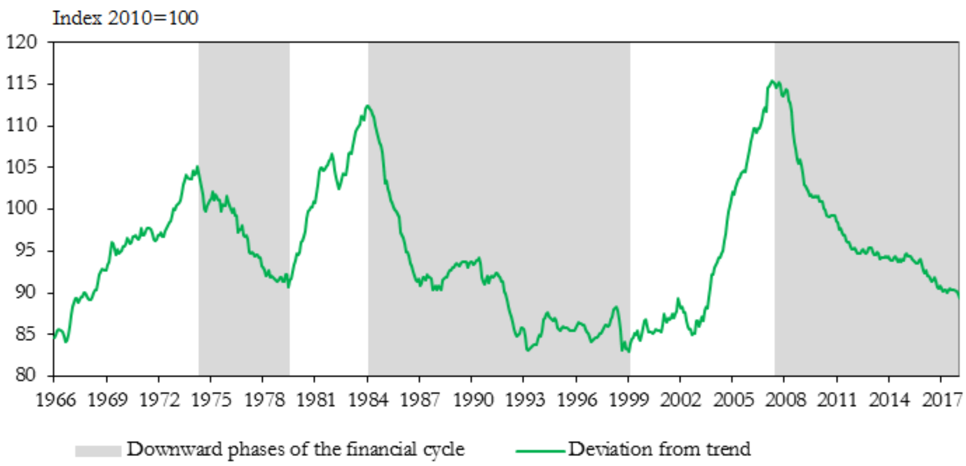
Figure 2.4: Financial index and HP filter (λ=27 648 000)



Source: Own calculations, SARB

In business cycle turning point analysis, the Bry and Boschan (BB) algorithm is usually applied for dating (Harding and Pagan, 2002). We adapt the BB algorithm for application to the financial cycle, i.e. we multiply the minimum duration of a cycle and phase by 4. For BB business cycles, the minimum duration of a phase of a cycle is 6 months, and the minimum duration for a full cycle is 15 months. For financial cycles, we use the Drehmann et al. (2012) criteria that the minimum duration of a phase is 27 months and the minimum for a full cycle is 60 months. Applying this methodology we find that, over the period 1966 to 2017, there have been three financial cycles in South Africa (figure 2.5). The financial index's deviation from trend reaches peaks in April 1974, January 1984 and May 2007 (table 2.1). At the end of the 2017 South Africa was still in a downward phase of the financial cycle.

Figure 2.5: Final financial cycle



Source: Own calculations

Table 2.1: Financial cycle dates at peaks and troughs

Peak	Trough
April 1974	July 1979
January 1984	February 1999
May 2007	

Source: Own calculations

We follow Hiebert et al. (2018) comparing the average length of the financial cycle to the South African business cycle (table 2.3). We find that the overall length of the financial cycle in South Africa is 17.3 years - very close to 17.1 in recent cross country research including South Africa (Gonzalez et al., 2015). It is also much longer than the average business cycle length (5.8 years), which is similar to Drehmann et al. (2010), who found that the financial cycle lasts between 5 and 20 years, with a median of 15 years. Financial cycles in South Africa are, therefore, around 3 times longer than business cycles. Table 2.2 compares the length and dates of the South African business cycles to the financial cycle.

Table 2.2: Dates and length of the business cycle compared to the financial cycle

Business cycle turning points		**Financial cycle turning points**		**Business cycle turning points**		**Financial cycle turning points**	
Upward phase	**Duration (months)**	**Upward phase**	**Duration (months)**	**Downward phase**	**Duration (months)**	**Downward phase**	**Duration (months)**
Jan 1966-May 1967	17	Jan 1966-Apr 1974	100	Jun 1967-Dec 1967	7		
Jan 1968-Dec 1970	36			Jan 1971-Aug 1972	20		
Sep 1972-Aug 1974	24			Sep 1974-Dec 1977	40	May 1974-Jul 1979	62
Jan 1978-Aug 1981	44	Aug 1979-Jan 1984	53	Sep 1981-Mar 1983	19		
Apr 1983-Jun 1984	15			Jul 1984-Mar 1986	21	Feb 1984-Jan 1999	182
Apr 1986-Feb 1989	35			Mar 1989-May 1993	51		
Jun 1993-Nov 1996	42			Dec 1996-Aug 1999	33		
Sep 1999-Nov 2007	99	Feb 1999-May 2007	98	Dec 2007-Aug 2009	21	Jun 2007-	126
Sep 2009-Nov 2013	51			Dec 2013-	48		
Average duration in years	**3.4**		**7.0**		**2.4**		**10.3**

Table 2.3: Summary of average length of cycles (in years)

Financial cycle			**Business cycle**		
Peak-to-trough	Trough-to-peak	Overall	Peak-to-trough	Trough-to-peak	Overall
10.3	7.0	17.3	2.4	3.4	5.8

Source: Own calculations

The average duration of business cycle downturns in South Africa is 2.4 years, and for upturns 3.4 years (table 2.2). Contrary to Hiebert et al. (2018), we find that, on average, financial cycle contractions (10.3 years) last longer than expansions (7.0 years). The long duration of financial cycle contractions shows us that deleveraging is a longer process (Hiebert et al., 2018).

The South African cycle is, therefore, similar in length to the UK (18.1 - 18.5 years), France (15.4 - 16.7) and Italy (15.6 - 19.2), depending on the method (Rünstler and Vlekke, 2018). It is also about the same length as estimated by Schüler et al. (2017) for the US and the UK (≈ 16.4 years).

2.3 Overview of the three South African financial cycle downward phases

Table 2.4 summarises growth in our three main financial variables: real house prices, real JSE all share index and total real domestic credit extended by all monetary institutions over the three financial cycle downward phases. This section provides a brief economic and policy overview of the different financial cycle downward phases.

Table 2.4: Growth between turning points

Financial cycle phases	Real house prices	Real JSE	Total real credit extended
1969/Q1-1974/Q1	35.7	40.7	69.5
1974Q2-1979Q3	-24.6	-41.3	5.1
1979/Q4-1983/Q4	56.6	4.9	29.2
1984Q1-1999Q1	-49.6	-22.1	60.3
1999/Q2-2007/Q1	189.2	174.2	94.4
2007Q2-	-15.2	-19.7	26.4
Upward phases	93.8	73.3	64.3
Downward phases	-29.8	-27.7	30.6

Source: Own calculations

2.3.1 Financial downward phase 1974 - 1979

The financial cycle downward phase of 1974 to 1979 coincided with a downswing in the South African business cycle. Over this period the South African economy was impacted by international structural changes including the creation of a free gold market and the breakdown of the Bretton Woods system of fixed exchange rates, which was replaced by an inconvertible dollar standard with floating exchange rates. The oil shock of 1973 caused oil prices to increase sharply at a time when industrial countries were already close to a business cycle downturn leading to world-wide higher inflation and lower economic growth, including in South Africa (Smit and van der Walt, 1982). The oil crisis had a marked impact on the balance of payments and on inflation. From 1974 to 1976, South Africa's imports rose sharply, and although the terms of trade was initially supported by a stronger gold price, it was followed by a marked deterioration, especially in 1975 (Smit and van der Walt, 1982).

Unfavourable international developments during 1976 to 1977, as well as domestic political instability and violent uprising put further downward pressure on the South African economy. The 1976 Soweto student uprising had a severe negative impact on confidence and economic performance (Luüs, 2005). House prices declined by 22.4% in real terms between 1976 and 1979 and capital inflows declined to such an extent that the current account deficit could no longer be financed by the capital account (Moolman, 2004). Policies were redirected to balance the current account, and restrictive monetary and fiscal policies were adopted. South Africa was caught in a "debt trap" (Moolman, 2004). The availability of credit to private households was strongly curtailed by bank credit ceilings which were in force in South Africa from 1967 to 1972 and again from 1976 to 1980 (Van der Walt, B.E. and Prinsloo, J W., 1993). During this period real house price growth contracted by 24.6%, while the JSE all share index fell by 41.3%, in conjunction with real credit extended slowing markedly to a rate of only 5.1% (see table 2.4), and average inflation rising to 11.9%[22].

2.3.2 Financial downward phase 1984 - 1999

Between 1984 and 1999, the financial cycle overlapped with three downward phases in the business cycle. This period was preceded by the international debt crisis of 1982 as well as a rise in protectionism from 1981 which adversely impacted world trade. This was worsened by the intensity of the 1981 to 1982 global recession (Van der Walt, B.E., 1989). In South Africa, the long post-war business cycle downswing from 1989 to 1993 was further exacerbated by severe drought conditions (Venter, 2019a) as well as continued political unrest and violence in South Africa. These events, especially those of the latter part of 1985, led to the debt standstill (Venter, 2019a), and the withdrawal of foreign loans and credit facilities to South Africa together with large capital outflows, adding further pressure to the balance of payments. Authorities prioritised the repayment of foreign debt, which translated into economic growth declining to a rate consistent with the current account surplus (Venter, 2019a). Despite property prices holding up well from 1981 to 1983 (Luüs, 2005), the efforts to rebalance the balance of payments account, together with increased political pressure and instability, resulted in the burst of the property price bubble, with real house prices declining sharply between 1984 and 1987 (Luüs, 2005) and kept in line with inflation up to 1991.

The housing market started its recovery in 1998 on the back of lower inflation and declining interest rates, as well as higher economic growth. After a brief interruption caused by the Asian

[22] Inflation targeting was introduced only in February 2000.

crisis (1997 - 1999), leading to a sharp depreciation in the exchange value of the rand and an increase in interest rates, house price growth resumed in late 1999. During this financial downward phase, real house price growth contracted by 49.6%, while the JSE all share index contracted by 22.1% (see table 2.4). Unlike the other two downward phases of the financial cycle, real credit extended continued to outperform the preceding upward phase growth, with real credit extended increasing by 60.3% during the period. Average inflation over this period was 15.7%.

2.3.3 Financial downward phase 2007 -

The recent downward phase of the financial cycle coincides with two business cycle downward phases. South Africa experienced a record length upward phase of the business cycle between 1999 and 2007 which was largely supported from 2003, by low inflation, accommodative monetary policy, and personal income tax relief, which led to higher disposable income growth and exceptionally strong economic growth due to strong consumer spending (Venter, 2009). From 2005, asset prices increased sharply making households more leveraged (similar to the global experience), resulting in household debt levels reaching a record high as a share of disposable income in 2005. The current account deficit made South Africa vulnerable to the 2007 US sub-prime crisis (Laubscher, forthcoming). Although debt grew sharply, debt servicing cost as a share of disposable income remained low as monetary policy remained fairly accommodative, resulting in households not realising the full extent of their risk exposure (Venter, 2009).

The National Credit Act (NCA) was enacted in March 2006 (effective from 1 June 2006) with the compliance sections coming into effect from 1 June 2007 and aims "to promote and advance the social and economic welfare of South Africans, promote a fair, transparent, competitive, sustainable, responsible, efficient, effective and accessible credit market and industry, and to protect consumers." (BASA, 2017). The Act further aims to encourage responsible borrowing by consumers to avoid over-indebtedness and reckless lending (Jourdan and Ellyne, 2015). Similar to De Wet et al. (2015), Jourdan and Ellyne (2015) conclude that the NCA facilitated credit booms from 2005 to 2008, and again during 2010 to 2014, thus indicating that the NCA has not been successful in reducing over-indebtedness, and therefore did not lessen the impact on consumers against the global financial crisis. Between 2006 and 2008 inflation accelerated rapidly and the increased interest rates slowed growth in consumer spending and demand from heavily indebted households which resulted in the 2008/09 economic recession in South Africa. The South African business cycle started to recover at the end of 2009, however, this period will be remembered for the poor business cycle recovery phase (Laubscher, forthcoming) as mortgage advances kept on slowing and real house prices decreased, while employment fell sharply and banks implemented tighter lending criteria[23]. Over the 2008 to 2013 period[24]. Growth in South Africa was negatively impacted by sluggish global growth and a slowdown in commodity price growth. Despite the significant reduction in the repurchase rate from 12% to 5%, the lacklustre recovery in consumption was a result of the sharp increase in debt levels before the 2007 financial cycle peak. The pace of deleveraging was negatively impacted by factors such as higher inflation, which eroded the disposable income of households, as well as domestic supply-side challenges, widespread drought conditions (Kemp, 2018) and policy uncertainty, which adversely affected confidence and growth in the economy. This latter period of the downward phase was seriously impacted by corruption, questions around state-capture and significant economic policy uncertainty (Laubscher, ming).

Table 2.4 show that real house price growth contracted by 15.2% over this period, while the JSE all share index contracted by 19.7%. However, that might be attributable to the large number of dual-listed companies on the JSE[25]. Growth in real credit extended slowed markedly from 94.4%, over the preceding financial cycle upswing, to 26.4% over this financial cycle downward phase. Unlike the previous two financial cycle phases, the SARB introduced inflation targeting in February 2000 (Venter, 2009), whereby monetary policy aims to keep inflation between 3% and 6%. During the 2007 to 2017 financial cycle downward phase the average inflation rate was much lower at 6.2%, compared to the previous two financial cycle downward phases, despite the rapid rise in house and other asset prices preceding the financial cycle peak.

2.4 A brief description of debt and deleveraging following the 2007 financial cycle peak in South Africa

According to Lo and Rogoff (2015), most of the work done on the role of leverage in worsening financial crisis outcomes has shown the importance in controlling leverage to stabilise the economy. It would therefore also be an important measure at the end of a financial crisis to see if there was a sufficient unwinding of leverage. At a macroeconomic level, to measure deleveraging, ratios such as debt-to-income and debt servicing cost to income are often used (Glick and Lansing, 2009; Fondeville et al., 2010). According to (Bhutta, 2012) because deleveraging entails repaying debt (which was accumulated in earlier periods) at a faster pace, the process of deleveraging involves taking resources away from other parts of economic activity such as consumption or savings

[23]It is difficult to measure the impact of the NCA which came into effect in 2007, as this coincided with the global economic slowdown. Although stricter lending criteria could have limited households' access to credit and households who did not qualify for credit, were likely forced to take up unsecured credit at much higher interest rates.

[24]During mid-2011, unsecured lending grew sharply and peaked at 40% as many of these loans were extended to workers in the mining sector as labour market disputes resulted in workers facing defaulting on their loans (see Venter (2009) for a full description).

[25]These are companies with both local and foreign operations where performance is driven by both local and international developments, including the impact of exchange rate movements. These companies typically have large market capitalisation on the JSE.

in order to repay debt. There exist different motivators for deleveraging, which are covered in chapter 4. The next section will evaluate macroeconomic leverage measures to determine to which extent households deleveraged after the recent 2007 financial cycle peak.

South Africa experienced a record length upward phase of the *business cycle* between 1999 and 2007, with the latter part of the upswing being characterised by exceptionally strong economic growth, as inflation moderated and monetary policy became more accommodative. Although the domestic economy at the time was already slowing, due to internal imbalances, the spillover from the global financial crisis had a severe impact on financial variables, such as house and asset prices and household debt.

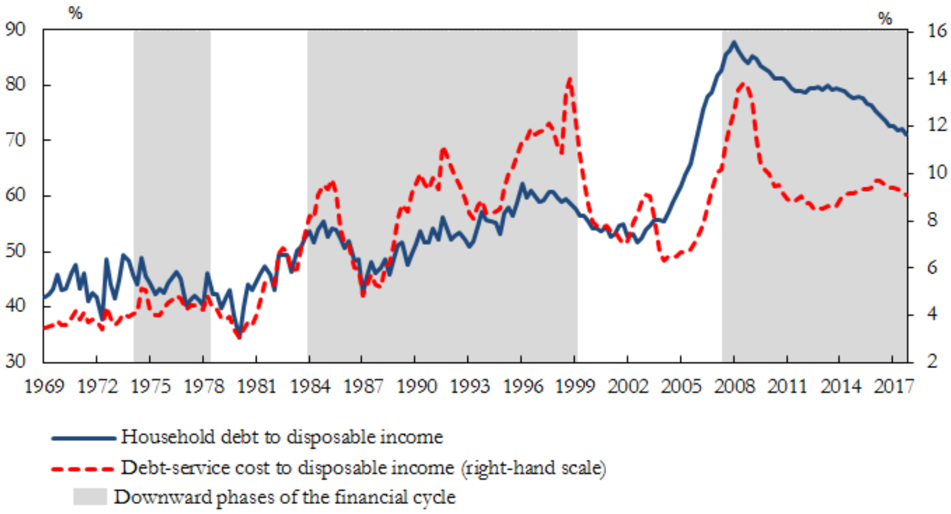
Total household debt-to-income increased significantly from 51.2% in September 2002 to 87.8% in March 2008 (its highest level measured since 1969) (figure 2.6). Shortly after the South African financial cycle reached its peak in May 2007, households started to deleverage, as their wealth deteriorated, relative to their stock of debt. Household debt-to-income has, however, only decreased to 71.1% by the end of 2017, still about 20 percentage points above pre-financial peak levels. Although household debt grew sharply over the 2002 to 2007 period, debt-servicing costs as a share of disposable income remained low, as interest rates stayed fairly accommodative up to 2005. Thus, households did not realise the full extent of their exposure (figure 2.6). Household debt-service costs as a proportion of income increased sharply after that, reaching a high of 13.8% in September 2008. As monetary policy became more accommodative following the global financial crisis, debt-service costs to income decreased to 8.5% in September 2012, before returning to 9% at end of 2017.

Mortgage advances are the single largest debt category, comprising around 43% of total credit extended by all monetary institutions, while vehicle loans contribute 12% and the remaining share belongs to other credit. Figure 2.7 shows that the ratio of both mortgage- and vehicle debt-to-income increased at a much faster pace than other consumer debt-to-income[26]. The increase in vehicle and other consumer debt-to-income was mostly driven by imports (mostly durable goods) as the exchange rate appreciated during this period, and leading up to the financial cycle peak (Venter, 2009). Mortgage- and vehicle debt-to-income decreased at a faster pace than other consumer credit after the financial cycle peak.

In South Africa, most mortgage loans have a variable interest rate, wherein households can deposit and are typically allowed to withdraw surplus funds. As house prices increased sharply pre-financial peak, households used surplus funds for consumption purposes, believing that the value of their houses would continue to grow quickly. After the housing bubble burst, house prices

[26] Other consumer debt includes general loans and overdrafts from banks as well as credit extended by non-banks such as retail accounts and accounts payable.

Figure 2.6: Ratio of total household debt-to-disposable income and total debt-service cost to disposable income*



*Disposable income is a national accounting aggregate measure and includes those with and without debt.
Source: SARB

declined sharply, resulting in many households not being able to sell their homes as they were left with little or even negative equity. Furthermore, banks put more stringent lending criteria in place[27]. Other household deleveraging resulted from paying off more capital in the initial high interest rate environment. Figure 2.7 shows a sharp increase in other consumer debt-to-income ratio at the end of 2009. It is likely that alternative credit sources were the only accessible funds for highly indebted households and/or households who did not meet the stricter lending criteria set by banks.

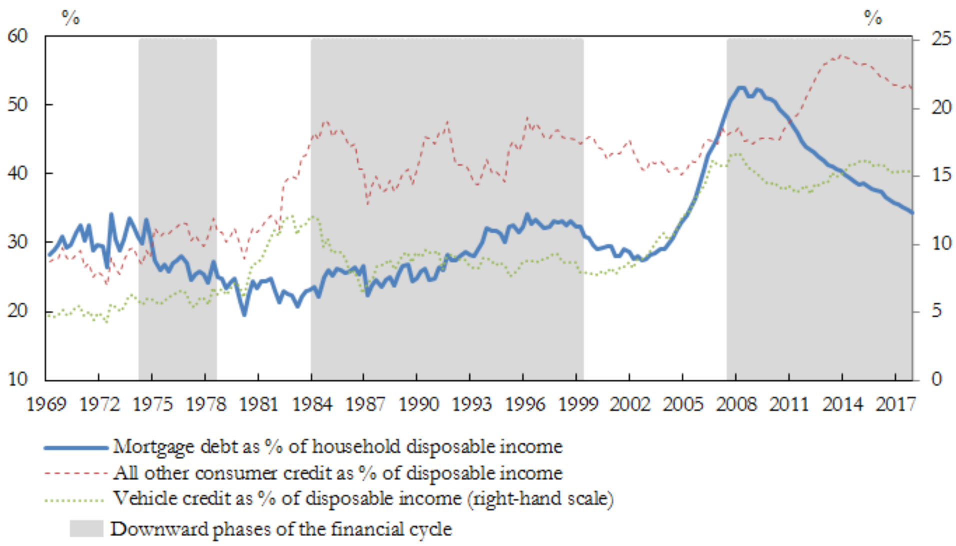
In March 2003, mortgage debt as a share of household income stood at 25.7%, before doubling to 52.5% in March 2008. By December 2017, households had only reduced their mortgage debt, as a percentage of income, to 34.4%.

The ratio of financing costs (interest and other lending costs) to income for mortgages, vehicles and other consumer credit, decreased between 2008 and 2013. This was in line with the fall in the repo rate (the rate to which banks link their prime lending rates) to historically low levels, from 12% to 5% (figure 2.8).

It is not only the demand for credit that slows after a financial bust, but also the level of credit supplied by the banking sector. Following Einarsson et al. (2015), we show in figure 2.9 that the asset to capital ratio of banks (bank leverage) rose sharply from 9.7% in 2001 to 18.6% in

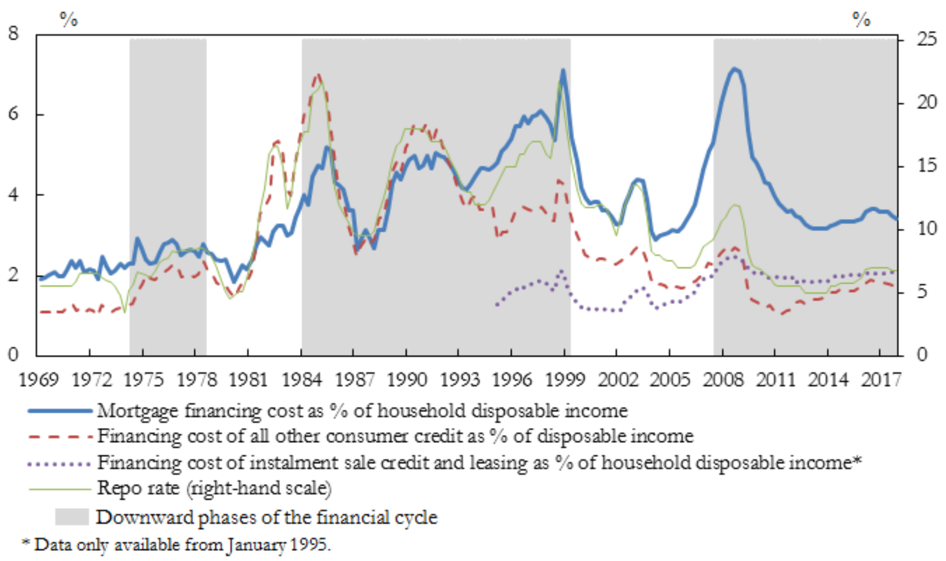
[27] It is difficult to measure the impact of the national credit act which came into effect in 2007, as it coincided with the economic slowdown. Stricter lending criteria also limited households' access to credit and households who did not qualify for credit, were basically forced to take up unsecured credit at much higher interest rates.

Figure 2.7: Ratio of household credit to disposable income* by debt category



*Disposable income is a national accounting aggregate measure and includes those with and without debt.
Source: SARB

Figure 2.8: Household debt-service cost to disposable income* by debt category



*Disposable income is a national accounting aggregate measure and includes those with and without debt.
Source: SARB

December 2008. Bank assets (mainly loans) increased sharply, before falling back to pre-financial peak levels only at the end of 2017. Supporting our earlier findings, figure 2.9 shows that banks have managed to bring this ratio down through credit repayment, limited or reduced lending, bad debt write-offs or a combination. The decrease in the household loan to deposit ratio, since its peak in January 2008, also suggests that banks are only now finding room to provide credit again.

Figure 2.9: Bank capital to total asset ratio (bank leverage) and loan to deposit ratio

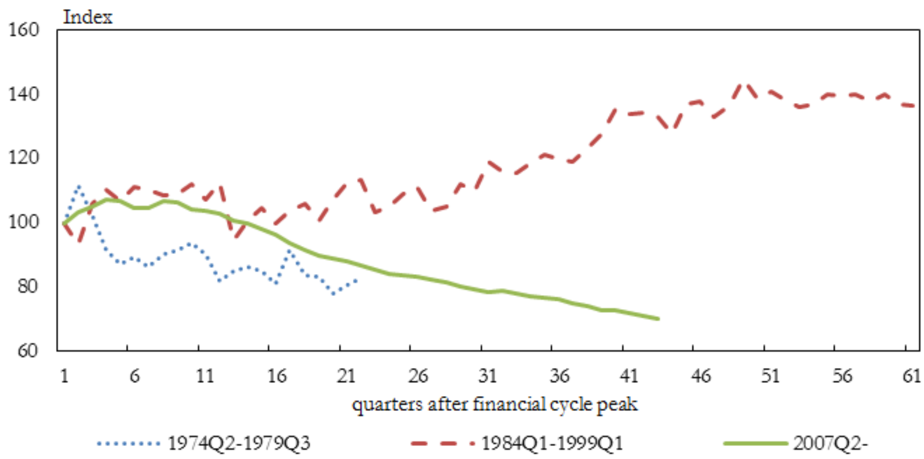
Source: SARB

2.5 Results

2.5.1 Comparing household debt deleveraging across downward phases of the financial cycle

We re-index our cycle peaks, setting each to 100 for our three debt variables, and compare how far South Africa has deleveraged during financial cycle downward phases. For the remainder of the chapter income refers to disposable income as a national aggregate and includes those with and without debt. We find that the mortgage debt-to-income ratio fell much faster and for a longer period (10 years) in the current downward phase compared to the two previous phases (figure 2.10). Our finding supports earlier claims that mortgage advances played a crucial role in the financial downswing, and that most of the deleveraging took place in this debt category.

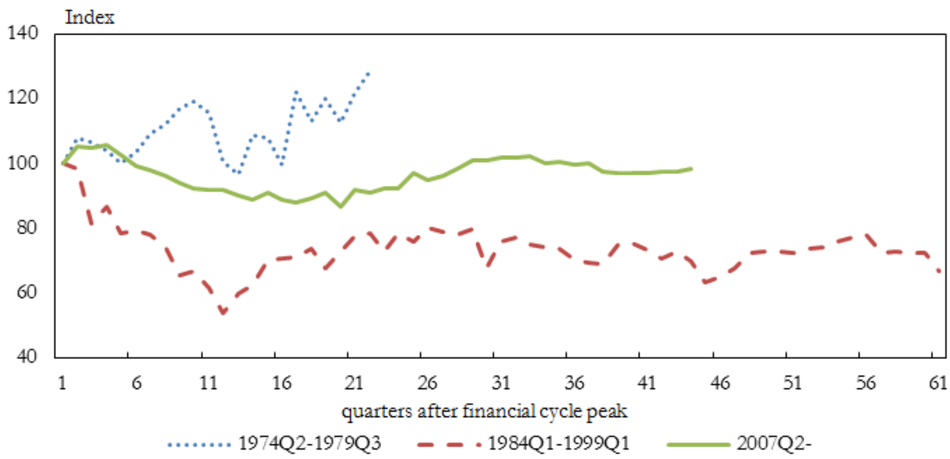
Figure 2.10: Financial cycle phase comparisons: Mortgage debt-to-income ratio



Source: Own calculations, SARB

The vehicle debt-to-income ratio declined only marginally following the latest financial cycle peak; however, it continued to hover around the 100 level, suggesting that very little deleveraging took place in the South African vehicle finance market. During the previous financial trough, the vehicle debt-to-income ratio initially fell more sharply, before stabilising at a lower level (figure 2.11), suggesting that there was initial deleveraging in this phase, which has not been as prominent in the current phase.

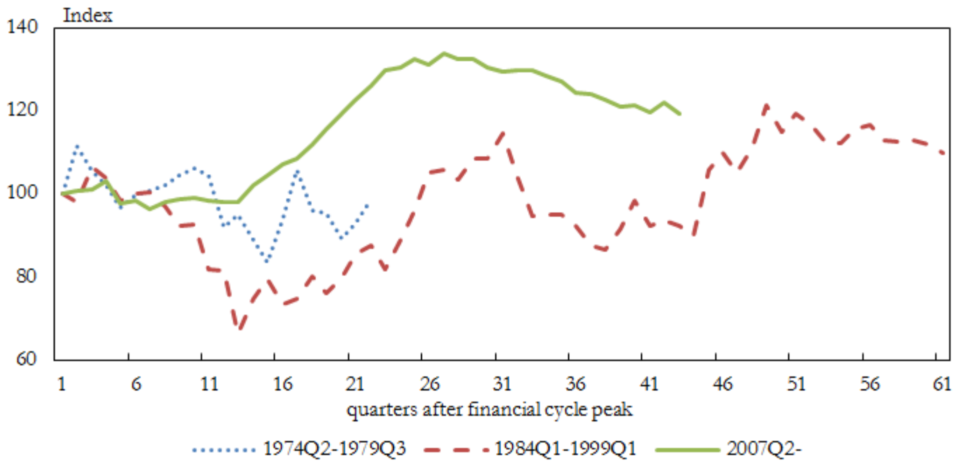
Figure 2.11: Financial cycle phase comparisons: Vehicle debt-to-income ratio



Source: Own calculations, SARB

The other consumer credit-to-income ratio initially declined (figure 2.12), but picked up sharply about 3 years after May 2007, possibly due to distress borrowing or debt consolidation. During the previous financial downward phase (January 1984 - February 1999) consumer credit initially fell much faster, compared to the other two phases. The 1984 - 1999 downward phase was likely driven by consumer credit, as opposed to mortgage credit. However, it is clear that mortgage credit rose during that downward phase, rather than fully unwinding by the start of the (March 1999 - May 2007) financial cycle upswing.

Figure 2.12: Financial cycle phase comparisons: All other consumer debt-to-income ratio



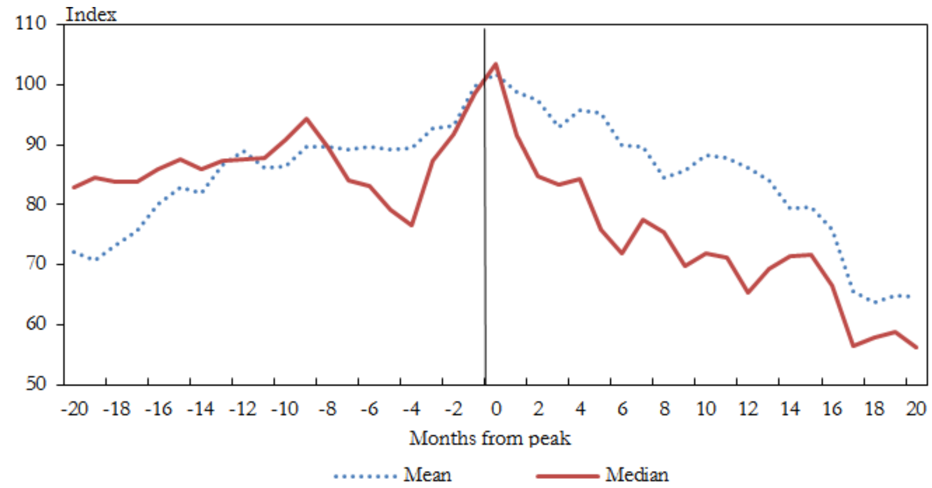
Source: Own calculations, SARB

2.5.2 Results: Phase average comparisons for financial sector variables

Figure 2.13 - 2.15 represents the average, or typical, behaviour of our three financial variables (20 quarters[28] before and 20 quarters after the three financial cycles that we have dated) to examine financial variable deflation paths. We follow Einarsson et al. (2015) using both the mean and median over the three cycles, although the mean and median are fairly similar for our three financial indicators. On average, see figure 2.13, we find that the JSE index peaked at the same time as the financial cycle peaked and decreased sharply thereafter. These results are similar to Reinhart and Rogoff (2009), who show that equity prices fall by 55 per cent, on average, over a downturn period of three and a half years.

[28]This is an arbitrary number of quarters. It is longer than what would usually be shown in business cycle literature as financial crises take much longer to build up and unwind.

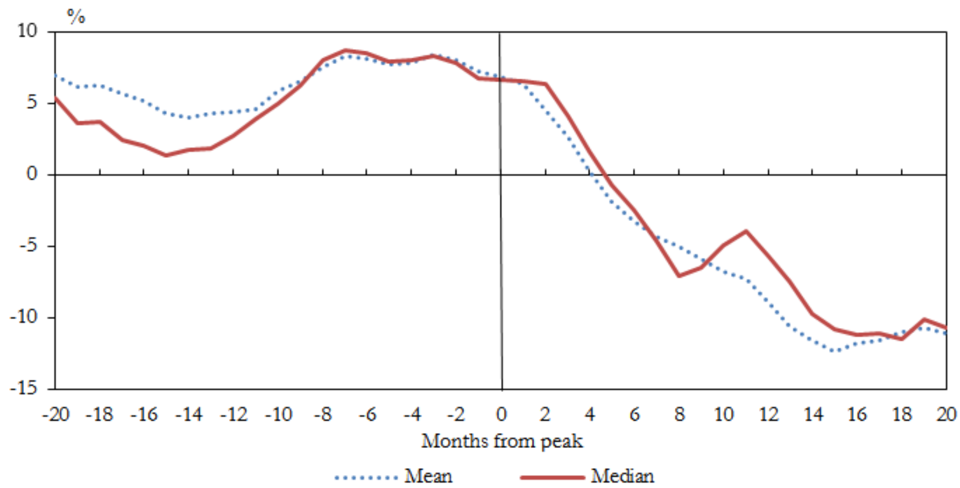
Figure 2.13: JSE: mean and median comparison



Source: Own calculations, SARB

Einarsson et al. (2015) find that real house prices peaked 4 quarters before a peak, falling significantly during the aftermath. We see a similar trend in South Africa's real house prices, where the peak is about 8 quarters before and growth, on average, falls sharply after a financial cycle peak is reached, see figure 2.14.

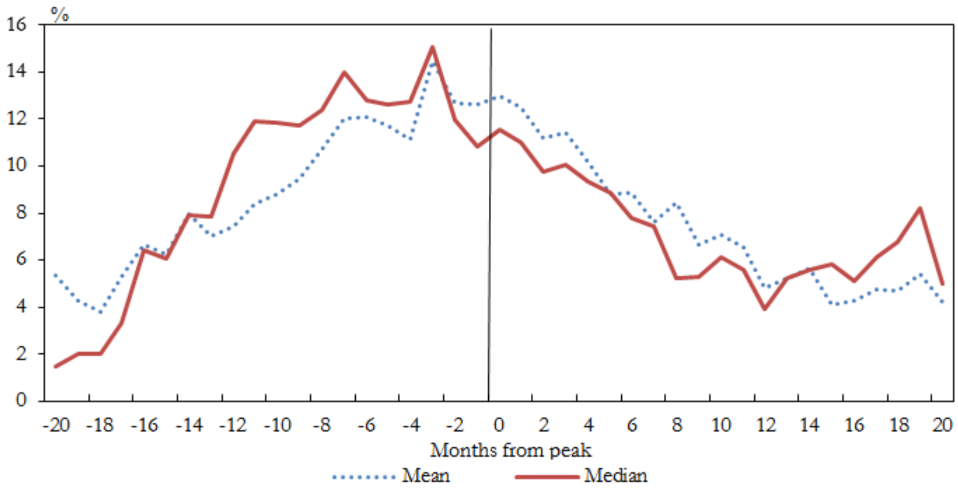
Figure 2.14: House price growth(y/y): mean and median comparison



Source: Own calculations, SARB

For credit, we see a sharp initial increase that peaks 3 quarters before a financial cycle peak, (see figure 2.15), followed by a sharp decline for about 12 quarters. According to Reinhart and Rogoff (2009), more often than not, house prices fall by about 35% over a six year period following a financial crisis. It does seem that house prices in the US and in other emerging economies declined more than in South Africa following the collapse of the most recent house price bubble, suggesting that South African house prices have not yet fully normalised.

Figure 2.15: Credit growth (y/y): mean and median comparison

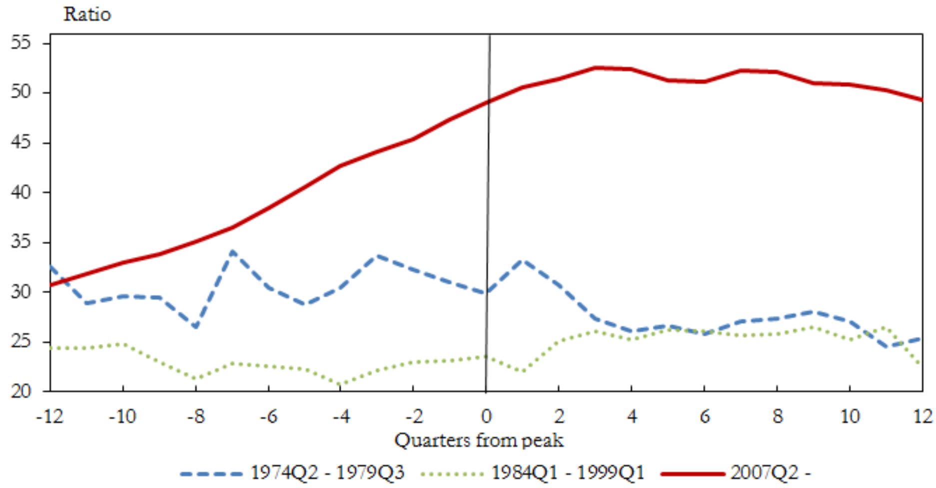


Source: Own calculations, SARB

2.5.3 Results: Phase comparison around turning point for debt variables

Similar to Einarsson et al. (2015), we compare movements in the recent downward phase in our three debt variables over the financial cycle to the other two downward phases. Because we only have three phases, we compare each phase directly, instead of using the mean and median as in Einarsson et al. (2015) (as used for the phase average comparisons of the financial sector variables in section 2.5.2). The ratio of mortgage debt-to-income during the current phase differs substantially from the previous two phases (figure 2.16). Preceding the recent financial downward phase there was a sharp increase in the debt-to-income ratio, providing evidence that this phase was to a large extent driven by mortgage debt. Since the most recent peak, mortgage debt-to-income has moderated slightly, but remains elevated, compared to the other two phases. Although the mortgage debt-to-income ratio remained high, growth in mortgage debt declined sharply after the recent financial cycle peak (see figure A.2.8).

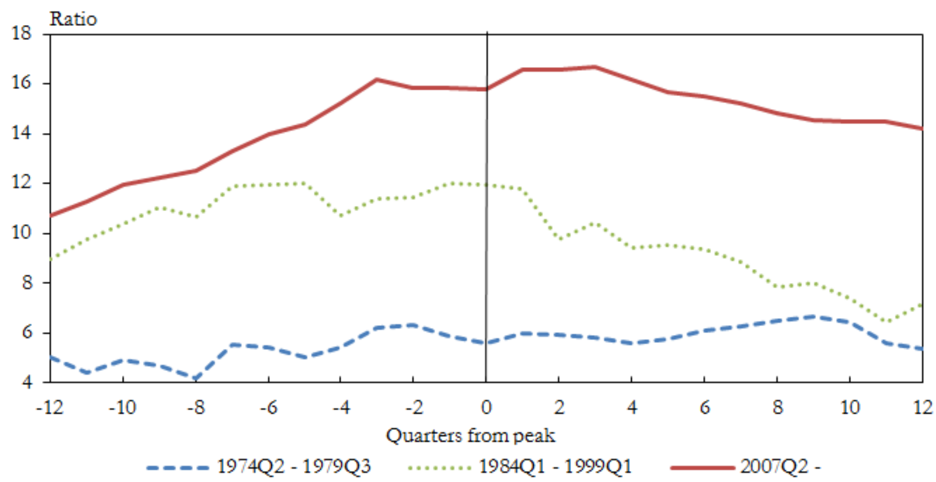
Figure 2.16: Phase comparison around turning point: Mortgage debt-to-income ratio



Source: Own calculations, SARB

Figure 2.17 shows that the vehicle debt-to-income ratio in the current phase increased at a faster pace than in the other two phases and also remained at high levels after the financial cycle peak. However, figure A.2.9 shows that the growth rate of vehicle debt over four quarters decreased sharply, even contracting 7 quarters after the financial cycle peak was reached.

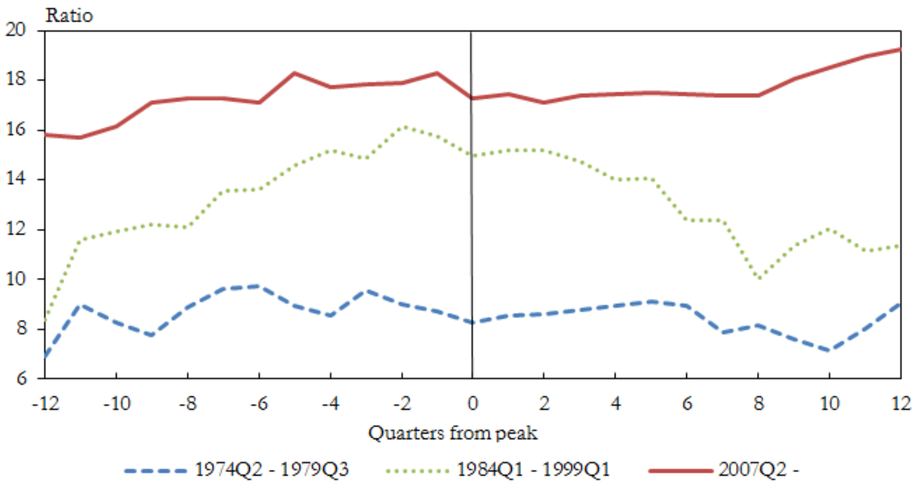
Figure 2.17: Phase comparison around turning point: Vehicle debt-to-income ratio



Source: Own calculations, SARB

The ratio of all other consumer debt-to-income reacted very similar to the 1974 financial downward phase. The all other consumer debt-to-income ratio remained high up to the financial cycle peak, however instead of declining as in the 1984 phase, this ratio started to increase soon after the peak was reached (figure 2.18). In the recent phase, this could be attributed to distress borrowing of households.

Figure 2.18: Phase comparison around turning point: All other consumer debt-to-income ratio



Source: Own calculations, SARB

Table 2.5 represents the average debt-to-income ratios over the various phases. The average total debt-to-income ratio in the latest downward phase is about 8.6 percentage points higher than the average over all the downward phases and higher than the average over the upward phases. This is due to debt levels becoming higher as the economy goes into a financial cycle downswing. The mortgage debt-to-income ratio is the one that stands out. During the latest financial cycle downswing the mortgage debt-to-income ratio was 10.7 percentage points higher than the average over all the downward phases as mortgage credit grew at a much faster pace than income over this period. Vehicle debt-to-income was also 5.2 percentage points above the average, while other consumer credit registered 6.2 percentage points above the average over all downward phases.

Table 2.5: Averages over the phases

Financial cycle phases	Total debt-to-income ratio	Mortgage debt-to-income ratio	Vehicle debt-to-income ratio	Other consumer debt-to-income ratio
1969/Q1-1974/Q1	44.2	30.4	5.2	8.7
1974Q2-1979Q3 (downward)	43.3	26.4	6.2	8.2
1979/Q4-1983/Q4	46.0	22.8	10.1	12.1
1984Q1-1999Q1 (downward)	53.7	28.3	8.8	15.0
1999/Q2-2007/Q1	60.3	32.9	10.7	16.3
2007Q2- (downward)	79.5	43.4	15.2	20.9
Upward phases	50.2	28.7	8.7	12.4
Downward phases	58.8	32.7	10.0	14.7

Source: Own calculations

We show in table 2.6 that the total credit growth in the latest downward phase slowed sharply from the preceding upward phase of the financial cycle. Total credit growth slowed from 7.3% in the preceding upswing to 2%[29]. Mortgage credit growth fell from 8.1% to 1.2%, while vehicle debt growth slowed from 10.9% at 2.5%. Other consumer credit slowed marginally from 4.3% to 3.3%. Consumers relied on other types of debt, likely unsecured debt, when they fell into financial difficulty, while at the same time banks implemented stricter lending criteria on credit lines.

[29]These growth rates are standardised by dividing the growth rate for each phase with the number of months in that phase.

Table 2.6: Growth over the phases

Financial cycle phases	Total credit growth	Mortgage growth	Vehicle debt growth	Other consumer credit growth
1969/Q1-1974/Q1	4.8	4.8	6.1	4.3
1974Q2-1979Q3 (downward)	3.3	2.5	6.4	4.7
1979/Q4-1983/Q4	9.3	6.0	12.7	14.8
1984Q1-1999Q1 (downward)	12.9	16.6	6.8	12.1
1999/Q2-2007/Q1	7.3	8.1	10.9	4.3
2007Q2- (downward)	2.0	1.2	2.5	3.3
Upward phases	7.1	6.3	9.9	7.8
Downward phases	6.1	6.8	5.3	6.7

The growth rates are standardised by dividing the growth between the upper (lower) and lower (upper) turning point with the number of months in between the phases.

Source: Own calculations

2.6 Conclusion

This chapter establishes a financial cycle for South Africa using growth cycle methodology as used by the SARB in dating the business cycle. We use real house prices, equity prices and credit extended to the household sector to create a composite financial index. By applying an HP filter adapted for financial cycles, we identify peaks and troughs for the South African financial cycle. Our financial cycle reaches peaks in April 1974, January 1984, and May 2007. We find that the overall length of the financial cycle in South Africa of 17.3 years. The financial cycle duration is much longer than the 5.8 year average business cycle. Financial cycles in South Africa are therefore around 3 times longer than business cycles. We find that on average financial cycle contractions (10.3 years), last longer than expansions (7.0 years). The long duration of financial cycle contractions show that deleveraging is a longer process.

We use these financial cycle turning point dates to determine to what extent South African households have deleveraged, with the emphasis on the most recent financial cycle downswing. We find that mortgage debt as a percentage of income was a large driver of the build-up of debt, peaking at 52.5% in March 2008. Since then, households have managed to bring this ratio down to 34.4% per cent by December 2017. The vehicle debt-to-income ratio declined only marginally following the financial cycle peak, suggesting that very little deleveraging took place in the South African vehicle finance market as vehicles are likely more cyclical with the business cycle than the financial cycle. The sharp increase in the other consumer debt-to-income ratio at the end of 2009 is probably a result of households seeking alternative credit sources due to stricter lending criteria from banks or having to make ends meet. Our results show a clear build-up of debt in the lead-up to the 2007/08 global financial crisis, and a slow and difficult deleveraging process that is still continuing.

Most of our variables behaved similarly across the different financial cycles, except for mortgage debt and other consumer credit, which show the extent to which households came under credit pressure. We also see that, as banks started to tighten their lending criteria, there was a sharp increase in other consumer credit. It should be noted that South Africa has a unique housing market and funding system with variable interest rates, increasing the elasticity between mortgages and interest rates. The deflation in house prices following the financial cycle peak is what most likely caused households to deleverage more in their mortgage bonds.

Lastly we find that on average during financial crises in South Africa, real house prices fall by 30%, while real stock prices fall by 28%. Total real domestic credit extended by all monetary institutions slows to about 31% on average over a downward phase (compared to 64% during an upward phase in the financial cycle). In the recent financial crises, growth in real house prices only fell by 15%, about half of the average. Similarly, stock prices fell by 20%, also not as much as average deleveraging over all financial downswings. The mortgage debt-to-income ratio was 10.7 percentage points higher than the average over all the downward phases as mortgage credit grew at a much faster pace than income over this period. Vehicle debt-to-income was also 5.2 percentage points above the average, while other consumer credit registered 6.2 percentage points above the average over all downward phases.

The fact that we could find evidence that households mostly deleveraged in the mortgage debt market assists us to understand the vulnerability of institutions and households regarding this type of debt, especially when the period coincides with a house price bubble. Having to deleverage from such high debt levels is a challenge, and we saw that even though households did manage to deleverage at a macroeconomic level (whether by choice, or by force in some instances, if their homes got repossessed) it was not an instantaneous process. At a macroeconomic level our conclusions can only stretch so far. One might be able to say that policy makers had to play a more active role in containing the house price bubble, despite no evidence of any other inflationary pressures, or that financial institutions should have been more prudent. The latter at least gave rise to most countries establishing macro-prudential authorities to keep a closer eye on the risks associated with financial instruments and institutions.

But, what we don't know is the real impact that the financial cycle, and the burst of the house price bubble, had on every-day citizens. The sharp pick-up in consumer credit at a macroeconomic level in 2009 suggests that households were struggling to either get access to other, more affordable credit, or that they were struggling to make ends meet and relied on consumer debt as a means to bridge the gap. In the next two chapters we extend our study to the microeconomic literature and data to gain further insights into which types of households were able to deleverage their mortgage debt, and the impact that that had on their economic behaviour. We also include vehicle debt, consumer debt and an additional category, other debt, which is likely not included at the aggregate level as macroeconomic measures are more associated with formal credit from banks. The other debt category includes informal debt such as micro loans, study loans from non-bank institutions, store card credit, loans from a loan shark or loans from family or friends. The drawback of using microeconomic data for financial, debt or income information is the high incidence of non-response and bracket responses. Chapter 3 aims to address these shortcomings by imputing both point estimates for bracket responses, and missing data, where possible. By establishing the upper turning point date of the financial cycle as May 2007 in this chapter, we can take advantage of this in chapter 4, where our survey conveniently starts in 2008, and is more-or-less in-line with the start of the deleveraging period.

Chapter 3

Data adjustment using multiple imputations by chained equations (MICE) and predictive mean matching

3.1 Introduction

Missing responses in household survey data are unavoidable and present a challenge for research. Researchers can choose to (i) ignore missingness by dropping missing observations; (ii) recode missing information to certain values; (iii) recode, as in (ii), while including controls for missingness; and (iv) impute missing imputations via single and multiple imputation (MI) approaches. In what follows, we focus on MI methods to deal with missing wealth information in the National Income Dynamic Study (NIDS). Unlike single imputation methods, such as regression imputation, where the imputed value is treated as an actual known value, MI incorporate statistical uncertainty (Azur et al., 2011) allowing for several different imputed data sets to be created.

When data is missing completely at random (MCAR) and few observations are missing, the missing observations can be ignored with negligible impact on both bias and power (Graham, 2009). If the missing share increases, but missing data remains MCAR, ignoring the missing observations reduces statistical power. However, MCAR is a strong assumption, and, therefore, ignoring missing data can lead to bias and power loss (Little and Rubin, 1986). As such, it would be more beneficial to explore other options, such as imputing the missing data. MI should provide more robust information than what is initially available in the survey data[30].

Non-responses are typically high for sensitive items such as income, assets, and debt. In

[30] Ground-breaking work on non-response in household surveys were largely driven by Ferber (1966), DeMaio (1980), Lillard et al. (1986) and Little (1988).

an attempt to gather information in the case of non-response, interviewers provide alternative options such as bracket responses. Bracket responses can provide a useful supplement to point value responses; it is an attempt to lower the non-response rate and provide some broad information. In cases where respondents do not want to provide any values at all, interviewers may try further elicitation techniques. In the case of assets, wealth and debt in NIDS, interviewers try to determine if the household does have assets or debt. Binary responses (e.g., yes, we have debt), when combined with additional survey data, can be used to impute other missing values (e.g., the amount of debt we have).

NIDS is a nationally representative panel survey. We use the first four waves from 2008, 2010/2011, 2012 and 2014/2015[31]. Wave 2 and 4 contain comprehensive asset and debt questions. Since these questions ask about sensitive information many of the data are missing. All four waves of household income questions allowed for bracket responses. For the wealth variables, most of the bracket options were only provided in Wave 4.

We make use of multivariate imputation by chained equation (MICE), which is a useful method for dealing with missing data[32]. Additionally, MICE provides for bounds, which allows for the imputation of a point value from a bracket response. Our variables of interest relate to household debt in order to measure deleveraging. There are many who responded that they have debt, but did not provide a point value. Therefore, we used this binary information (have debt, yes/no) to impute a point value for those who said that they have debt. In chapter 4 where we create a panel dataset we would like to include as much information as possible on income and household debt across the waves. By imputing, we increased our point value observations for total debt by 1 467 in Wave 1, 823 in Wave 2, 1 051 in Wave 3 and 1 062 in Wave 4. In chapter 4 we estimate the impact of income and other household characteristics on deleveraging in total debt, mortgage debt, vehicle debt, consumer debt and other debt.

3.2 Literature review

3.2.1 Unfolding brackets and imputing item non-responses

Non-response rates are typically high for sensitive items such as income and wealth (Riphahn and Serfling, 2005; Moore and Loomis, 2001). Household members are either not comfortable providing the type of information required (Hurd, 1999; Juster et al., 2007) or they do not know the exact information (Nwanzu, 2010). Possibly, the respondent does not trust the interviewer

[31] Southern Africa Labour and Development Research Unit (2016a), Southern Africa Labour and Development Research Unit (2016b), Southern Africa Labour and Development Research Unit (2016c) and Southern Africa Labour and Development Research Unit (2016d).

[32] MICE is also referred to as 'fully conditional specification' or 'sequential regression MI' in the literature.

(Riphahn and Serfling, 2005). It is therefore important to understand the determinants of non-responses. Since the early 1980s, psychologists and survey methodologists have worked together to get a better understanding of cognitive and communicative processes related to survey responses (Tourangeau, 1984). Extensive guidelines have, since, been developed to avoid pitfalls that can readily be avoided (Sudman et al., 1996; Tourangeau et al., 2000). Riphahn and Serfling (2005) suggest that the cognitive and rational choice models dominate the literature. Cognitive models consist of stages of answering a question, based on the respondents ability, while rational choice models suggest that respondents refuse to answer if they do not trust the interviewer, and, therefore, would be more likely to not make an effort to recall or provide information.

A characteristic feature of survey data on household wealth is the high incidence of missing data. Roughly, one in three respondents who report owning an asset are either unable or unwilling to provide an estimate of the value of the asset (Juster et al., 2007). A partial solution to this problem is to devise a series of questions that put the respondent's value into a quantitative range (that allows less than a certain amount, more than that amount, or even don't know or refused[33]). These quantitative ranges are called unfolding brackets, and they represent a survey innovation that substitutes range data for completely missing data (Juster et al., 2007). Although bracket values are not as good as point values, they provide a way to collect information from households not comfortable disclosing point values. Juster et al. (2007) and Hurd (1999) show that the information contained by a bracket response provides enough additional information to produce efficiency gains and reduce the imputation error.

The main contributors to unfolding brackets in the South African literature are Posel and Casale (2005), Vermaak (2012), Von Fintel (2007), Wittenberg (2008) and Wittenberg (2014). These authors use single imputation methods for determining point values from bracket responses via means, mid-points and conditional means; mid-points are mostly favoured. The mid-point method assigns the mid-point value of each bracket to the representative response in that bracket range (Wong et al., 2016). This procedure however introduces artificial spikes at the imputed values and is difficult to use when brackets are open-ended, especially at the top (where there is no obvious mid-point), although Von Fintel (2007) and Yu (2013) suggest that the top boundary can be quantified as 1.1 times the lower bracket boundary. Personal communication with Charles Simkins, as cited in Wittenberg (2014), suggests that the lower bracket boundary could even be doubled[34].

Apart from the mid-point method, Posel and Casale (2005) also test the actual average mean

[33] In NIDS for example, the brackets for the question on current cash value in pension will state 'cash value of pension/annuity more than or less than R50 000?' with response options: don't know, refuse, more than, about equal to or less than?

[34] In the published Stata code for income brackets, NIDS uses double the lower top-bracket for household income in Wave 2, 3 and 4, and 1.5 in Wave 1.

method, where all point values are divided into their corresponding brackets and the mean of the point values are then assigned to each of the brackets[35]. The authors find little difference between their average mean approach and the mid-point approach, except at higher and lower earnings brackets. Posel and Casale (2005) further use OLS regression to estimate coefficients for those who provided point values and then use those coefficients to estimate earnings functions of the group providing only bracket responses. As there may be a selection effect in this method, they further apply Heckman selection to account for this. Lastly, they estimate OLS regressions for each of the brackets for the group that provided point values and use those coefficients on the group who only provided bracket responses. Of the five methods, the OLS regression performed the least favourably, as it did not take the bracket information into account. Estimates, however, from the other methods produced highly consistent summary measures, emphasising the importance of bracket information, when estimating point values for bracket responses.

Evidence from Posel and Casale (2005) and Von Fintel (2007) suggest that mid-point values for earnings brackets perform similar to other more advanced methods. However, attention has been shifting away from deterministic imputation methods, like mid-points, towards methods taking cognisance of the imputation process and the underlying distribution of the data (Wittenberg, 2014). When bracket information is not available, item non-responses can still be imputed to create a more complete set of analysis data (see Daniell, 2009). Methods include simple imputation, regression imputation, hot deck imputation, nearest neighbour imputation, predictive mean matching and MI methods (see Durrant, 2005, for details). We make use of a combination of nearest neighbour, predictive mean matching and MI to impute missing values for the NIDS survey. We also compare our results to the publically provided NIDS data, where regression imputation is used.

Further approaches to imputing missing values, which in fact take the distribution and standard errors explicitly into account, include drawing the standard errors from a predetermined distribution or from an observed empirical distribution. Nonparametric techniques, such as hot deck imputations, involve replacing missing values with observed values from a respondent that is similar with respect to selected characteristics such as age, gender, race or employment (Andridge and Little, 2010). Von Fintel (2007) compares mid-point estimation to conditional mean imputation from both a lognormal and a pareto distribution, as well as interval regression, which incorporates earnings into a likelihood function. Similar to Posel and Casale (2005), Von Fintel (2007) shows that it is important to include bracket information and that the typical South African household survey bracket structure underpins reasonably stable parameters for earnings functions, regardless of the imputation approach.

[35] Also see Casale (2004); Posel and Casale (2005); Cichello et al. (2012).

Another well-known method for generating imputations is predictive mean matching (pmm) (Little, 1988), which imputes missing values by matching the nearest-neighbour based on the expected values of the missing variables conditional on the observed characteristics (Vink et al., 2014). It is important to note that observations are matched on the closeness of the predicted outcomes, and the imputed value will be allocated the actual observed value of the matched neighbour (not the predicted value that was used for the match). The obvious implication is that imputation via pmm requires observed point values for matching, which may not always exist, for the survey of interest[36].

Vermaak (2012) and Wittenberg (2014) use MI methods, which enables better estimates of the standard errors and more accurately reflects the underlying uncertainty in the imputation generating process. Vermaak (2012) determines the impact of MI on estimated poverty lines for South Africa. The method is used to impute both missing data and to impute missing data for restricted intervals, resulting in higher mean earnings, suggesting that the data were not missing at random. However, incorporating imputations did not result in a significant difference in the estimated poverty lines, when compared to ignoring missing values and using mid-points. Wittenberg (2014) also finds that relying on one imputation will lead to bias and inconsistent estimates.

3.2.2 Multiple imputations

Little and Rubin (1986) and Rubin (1987) transformed the discussion, introducing the idea of MI, where missing values are replaced with simulated values. Instead of replacing missing data or brackets with only one imputed estimate, MI allowed for several imputed values. The missing values are imputed based on the observed values for a given individual and the relations observed in the data for other individuals, assuming that the observed variables were included in the imputation model (Schafer and Graham, 2002). Because MI involves creating multiple estimates for each missing value, the analysis of multiply imputed data must take into account uncertainty in the imputations to yield more accurate standard errors (Greenland and Finkle, 1995).

According to Little and Rubin (1986) missingness can be defined in three ways:

- Missing completely at random (MCAR) - The missing values do not depend on observed or unobserved variables. The missing cases can therefore be seen as randomly missing (Wayman, 2003), and the only penalty is a loss of power due to fewer observations. This

[36] See Wittenberg (2014), where bracket responses were only collected in the 1996 October household survey. To estimate point values, Wittenberg (2014) drew data from the empirical distribution of the 1997 October household survey (adjusted for inflation), where point values were available.

assumption is stronger than necessary and, in practise, it can be replaced with the more relaxed Missing at Random assumption.

- Missing at Random (MAR) - The missing values depend on the observed data, can be fully described by other variables in the dataset and are not dependent on the missing data. This assumption underlies most imputation procedures (Nicoletti and Peracchi, 2006). For example, even though respondents at the lower and upper end of the income distribution are less likely to provide survey responses than those in the middle, these missing data points are related to demographics and other socioeconomic variables, which can be observed in the data (Pedersen et al., 2017).
- Missing not at random (NMAR) - The probability of missing values depend on unobserved data. This is also referred to as nonigorable missingness in the literature, while MCAR and MAR imply ignorable missingness.

According to Allison (2000) there are a few conditions that should be satisfied before MI can be used. These are:

1. The data must be missing at random (MAR).
2. We need to apply an estimator that matches the variable type[37].
3. The model used for the analysis must match the model used in the imputation. It is suggested that the same variables used in the final regression should also be used in the imputation model (Allison, 2002).

3.3 Methodology: Multiple imputation and predictive mean matching (pmm)

MICE can be implemented under the MAR assumption (Raghunathan et al. (2001) and Van Buuren and Groothuis-Oudshoorn (2011)), such that missing values depend only on observed information (Azur et al., 2011)[38]. MI generates multiple imputed values which replaces missing values, creating multiple unique data sets.

[37] Packages such as MICE automatically choose linear regression models for continues data and categorical response models for discrete data.

[38] Unfortunately there is no specific test for MAR (Kwak, 2010); however, the VIM (Visualization and Imputation of Missing Values) package in R is a useful tool to examine the correlation between missing data and other observed variables.

Suppose we have $X_1, X_2, ...X_p$ variables. If X_1 has missing values, we fit a model that is conditional on all the other variables, $X_2, ..., X_p$[39]. The missing value will then be replaced by the matched actual value for pmm, or the predicted values for the other types of models that match the data[40]. Similarly, if X_2 has missing values then $X_1, X_3...X_p$ variables will be used in the prediction model as independent variables.

In other words, for every variable in X_{-p} that precedes X_p in the sequence of variables, its value from iteration t is used (including the imputed values). Also, for every variable in X_{-p} that follows X_p in the sequence, its array of imputed values from iteration $t-1$ is used.

The steps can be summarised as follows:

1. Estimate a linear regression of the X's on X_p and produce a set of β coefficients using only observed values to estimate. $X_1 = X_2^t \beta_{12} + X_3^t \beta_{13} + ... + X_p^t \beta_{1p} + \varepsilon_1$ with $\varepsilon \sim \mathcal{N}(0, \sigma_1^2)$.

2. Draw a new set of coefficients β^* from its posterior distribution using predictive mean matching. Typically this is a random draw from $P(X)$, a multivariate normal distribution of X, with mean β and covariance matrix of β (with an additional draw for the residual variance)[41].

3. Use β^* to generate predicted values for X for all cases (both for missing and non missing).

4. For each missing value of X match the predicted values of the observed values to the predicted values of the missing data.

5. Randomly select one of, in this case 5, nearest neighbour matches and assign the observed value to the missing data using the predicted matches.

6. Repeat step 2 to 5 for each complete data set. In our case, we repeat 10 times.

These steps are applied sequentially, and, after the imputation of the last variable, iteration t is considered complete. The iteration number can be between 10 and 20 (Van Buuren and Groothuis-Oudshoorn, 2011). Once the cycle is completed, multiple datasets are generated differing only in their imputed values.

Gibbs sampling, in which the parameters and missing values are drawn iteratively from appropriate conditional distributions, is used to obtain the joint posterior distribution of parameters

[39] A full description of the model can be found in Van Buuren et al. (2006) and Van Buuren and Groothuis-Oudshoorn (2011) and Christelis (2011).

[40] We use automatic model selection for the imputation models. In other words, as each variable is imputed in turn, the model can be specified as either pmm for numeric variables, logistic regression for 2 factors, multinomial logit for 2+ factors or ordered logit for 2+ ordered factor.

[41] The formula can be found in appendix A of Van Buuren et al. (2006).

and missing values given observed data. It is possible that the specification of two conditional distributions $P(X1|X2)$ and $P(X2|X1)$ are incompatible, so that no joint distribution $P(X1, X2)$ exists. Therefore, as the parameter vector of the joint distribution of X is replaced by the P different parameter vectors of the P conditional expectations, the posterior distribution is generated by a Gibbs sampler with data augmentation. To get convergence to the stationary distribution of X, we iterate the Gibbs sampler until we have a number of iterations indicating convergence of the distribution of the missing values of all variables in our system. Given that the imputations are sequential, we first impute the demographic variables, then the interaction variables and lastly our variable of interest. We set the visiting sequence in the MICE imputation specification.

3.4 Overview of the NIDS survey data and variables for imputation

NIDS is a South African panel that follows individuals across time (over different waves) and is considered to be representative of the South African population. NIDS is a comprehensive survey that covers topics regarding household finances such as income, debt, and assets. It further asks questions, among others, on poverty, well-being, labour markets, education, and health (NIDS, 2018). The questionnaire covers households, adults, and children. We use the first four waves of the survey, conducted in 2008, 2010/2011, 2012, and 2014/2015. As our area of interest is household deleveraging, we focused on analysing data collected on household income and debt, as well as individual debt. In chapter 4 we attach these results to a household representative and follow them over time to establish to what extent households have deleveraged between wave 1 and the subsequent waves. Due to income bracket responses and the high incidents of missing values, for debt outstanding in the NIDS survey, we need to impute for these.

First, we impute for bracket responses provided in the household income question. The brackets differ across the waves and are imputed separately for each bracket and wave. Second, we impute the household level question on property debt outstanding. Third, we impute debt variables where individuals responded that they have debt, but do not provide a value. We impute for an anomaly in wave 2 regarding individual debt categories, where unlike in the other waves, NIDS rolled out two phases of interviews. In the first phase (phase 1) the questions regarding individual debt were asked. In the second phase (phase 2) these questions were not included in the interview (Daniels et al., 2014). We assign these phase 2 non-response values based on their wave 1 and wave 3 responses (i.e. if the respondent stated that they have debt in wave 1 and wave 3, they were assumed to have had debt in wave 2 and their outstanding debt value was imputed for). We also impute in this section for individual level property debt which in chapter 4 is used to derive a household property debt outstanding variable from both the individual and household responses.

3.4.1 Unfolding household income brackets

NIDS report household income in point values, and in brackets. We unfold these brackets using MI and take the average of the 5 imputations as the point value for the bracket. The imputations are bounded[42] by the bracket limits provided by NIDS. For the upper bound, where no upper limit is set in the survey, we use the 99.9th percentile of the point values as this allows the exclusion of some extreme values (see table 3.1).

Table 3.1: Bracket responses for household income by wave

Wave 1	Wave 2	Wave 3	Wave 4
R 1 - R 200	R 0 - R 699	R 0 - R 499	R 0-R 749
R 201 - R 500	R 701 - R 1 299	R 501 - R 1 399	R 751 - R 1 499
R 501 - R 1 000	R 1 301 - R 2 299	R 1 401 - R 2 999	R 1 501 - R 2 999
R 1 001 - R 1 500	R 2 301 - R 4 699	R 3 001 - R 4 499	R 3 001 - R 5 999
R 1 501 - R 2 500	R 4 701 - R 10 999	R 4 501 - R 9 499	R 6 001 - R 10 999
R 2 501 - R 3 500	R 11 000 - R 229 121.6	R 9 501 - R 23 499	R 11 001 - R 26 999
R 3 501 - R 4 500		R 23 500 - R 236 850	R 27 001 - R 106 055
R 4 501 - R 6 000			
R 6 001 - R 8 000			
R 8 001 - R 11 000			
R 11 001 - R 16 000			
R 16 001 - R 30 000			
R 30 001 - R 50 000			
R 50 001 - R 88 975			

Source: NIDS
Upper brackets are the 99.9th percentile of the point values. For Wave 2 to Wave 4 the in-between values were provided as point values in the question and therefore used as point values and not imputed.

For the bracket imputations, we use *value of the house*, *mode of the household race*, *maximum level of education in the household*, *median age of the household*, *province* and *household size*. The selection of household demographic transformations (mode, maximum and median) follows the approach used by NIDS for household imputations. However, in this case, NIDS used mid-points for the income bracket imputations and unfolded the upper bound by doubling it in Wave 2, 3 and 4 and multiplying it by 1.5 in Wave 1. We show that using either of the two methods does not make a large difference in the result of of the income variable (see figure 3.1).

The results show that we increase the household income response rate from 75% to 81% in Wave 1, 84% to 94% in Wave 2, from 90% to 97% in Wave 3 and from 95% to 98% in Wave 4 (table 3.2). Similar to results found in the South African literature for household survey income brackets[43], we also confirm that using mid-points or MI produces similar distributions for NIDS

[42] MICE provides a flexible procedure for bounded imputations.

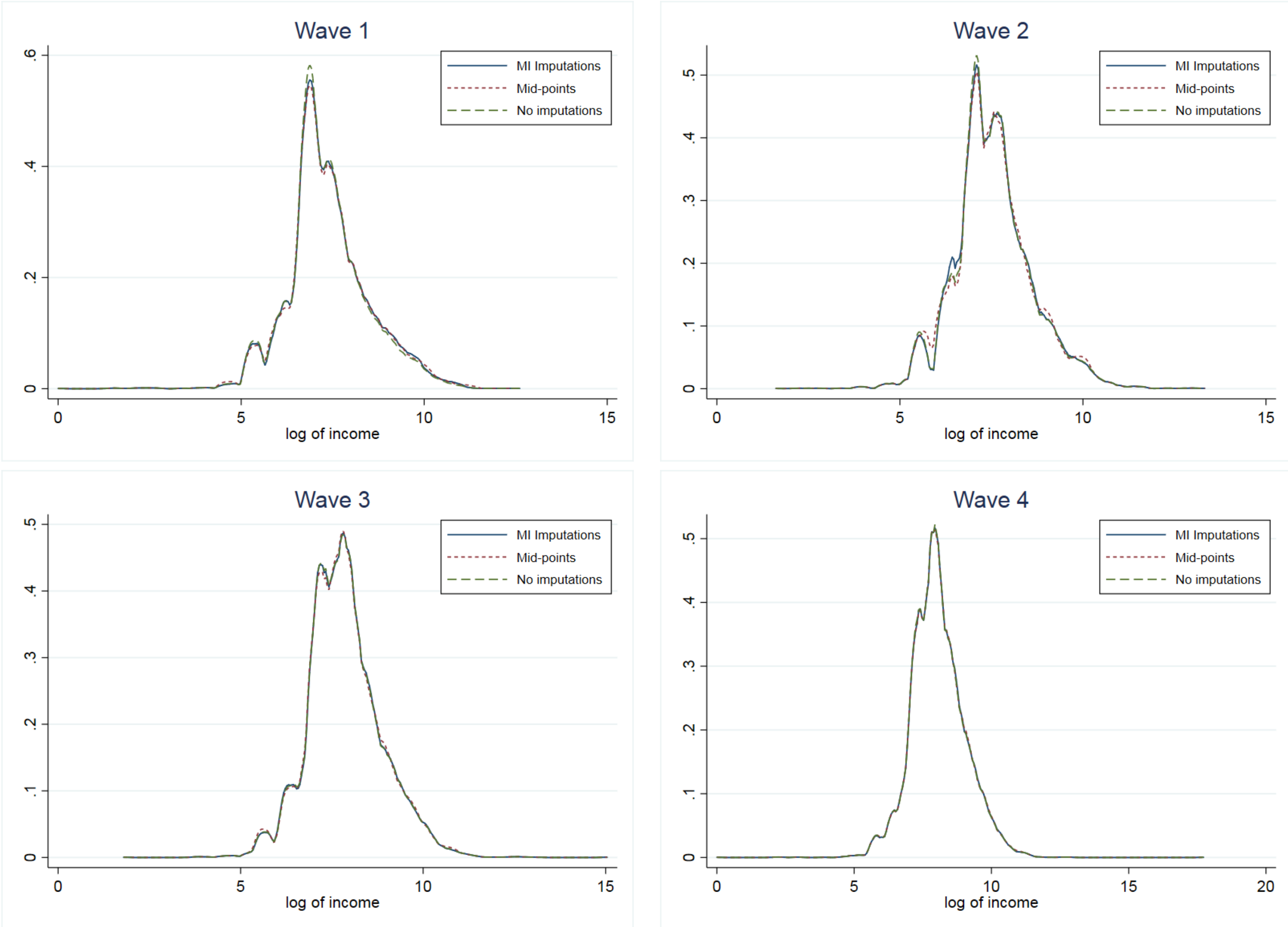
[43] See Posel and Casale (2005), Vermaak (2012), Von Fintel (2007), Wittenberg (2008) and Wittenberg (2014).

data. The mean household income from using MI is consistently lower than those for mid-points, suggesting that the mid-point method perhaps overstates incomes in the bracket (table 3.3).

To test if the Gibbs sampler converged, we follow Van Buuren and Groothuis-Oudshoorn (2011) and plot the mean and standard deviations against their iterations. Figure 3.3 plots the Gibbs sampler for each of the upper bounds of the income brackets. When plotting the Gibbs sampler we can determine convergence by inspecting the different sequences. On convergence, the sequences should be freely intermingled with each other, without showing any definite trends. Convergence occurs when the variance between different sequences is not larger than the variance within each individual sequence (Van Buuren and Groothuis-Oudshoorn, 2011). We also confirm convergence using the Gelman and Rubin (1992) test[44]. This test provides a Rhat statistic that is approximately the square root of the variance of the mixture of all chains, divided by the average variance within the chain (Gelman and Hill, 2007). We used the more stringent criterion where Rhat ≤ 1.1 (a less stringent criteria will be if Rhat ≤ 1.2 (Su et al., 2011). If Rhat is much greater than 1, the chains have not mixed well. In our case, apart from the graphical confirmation, Rhat was not greater than 1.1 for all income bracket parameters. The upper brackets of household income showed a healthy Gibbs sampler convergence.

[44]The author would like to thank a reviewer for suggesting this test as an additional check for convergence.

Figure 3.1: Kernel densities comparing multiple imputation and mid-points for unfolding household income brackets



Source: Own calculations, NIDS

Table 3.2: Description of household income by wave

	Wave 1	Wave 2	Wave 3	Wave 4
Total number of observations	7 296	9 016	10 114	11 732
Income reponses	7 296	6 782	8 033	9 618
Responded	5 440	5 718	7 262	9 134
Non-response	1 856	1 064	771	484
Non-response, but provided bracket	474	651	493	325
% reported point value (if asked the question)	74.6	84.3	90.4	95.0
% reported point value plus bracket	81.1	93.9	96.5	98.3
Total percentage point increase in response rate	6.5	9.6	6.1	3.4
Upperbound	99.9th	99.9th	99.9th	99.9th
Value	R 88 975	R 229 122	R 236 850	R 106 055

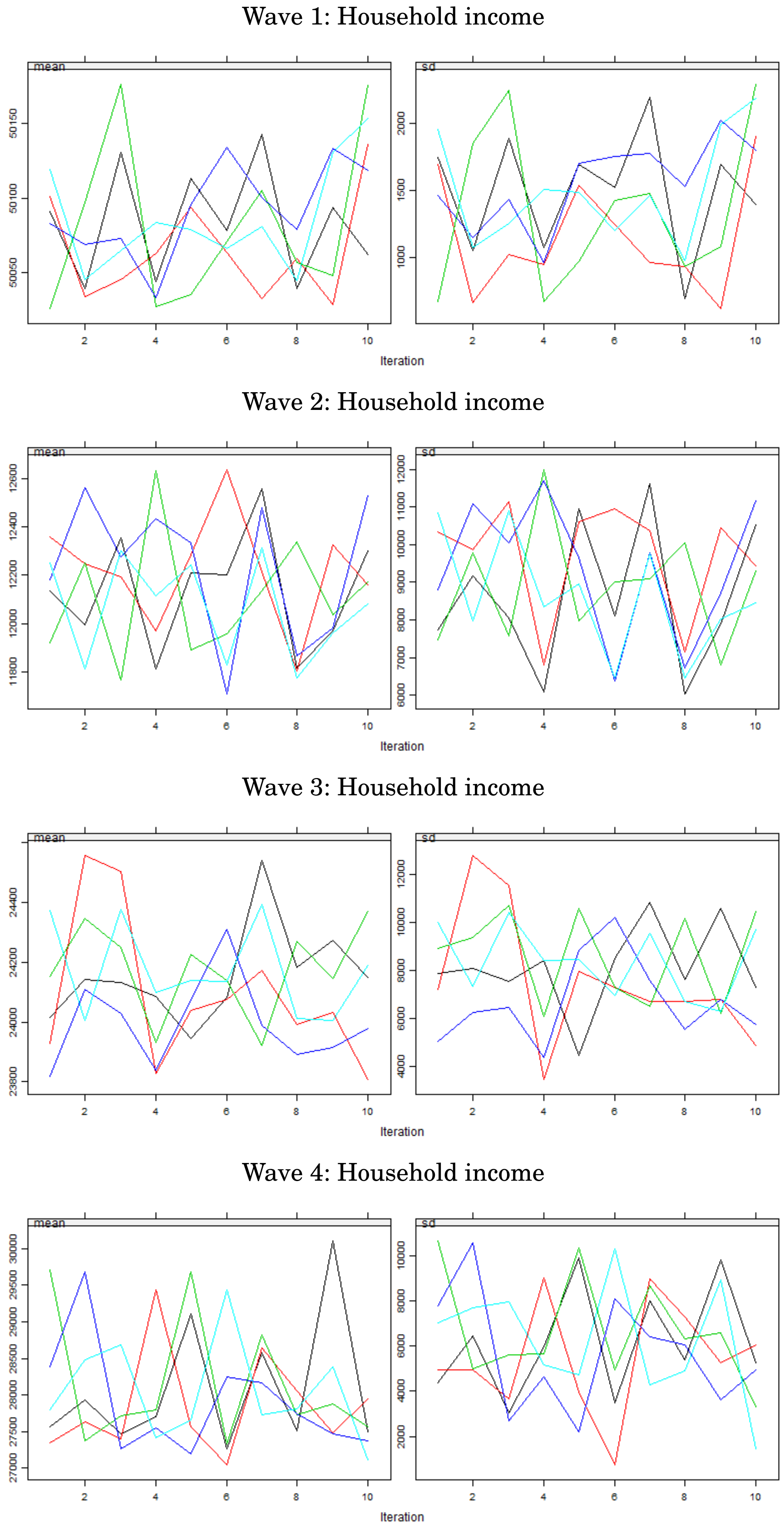
Source: Own calculations, NIDS

Table 3.3: Comparing means from different imputation methods and no imputations for household income

Method used	Wave 1	Wave 2	Wave 3	Wave 4
No unfolding of brackets	R 3 094	R 4 025	R 5 067	R 10 680
Mid-point unfolding of brackets	R 3 394	R 4 030	R 5 089	R 10 667
Multiple imputation unfolding of brackets	R 3 299	R 4 004	R 5 056	R 10 639

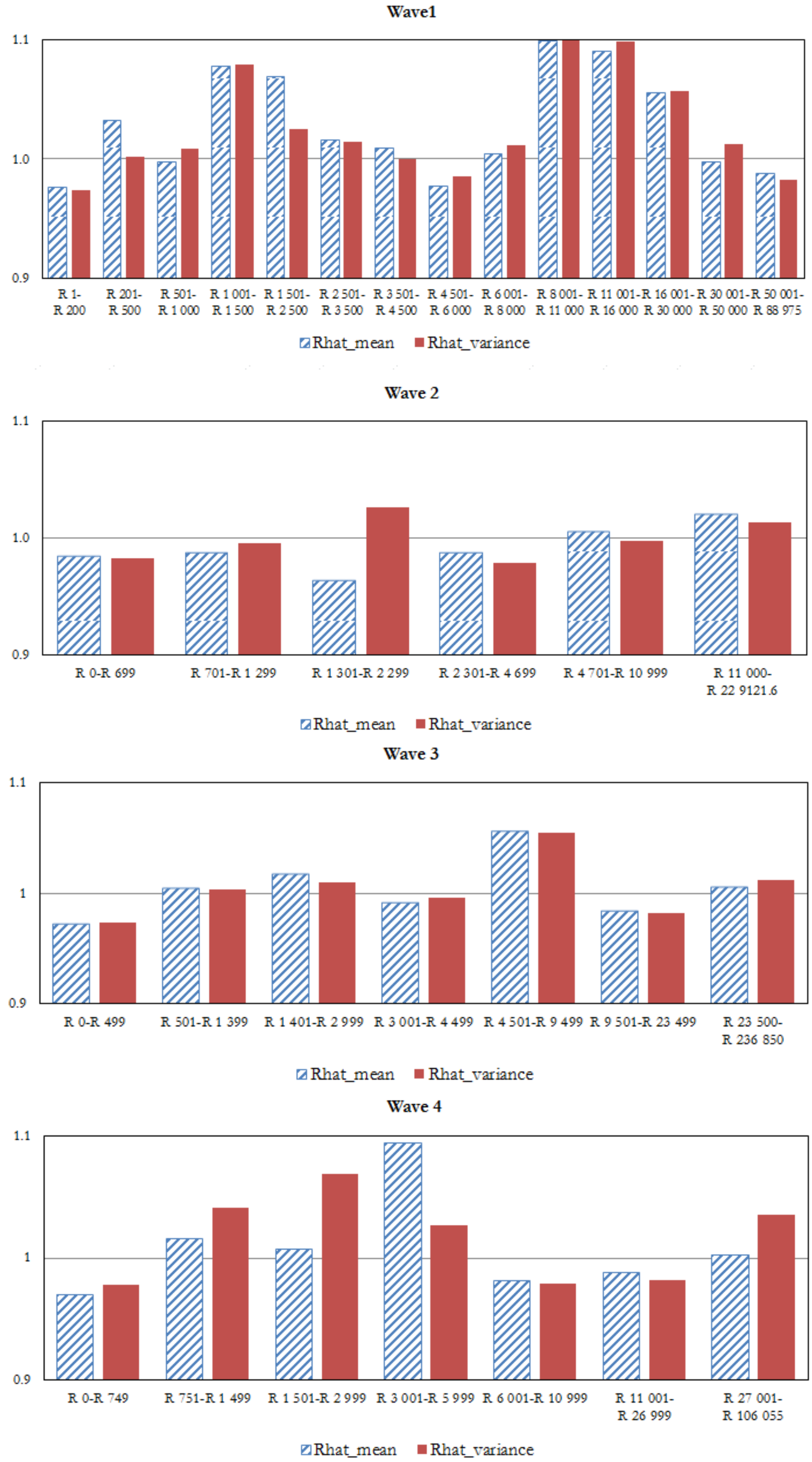
Source: Own calculations, NIDS

Figure 3.2: Convergence of Gibbs sampler for the upper bracket of household income



Source: Own calculations, NIDS

Figure 3.3: Rhat for convergence of Gibbs sampler for the upper bracket of household income



Source: Own calculations, NIDS

3.4.2 Imputing debt outstanding

This section evaluates the imputations of debt outstanding for the households and individuals that reported that they did have a certain debt type, but provided no value for the amount outstanding (they gave a yes/no answer to the question on whether they had debt outstanding). NIDS also provide code for regression imputations. However, their regression imputations have limitations (e.g. imputations are only done for variables if there are at least 100 observations and more than a 40% combined observation and participation rate). For MI, we do not have these limitations. However, unlike regression imputation, we can have multicollinearity when including too many similar demographic variables in the prediction matrix, as they are all used at the same time and may be linearly related and the matrix will be computationally singular and not solve. However, by setting the diagonals of the predictor matrix to zero it eliminates the possibility of not solving, as duplicate information is excluded when imputing. Furthermore, for MI, if there are too few observations, such as only one, imputations will fail, however we did not have any examples of this in our data.

Table 3.4 is a summary of the variables imputed and the "X" indicate for which waves of the survey the variables were available. The first variable we impute is a household level variable. It is based on a set of survey questions attempting to determine if the respondent's property is fully paid off, and if not, and the amount of outstanding debt was not provided, it was imputed. Similarly, based on the survey questions, we imputed for individual who responded that they had debt outstanding for the different individual debt categories as shown in table 3.4, but did not give an amount outstanding. As shown in the table 3.4 a separate question for if the respondent has a loan from a friend or a family member was only asked in Wave 2 and Wave 4, while the loan category was combined in Wave 1 and Wave 3. These were imputed in the same way.

Table 3.4: Debt variables available and imputed by wave

	Wave 1	Wave 2	Wave 3	Wave 4
Household property debt outstanding	x	x	x	x
Individual vehicle debt outstanding	x	x	x	x
Individual bank debt outstanding	x	x	x	x
Individual micro debt outstanding	x	x	x	x
Individual Mashonisa debt outstanding	x	x	x	x
Individual student loan from bank outstanding	x	x	x	x
Individual student loan from other outstanding	x	x	x	x
Individual credit card debt outstanding	x	x	x	x
Individual store card debt outstanding	x	x	x	x
Individual hire purchase debt outstanding	x	x	x	x
Individual loan from family or friend	x		x	
Individual loan from friend		x		x
Individual loan from family		x		x
Individual bond owing	x	x	x	x

Source: NIDS

3.4.2.1 Household property debt outstanding

For property debt outstanding NIDS has an individual and household level question. We used both these questions in chapter 4 to create a total household property debt outstanding variable. We impute both the household level property debt outstanding as well as the individual property debt outstanding. Individual property debt outstanding is discussed with the other individual debt outstanding variables in the next section. We impute for households who said that they owned the dwelling but it was not fully paid off, however they did not provide an amount outstanding. See table 3.4 for how the questions were asked in the survey.

By imputing for households who reported owing money on a dwelling, but did not provide a value, we almost double the number of responses (see table 3.5). We also show that by doing this (table 3.6), we bring the average of property debt down, compared to not imputing. In Wave 4 the NIDS imputation, using regression, results in an even lower average property debt than the MI impute procedure. The differences in the kernel densities between the MI, regression imputations and no imputations are reported in figure 3.5. We also report the Gibbs sample convergence in figure 3.6 for household debt. As the sequences freely intermingle, we confirm a healthy convergence. The Gelman and Rubin (1992) test result also confirms convergence where the Rhat statistics are all below 1.1 as shown in figure 3.7.

Figure 3.4: NIDS question on household debt outstanding on property

Question on property ownership of the household

D4	Does a household member own this dwelling?	
	Yes	1
	No → **SKIP TO D10**	2

Question on if the property is fully paid off

D6	Is this property fully paid off?	
	Yes → **SKIP TO D9**	1
	No	2
	Refuse	-8

Question on amount outstanding on property debt for the household

D7	What is the amount of the bond still owing on this property?	
	Amount	**R**
	Refuse	-8
	Don't know	-9

Source:NIDS

Table 3.5: Number of respondents before and after imputations for households who responded that they have property debt, but did not provide a value

Method used	Wave 1	Wave 2	Wave 3	Wave 4
Original responses	313	264	226	244
Imputed responses	304	280	145	143
Total responses	617	544	371	387

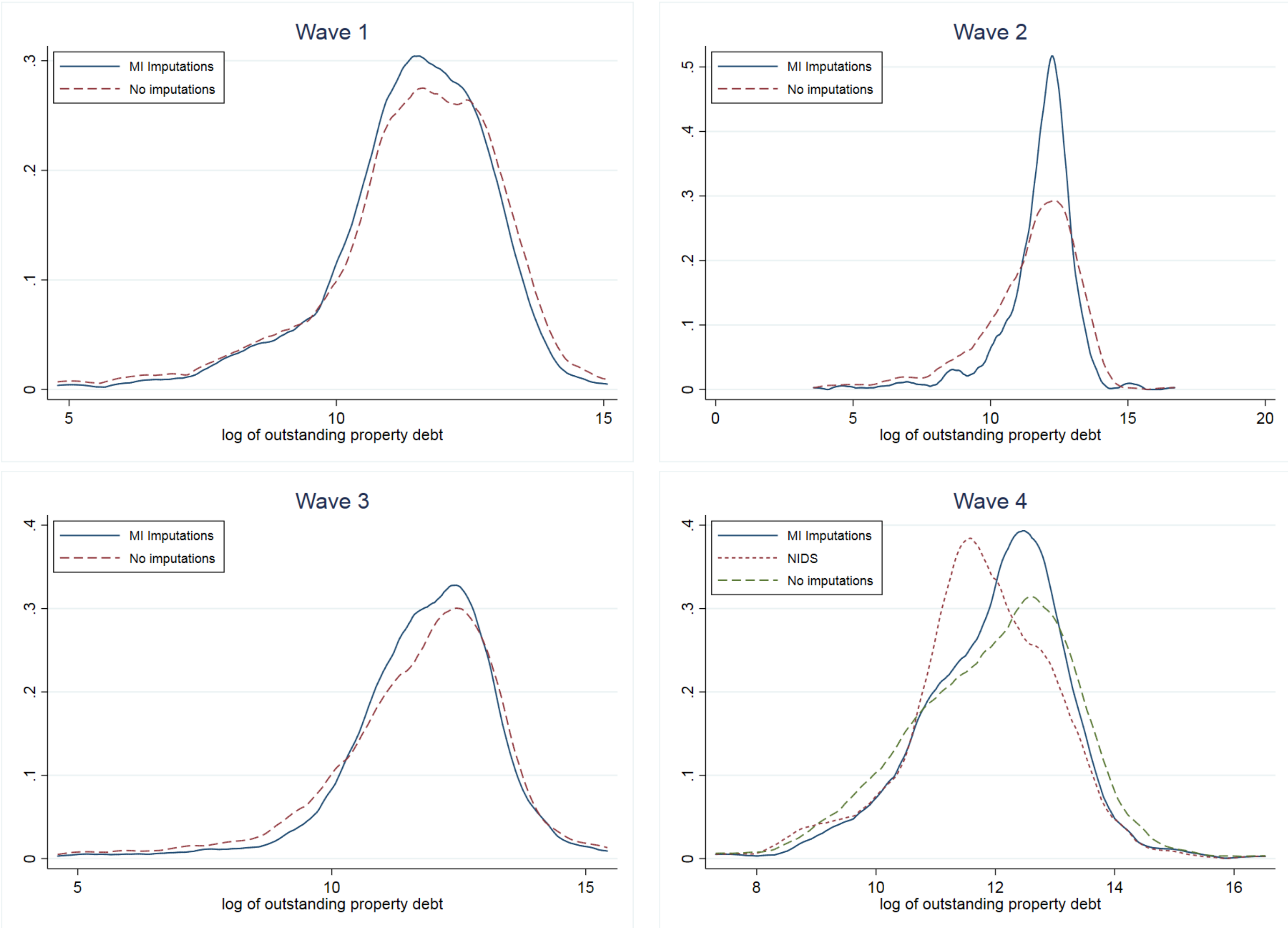
Source: Own calculations, NIDS

Table 3.6: Comparing means from different imputation methods and no imputations for property debt

Method used	Wave 1	Wave 2	Wave 3	Wave 4
No imputations	R 237 328	R 286 174	R 315 265	R 368 651
MI imputed	R 198 728	R 241 570	R 292 066	R 323 632
NIDS imputed	None	None	None	R 279 827

Source: Own calculations, NIDS

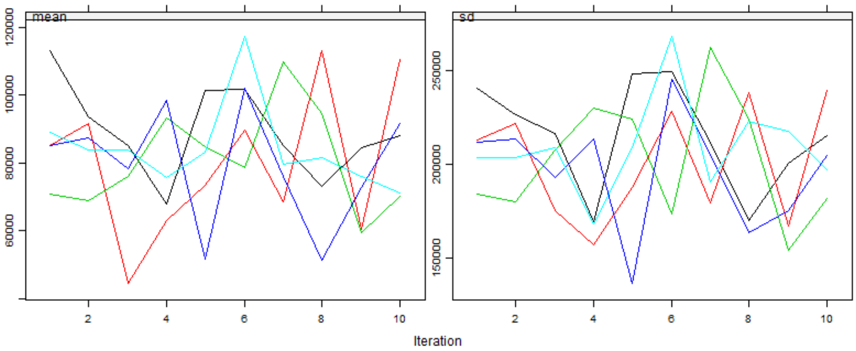
Figure 3.5: Kernel densities comparing multiple imputation and NIDS imputed (where applicable) for other household property debt outstanding



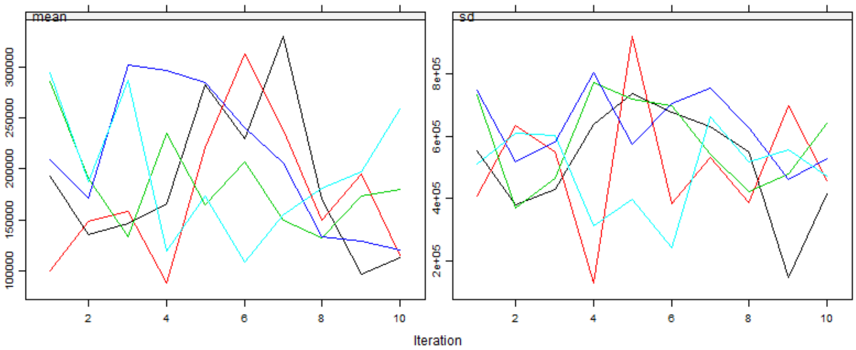
Source: Own calculations, NIDS

Figure 3.6: Convergence of Gibbs sampler for household debt

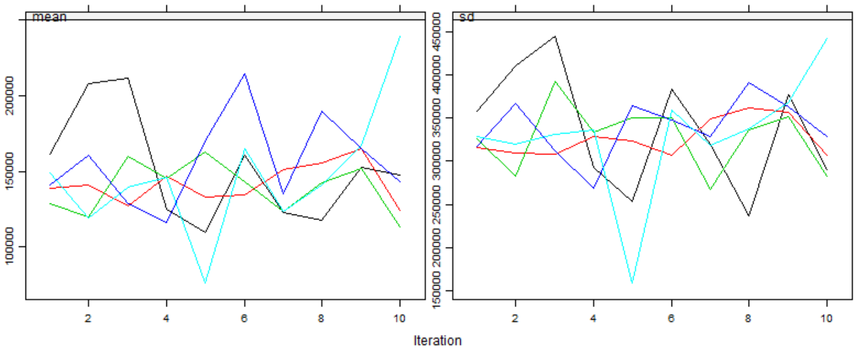
Wave 1: Household debt



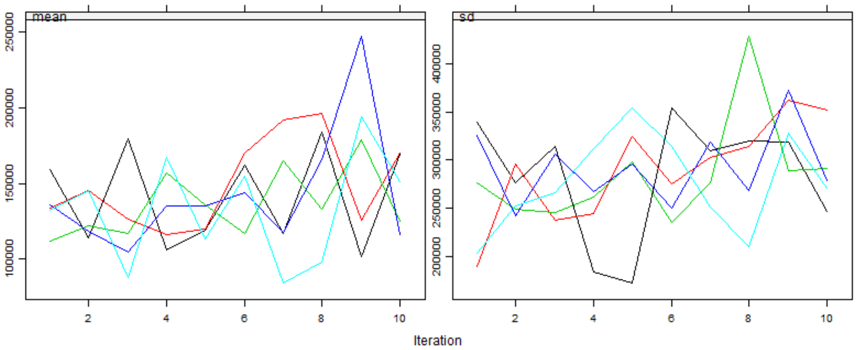
Wave 2: Household debt



Wave 3: Household debt

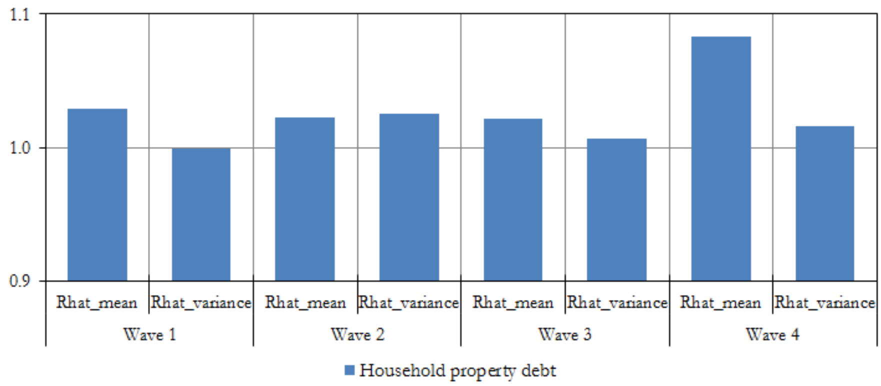


Wave 4: Household debt



Source: Own calculations, NIDS

Figure 3.7: Rhat for convergence of Gibbs sampler for household debt



Source: Own calculations, NIDS

3.4.2.2 Individual debt outstanding

As mentioned earlier, there was the two-phase anomaly in Wave 2, where NIDS conducted a phase 1 interview, asking if individuals have debt, while not asking the respondents in phase 2 these questions (Daniels et al., 2014), resulting in a lower response rate. In order to increase Wave 2's response rate, we use information from Wave 1 and Wave 3 to infer whether the person also has this type of debt in Wave 2. These were then imputed[45]. Also see Daniels and Augustine (2016) for an overview of the NIDS wealth, including debt, variables for Wave 4. In the next section we describe the imputations for individual debt questions. Figures 3.8 show how the questions are asked in the questionnaire. Ownership of a vehicle is used as an example.

[45]It is possible that for very short-term debt, household may have deleveraged fully between the waves. The authors would like to thank a reviewer for pointing this out. However, we only make this assumption for a combined 31 individual with store, and credit card debt, which is likely too small of a share of the total imputations to make a difference to the results.

Figure 3.8: NIDS question on individual debt ownership and total amount outstanding

		1 Do you personally have a [...]? **Interviewer: If no, → SKIP TO NEXT**		2 What was the value of your payment on your [...] last month? **Interviewer: If don't know, write -9 If none, write 0**	3 What is the remaining outstanding balance on your [...]? **Interviewer: If don't know, write -9 If none, write 0**
		Yes	No	Rands	Rands
G11	Home loan / Bond	1	2		
G12	Personal loan from a bank	1	2		
G13	Personal loan from a micro-lender	1	2		
G14	Loan with a Mashonisa	1	2		
G15	Study loan with a bank	1	2		
G16	Study loan with an institution other than a bank	1	2		
G17	Vehicle finance (car payment)	1	2		
G18	Credit card	1	2		
G19	Store card (For example, Edgars, Foschini or Woolworths store card)	1	2		
G20	Hire purchase agreement	1	2		
G21	Loan from a family member or friend	1	2		

Source:NIDS

The responses for Wave 1, Wave 3 and Wave 4 are shown in table 3.7, while the responses, with a focus on the two-phase interview, are shown in table 3.8. For Wave 1, 2 and 4, we impute a debt outstanding value from those who responded yes to the question on do they have debt, but provided no debt amount outstanding. For Wave 2, we firstly inferred that those who were not asked the question in phase 2 had debt based on their debt status in Wave 1 and Wave 3. We then imputed the amount of debt outstanding based on the answers from phase 1 and the inferred answers from phase 2.

Table 3.7: Responses to individual debt outstanding questions (Wave 1, Wave 3 and Wave 4), example of vehicle debt

Has vehicle finance (car payment)?	Number of observations
Refused	8
Missing	63
Yes	400
No	15 159
Total	15 630

Source: NIDS

Table 3.8: Responses to individual debt outstanding questions (Wave 2), example of vehicle debt

Has vehicle finance (car payment)?	Number of observations
Don't know	2
Refused	49
Missing	12
Not asked in Phase 2	733
Yes	182
Not asked in Phase 2	16 651
Total	17 629

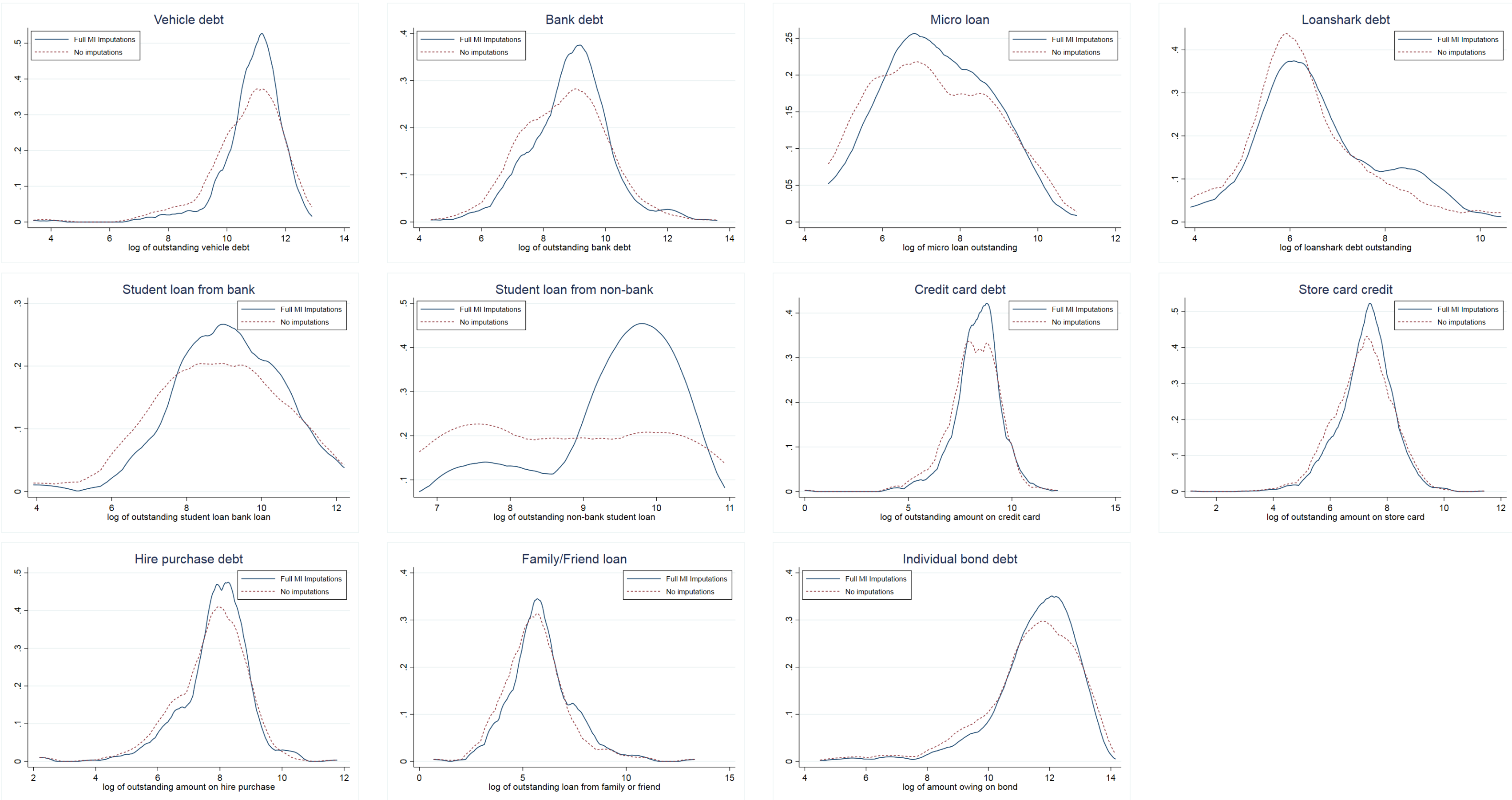
Source: NIDS

We report the imputations for individual total outstanding debt on the dwelling owned. We use individual level information and the household income variable for imputations. Individual information consists of *race*, *gender*, *education*, *age*, age^2, *race*gender*, *married* and *province*. We use the mean of the unfolded brackets for income and impute the additional debt participation variables where income is an independent variable. We allow for credit, store card and bond owing to be zero.

Figures 3.9 to 3.12 show the different distributions for the debt variables for each wave of the survey. For Wave 1 and Wave 3 there were no NIDS imputations, so the results only show the MI imputations versus no imputations, while for Wave 4, where NIDS imputations are available, the results are compared to no imputations and MI imputations. The distributions look fairly similar, however, for Wave 1 and Wave 2, the imputations for student loans from a non-bank institution for the MI are more negatively skewed. The Gelman and Rubin (1992) test results are shown in figure 3.13 and shows convergence of the Gibbs sampler for all individual debt imputations[46].

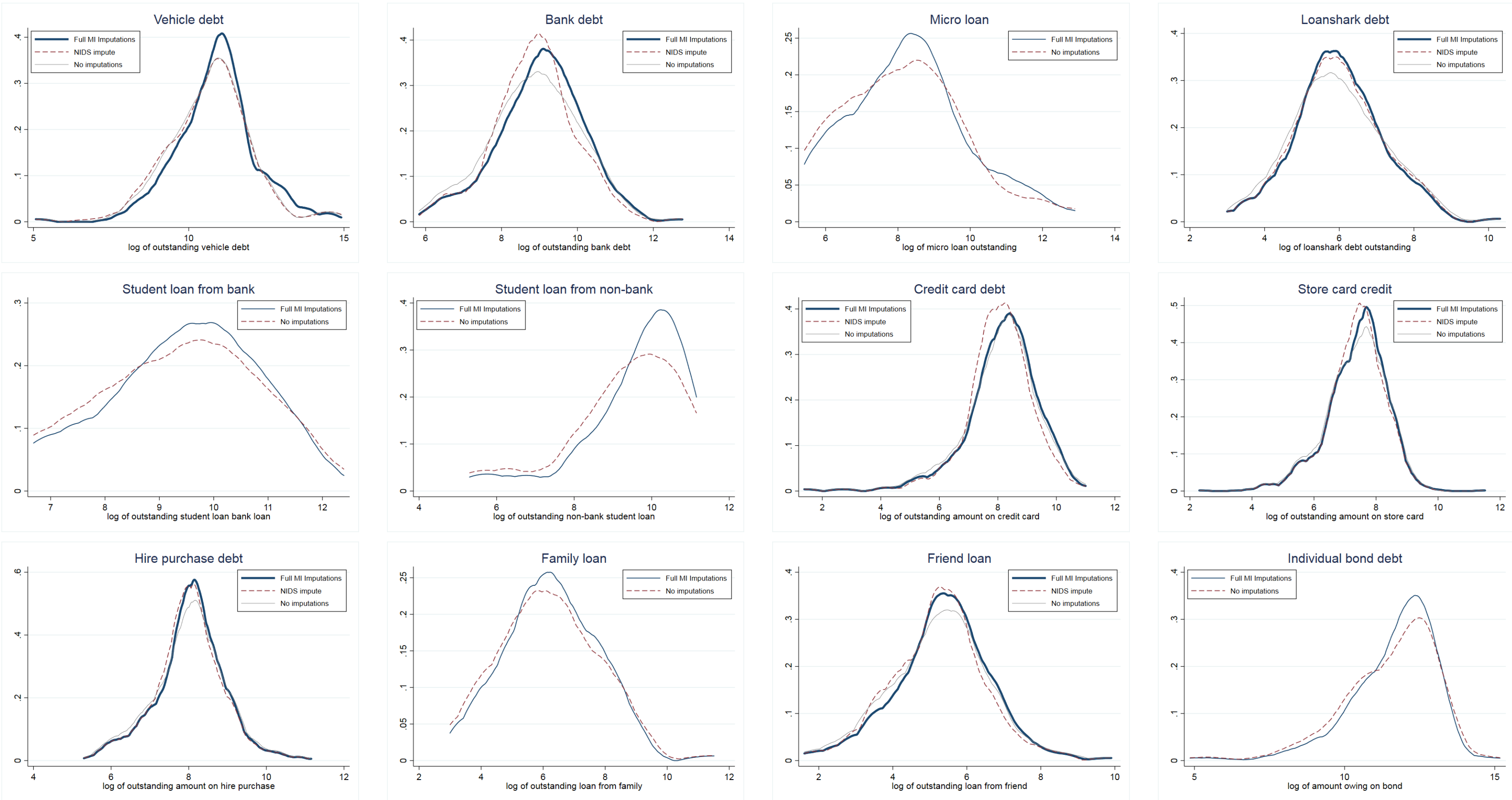
[46]The Gibbs sampler convergence graphs are available from the author.

Figure 3.9: Wave 1 imputations



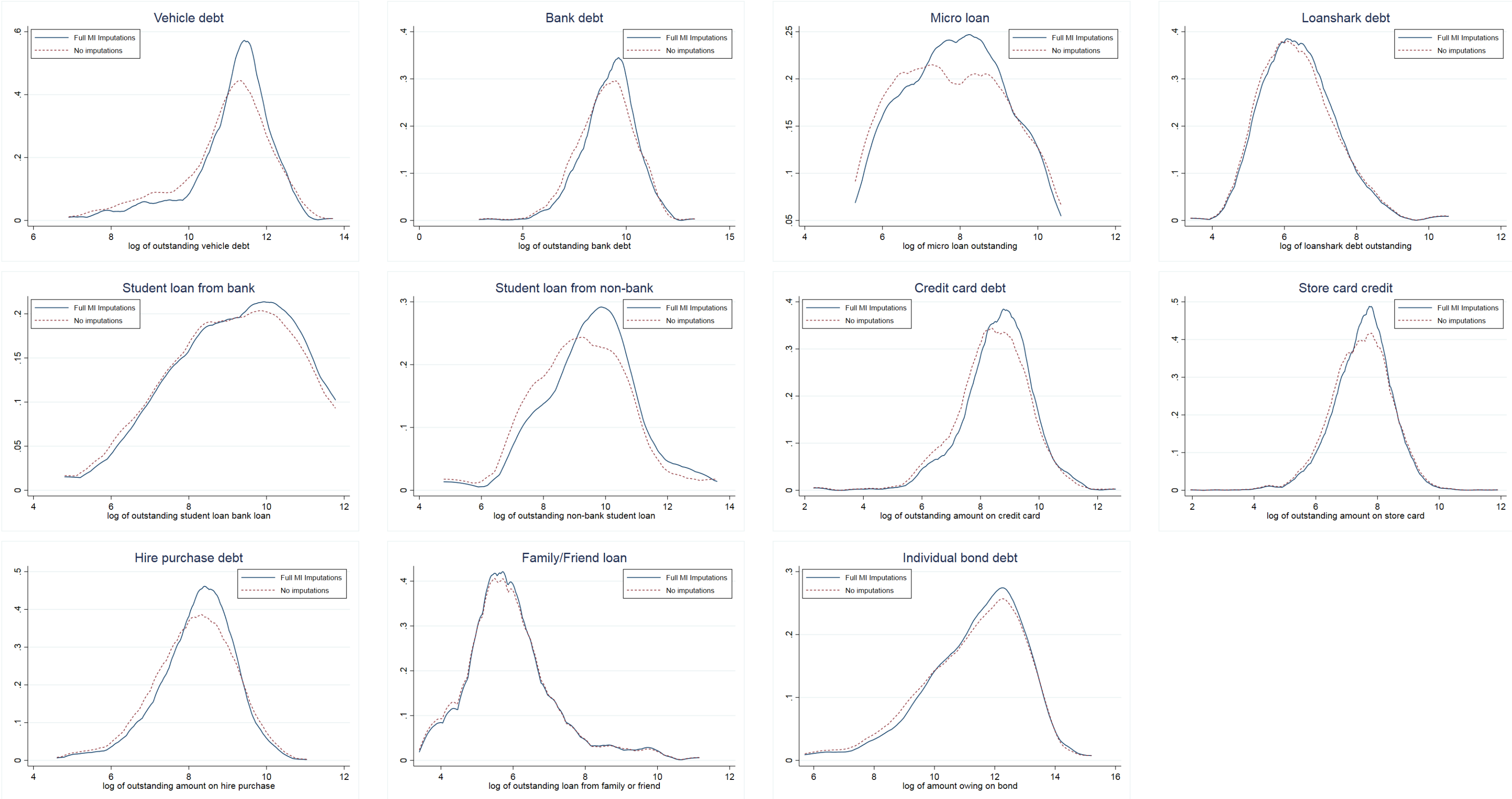
Source: Own calculations, NIDS

Figure 3.10: Wave 2 imputations compared to NIDS imputations (when applicable)



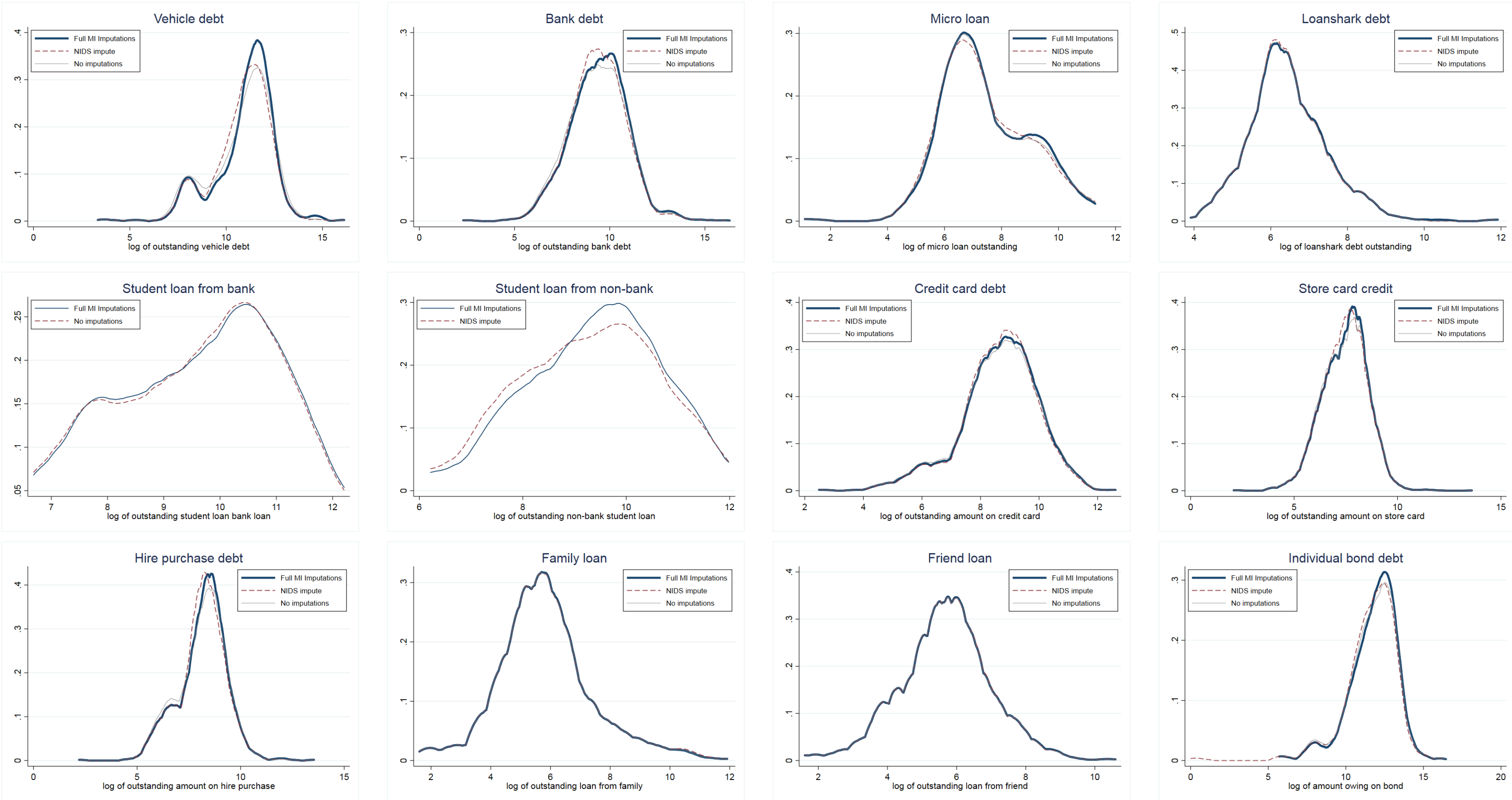
Source: Own calculations, NIDS

Figure 3.11: Wave 3 imputations



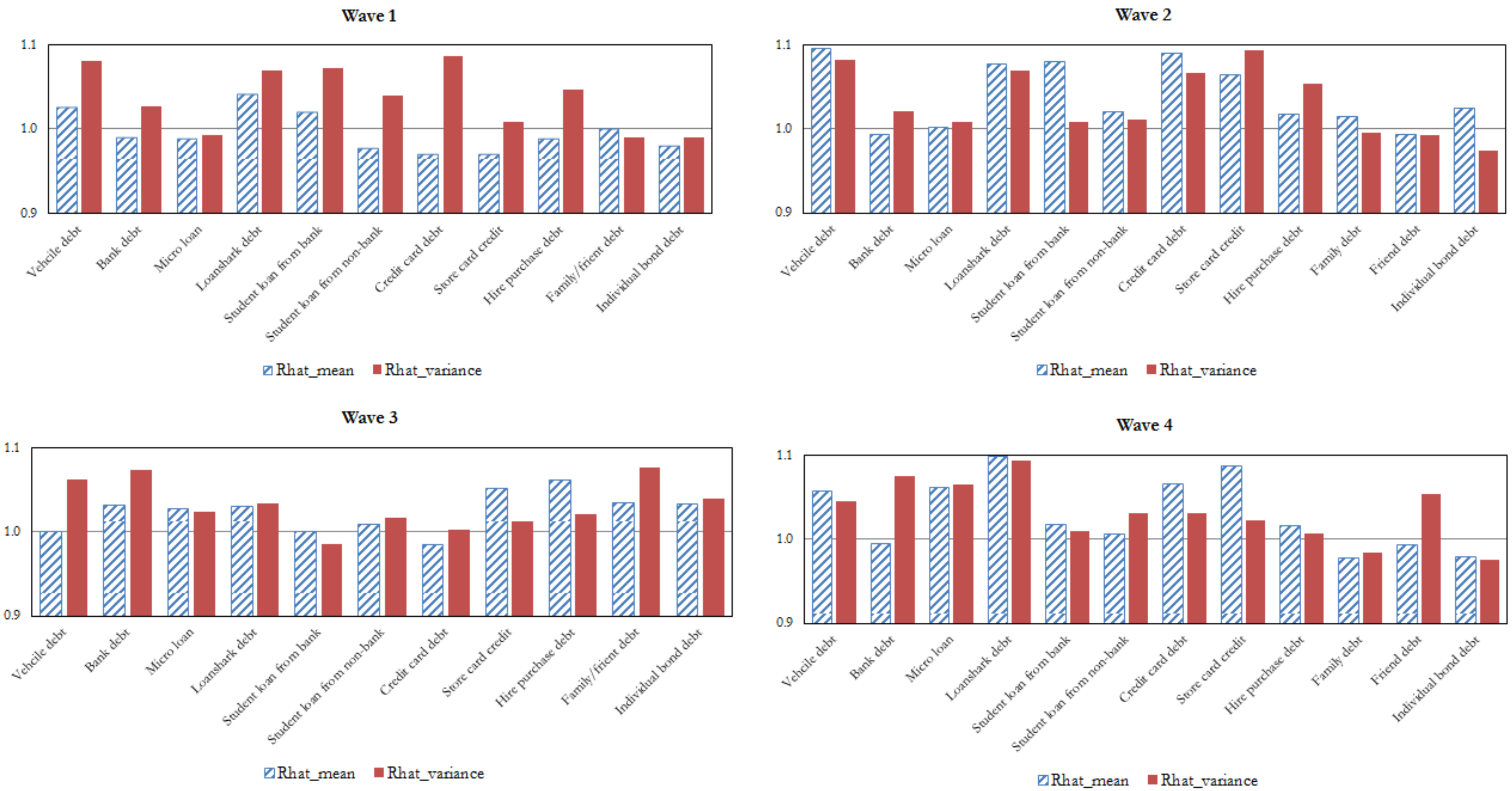
Source: Own calculations, NIDS

Figure 3.12: Wave 4 imputations compared to NIDS imputations (when applicable)



Source: Own calculations, NIDS

Figure 3.13: Rhat for all imputed individual debt types



Source: Own calculations, NIDS

When adding all the actual point responses for the individual debt variables across the waves, see table 3.9, we find that by imputing values, as described above, we lifted the number of observations, in some instances even by double. For Wave 1 we increase the number of responses from 3 350 to 4 817. For Wave 2, it is from 2 323 to 3 146, which is more than the NIDS imputations that lifts the number only to 2 984 because, as mentioned earlier, we impute for the debt participation questions that were not asked in the second phase of Wave 2. For Wave 3, we manage to improve the response number from 4 003 to 5 054, and for Wave 4 from 7 952 to 9 014 when using MI.

We also show that imputing for non-responses does not change the averages (table 3.10) of the debt variables or their distributions (except for the non-bank student loans in Wave 1 and Wave 2), which implies that the data was initially MAR and, therefore, imputations provide additional data points. Thus, by using MI, information regarding the distribution of the imputations is left intact when utilising regression analysis. We, however, in chapter 4 aggregate the information up to a household level, which then discards the distribution of the imputations.

Table 3.9: Number of responses before and after NIDS imputations and MI imputations

	Wave 1		Wave 2			Wave 3		Wave 4		
	Point values	Total including imputations (MI)	Point values	Total including imputations (NIDS)	Total including imputations (MI)	Point values	Total including imputations (MI)	Point values	Total including imputations (NIDS)	Total including imputations (MI)
Vehicle debt outstanding	223	400	140	181	191	176	259	361	435	435
Bank debt outstanding	351	523	316	413	421	592	814	1 225	1 411	1 411
Micro debt outstanding	50	81	41	41	51	45	59	196	211	211
Mashonisa debt outstanding	94	137	132	158	158	215	238	339	345	345
Student loan from bank outstanding	31	58	32	32	39	25	29	46	46	48
Student loan from other outstanding	17	36	22	22	30	27	39	60	60	76
Credit card debt outstanding	538	762	258	332	345	390	543	609	651	651
Store card debt outstanding	1 175	1 572	928	1 054	1 074	1 582	1 887	3 289	3 528	3 528
Hire purchase debt outstanding	338	457	249	296	296	489	634	807	907	907
Loan from family or friend	177	250				204	229			
Loan from friend			124	155	155			679	684	684
Loan from family			81	81	100			341	342	342
Bond owing	356	541		219	286	258	323		319	376
Total debt response rate	3 350	4 817	2 323	2 984	3 146	4 003	5 054	7 952	8 939	9 014
% increase with imputations		43.8		28.5	35.4		26.3		12.4	13.4

Source: Own calculations, NIDS

Table 3.10: Means of debt variables before and after imputations by NIDS and MI

Vehicle debt outstanding	Wave 1	Wave 2	Wave 3	Wave 4
No imputations	R 73 521	R 124 841	R 93 508	R 146 464
NIDS imputations	None	R 124 858	None	R 131 153
MI	R 75 661	R 135 108	R 99 676	R 155 384
Bank debt outstanding				
No imputations	R 16 692	R 14 952	R 18 998	R 58 280
NIDS imputations	None	R 13 313	None	R 52 745
MI	R 17 902	R 15 587	R 19 981	R 56 695
Micro debt outstanding				
No imputations	R 4 419	R 19 838	R 6 299	R 6 471
NIDS imputations	None	None	None	R 6 508
MI	R 4 014	R 19 982	R 5 997	R 6 427
Mashonisa debt outstanding				
No imputations	R 1 811	R 989	R 1 252	R 1 482
NIDS imputations	None	R 942	None	R 1 468
MI	R 2 098	R 916	R 1 223	R 1 565
Student loan from bank outstanding				
No imputations	R 23 201	R 28 599	R 25 549	R 30 498
NIDS imputations	None	None	None	None
MI	R 22 639	R 28 193	R 26 070	R 30 920
Student loan from other outstanding				
No imputations	R 13 343	R 21 527	R 46 346	R 22 649
NIDS imputations	None	None	None	None
MI	R 15 426	R 23 901	R 47 319	R 23 573
Credit card debt outstanding				
No imputations	R 5 028	R 5 325	R 8 974	R 11 192
NIDS imputations	None	R 5 383	None	R 11 219
MI	R 5 997	R 5 628	R 9 948	R 11 283
Store card debt outstanding				
No imputations	R 1 930	R 2 345	R 2 814	R 3 317
NIDS imputations	None	R 2 333	None	R 3 216
MI	R 2 014	R 2 356	R 2 802	R 3 338
Hire purchase debt outstanding				
No imputations	R 3 986	R 4 880	R 5 416	R 7 374
NIDS imputations	None	R 4 566	None	R 7 020
MI	R 4 319	R 4 729	R 5 467	R 7 444
Loan from family or friend				
No imputations	R 4 642	None	R 1 405	None
NIDS imputations	None	None	None	None
MI	R 3 859	None	R 1 390	None
Loan from friend				
No imputations	None	R 567	None	R 737
NIDS imputations	None	R 502	None	R 736
MI	None	R 541	None	R 743
Loan from family				
No imputations	None	R 2 444	None	R 2 085
NIDS imputations	None	None	None	R 2 215
MI	None	R 2 197	None	R 2 081
Bond owing				
No imputations	R 184 909	R 232 048	R 224 795	R 323 170
NIDS imputations	None	None	None	None
MI	R 184 834	R 227 314	R 231 549	R 364 990

Source: Own calculations, NIDS

3.5 Conclusion

As we use NIDS data to measure and analyse household debt and deleveraging from a micro econometric perspective in chapter 4, we established that, typical to most household surveys, the incidence of non-response to sensitive questions, such as on income, assets and debt, were quite high in the NIDS data. We therefore considered different options available on how to use additional information gathered by interviewers, such as bracket responses or other elicitation techniques, to impute point or value estimates in this chapter.

We used the first four waves from 2008, 2010/2011, 2012 and 2014/2015, which corresponds to our deleveraging period established in chapter 2. We used MICE to impute missing data and point values from bracket responses, as MICE allows for bounds imputation. We focused our imputations on income and household debt in order to measure deleveraging where there are many who responded that they have debt, but do not provide a point value. We used this information to impute a point value for those who said that they have debt. In chapter 4 we create a panel dataset which includes as much information as possible on income and household debt across the waves.

MICE can be implemented under the MAR assumption (such that missing values depend only on observed information). MI generates multiple imputed values, which replace missing values, creating multiple unique data sets. MI has the benefit of keeping the information regarding the distributions of the imputations intact. We, however, in chapter 4 aggregate this information up to a household level, which then discards the distribution benefit of the imputations.

Considering different options for dealing with missing data is always important. Our analysis found little difference between making use of mid-points to unfold bracket responses compared to missing data imputations using MI methods, similar to findings from the South African literature. We increase the household income response rate from 75% to 81% in Wave 1, 84% to 94% in Wave 2, from 90% to 97% in Wave 3 and from 95% to 98% in Wave 4.

When we impute the individual debt variables for those who responded that they were debt participants, we increased the total number of observations for all debt types by 43.8% in Wave 1, 35.4% in Wave 2 (including those that we derived from responses in Wave 1 and Wave 3 when the question was not asked in phase 2 of Wave 2), 26.3% in Wave 3 and 13.4% in Wave 4.

We also show that imputing for non-responses does not change the averages of the debt variables or the distribution (except for the non-bank student loans in Wave 1 and Wave 2), which implies that the data was initially MAR. Therefore imputations provide additional data points when we utilise regression analysis in chapter 4.

In chapter 4 we make use of our imputed data to differentiate between different debt categories, i.e. mortgage debt, vehicle debt, consumer debt and other debt. We also use our point values for income bracket responses to create a continuous income variable which we can use to analyse debt behaviour by income quintiles. As our goal is to measure deleveraging, by default, the change in debt between waves will only be for those who reported debt in both waves under consideration. Therefore, despite our best attempts to impute for missing debt values, we do find that in some instances for smaller debt categories, such as vehicle debt, certain income quintiles may have only reported debt in one wave, and not the comparative wave, and therefore would fall out of the deleveraging sample.

CHAPTER 4

DELEVERAGING: AN ANALYSIS OF MICRO PANEL DATA USING NIDS

4.1 Introduction

This chapter focuses on how the financial crisis, and the debt overhang from high pre-crisis debt levels, especially in the mortgage market, impacted households and where households managed to deleverage. We also emphasize the impact that deleveraging has on consumption. As households try to restore the health of their balance sheets, consumption-led growth stagnates slowing the post-crisis economic recovery. Under these circumstances, where household financial positions are severely impacted, it is not unreasonable to believe that these shocks will result in heterogeneous household responses (see Dynan, 2012b), which should be brought to the attention of policy makers.

South Africa's weak economic performance following the financial cycle peak in May 2007 triggered challenging policy response questions. Before the peak, annual economic growth averaged around 4.1% (1999 - 2007). The high uptake of debt in the latter period, and the subsequent fall in house prices following the financial cycle peak (discussed in chapter 2), resulted in household deleveraging. McCarthy and McQuinn (2017a) suggest that when households start paying off their debt, it often results in a decline in consumption and/or an increase in savings levels, which translates into sluggish economic growth. After the May 2007 peak, annual economic growth averaged around 1.8% (2008-2017). Moreover, the South African economy, apart from the business cycle downward phase recorded between 2007 and 2009, entered (and continues to remain in) a second business cycle downward phase at the end of 2013 (and up to the start of 2019).

McCarthy and McQuinn (2017a) suggest that after the financial crisis, the correction in house prices in some Organisation for Economic Co-operation and Development (OECD) member countries resulted in many households engaging in a process of deleveraging, which impacted consumption, growth and savings. Dynan (2012b) highlights the weak recovery in consumption growth following the US crisis, compared to typical previous economic recoveries, while Pistaferri (2016) attributes the drag on consumption to not only the deleveraging process, which he argues has fizzled out somewhat, but also to weak income and employment growth, the distribution of income and the willingness of financial institutions to make credit available as easily as they had before. McCarthy and McQuinn (2017a) and Dynan (2012a) make two additions to the list –wealth, especially as the post-crisis period was characterised by a sharp fall in house prices, and future income/economic uncertainty, where weak income growth and unemployment played a big part in the slow economic recovery.

Similar to the global experience, the lacklustre growth in the South African economy following the financial cycle peak was largely a result of the pre-boom financial debt burden that was driven by mortgage debt. This is also the sector in which a large part of the deleveraging happened following the peak. High leverage among households was due, in part, to rising house prices in an accommodative monetary policy environment. As house prices started to fall (by about 15% in South Africa's case) households had limited ability to take out new loans, refinance or sell their homes, given income shocks and rising unemployment rates[47].

Drawing purely on macro data, it is often difficult to find clear evidence of the workings of the interest rate or consumption channels, because macro data reflects the average over different types of households and blurs the transmission effect that may only hold for specific groups (Gomez-Salvador et al., 2011). The analysis of deleveraging and the impact of the financial crisis at a household level is motivated by potential heterogeneous responses to shocks across different groups of the population. According to Dynan (2012b) and Cooper and Dynan (2016), if all households reacted the same way when facing economic challenges, the aggregate data would sufficiently reflect this. As this is not the case, we rely on micro data for a better understanding of household debt and deleveraging dynamics. According to André (2016), the study of the distribution of debt across households is necessary to ascertain more sufficiently the risk to the financial system and the macro economy. Our results suggest that even if deleveraging happened at an aggregate level, only those in the upper income quintiles were able to deleverage.

Micro-data based studies analysing household debt have gained prominence in recent years (Mian and Sufi, 2010; Mian et al., 2013; Dynan, 2012a; McCarthy and McQuinn, 2017b). A concern for policy-makers involves the timing of deleveraging and the uptake of new credit, which is a necessary condition for consumption and growth. Without sufficient deleveraging, households will not be able to create financial space for the increased demand that is necessary for the next

[47] See McCarthy and McQuinn (2017a) for an example of the Irish economy, where house prices fell by 50%.

growth cycle. Dynan and Edelberg (2013), using micro panel data, show that US households have not made much progress in terms of debt reduction and that debt ratios remain high for some households, even above pre-crisis levels. To emphasise the impact of the mortgage market, their sample is split into homeowners and non-homeowners. Their estimates show that consumption spending for households with high mortgage debt-to-income ratios was especially weak. They conclude that households may take years to reduce their debt to pre-crisis levels. Similar to Dynan and Edelberg (2013), Baker (2014) suggests that the decrease in consumption may not purely be due to higher debt levels or liquidity constraints, but might be because highly indebted households hold back consumption so that they can attain, what they perceive to be, a more controllable debt level.

Mian et al. (2013) use US micro data to show that household consumption is very responsive to shocks in housing net worth. They also find that there was a large distributional effect in that poorer and more leveraged households decrease their spending significantly more. Bhutta (2012) shows that deleveraging in the US mortgage market is not driven by active deleveraging, but rather a sharp decline in debt accumulation due to lower demand, as access to credit became constrained, as well as a decline in the number of borrowers, as financially distressed borrowers and investors left the mortgage market. Dynan (2012a), having controlled for wealth levels, concludes that elevated leverage appears to be associated with weak consumption growth. Cooper (2012) and Dynan and Edelberg (2013) also support these findings. Cooper (2012) shows that this negative relationship existed prior to the financial crisis, but that debt could have had a larger impact on consumption, recently, as more households were in higher leveraged positions than before the crisis.

In the UK, Bunn and Rostom (2014) suggest that the reason highly leveraged households deleverage more is that they had disproportionally less access to new credit. Furthermore, highly indebted households could have become more concerned about their balance sheet positions and future incomes; therefore, they cut back more on consumption and leverage. McCarthy and McQuinn (2017a), using an Irish data set, also show that, when controlling for wealth effects, deleveraging has a negative and statistically significant impact on consumption, although the effect is economically small.

Building on chapter 2's macroeconomic analysis, this chapter exploits household survey data to gain insights into how debt is distributed in the South African economy, and who was able to deleverage after the financial cycle peak in May 2007. Most other studies usually only observe the drivers of debt or high leverage (see Coletta et al., 2014; Dynan and Kohn, 2007; Bhutta, 2012; Wildauer, 2016). The use of micro data will assist us in accounting for the heterogeneous responses of households to financial shocks. As a developing economy with high income-inequality, both income and debt are unevenly distributed among South African households, this further supports the rationale for using household level data in our analysis. This paper makes use of the first four available waves of the NIDS, and, in part, exploits the panel structure to determine the drivers and impact of household deleveraging after the South African financial cycle peak. A benefit of the timing of the NIDS study is that the NIDS data, more or less, coincides with the start of the financial downswing in 2007[48].

We proceed by using imputations from chapter 3 to create various household debt outstanding variables. We make use of the change in household debt outstanding in Wave 1 - 2, Wave 1 - 3 and Wave 1 - 4 to determine if households deleveraged. We also create a unique household identification variable which allows us to follow households over the period, which has not been done with the NIDS data before. We show in this chapter that high income households hold different debt types compared to low income households. We also show that mortgage debt is held primarily by high income households, which we showed in chapter 2 dominates debt at the aggregate level.

4.2 Overview of the NIDS data

NIDS is a South African panel that follows individuals, and is designed to be representative of the South African population. Individuals are tracked from wave to wave, even if they move in or out of any particular household. For our analysis, we use the first four waves of the survey conducted in 2008, 2010/2011, 2012, and 2014/2015[49].

Consistent with the groupings in chapter 2, we group the different debt types into mortgage debt, vehicle debt and other consumer debt. We further include a category for informal credit[50], which we refer to as other debt. This category is included in the NIDS questionnaire, but mostly not in chapter 2's definitions of debt, as macroeconomic data in aggregate debt comes mostly from formal financial institutions.

Although there are many benefits to longitudinal data, the fact that NIDS has been designed to follow individuals makes it nearly impossible to follow households across waves, as households are not identifiable across waves, except where they contain the same individuals

[48] Other South African studies that use the NIDS data to analyse debt behaviour include Choonoo (2016) who looks at determinants of debt servicing cost and Ntsalaze and Ikhide (2016) who look at the prevalence of over-indebtedness.

[49] In the first survey round 7 296 households were interviewed; 9 016 households in the second round, 10 114 in the third wave, and 11 732 in the fourth wave. This includes households that did not successfully complete the household questionnaire. Out of the total sample, only 5 115 households were successfully interviewed in all four waves (Southern Africa Labour and Development Research Unit, 2016e).

[50] Informal debt consists of micro loans, study loans from non-bank institutions, store card credit, loans from a loan shark or loans from family or friends.

(Southern Africa Labour and Development Research Unit, 2016e). One way around this, which many researchers use, is to follow only the household head across the different waves. However, the household head is self-defined and is a construct to determine relationship status to other members in the household. No guidance is given that the household head must be the eldest, highest earner or of a specific gender (NIDS, 2018). In other words, it is possible that household heads change across waves.

Because we aim to measure household debt over the different waves, we construct a unique household identifier. We select one person in each household and aggregate all household-level variables to that respondent. Because household heads are self-defined, certain conditions had to be specified to get a relevant household representative. First, the household representative needs to be at least 18 years old[51] and have successfully completed the adult questionnaire[52]. Second, to ensure that the key person is a good representation of the household (Cull and Scott, 2010), we set the condition that the selected person is the household head or the key decision maker over all household expenditure[53]. Lastly, when there is still uncertainty, we follow the adult who joins the new household that contains most of the baseline household members[54]. In the end there are 7 263 households in Wave 1, 5 652 households in Wave 2, 5 691 in Wave 3, and 5 402 in Wave 4.

Although there have been studies on debt and debt determinants in South Africa, little is known about who suffers the most when debt levels are high and who deleverages. We established in chapter 2 that, at the aggregate level, household debt increased in the build up to the financial cycle peak; dated to be May 2007. We also showed that debt and debt-to-income ratios only started to decrease around 2 to 4 quarters after the peak. As the first wave of NIDS was conducted in 2008, it presents us with an opportunity to see to what extent households were able to deleverage following the peak. The panel structure in the NIDS data provides an opportunity to measure household debt across waves to determine whether household leverage has been increasing or decreasing.

[51]In South Africa, obtaining a loan is conditional on being over the age of 18. We therefore drop households where all household members are underage. We also drop households for which we cannot obtain any information on the age of respondents. Where only one adult exists in the household, we follow that person. Where many adult household members drop out of the survey, we follow the person that is tracked the longest.

[52]While having successfully completed the adult questionnaire is one of our conditions, we loosen this restriction in cases where no other adult exists in the household. Only one adult questionnaire was not successfully completed across all the survey rounds. In the case of unsuccessful completion (oddly also in cases of successful completion), two of our variables of interest, education and employment status, have missing observations.

[53]The first condition is that the key respondent is the household head and/or the main decision maker (of large and daily household expenditure) in all the survey rounds that the household was tracked. Where there remain unidentified households, the restriction is loosened in a gradual manner across various iterations until one adult household representative per household is derived.

[54]The author would like to thank Manuela Gunther for her contribution with regards to the establishment of the unique identifier.

We aim to establish if households deleveraged, given their original balance sheet in Wave 1. For this reason, we use the calibrated (post-stratification) weights[55] instead of the panel weights[56] provided. As we match those who had debt across the waves[57], selection bias may arise, since those who do not report debt in subsequent waves may not be random[58].

Table 4.1 presents the weighted sample statistics for each survey year. The average age of the respondent at the start of the survey is 43 years. About 37% of household representatives were married. Roughly in line with the 2015 mid-year population estimates (Statistics South Africa, 2015), we find that around 77% of respondents are African, about 48% of respondents are female, and 67% of households reside in urban areas. We detect some compositional changes concerning the population group; for instance the share of White respondents increases from 12.8% in 2008 to 14.5% in 2014/15. This is higher than the mid-year population estimate of 8.7%. On average, respondents have attained nine years of education[59]. We further find that in 2008, on average, 65% of households have at least one household member in full-time employment, increasing to 74% in 2014/2015[60] and about 45% of the households received government grants in 2014/2015. Lastly, the average household consists of approximately four members (approximately one quarter of those are under 18 years old).

[55]The post-stratification weights are calibrated to represent the mid-year population estimates released by Statistics South Africa in 2015 (Chinhema et al., 2016). They adjust the design weights such that the age-sex-race group cell totals in NIDS match the population statistics. The distribution by province also corresponds to the estimated population and weights are constant within households.

[56]Panel weights intend to correct for attrition bias which arises when individuals, who were successfully interviewed in Wave 1, might not have been re-interviewed in other waves. The panel weights are the inverse of the probability of being in the sample (Southern Africa Labour and Development Research Unit, 2016e).

[57]By selecting only those who had debt, we are possibly ignoring people who may have paid off their debt in full. The author would like to thank one of the reviewers for pointing this out. Unfortunately we only had this information available for those who had mortgage debt, however by including these, none of our main relationships of interest changed. By including these respondents, the estimation sample (for those who had debt in Wave 1) increase by 57 observation between Wave 1 and Wave 4; 79 between Wave 1 and Wave 2 and 69 between Wave 1 and Wave 3.

[58]Although we do not adjust for this directly, we do test for possible selection bias by estimating the probability of reporting debt in Wave 1 and not in subsequent waves.

[59]In case of missing variables for education, we replace missing values with the average of the previous and subsequent survey round, where the information is available.

[60]As 900 values are missing regarding the respondent's employment status, we represent employment in the household by means of a dummy variable: having at least one member in the household employed or not.

Table 4.1: Weighted demographic and sample characteristics

Survey Year	2008 (Wave 1)	2010/11 (Wave 2)	2012 (Wave 3)	2014/15 (Wave 4)
Sample size	2 493	1 672	2 108	2 849
Age of respondent (mean for in 18 years +)	43.3 (14.7)	46.1 (14.4)	47.8 (14.2)	49.8 (14.1)
Married respondents (in %)	36.5 (48.2)	39.8 (49.0)	36.6 (48.2)	43.4 (50.0)
Respondent's population group (in %)				
African	76.6	76.1	75.8	75.2
Coloured	8.2	8.1	8.5	8.1
Asian/Indian	2.4	2.3	2.2	2.1
White	12.8	13.5	13.4	14.5
Female respondents (in %)	48.2 (49.9)	47.8 (50.0)	48.8 (50.0)	48.4 (50.5)
Respondents living in an urban area (in %)	67.0 (47.0)	65.8 (47.4)	68.7 (46.4)	68.5 (46.5)
At least one adult employed in household (in %)	64.8 (47.8)	64.9 (47.7)	70.0 (45.8)	74.2 (43.6)
Household receives welfare grant (in %)	37.9 (48.5)	43.4 (49.6)	44.8 (49.7)	45.4 (49.8)
Household Composition				
Household Size	3.5 (2.5)	3.8 (2.7)	3.7 (2.7)	3.7 (2.7)
Share of Children (<18 years)	27.0 (26.0)	26.0 (25.0)	25.0 (25.0)	24.0 (25.0)
Education of respondent (in mean years)	8.6 (4.4)	8.7 (4.4)	8.7 (4.5)	9.0 (4.4)

Standard deviation reported in (). We use the post-stratification weights. The sample are for those who had debt (including zero) outstanding in each respective wave.

Source: Own calculations, NIDS

We remove the price effect to make waves comparable; therefore, where debt and income values are reported, they are in real terms, after tax. Using consumer price data, we deflate annual household income to reflect real income at constant November 2014 prices, when most of the surveys for Wave 4 were completed. We show in table 4.2 that both median and mean income increased marginally over the sample period. We report median debt and debt changes (in the deleveraging section) to mitigate extreme values that may drive the results, especially where the reported debt sample is small, as in our case, even after imputations (also see Dynan (2012a)).

Median [mean] annual real household income increased from R 31 164 [R 88 034] to R 46 006 [R 330 595] between Wave 1 - 4 (see table 4.2[61]). Median [mean] annual real household consumption amounted to R 33 433 [R 91 106] in Wave 1, increasing to R 41 217 [R 96 903] in Wave 4. The higher consumption, compared to income in Wave 1, could reflect that households were over-leveraged and the difference between income and consumption was covered by borrowing, especially if households drew on their mortgages for consumption purposes (as they expected house values to continue rising). It could also be due to under-reporting of income or over-approximation of consumption, but, unfortunately, we cannot determine this from the data. To account for the context of high income inequality, we consider income across income quintiles. In table 4.2 we disaggregate the change across the income distribution. The income gap that is characteristic for South Africa is also visible in the NIDS data. In Wave 4, the median [mean] household income of the bottom quintile is R 12 000 [R 10 872], while the median [mean] at the top quintile is R 168 599 [R 965 952].

We further note that the median debt amount outstanding among indebted households has decreased relative to 2008 levels (see table 4.2). The median [mean] real amount outstanding, for those who had debt, was R 13 669 [R 141 871] in Wave 1. In Wave 3 the outstanding amount dropped to R 11 542 [R 126 089] before decreasing [increasing] to R 6 925 [R 164 316] in Wave 4. When we disaggregate debt outstanding into debt types and by income quintiles (table C.1.1) we see that the decrease in median total debt outstanding, in value terms, was most notable in the top income quintile.

After incorporating all our imputations for debt, we plot the kernel densities in figure 4.1. The total debt outstanding in Wave 1 and Wave 2 are bimodal, likely a result of households suddenly finding themselves more indebted after the financial cycle peak was reached. This is no longer the case in Wave 3 and Wave 4 as debt levels were either lowered voluntarily or through defaults. All debt categories display skewness, which could warrant further investigation regarding optimal modelling methods.

[61] We use the unimputed household income question from NIDS, together with our imputed values for the brackets to derive our income variable.

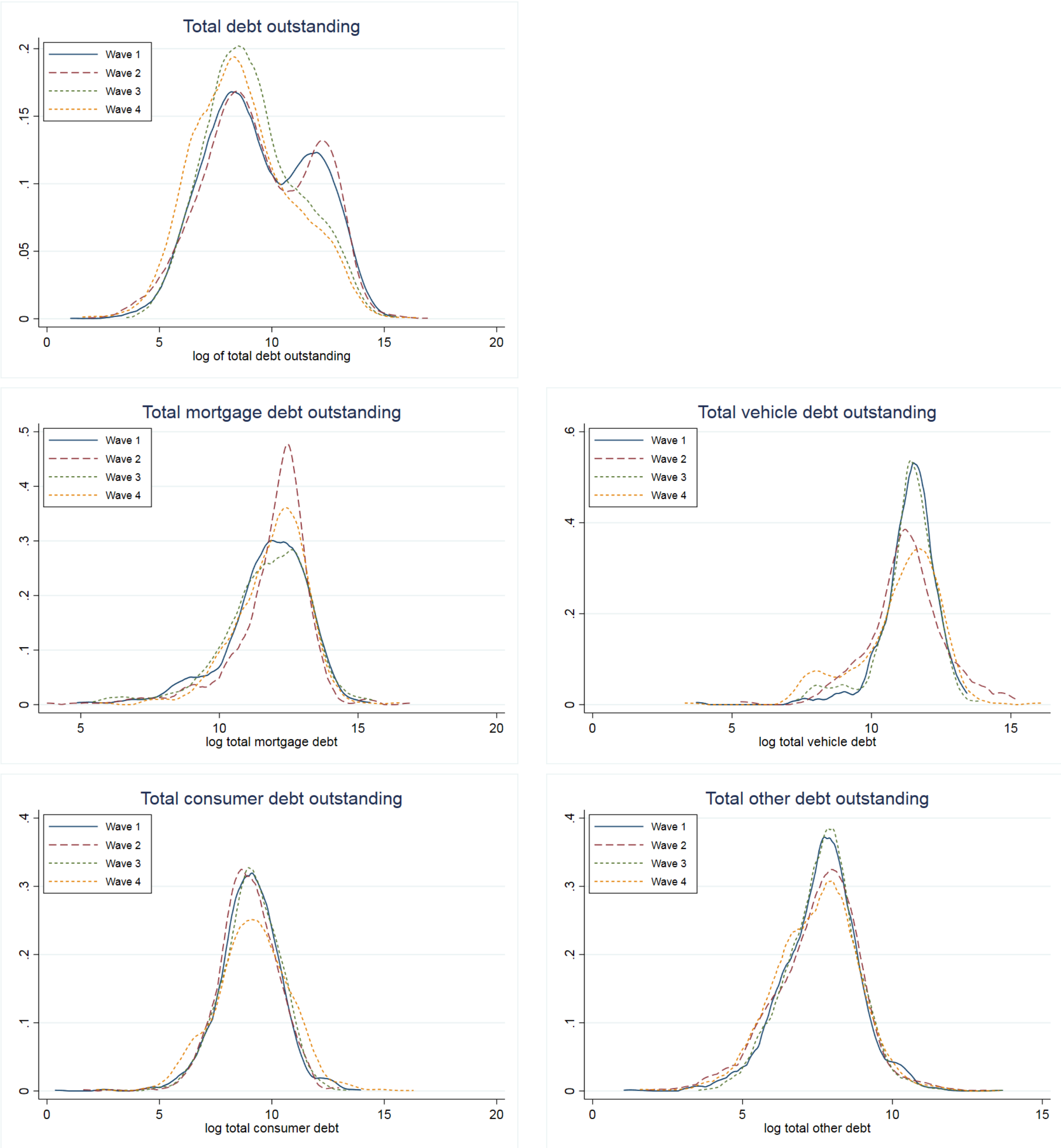
Table 4.2: Weighted income, expenditure and debt characteristics of the sample who had debt

Survey Year	2008 (Wave 1)	2010/11 (Wave 2)	2012 (Wave 3)	2014/15 (Wave 4)
Sample size	2 493	1 672	2 108	2 849
Annual Income of Households	R 31 164 [R 88 034]	R 34 601 [R 135 836]	R 40 233 [R 126 800]	R 46 006 [R 330 595]
Income quintile 1	R 8 288 [R 8 178]	R 7 582 [R 8 038]	R 9 551 [R 9 151]	R 12 000 [R 10 872]
Income quintile 2	R 16 102 [R 16 331]	R 17 086 [R 16 377]	R 20 529 [R 20 821]	R 23 349 [R 22 725]
Income quintile 3	R 24 646 [R 24 741]	R 26 775 [R 27 018]	R 32 982 [R 32 778]	R 35 903 [R 35 302]
Income quintile 4	R 43 381[R 44 140]	R 45 132 [R 45 148]	R 54 745 [R 54 175]	R 60 000 [R 60 821]
Income quintile 5	R 146 732 [R 243 549]	R 148 763 [R 373 723]	R 164 910 [R 363 752]	R 168 599 [R 965 952]
Annual consumption of Households	R 33 433 [R 91 106]	R 32 058 [R 90 435]	R 33 643 [R 81 814]	R 41 217 [R 96 903]
Debt outstanding	R 13 669 [R 141 871]	R 22 746 [R 177 452]	R 11 542 [R 126 089]	R 6 925 [R 164 316]
Income quintile 1	R 2 877 [R 38 013]	R 4 378 [R 107 324]	R 2 290 [R 47 298]	R 1 613 [R 17 845]
Income quintile 2	R 2 892 [R 14 734]	R 3 800 [R 46 058]	R 3 791 [R 14 845]	R 2 004 [R 14 910]
Income quintile 3	R 2 954 [R 18 594]	R 4 674 [R 45 449]	R 3 486 [R 118 644]	R 2 950 [R 57 658]
Income quintile 4	R 6 675 [R 35 261]	R 8 149 [R 86 137]	R 6 413 [R 37 513]	R 4 107 [R 19 266]
Income quintile 5	R 63 521 [R 240 229]	R 77 727 [R 261 800]	R 53 458 [R 200 687]	R 42 026 [R 341 718]
Mortgage debt	R 180 754 [R 329 429]	R 252 727 [R 366 578]	R 194 686 [R 335 742]	R 229 813 [R 524 473]
Vehicle debt	R 99 923 [R 121 549]	R 83 147 [R 170 179]	R 96 471 [R 158 726]	R 85 854 [R 168 896]
Consumer debt	R 8 032 [R 18 704]	R 8 696 [R 17 244]	R 12 368 [R 22 502]	R 11 020 [R 87 964]
Other debt	R 2 201 [R 4 261]	R 2 507 [R 4 943]	R 2 298 [R 7 492]	R 2 000 [R 4 936]

All values reported are in real terms (November 2014). Both medians and [means] are reported. Results are weighted using the post-stratification weights. A breakdown of the median [mean] debt type outstanding by income quintiles and waves are shown in table C.1.1. The sample covers those who had debt (including zero) outstanding in each respective wave.

Source: Own calculations, NIDS

Figure 4.1: Kernel densities of debt distributions for the different debt types by wave

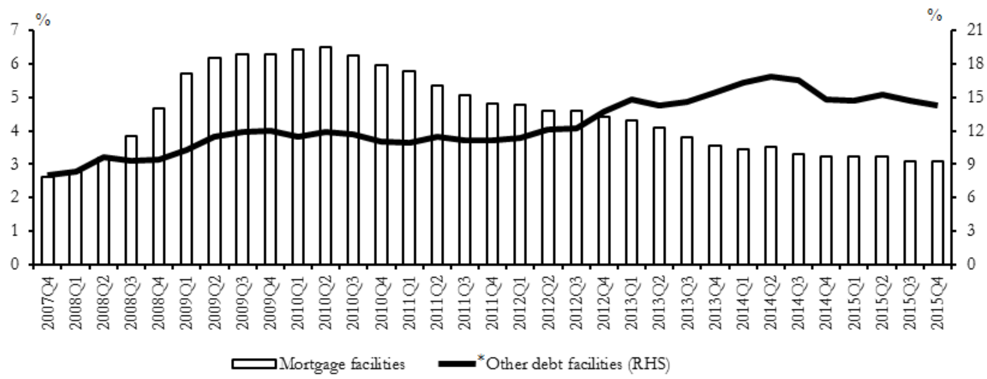


Source: Own calculations, NIDS

4.3 Debt landscape

South Africa has a unique debt landscape given its high level of income inequality and exclusion from formal financial services, largely amongst the poor (Matsebula and Yu, 2017). Data collected from the National Credit Regulator (NCR) shows that consumers struggled to meet their debt obligations at the start of the financial cycle peak (in this case we use 2017Q4 as this is the start of the NCR data). We show in figure 4.2 the share of account holders who were in arrears for 90 days or more. The data shows a sharp increase in the share of mortgage account holders who fell behind with payments, increasing from 2.6% in 2007Q4 to a peak of 6.5% in 2010Q2. This suggests that mortgage holders were initially hit harder than other debt holders during the global financial crisis. After the peak, the share decreased gradually, as households managed to repay their debt, underwent debt counselling (a process where consumers could negotiate a repayment plan by restructuring payments[62]), were forced to sell their property or had their property repossessed by the financial institution to whom the debt was owed. Total other debt (excluding mortgage debt), however, increased gradually, only reaching a peak in 2014Q2, when 16.9% of account holders were behind by 90 days or more in repayments.

Figure 4.2: Percent of account holders in arrears for 90 days or more

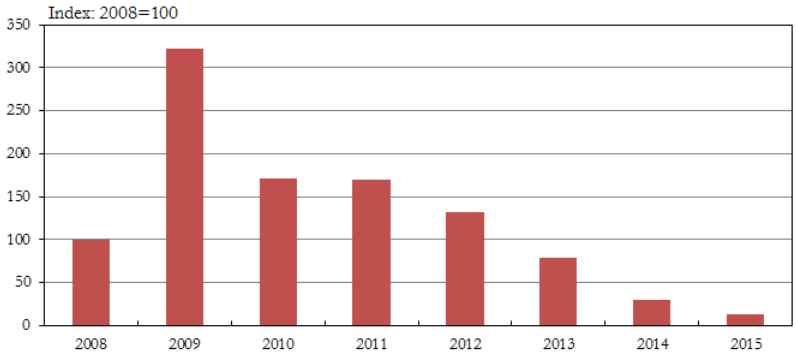


*Other debt includes secured and unsecured credit, credit facilities and short-term credit.
Source: National Credit Regulator (2018)

[62]See Naicker and Md. Kabir (2013).

There was also a spike in repossession of houses in 2009, between Wave 1 and Wave 2, which could have inflated the level of initial deleveraging, however this effect likely dissipated after Wave 2 as shown in figure 4.3.

Figure 4.3: Index of the number of house repossessions between 2008-2015



*Other debt includes secured and unsecured credit, credit facilities and short-term credit.

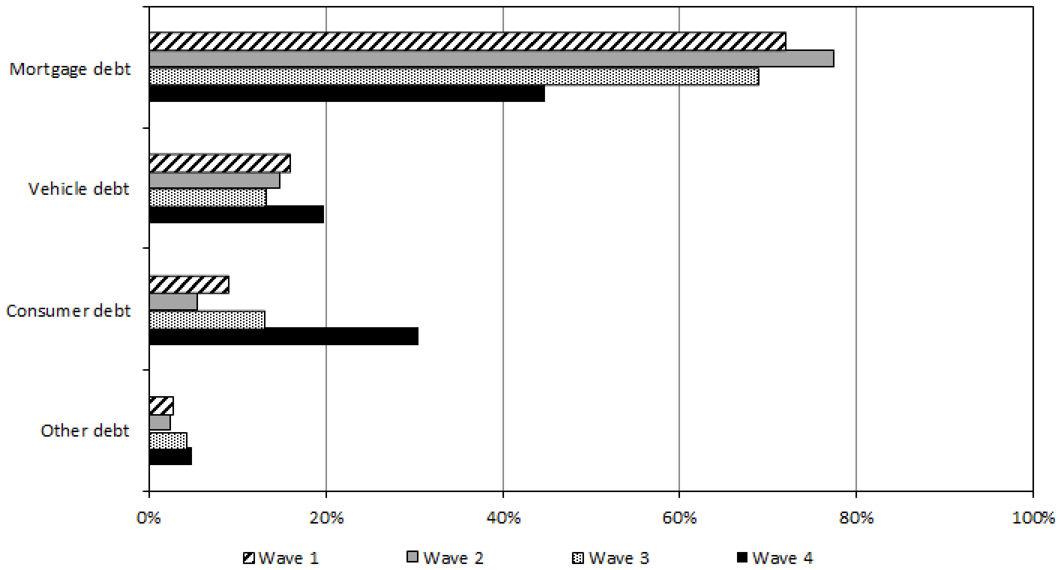
Source: Own calculations, SARB

Note that actual number of repossessions are not publicly available from the SARB.

We measure deleveraging in terms of total amount outstanding for those who reported debt in both the first and, respective, subsequent waves. We also calculate household deleveraging by taking the latter as a share of total annual income, which allows us to see who bore the brunt of the financial crisis and where households managed to deleverage (following the recent financial cycle peak).

In figure 4.4 we illustrate the share of the different debt types as a percentage of total household debt outstanding. Apart from showing that mortgage debt made up the largest share of outstanding debt, followed by vehicle and consumer debt, we also show that, after initially increasing in Wave 2, the share of mortgage debt outstanding was the only debt category that decreased substantially in subsequent waves, confirming the results that we saw at the aggregate level. The share of consumer debt to total debt increased noticeably in Wave 4, from 9.1% to 30.4%, which we have suggested in chapter 2 was likely due to distressed borrowing.

Figure 4.4: Percent of total debt outstanding by wave and debt type for those who had debt



Source: Own calculations, NIDS

Table 4.3 shows that, of our total sample, 33.4% of households had debt in Wave 1, increasing to 52.7% in Wave 4[63]. What stands out is that the share of mortgage debt holders decreases across the waves (likely due to repossessions or distressed sales and/or the reluctance of banks to extend new credit over this period as well as a sharp increase in debt participation). For consumer and other credit, however, the share of households who held these types of debt increased, again likely due to distressed borrowing needs. Of the different debt types, consumer and other debt holding were the largest shares in our sample.

Table 4.3: Total share by debt type, for those who had debt

	Wave 1	Wave 2	Wave 3	Wave 4
Mortgage debt	29.3%	30.5%	17.5%	10.7%
Vehicle debt	14.5%	9.4%	8.6%	9.2%
Consumer debt	48.1%	41.9%	52.9%	48.9%
Other debt	65.9%	60.7%	67.7%	76.5%
Total share of sample who had debt	33.4%	29.3%	37.0%	52.7%

Shares won't add up to 100%, as households can have more than one debt type. A breakdown of the debt categories by income quintiles are shown in table C.1.2.

Source: Own calculations, NIDS

Table C.1.2 shows debt participation by income quintile, for those who had debt. Unsurprisingly, we find that the top income quintile has the highest total debt participation (i.e. number

[63]While more households hold debt products, their median loan values have decreased, especially in Wave 1 - 3 (refer to earlier table 4.2.)

of debt products per household). In Wave 4, 80.9% of top income quintile households have some debt. Only 33.4% of households in the lowest income quintile had debt in Wave 4. In table 4.4 we report the average interest rates by debt category as reported by banks (we matched the periods up to the NIDS waves, and calculated the average prevailing interest rate over each of the waves). The highest interest rates are charged on consumer credit, such as micro loans, store card credit and loan shark loans[64]. By matching the debt types from our NIDS sample to the interest rates reported by banks, we see that the lowest income quintile mainly holds debt associated with high interest rate products such as micro loans, credit card and loan shark debt. At the same time, we find that the median [mean] number of debt products, an indebted household holds increases as income increases. Indebted households in the bottom income quintile have, a median [mean] of 1 [1.2] debt products, while the median indebted household in the top income quintile has 2 [1.8].

Table 4.4: Average annual interest rates (in %) by Product and Survey Wave

Loan	Bank	Vehicle	Leasing finance[1]	Home loans	Credit cards	Micro loans	Store card	Loan shark[2]
Wave 1	15.8	14.2	13.4	13.5	17.9	42.9	35.6	42.9+
Wave 2	11.0	11.1	9.6	8.2	15.8	30.0	22.7	30.1+
Wave 3	10.7	10.4	8.9	7.7	15.4	29.3	21.4	29.3+
Wave 4	13.0	10.8	10.0	8.8	16.1	29.3	22.9	29.3+

[1] Include hire purchase loans.
[2] Loan shark interest rates are assumed to be at least as high as micro loan interest.
Sources: Own calculations, SARB and Wood (2016)

We show that consumer and other credit is the most common type of debt in all four survey waves (also see table C.1.2). Typically higher interest rates are associated with unsecured lending, such as consumer credit. We also see a spike in this type of credit from Wave 3. The top 40% of households also hold a large share of consumer credit, but they are more likely to be able to afford higher interest rates. Mortgage loans on the other hand are mostly held by the top income quintile (the bottom income quintile had about 25%-33% of total debt products as mortgage loans in Wave 1 and Wave 2). Although we do not see a decrease in the amount of mortgage debt outstanding, we do see the participation rate in mortgage loans decreasing (41% of the top income group held mortgage debt in 2008 compared to 25.6% in Wave 4).

[64]The interest rates on loan shark loans are not reported and we therefore assume that interest on these loans are at least as high as those levied on micro loans by banks.

4.4 Deleveraging

4.4.1 Defining deleveraging

We follow Bhutta (2012) and define deleveraging as a decline in the absolute value of outstanding debt[65]. We measure deleveraging by the change in debt between Wave 1 and the subsequent waves. We compare all deleveraging to the initial period (Wave 1) to establish how households initial conditions impacted their ability to deleverage. We therefore take the difference in Wave 1 - 2, which constitutes a short-run effect, as well as Wave 1 - 3 and Wave 1 - 4 which gives a longer run view. Our focus will be on deleveraging over the full sample (Wave 1 - 4). We condition for those who had debt outstanding in both waves, which results in a loss of observations due to some households not reporting debt after Wave 1. If debt increased between Wave 1 and subsequent waves, households did not deleverage, if debt decreased, households deleveraged.

We show in table 4.5 that a large part of the decrease in the median total debt outstanding happened after Wave 2. The decrease in the median mortgage debt outstanding was the main driver of total deleveraging between Wave 1 and all subsequent waves. In Wave 1 - 4, both the median and the mean mortgage debt declined. Deleveraging in the mortgage debt category could also arise from households substituting home ownership with renting. In Wave 1 - 2 a decline in vehicle debt also supported total deleveraging.

4.4.2 The deleveraging sample

At the median, we show that deleveraging took place between all waves (table 4.5), compared to Wave 1. As we are interested in who deleveraged following the financial cycle peak, we focus on the characteristics of those who deleveraged between Wave 1 (the period directly following the peak) and Wave 4 (where deleveraging is still occurring). Table 4.6 gives an overview of the sample characteristics based on whether households deleveraged or not.

We condition the sample for households that were successfully interviewed in Wave 1, and in which at least one adult successfully completed the survey, but allow for households to drop in and out of the survey in subsequent waves[66]. We further condition on households that reported debt (numerical amounts including zero) in Wave 1 and in each, respective, subsequent wave, and therefore had a positive or negative change in their debt. We condition on the characteristics of households at the start of the survey (Wave 1).

[65] In McCarthy and McQuinn (2017a) a custom designed household survey commissioned by the Central Bank of Ireland included a direct question regarding actions taken to deal with debt concerns. The authors created a dummy variable from these actions taken to capture deleveraging.

[66] NIDS differentiates between household, adult and child questionnaires. In the context of NIDS, dropping out can mean that the household was not located, or did not answer the household questionnaire successfully.

Table 4.5: Change in debt outstanding over the NIDS waves

	obs	Wave 1 - Wave 2
Total debt	934	R -96 [R 40 959]
Mortgage debt	254	R -27 720 [R 51 629]
Vehicle debt	78	R -16 174 [R 51 629]
Consumer debt	309	R 8 [R 447]
Other debt	430	R 566 [R -8]
	obs	Wave 1 - Wave 3
Total debt	1089	R -301 [R 4 072]
Mortgage debt	227	R -40 132 [R 28 451]
Vehicle debt	68	R 1 796 [R 22 357]
Consumer debt	380	R 3 436 [R 10 384]
Other debt	568	R 465 [R 607]
	obs	Wave 1 - Wave 4
Total debt	1316	R -229 [R 77 209]
Mortgage debt	183	R -59 175 [R -69 917]
Vehicle debt	66	R 45 192 [R 69 871]
Consumer debt	457	R 5 610 [R 62 062]
Other debt	740	R 305 [R 4 555]

All values reported are in real terms. Medians are reported and means in [ ]. Results are weighted using the post-stratification weights. A breakdown of the changes in debt type, income quintiles and waves are shown in table C.2.1. Totals will not add up as respondents can have more than one debt type.

Source: Own calculations, NIDS

The average age of those that deleveraged and those who did not is similar (early to mid-40's). In Wave 3 and 4, compared to Wave 1, the typical deleveraging age is two years older. The majority of those who deleveraged are married (54%). Most of the sample has at least one person employed in the household, while the household representative has an average of 10-11 years schooling. The average share of children in the household is 1 in 4, as is the average share of grant recipients (any type of grant). The majority of the sample is male, especially for the deleveraging sample. The sample is representative of mostly African households, followed by White, Coloured and Asian/Indian households.

Median [mean] income, for Wave 1 - 4, is higher for the deleveraging group R 83 289 [R 155 671)] compared to the non-deleveraging group R 58 017 [R 109 850]. There is also a difference between the groups in terms of where they lie within the income quintiles. About 61% of those who deleveraged are in the top income quintile. Of those who did not deleverage, 10% are in the bottom quintile compared to 6% for those who did deleverage.

Our debt variables offer further insight. Total debt outstanding for the deleveraging group was much higher than the non-deleveraging group R 54 914 [R 196 491] compared to R 4 401 [R 59 254]. The total real house value of those who deleveraged is also higher than those who did not deleverage (these findings are similar to McCarthy and McQuinn (2017a)). Similar to the total, the medians [means] for all other debt types were higher for the deleveraging group than for the non-deleveraging group.

Table 4.6: Characteristics of deleveraged and non-deleveraged households

	Wave 1 to Wave 2		Wave 1 to Wave 3		Wave 1 to Wave 4	
Characteristics	% of Deleveraged	% Non-deleveraging	% of Deleveraged	% Non-deleveraging	% of Deleveraged	% Non-deleveraging
Average Age	43.6	43.8	45.1	42.2	44.3	41.9
Married	53.6	49.0	55.6	47.4	54.2	43.4
At least one person employed in the household	85.6	80.9	83.1	84.3	84.9	83.6
Average education of the household representative	11.0	10.4	10.6	10.9	10.3	10.3
Average share of children in the household	27.1	27.5	26.7	26.0	26.2	28.2
Average share of grant receivers in the household	17.8	28.9	24.5	26.0	28.2	29.8
Gender of household representative						
Female	38.8	45.9	41.5	46.0	43.9	49.0
Population group of household representative						
African	59.5	67.2	59.5	68.0	66.7	73.3
Coloured	13.2	13.4	13.6	9.8	11.1	9.7
Asian/Indian	5.6	2.7	5.2	4.8	3.4	3.3
White	21.7	16.7	21.7	17.5	18.7	13.8
Average annual real household income	R 132 032 [R 245 362]	R 74 429 [R 132 853]	R 99 475 [R 200 928]	R 77 083 [R 145 913]	R 83 289 [R 155 671]	R 58 017 [R 109 850]
Income quintiles						
Income quintile 1	3.5	5.7	2.5	5.8	5.5	10.1
Income quintile 2	3.6	6.5	7.5	6.6	6.9	9.7
Income quintile 3	6.1	10.8	8.7	7.8	10.3	11.9
Income quintile 4	16.4	20.9	14.5	25.4	16.8	22.2
Income quintile 5	70.4	56.1	66.8	54.4	60.7	46.2
Average annual real household expenditure	R 149 444 [R 213 906]	R 92 209 [R 150 436]	R 127 503 [R 203 531]	R 90 765 [R 163 148]	R 105 633 [R 169 573]	R 67 456 [R 135 043]
Total real household debt	R 139 258 [R 297 672]	R 5 907 [R 65 669]	R 106 506 [R 245 198]	R 4 164 [R 63 610]	R 54 914 [R 196 491]	R 4 401 [R 59 254]
Total real value of house	R 2 169 756 [R 3 485 887]	R 888 416 [R 2 238 094]	R 1 967 497 [R 4 206 288]	R 1 221 978 [R 3 375 065]	R 1 396 985 [R 3 649 594]	R 510 092 [R 2 248 132]
Total real mortgage debt	R 300 255 [R 418 302]	R 116 139 [R 167 904]	R 218 560 [R 358 597]	R 109 330 [R 186 082]	R 203 455 [R 340 378]	R 132 908 [R 194 998]
Total real vehicle debt	R 114 721 [R 136 484]	R 75 726 [R 95 182]	R 104 114 [R 131 355]	R 66 748 [R 86 658]	R 104 114 [R 133 562]	R 88 606 [R 86 139]
Total real consumer debt	R 14 140 [R 27 496]	R 4 841 [R 8 895]	R 11 247 [R 22 794]	R 4 401 [R 12 099]	R 11 568 [R 24 774]	R 5 994 [R 10 861]
Total real other debt	R 3 021 [R 6 016]	R 1 894 [R 4 119]	R 2 954 [R 6 542]	R 1 772 [R 3 218]	R 2 954 [R 5 723]	R 1 856 [R 4 152]

All continuous values reported are in real terms. Medians are reported and means in [ ]. Results are weighted using the post-stratification weights. All respondents had to have reported debt in Wave 1 and in all subsequent waves respectively (including zero).

Source: Own calculations, NIDS

4.5 Empirical strategy

To explore the determinants of household deleveraging after the financial cycle peak of May 2007, we utilise the panel data to determine if households decreased their debt over Wave 1 - 2, Wave 1 - 3 and Wave 1 - 4. Various modelling approaches can be used to explore the determinants of deleveraging. For our analysis we selected a binary model, which allows us to model the dichotomous variable for households who deleveraged (1) versus households who did not (0). We specify the following probit model where $Y_{i,j}$ is a latent variable that takes on the following:

$$Y_{i,j} = \begin{cases} 1, & \text{if } Debt_{i,j} - Debt_{i,1} < 0. \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

where j=2, 3 and 4.

$$Prob(Y_{i,j} = 1 | X_{i,1}, Z_{i,1}) = \Phi(\alpha + \beta X_{i,1} + \gamma Z_{i,1}) \tag{2}$$

where $Y_{i,j}$ is a dummy variable equal to one if a household's debt decreased over Wave 1 - 4, and zero otherwise. We follow McCarthy and McQuinn (2017a) and Dynan (2012a) by controlling for household characteristics ($X_{i,1}$) and other measures of income and debt ($Z_{i,1}$). We also run the same model for Wave 1 - 2, which constitutes short run changes, as well as Wave 1 - 3. We summarise the description of the variables in table 4.7. For the probit model, the errors are assumed to follow a normal distribution.

We condition our controls on Wave 1 characteristics. We postulate a base model where households, who have debt in Wave 1 and subsequent waves, are able to deleverage based on their financial resources, such as income, and household liquidity. We expect that households with higher financial resources should be able to deleverage more, relative to households with limited financial resources. We use income quintiles to account for possible non-linearity in our income variable. Given the high number of social grant recipients in South Africa (around 45% of households representatives in Wave 4), we test to see if this form of income assists households to deleverage.

Income inequality is taken into account as we see that income in South Africa is fairly skewed along racial lines (Statistics South Africa, 2017). We therefore include race as an explanatory variable as the race of the household representative may impact the access that households have to certain resources, such as income. Race is a dummy variable representing each of the four main racial groups in South Africa, with Africans being the omitted category.

We also include a dummy variable for employment. We allow for not only the household representative to be employed, but at least one person in the household. This caters for resource sharing that could take place in the household, and may impact a household's ability to deleverage. Given the potential link between education and income potential, we include years of education as a possible explanatory variable in our determinants of deleveraging.

We further control for traditional demographic variables, such as the share of children in the household, gender, age, age squared and the geographical area where households reside. It is further possible that married households have shared or dual income and debt, which could allow them to pool resources for deleveraging.

McCarthy and McQuinn (2017a) include a control for loan-to-value ratio to test if high levels of indebtedness, relative to assets, motivates deleveraging. We use the mortgage debt to house value ratio in Wave 1 as a proxy for the loan-to-value ratio. In South Africa, real house prices fell by 15% since the start of the financial downward phase in May 2007, resulting in lost housing stock values. To account for this loss in value, we include additional controls for highly leveraged households by including ratios for mortgage debt outstanding to income. We also include vehicle, consumer and other debt-to-income ratios. We further control for a proxy of household liquidity. We include a variable introduced by McCarthy and McQuinn (2011) whereby liquidity is measured by the mortgage repayment to income ratio[67].

Brown et al. (2005); Christelis et al. (2015); McCarthy and McQuinn (2017b) found that there is a positive relationship between optimistic financial expectations and the amount of debt taken on. Future income uncertainty relating to economic variables such as income and unemployment rates could therefore increase financial uncertainty and impact the deleveraging process. Households who have an adverse view of their future financial position may opt to save, instead of deleverage, towards what they see as an adequate liquidity buffer, to cover future expenditure in difficult times. Furthermore, if a household's expectation of being worse off is realised, they may not have the available means to deleverage. McCarthy and McQuinn (2017a) find that an expected deterioration in future financial position leads to a reduction in deleveraging. We test this hypothesis by including a dummy variable for households that saw their position in 2 years' time being worse off than now (for Wave 1 - 2), and worse off in 5 years from now (for Wave 1 - 3 and Wave 1 - 4). We then restrict our sample to only households who had mortgage debt[68].

[67]They argue that it was especially pertinent in the Irish economy at the time, as many Irish households were experiencing mortgage repayment difficulties. Due to a large part of South Africa's difficulty also resulting from the mortgage market, we included this measure in our estimation.

[68]The author would like to thank one of the reviewers for suggesting that we test this with the restricted sample.

Table 4.7: Description of variables

Variable	Description
Gender	Dummy variable where 1 is female, 0 is male. Male is our omitted category.
Married	1 is married and 0 is not married (omitted category: not married.)
Age	Age of the representative
Education	Years of schooling (education) derived from the education category variable
Household employed	1 if at least one person in the household is employed, 0 otherwise. (Omitted category: No one employed in the household)
Income	Income represents household income from the household questionnaire together with imputations for income brackets. Monthly income was multiplied by 12 to obtain annual income. We take the log of annual income.
Consumption	Annual real household consumption calculated as the sum of food and non-food expenditure on a monthly basis and then multiplied by 12.
Income quintile 1-5	The income variable is divided into 5 equal parts, each representing 20% of the income distribution. The top 20% therefore represents the top 20% of the income distribution. (Omitted category: bottom income quintile)
Share of Children (<18 years)	Children in the household younger than 18 as a share of total household size
Any government grant	A dummy variable where 1 is if the household has at least one (and any type of) grant and 0 if none. (Omitted category: none)
Geographical area	1 traditional, 2 urban and 3 farm. (Omitted category: farm areas)
Loan-to-value ratio	House debt outstanding to house value ratio
Mortgage debt-to-income ratio	Mortgage debt outstanding to income ratio
Vehicle debt-to-income ratio	Vehicle debt outstanding to income ratio
Consumer debt-to-income ratio	Consumer debt outstanding to income ratio
Other debt-to-income ratio	Other debt outstanding to income ratio
Mortgage debt-repayment-to-income ratio	Mortgage debt repayment (annual) to annual income ratio
Future expectations	This question asks participants to imagine a six step ladder where the poorest people in South Africa stand on the bottom (the first step) and the richest people in South Africa stand on the highest step (the sixth step). This question asks where households see themselves in 2 and 5 years' time compared to now. We take the difference in the steps as an indication of if they see themselves becoming worse off or better off. We code worse off as 1.

Source: NIDS

4.6 Results and discussion

4.6.1 Results

We applied the post-stratification weights in all models, unless otherwise specified. Although these weights are designed to make our results representative of the population, our reduction in sample size likely impacted the representativeness of the population. While this limits the breadth of the conclusions that can be drawn from this study, we still find statistically significant relationships with our limited data set. It could be beneficial to explore other modelling approaches, including non-parametric estimation. Table 4.8 shows the results (marginal effects) from our various models[69]. The detailed results for Wave 1 - 2 and Wave 1 - 3 are shown in table C.3.1 and table C.3.2.

We start with our base model (column 1), where households who lived in an urban area and have a higher income are more likely to deleverage. Although not significant, the sign for those with at least one person employed in the household is positive. We also find that households who are married have a higher probability of deleveraging, although this only becomes statistically significant from column 3. Similar to McCarthy and McQuinn (2017a), we do not find the loan to value ratio to be significant in our base equation for Wave 1 - 4[70]. McCarthy and McQuinn (2017a) suggest that it is the ability to repay rather than the amount of indebtedness that motivates the deleveraging decision.

In column 2 we control for income quintiles instead of income to account for possible non-linear income effects which can be masked at the total level. Our omitted category is the bottom 20% of households. We see that the probability that those in the upper income quintile deleverage is 16.5% higher than the bottom income group for Wave 1 - 4. We also show in column 6 and 7 that compared to the bottom income quintile, higher income quintiles were generally more likely to deleverage between Wave 1 - 2 (income quintiles 3, 4, and 5) and Wave 1 - 3 (income quintiles 2, 3, 4 and 5).

When we include additional controls for highly leveraged households, by including ratios for mortgage, vehicle, consumer and other debt outstanding to income ratios (column 3), we find that a high mortgage debt outstanding to income ratio increased the probability of deleveraging in all waves. In the short run, the probability increased by 3% and in the longer run by 10.7% and 5%, respectively[71]. Bar Wave 1 - 3, households with high vehicle debt-to-income ratios have a lower

[69] We also show the non-weighted results for our probit regressions in table C.6.1 to table C.6.6. We find the results are similar in all cases when un-weighted.

[70] For Wave 1 - 3, however, we do find that a high loan to value ratio resulted in a higher probability of deleveraging.

[71] Even when restricting our sample to mortgage holders, the coefficient remain about the same at 2%, 9% and 4%. The author would like to thank one of the reviewers for suggesting that we test this with the restricted sample.

probability of deleveraging by 6% and 7% respectively.

Households with high consumer debt-to-income ratios were also more likely to deleverage across all periods under review. For Wave 1 - 2, the marginal effect on deleveraging was 38.9%, tapering off to 13.1% in Wave 1 - 4. In the short run (Wave 1 - 2) households with a higher other debt-to-income ratio were 33.8% more likely to deleverage, but in the longer run (Wave 1 - 4) however, a higher other debt-to-income ratio actually resulted in households being less likely to deleverage by around 7%.

When we further control for liquidity (mortgage repayment to income ratio) we see that this variable is not significant (see column 4, 6 and 7) in any of our periods under consideration. When testing the relationship suggested by Brown et al. (2005); Christelis et al. (2015); McCarthy and McQuinn (2017b) between future income uncertainty and the impact on the deleveraging process, we find that households who expected their financial position to be worse in future were less likely to deleverage (although this was only significant for Wave 1 - 3). The full set of results is shown in column 5, and for Wave 1 - 2 (column 6) and Wave 1 - 3 (column 7). This is similar to findings by McCarthy and McQuinn (2017a).

Table 4.8: Probit estimation: dependent variable deleveraging - marginal effects

	Wave 1 - 4					Wave 1 - 2	Wave 1 - 3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
At least one adult employed in the household	0.061 (0.93)	0.066 (0.97)	0.084 (1.22)	0.085 (1.22)	0.084 (1.23)	0.012 (0.16)	-0.048 (-0.60)
Household who receive at least one welfare grant	0.023 (0.43)	0.021 (0.40)	0.038 (0.74)	0.038 (0.74)	0.038 (0.73)	-0.078 (-1.29)	-0.016 (-0.27)
Children Share	-0.109 (-1.04)	-0.115 (-1.08)	-0.140 (-1.35)	-0.140 (-1.35)	-0.139 (-1.33)	-0.012 (-0.10)	0.041 (0.37)
Female	-0.032 (-0.64)	-0.037 (-0.73)	-0.039 (-0.78)	-0.039 (-0.78)	-0.039 (-0.79)	-0.075 (-1.42)	-0.091* (-1.82)
Married	0.075 (1.49)	0.083 (1.61)	0.088* (1.72)	0.088* (1.71)	0.086* (1.68)	-0.040 (-0.74)	-0.054 (-1.05)
Coloured	-0.019 (-0.25)	-0.025 (-0.33)	-0.022 (-0.28)	-0.022 (-0.28)	-0.022 (-0.28)	-0.018 (-0.22)	0.022 (0.32)
Asian/Indian	0.016 (0.10)	0.049 (0.31)	0.007 (0.04)	0.007 (0.04)	0.007 (0.04)	0.137 (1.02)	-0.043 (-0.31)
White	-0.035 (-0.39)	-0.006 (-0.07)	0.005 (0.06)	0.006 (0.06)	0.006 (0.07)	-0.015 (-0.19)	0.011 (0.15)
Education	-0.008 (-1.07)	-0.005 (-0.71)	-0.006 (-0.82)	-0.006 (-0.82)	-0.006 (-0.83)	-0.000 (-0.00)	-0.016** (-2.05)
Age	-0.015 (-1.31)	-0.013 (-1.27)	-0.014 (-1.21)	-0.014 (-1.21)	-0.014 (-1.20)	0.021 (1.60)	0.015 (1.36)
Age squared	0.000 (1.58)	0.000 (1.54)	0.000 (1.46)	0.000 (1.46)	0.000 (1.46)	-0.000 (-1.64)	-0.000 (-0.93)
Live in a traditional area	0.114 (1.09)	0.117 (1.13)	0.110 (1.07)	0.110 (1.07)	0.111 (1.07)	0.209** (2.02)	-0.181* (-1.72)
Live in an urban area	0.197** (2.07)	0.199** (2.12)	0.167* (1.78)	0.167* (1.78)	0.167* (1.78)	0.165* (1.88)	-0.092 (-0.97)
Ln(Income)	0.067*** (2.74)						
Loan-to-value ratio	-0.001 (-0.42)	-0.001 (-0.44)	-0.005 (-1.63)	-0.005 (-1.63)	-0.005 (-1.64)	-0.003 (-0.86)	0.357* (1.72)
Income quintile 2		0.026 (0.26)	0.062 (0.62)	0.062 (0.62)	0.062 (0.62)	0.143 (1.16)	0.359*** (3.36)
Income quintile 3		0.090 (0.98)	0.116 (1.23)	0.116 (1.23)	0.116 (1.23)	0.243** (2.16)	0.380*** (4.36)
Income quintile 4		0.048 (0.57)	0.065 (0.72)	0.065 (0.72)	0.065 (0.72)	0.249** (2.26)	0.196*** (2.58)
Income quintile 5		0.165* (1.89)	0.191** (2.03)	0.191** (2.03)	0.191** (2.03)	0.390*** (3.58)	0.394*** (4.94)
Mortgage debt-to-income ratio			0.046*** (3.97)	0.046*** (3.88)	0.046*** (3.88)	0.036** (2.18)	0.107*** (4.26)
Vehicle debt-to-income ratio			-0.071*** (-4.06)	-0.071*** (-4.04)	-0.071*** (-4.04)	-0.059** (-2.44)	0.170* (1.87)
Consumer debt-to-income ratio			0.131*** (3.59)	0.131*** (3.56)	0.131*** (3.56)	0.389*** (3.28)	0.139** (2.00)
Other debt-to-income ratio			-0.076** (-1.98)	-0.076** (-1.98)	-0.075** (-1.97)	0.338** (2.26)	-0.077 (-1.50)
Mortgage repayment-to-income ratio				-0.000 (-0.12)	-0.000 (-0.12)	0.003 (0.63)	-0.014 (-1.29)
Future uncertainty (worse off)					-0.005 (-0.05)	-0.070 (-0.77)	-0.228*** (-2.60)
Observations	1 042	1 042	1 042	1 042	1 042	747	859

t statistics in parentheses.

* p<0.10 ** p<0.05 *** p<0.01

Due to the small size in the Asian/Indian sample these results should be read with caution. Results are marginal effects. Results are weighted using post-stratification weights. Exclusion categories are: male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future. Future uncertainty refers to in 5 years' time for Wave 1 - 3 and Wave 1 - 4, as compared to 2 years' time in Wave 1 - 2. Column 5, 6 and 7 are the same equations, compared over the different waves. For the full equation results for columns 6 and 7 , please see table C.3.1 and table C.3.2. All respondents had to have reported debt in Wave 1 and in all subsequent waves respectively.

Source: Own calculations, NIDS

As we have shown that most of the deleveraging happened at the higher income quintiles and for those who had high debt-to-income ratios, we further explore this by interacting each of the debt-to-income ratios for the four different debt types with the log of annual real income[72]. The full estimation results are shown in table 4.9. We see that the coefficient for each of the interactions between income and the different debt-to-income ratios are positive and significant. The effects of the interactions are taken at a point in each of the debt-to-income distributions, i.e. at the 75th, 90th, 95th and 99th percentile of the distribution[73]. The aim of taking the effect at selected points over the debt-to-income distribution is to determine the effect of a one unit change in the log of income on the probability of deleveraging, while holding all other variables at the mean, and each debt category constant at the above percentiles, respectively.

We plot the results in figure 4.5[74] for Wave 1 - 4. We show that as the log of annual real income increases by one unit the probability of deleveraging, where mortgage debt-to-income is held constant at the 75th percentile, increases by 7.4%, while at the 90th percentile the probability increases by 10.7%, 95th percentile by 11.0% and at the 99th percentile, 0.4%. The sharp drop off in the probability of deleveraging for those with high mortgage, vehicle and consumer debt to income ratios at the 99th percentile is likely due to these households, despite having higher debt to income ratio's, not needing to deleverage as their income increase, as they likely have the means to manage their debt levels. The trend is however different for the category other debt to income. Perhaps it is because other debt to income is higher cost debt, and it is more in the interest of all households, including the top 99th percentile, to deleverage this debt as their income increases.

[72]The results for Wave 1 - 2 and Wave 1 - 3 are reported in table C.4.1 and table C.4.2.
[73]Except for the vehicle debt-to-income ratio where we exclude the 75th percentile as the value is zero.
[74]The results for Wave 1 - 2 and Wave 1 - 3 are reported in figure C.4.1 and figure C.4.2.

Table 4.9: Probit model for deleveraging when controlling for the interaction between income and various debt-to-income ratios for Wave 1 - 4

	Deleveraging over Wave 1 - 4			
Deleveraging	(1)	(2)	(3)	(4)
At least one adult employed in the household	0.259 (1.35)	0.165 (0.96)	0.137 (0.76)	0.152 (0.88)
Household who receive at least one welfare grant	0.154 (1.10)	0.034 (0.24)	0.066 (0.47)	0.060 (0.43)
Children Share	-0.485* (-1.72)	-0.310 (-1.07)	-0.196 (-0.69)	-0.237 (-0.85)
Female	-0.091 (-0.67)	-0.070 (-0.51)	-0.076 (-0.57)	-0.099 (-0.76)
Married	0.169 (1.21)	0.127 (0.93)	0.173 (1.28)	0.172 (1.27)
Coloured	-0.072 (-0.33)	0.018 (0.09)	-0.020 (-0.09)	-0.049 (-0.25)
Asian/Indian	-0.351 (-0.82)	0.169 (0.39)	0.241 (0.55)	0.020 (0.04)
White	-0.038 (-0.15)	0.013 (0.05)	-0.036 (-0.16)	-0.093 (-0.39)
Education	-0.030 (-1.55)	-0.027 (-1.39)	-0.017 (-0.93)	-0.018 (-0.98)
Age	-0.043 (-1.35)	-0.040 (-1.30)	-0.043 (-1.35)	-0.040 (-1.30)
Age squared	0.001 (1.60)	0.001 (1.56)	0.001 (1.63)	0.001 (1.59)
Live in a traditional area	0.265 (0.88)	0.379 (1.26)	0.384 (1.33)	0.322 (1.02)
Live in an urban area	0.403 (1.44)	0.586** (2.11)	0.576** (2.19)	0.558* (1.89)
Loan-to-value ratio	-0.054 (-0.88)	-0.002 (-0.25)	-0.007 (-0.84)	-0.003 (-0.37)
Mortgage repayment-to-income ratio	-0.001 (-0.32)	0.014 (0.42)	-0.002 (-1.28)	0.001 (0.21)
Future uncertainty (worse off)	-0.081 (-0.36)	-0.114 (-0.53)	0.024 (0.11)	-0.073 (-0.34)
Ln(Income)	0.164** (2.10)	0.105 (1.41)	0.145* (1.84)	0.197*** (2.71)
Mortgage debt-to-income ratio	-0.398*** (-2.69)			
Ln(Income) # Mortgage debt-to-income ratio	0.060*** (3.39)			
Vehicle debt-to-income ratio		-2.616*** (-3.07)		
Ln(Income) # Vehicle debt-to-income ratio		0.289*** (3.36)		
Consumer debt-to-income ratio			-5.548*** (-3.43)	
Ln(Income) # Consumer debt-to-income ratio			0.676*** (3.76)	
Other debt-to-income ratio				-1.355** (-2.01)
Ln(Income) # Other debt-to-income ratio				0.205* (1.95)
Constant	-1.423 (-1.41)	-0.934 (-0.96)	-1.554 (-1.56)	-1.988** (-2.00)
Observations	1 042	1 042	1 042	1 042

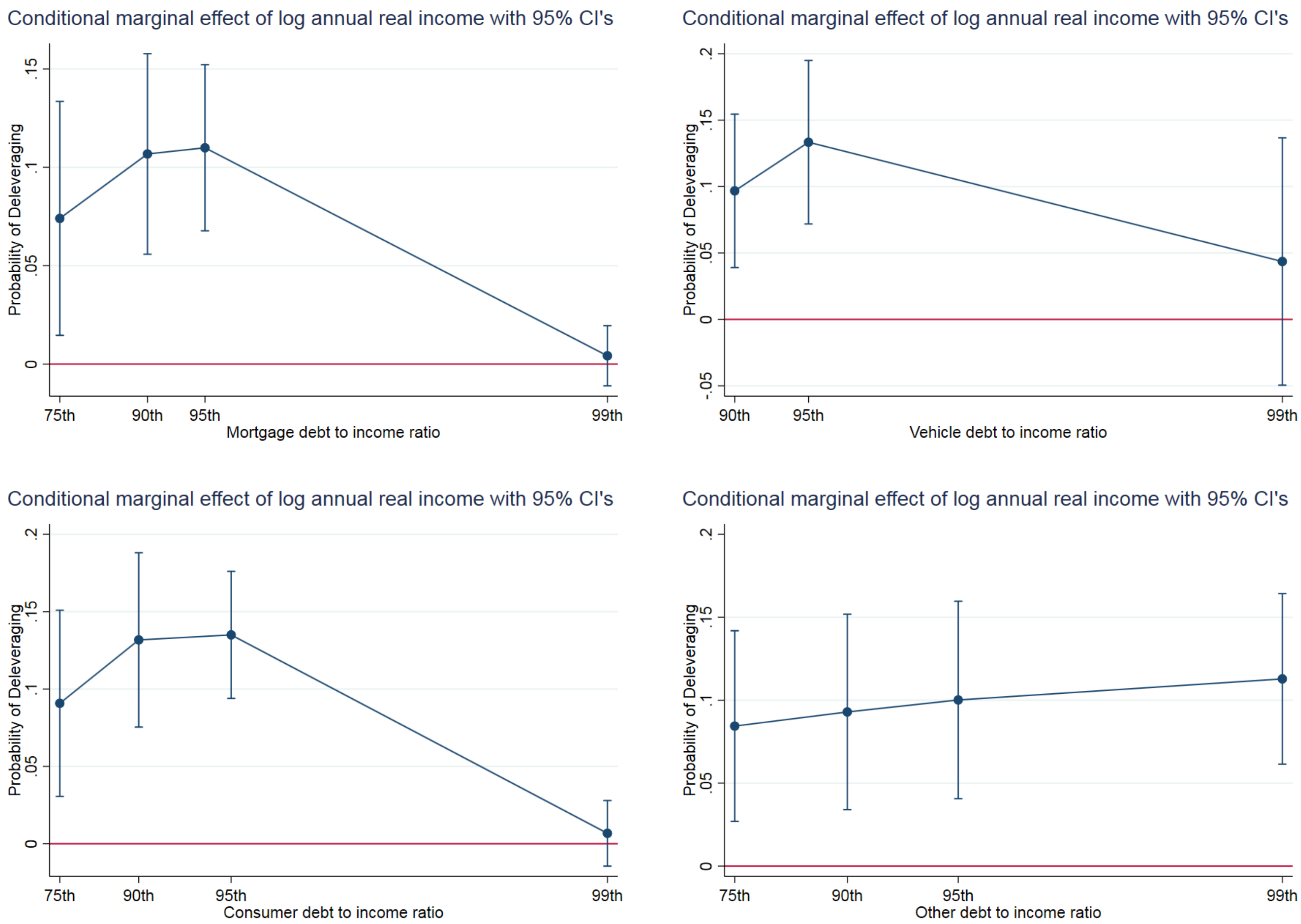
t statistics in parentheses

* p<0.10 ** p<0.05 *** p<0.01

Due to the small size in the Asian/Indian sample these results should be read with caution. Results are not in marginal effects. Results are weighted using post-stratification weights. Exclusion categories are: male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future. Future uncertainty refers to in 5 years' time for Wave 1 - 4. All respondents had to have reported debt in Wave 1 and in all subsequent waves respectively. For the Wave 1 - 2 and Wave 1 - 3 results, please see table C.4.1 and table C.4.2.

Source: Own calculations, NIDS

Figure 4.5: Effect of a change in log income on deleveraging at selected points in the debt-to-income distribution for Wave 1 - 4



CI - Confidence interval. Results are shown at the 75th, 90th, 95th and 99th percentile of debt-to-income and income (while keeping all other variables at the mean), except for vehicle debt-to-income, that is zero at the 75th percentile and therefore excluded. See figure C.4.1 and figure C.4.2. Results are weighted using post-stratification weights. All respondents had to have reported debt in both Wave 1 and Wave 4. Non-weighted results are similar.

Source: Own calculations, NIDS

When we restrict our sample to those who have mortgage debt (see table 4.10) we find that the sign for those with at least one person employed in the household is positive over all periods, and positive and significant between Wave 1 - 4. We also find that female and married household representatives have a lower probability of deleveraging, although this is only statistically significant between Wave 1 - 3. Between Wave 1 - 4, older households, and households with a higher education are significantly less likely to deleverage. We find, similar to our full sample, that a high loan to value ratio results in a higher probability of deleveraging between Wave 1 - 3.

When we control for income quintiles we see a positive relationship between the highest income quintile and deleveraging. Although only significant between Wave 1 - 3, it does suggest that compared to the lowest income quintile, higher income quintiles are generally more likely to deleverage between Wave 1 - 2 (income quintiles 3, 4, and 5), Wave 1 - 3 (income quintiles 2, 3, 4 and 5), and Wave 1 - 4 (income quintiles 3 and 5).

When we include ratios for mortgage, vehicle, consumer and other debt-to-income ratios, we find that a high mortgage debt-to-income ratio increases the probability of deleveraging in all waves, albeit only significantly so in Wave 1 - 3 and Wave 1 - 4. In the short run, the probability increases by 2% and in the longer run by 9% and 4%, respectively[75]. Similar to our full sample, mortgage owners, except for Wave 1 - 3, with a high vehicle debt-to-income ratio have a lower probability of deleveraging by 3% and 6% respectively.

Households with high consumer debt-to-income ratios are more likely to deleverage between Wave 1 - 2 and Wave 1 - 3, while households with a higher other debt-to-income ratio were more likely to deleverage in all three periods, by 31% (although not significant), 144% between Wave 1 - 3 (significant) and 60% (not significant) between Wave 1 - 4. Therefore, households with a mortgage, and a high level of high-cost debt-to-income ratios, are more likely to deleverage (bar consumer-debt-to-income between Wave 1 - 4).

When we further control for liquidity (mortgage repayment to income ratio), we see that between Wave 1 - 3, higher repayment has a significant and negative (although the coefficient is small) impact on deleveraging, for the other periods, the coefficients are zero and not statistically significant. We further find that households who expect their financial position to be worse off in future are 31% less likely to deleverage (although this was only significant for Wave 1 - 3).

[75] These coefficients are similar to our full sample, which had probabilities of 3%, 10.7% and 5%.

Table 4.10: Probit results for those with mortgage debt

Households holding mortgage debt	Wave 1 - Wave 2	Wave 1 - Wave 3	Wave 1 - Wave 4
At least one adult employed in the household	0.011 (0.09)	0.156 (1.15)	0.266** (2.31)
Household who receive at least one welfare grant	-0.152 (-1.40)	0.001 (0.01)	0.150 (1.39)
Children Share	-0.024 (-0.14)	0.266* (1.76)	0.103 (0.62)
Female	-0.045 (-0.55)	-0.140** (-2.03)	-0.047 (-0.62)
Married	-0.068 (-0.85)	-0.164** (-2.28)	-0.008 (-0.10)
Coloured	-0.038 (-0.34)	0.169** (2.06)	-0.122 (-1.15)
Asian/Indian	0.154 (1.40)	0.070 (0.49)	0.166 (1.39)
White	-0.083 (-0.87)	0.152* (1.88)	0.060 (0.66)
Education	0.003 (0.19)	-0.006 (-0.36)	-0.031** (-2.14)
Age	0.018 (0.73)	-0.022 (-1.13)	-0.063*** (-2.63)
Age squared	-0.000 (-0.59)	0.000 (1.42)	0.001*** (2.83)
Live in a traditional area	-0.227 (-0.92)	-0.255 (-0.90)	0.166 (0.70)
Live in an urban area	-0.205** (-1.97)	-0.137 (-0.86)	-0.032 (-0.17)
Loan-to-value ratio	-0.004 (-1.24)	0.304** (1.97)	-0.016 (-0.65)
Income quintile 2	0 (.)	0.627*** (2.73)	-0.0183 (-0.06)
Income quintile 3	0.390* (1.80)	0.808*** (7.89)	0.112 (0.41)
Income quintile 4	0.115 (0.49)	0.373*** (2.62)	-0.002 (-0.01)
Income quintile 5	0.160 (0.70)	0.543*** (4.87)	0.133 (0.59)
Mortgage debt-to-income ratio	0.018 (1.11)	0.090*** (3.78)	0.038** (2.49)
Vehicle debt-to-income ratio	-0.034 (-1.46)	0.022 (0.46)	-0.060*** (-2.62)
Consumer debt-to-income ratio	0.346 (1.60)	0.137 (0.75)	-0.072 (-0.58)
Other debt-to-income ratio	0.308 (0.53)	1.442** (2.10)	0.590 (1.28)
Mortgage repayment-to-income ratio	0.004 (0.98)	-0.019** (-1.96)	0.001 (0.51)
Future uncertainty (worse off)	-0.028 (-0.25)	-0.306*** (-3.21)	0.025 (0.20)
Observations	264	277	279

t statistics in parentheses.

* p<0.10 ** p<0.05 *** p<0.01

Due to the small size in the Asian/Indian sample these results should be read with caution. Results are marginal effects. Results are weighted using post-stratification weights. Exclusion categories are: male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future. Future uncertainty refers to in 5 years' time for Wave 1 - 3 and Wave 1 - 4, as compared to 2 years' time in Wave 1 - 2. All respondents had to have reported that they had mortgage debt in Wave 1.

Source: Own calculations, NIDS

4.6.2 Discussion

Results from our base model (column 1), where households who live in an urban area and have a higher income are more likely to deleverage, were expected, because households in urban areas are likely to earn higher income and have more access to financial products and information. Although our coefficient for households who have at least one person employed is not significant, it is positive, which one would expect; households who have employment, likely receive an income and thus have the means to deleverage. It could be that employment is not significant, whereas income is, suggesting that having a job in itself is not enough, but rather having sufficient financial resources (i.e. higher income) is significant for deleveraging. However, when restricting our sample to mortgage holders, we find that households who have at least one person employed are more likely to deleverage in all waves, significantly so in Wave 1 - 4. In column 3, we show that households who are married have a higher probability of deleveraging. It could be that married households may have a dual income, which could assist in deleveraging.

Although only significant in our restricted sample for mortgage holders, higher education and age have negative coefficients in Wave 1 - 4, suggesting that a higher level of education or being older does not assist in deleveraging.

In both the base model and our restricted mortgage holder sample, the loan to value ratio is not significant for Wave 1 - 4 and is similar to the findings of McCarthy and McQuinn (2017a); however for Wave 1 - 3, we do find that a high loan to value ratio resulted in a higher probability of deleveraging. This is likely due to the initial decrease in interest rates which supported household deleveraging until the end of 2014, when rates increased again, making it difficult for households to deleverage.

When we control for income quintiles instead of income we find that, compared to the bottom income quintile, higher income quintiles are generally more likely to deleverage between Wave 1 - 2 and Wave 1 - 3, while the top income quintile is more likely to deleverage in Wave 1 - 4. This supports our base hypothesis that higher income households have more financial resources to deleverage, compared to lower income households. This was also true for our mortgage holder model, although only significant for all income quintiles in Wave 1 - 3, compared to the lowest income quintile.

Households with higher leverage in mortgage and consumer debt were more likely to deleverage[76]. When looking only at the mortgage debt sample, households with high mortgage debt-to-income ratios were significantly more likely to deleverage between Wave 1 - 3 and Wave 1 - 4. This could be because households with high leverage ratios may need to deleverage to restore

[76] This is also true for Wave 1 - 2 and Wave 1 - 3.

their credit access or gain access to new credit (Bunn and Rostom, 2014).

Households with high mortgage debt deleverage more either because mortgage debt is highly sensitive to interest rate changes or that debt decreases as a result of repossession[77] or downscaling to more affordable housing. The sensitivity to changes in interest rates can however change over time as lenders become more or less conservative (see Dynan and Edelberg, 2013). McCarthy and McQuinn (2017a) suggest that households may deleverage in order to keep their leverage close to some target level. South Africa implemented the NCA in 2007 (see De Wet et al. (2015) as well as Paile (2013) for a full review of the impact of the NCA on debt), which introduced caps on interest rates charged on consumer debt and tried to address reckless lending, and may have reduced the uptake of excessive levels of credit by households[78]. Having higher vehicle[79] and other debt-to-income ratios resulted in a lower probability to deleverage. Although in Wave 1 - 3, households with high vehicle debt-to-income ratios were more likely to deleverage, this could again be driven by repossessions during the period and lower interest rates[80]. We also see less vehicle ownership in the bottom income quintiles, where households may make more use of public transport due to the high cost of vehicle ownership.

Households with high consumer debt-to-income ratios were also more likely to deleverage across all periods under review. This is likely linked to households initially repaying this high cost debt as a priority, but, as access to new bank loans became more difficult, households had to rely on this type of debt for everyday items and the impact on deleveraging became smaller. Other credit is also a form of distress borrowing. We see that similar to the initial stages, households with high other debt-to-income ratios were more likely to deleverage, however as households became worse off, they had to rely on other types of debt to manage their living expenses. We find similar findings in our mortgage debt sample.

When we further control for liquidity (mortgage repayment to income ratio) we see that this variable is not significant (see column 4). This again reinforces the notion that it is the ability to pay (income) rather than the amount outstanding that drives deleveraging.

Although this was only significant for the Wave 1 - 3 period (for both the base model and the restricted sample), we find that households who viewed their financial position as worsening in future were less likely to deleverage. McCarthy and McQuinn (2017a) similarly showed that an expected deterioration in future financial position leads to a reduction in deleveraging. This could

[77] See section 4.3 where we show that this likely had more of an impact between Wave 1 and Wave 2.

[78] The NCA also allowed lenders to have better access to information regarding customers' credit scores with the aim to avoid consumers becoming highly indebted.

[79] This could possibly be due to the continuous vehicle replacement cycle and vehicle price increases.

[80] Although in South Africa a portion of vehicle finance has fixed interest rates, for those with variable interest rates, interest rates fell by 700 basis points over this period.

be driven by two factors; firstly, if households see themselves worse off in future, they may look to save[81] towards what they see as an adequate liquidity buffer, to cover expenditure in difficult times. Secondly, if a household's expectation of being worse off is realised, they may not have the available means to deleverage.

We show two things by taking the effect at selected points over the debt-to-income distribution to determine the effect of a one unit change in the log of income on the probability of deleveraging, while holding all other variables at the mean, and each debt category constant at 75th, 90th, 95th and 99th percentile of the distribution[82]. We firstly show that households with higher income and higher debt-to-income ratios are more likely to deleverage, and secondly, that, although higher debt-to-income ratios and those with higher incomes are more likely to deleverage, at the 99th percentile, this is not the case.

4.6.3 Impact of deleveraging on household consumption

Having high debt in itself does not necessarily have an impact on consumption (Dynan, 2012a). Pistaferri (2016) suggests that households face a number of different shocks at the same time when an asset bubble burst. The first of these is a wealth loss. For example, when house prices fell sharply, households who were over exposed in terms of debt in the mortgage market, faced large wealth losses in the wake of the financial crisis. As a response to this wealth loss, and possible employment and income losses, households reduced consumption. Second, higher leverage is also associated with reduced access to additional credit, such that households are less likely to be able to refinance their mortgages, as shown by Dynan and Edelberg (2013). Their findings also show that households were more likely to cut back consumption, especially from 2009. Third, is what Pistaferri (2016) refers to as a "leverage" effect: when debt ratios rise fast and to unmanageable levels, households address their balance sheet positions by paying off their debt at a faster rate, while cutting back consumption.

For these reasons, we further aim to determine the impact of household deleveraging on consumption, which also gives us an idea of the possible impact on the speed of an economic recovery. Dynan (2012a) shows that high leverage has a noticeable (but small) negative impact on consumption, with wide confidence bands. Similarly, McCarthy and McQuinn (2017a) find a negligible small negative, but statistically significant, impact of deleveraging on consumption.

[81]Although households with mortgage debt, and an access facility, could use this as a means to save, households who have an adverse view of their future financial position may opt to rather save in traditional savings/investment accounts, given that access facilities can easily be withdrawn during difficult times by mortgage providers.

[82]Except for the vehicle debt-to-income ratio where we exclude the 75th percentile as the value is zero.

We use the same controls that we used for our baseline model to determine the impact of deleveraging on consumption. However, instead of a probit model, we estimate a linear regression model where:

$$\Delta C_{i,j} = \alpha + \beta X_{i,1} + \lambda Y_{i,j} + \rho \Delta I_{i,j} + \gamma Z_{i,1} + \varepsilon_{i,j} \tag{3}$$

where $Y_{i,j}$ was defined in equation (1), I represents income, and Z debt characteristics

$$\Delta C_{i,j} = C_{i,j} - C_{i,1}$$

and similarly for $\Delta I_{i,j}$.

$$j = \{2, 3, 4\}$$

Our dependent variable is the change in consumption between Wave 1 and all subsequent waves ($\Delta C_{i,j}$). We further control for the same variables as in our equation 2 (household characteristics ($X_{i,1}$) and debt controls ($Z_{i,1}$)). We split out income $I_{i,j}$ and control for the change in income in Wave 1 - 2, Wave 1 - 3 and Wave 1 - 4; and for deleveraging between the same set of waves $\rho Y_{i,j}$. We condition all other variables on Wave 1 (our initial conditions). We focus our discussion on Wave 1 - 4 (see table 4.11). Different from McCarthy and McQuinn (2017a), education has a negative and significant relationship with consumption, possibly because highly educated households have a more prudent approach to finances due to better financial literacy, or because these households have more access to debt, and are therefore more leveraged, resulting in them having to cut back consumption relatively more. Furthermore, they may have smoothed consumption by taking on higher debt earlier in their lives, with the view of a higher future income (Dynan, 2012a).

As expected, having more children in the household is positively related to consumption, as is being employed, although they are not statistically significant. McCarthy and McQuinn (2017a) found that larger households increased their consumption significantly. As expected our results also show that a change in income had a significant and positive impact on consumption. Therefore, as household income increases it will have a positive impact on consumption and indirectly economic growth through the consumption channel, but only in the longer run (Wave 1 - 4). Turning to leverage measures, higher mortgage and consumer debt-to-income had a positive and significant correlation with consumption, while vehicle and other debt had a negative association with consumption. It could be that both mortgage and consumer credit allows for continued access to credit, which is not possible through a fixed period loan such as a vehicle loan. Again in the immediate period (Wave 1 - 2) deleveraging had no significant impact on consumption and the sign was, in fact, positive. In the longer run, however, for both Wave 1 - 3 and Wave 1 - 4, the sign of the coefficient is negative, and in Wave 1 - 4 it is statistically significant. Finally, we show that deleveraging has a negative and significant impact on consumption over the full sample period. Similar to Dynan (2012a) we have a wide confidence interval, and similar to both Dynan (2012a) and McCarthy and McQuinn (2017a), when adjusted for the period (2008-2015/Wave 1 - 4), i.e. 8 years, we find that households who deleveraged saw a drop in average consumption over a year of R 3 415 (R 27 320/8 years). This is even less than reported by McCarthy and McQuinn (2017a), who found that consumption decreased by € 78.76 per month, or € 945 over one year (€ 78.76*12). These results roughly translate to R 10 330 between May 2012 and February 2013 (assuming an average €/R exchange rate of 10.93 over the period), which, according to McCarthy and McQuinn (2017a) is economically insignificant, even though it is statistically significant. Our findings offer additional evidence that deleveraging has a very small negative direct impact on household consumption.

Table 4.11: OLS regression on the impact of deleveraging on consumption between Wave 1 and subsequent waves

	Δ consumption Wave 1 - Wave 2	Δ consumption Wave 1 - Wave 3	Δ consumption Wave 1 - Wave 4
Households who deleveraged	4 246 (0.20)	-29 849 (-1.50)	-27 320* (-1.89)
At least one adult employed in the household	45 615* (1.67)	32 210 (1.11)	9 434 (0.60)
Household who receive at least one welfare grant	39 507** (2.10)	2 573 (0.16)	-8 443 (-0.69)
Children Share	14 909 (0.36)	30 616 (0.50)	14 423 (0.33)
Female	-8 915 (-0.26)	-13 167 (-0.59)	17 832 (1.02)
Married	16 372 (0.51)	-22 486 (-1.18)	9 358 (0.60)
Coloured	-8 210 (-0.49)	-29 490 (-1.29)	17 633 (0.83)
Asian/Indian	-88 540 (-1.17)	-53 405 (-0.58)	-122 458 (-1.47)
White	83 160 (1.30)	-89 100*** (-3.33)	-8 541 (-0.25)
Education	-3 892 (-1.18)	-7 577** (-1.96)	-6 654** (-2.10)
Age	-277 (-0.06)	-2 661 (-0.49)	2 767 (0.60)
Age squared	-17.98 (-0.38)	13 (0.19)	-60 (-1.03)
Live in a traditional area	-10 828 (-0.26)	-33 626 (-0.92)	3 564(0.18)
Live in an urban area	-24 421 (-0.63)	-9 722 (-0.31)	12 184 (0.68)
Δ income	0.055 (1.49)	-0.001 (-0.15)	0.206** (2.40)
Loan-to-value ratio	373 (0.76)	-823 (-0.52)	740** (2.40)
Mortgage debt-to-income ratio	5 851 (1.31)	3 466 (1.43)	3 660* (1.85)
Vehicle debt-to-income ratio	-8 122 (-1.24)	1 173 (0.16)	-5 674* (-1.95)
Consumer debt-to-income ratio	7 055 (0.25)	-5 332 (-0.33)	9 366 (1.56)
Other debt-to-income ratio	-2 428 (-0.13)	-3 790 (-0.29)	-6 834 (-1.20)
Mortgage repayment-to-income ratio	-200 (-0.72)	7 303 (1.19)	-118 (-0.87)
Future uncertainty (worse off)	17 519 (0.72)	11 549 (0.28)	5 485 (0.22)
Constant	32 831 (0.28)	170 311 (1.45)	41 583 (0.55)
Observations	702	820	1002

t statistics in parentheses

* p<0.10 ** p<0.05 *** p<0.01

Future uncertainty refers to in 5 years' time for Wave 1 - 3 and Wave 1 - 4, as compared to 2 years' time in Wave 1 - 2.

Due to the small size in the Asian/Indian sample these results should be read with caution.

t statistics in parentheses.

* p<0.10 ** p<0.05 *** p<0.01

Due to the small size in the Asian/Indian sample these results should be read with caution. Results are weighted using post-stratification weights. Exclusion categories are: non-deleveragers, male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future. Future uncertainty refers to in 5 years' time for Wave 1 - 3 and Wave 1 - 4, as compared to 2 years' time in Wave 1 - 2. Non-weighted results are in table C.6.7.

Source: Own calculations, NIDS

4.6.4 Possible selection bias

Although our results are in line with international literature, because our sample only contains households who had debt in Wave 1, compared to subsequent waves, our results may suffer from selection bias. This may be further exacerbated by the creation of matched households. In other words those households who do not report debt in the following waves, compared to Wave 1, may not be random. We test this by estimating the probability that households reported debt in Wave 1 and not in the subsequent waves (separately for Wave 1 - 2; Wave 1 - 3 and Wave 1 - 4). These results are reported in table C.5.1. NIDS reports that 78% of individuals who were interviewed in Wave 1 were successfully interviewed in Wave 4. NIDS shows an attrition rate of 50% for the White population group, which is the highest among all race groups, followed by 42.9% for Asian/Indian in Wave 4, the second highest (Chinhema et al., 2016). Therefore these coefficients should be interpreted with some caution.

By creating a matched household debt deleveraging panel, we lose many households who reported debt in Wave 1 and not in the subsequent waves[83]. Our results show that those who do not report debt in subsequent waves (compared to Wave 1) are not completely random. Households with at least one member employed have a higher probability to not report debt again in all the following waves. As shown by NIDS, we also have a significant probability that White households do not report debt after Wave 1. In Wave 1 - 4, households with a high loan to value ratio were also more likely not to report debt in Wave 4. Over the same period, households with high mortgage debt-to-income and high consumer debt-to-income ratios were more likely to not report debt in Wave 4, although the marginal effect is relatively small. We find that compared to the lowest income quintile, households in higher income quintiles were more likely to not report debt again in Wave 4, except for income quintile 5 where it is not significant[84]. Apart from the coefficient for the White population group, the marginal impacts are relatively small for the other variables, suggesting that sample selection might not have a large impact on our results; however, it should be noted.

Lastly, Dynan (2012a) illustrates that the distribution of wealth in the US is skewed, with a long right tail for which they adjust by applying a transformation that down weights the impact of outliers in their regression analysis. We find that we do have longer tails in our income and debt variables, but they are not specifically skewed to one side. However, other estimation, or as in Dynan (2012a), other data transformation methods can be explored in future work.

[83] We lose 630 observation in Wave 1 - 2; 1 361 in Wave 1 - 3 and 1 634 in Wave 1 - 4.

[84] One should note here that if we do not control for population group, this income quintile is significantly more likely to not report debt in Wave 4, suggesting that there is a high correlation between income quintile 5 and White households, which is not surprising, given the inequality along racial lines in South Africa.

4.7 Conclusion

After the global financial crisis, many policy makers were searching for clarity regarding the timing and impact household deleveraging might have on the economy, especially with regards to the uptake of new credit and an anticipated increase in consumption and economic growth, as this has a direct bearing on inflation and, hence, monetary policy. The 2007/08 global financial crisis, and the pre-crisis peak of the financial cycle in South African in May 2007, resulted in over-leveraged positions for a large part of the population, especially in the mortgage market.

Our sample for deleveraging versus non-deleveraging households show that households who deleveraged tended to have higher income, real debt and house values than our non-deleveraging sample. Thus, our deleveraging sample was more leveraged to begin with, compared to the non-deleveraging sample.

By analysing household debt positions from a micro economic perspective, we were able to confirm that deleveraging after the recent financial cycle peak was mostly driven by married households in urban areas and those who were in the highest income quintile. We also identified that even if deleveraging seemed to have happened at an aggregate level, it is mostly the higher income households with mortgage and consumer credit that deleveraged. However, at the absolute top of the distribution, little effect is uncovered.

We further show that employment is not a major driver of deleveraging. Therefore, even as the economy starts to recover, and employment opportunities are created, we may not observe significant deleveraging, since having a job, in itself, does not provide adequate financial resources for households to deleverage in South Africa.

Due to the nature of our data, we tested for sample selection bias by estimating the probability of not reporting debt in respective, subsequent, waves. We did find that in some of our variables there was a significant probability that households did not report debt in follow-up waves, however, apart from the marginal effect for White households, the rest of the results were relatively small. We should, however, acknowledge that there may be some bias when interpreting our results. It is possible to, in future research, explore ways in which we could account for this. Furthermore, the results can only be seen as associations, as it is possible that there are unobservable factors that are correlated with the control variables, and therefore we cannot call these results causal.

An important policy conclusion to draw from the results is that it is mostly those with the means to deleverage that do so, and mainly in the form of mortgage and consumer credit categories. There is no indication that those in the lower income quintiles are able to deleverage.

Disconcertingly, this means that households have to find other means to assist deleveraging, which likely increases policy uncertainty and postpones the economic recovery and the uptake of new credit.

We tested this hypothesis by evaluating the impact that deleveraging had on consumption and found that, similar to findings in the literature, deleveraging had a negative and significant impact on consumption. However, also in line with international findings, our results have wide confidence intervals, and the coefficient of the consumption response was inconsequential at R 3 415 on average per year over the period 2008-2015. Future research should aim to establish how important financial decisions regarding savings and other wealth effects could further impact the deleveraging decision and consumption responses, as well as other deleveraging channels through which the financial cycle downward phase impacts consumption and the economic recovery.

CHAPTER 5

CONCLUSION

Despite many countries having flexible monetary policy and exchange rate regimes, Jordà et al. (2015), they were still not able to avoid a deep global economic and financial crisis. As the world became accustomed to easier access to credit and significant growth in house (and other asset) prices, even highly indebted households' balance sheets did not, at the time, seem to be over-extended (Dynan, 2012a). However, the 2007/08 global financial crisis reminded us that conditions can and do change. The 2007/08 crisis was different from typical post war recessions as financial booms originated in an environment of low and stable inflation and became what Koo (2013) refers to as a 'balance sheet' recession. Before such a recession, the preceding boom is much longer because inflation is contained in the eyes of policy makers. This allows asset prices to continue to inflate, resulting in a much larger debt overhang in the aftermath.

The 2007/08 global financial crisis raised important questions about the behaviour of financial cycles and the length of time it takes households to deleverage from the peak, especially when the cycle is largely driven by an asset bubble. Monetary policy makers are particularly interested in when a new credit cycle will start and how long it will take for imbalances to work through the economy. The economic consequence of a burst asset bubble and subsequent financial downswing differ significantly from 'normal' recessions. For one, they result in very deep and severe recessions, as well as prolonged and weak recoveries (see Reinhart and Rogoff, 2009).

Although the nature of the financial cycle has been studied by Farrell and Kemp (2018) using credit extension, house prices and equity prices[85], knowledge of the behaviour of household debt and financial variables over the South African financial cycle is limited. There is also no clear empirical evidence as to whether or not South Africa has reached the lower turning point in this financial cycle. It was therefore necessary to date the financial cycle turning points in South Africa to enable us to determine to what extent South African households have deleveraged over this cycle, from a macroeconomic perspective, and compare this cycle to previous cycles to determine if we are on track with the recovery.

We used a similiar approach to the SARB's composite business cycle indicator methodology for constructing a composite financial cycle indicator for South Africa. We included the real house price index, the real JSE index and total real credit extended. In dating the reference financial cycle, we followed a combination of the official dating procedure for business cycle turning points by the SARB, and the procedure recommended by the Basel Committee on Banking Supervision (2010) which suggests following Drehmann et al. (2010), where the financial cycle should be four times longer than the business cycle. Different detrending techniques can be used to establish financial cycles, we used the popular HP filter to detrend our financial cycle indicator.

[85] Other work includes Boshoff (2005) and Boshoff (2010).

Using our dating procedure we identified peaks and troughs for the South African financial cycle. We dated the South Africa financial cycle peak as May 2007. As at December 2017 a lower turning point has not yet been reached, therefore South Africa was still in the downward phase of the financial cycle at the end of 2017. We have established that the South Africa financial cycle is around 3 times longer than the business cycle. The overall length of the financial cycle is 17.3 years –much longer than the 5.8 year average business cycle. We find that, on average, financial cycle contractions (10.3 years) last longer than expansions (7.0 years).

Our results show a clear build-up of debt in the lead-up to the financial cycle peak, and a slow and difficult deleveraging process that is still continuing. We find that mortgage debt as a percentage of income was a large driver of the build-up of debt, peaking at 52.5% in March 2008. Households have managed to bring this ratio down to 34.4% by December 2017. The vehicle debt-to-income ratio declined only marginally following the financial cycle peak, suggesting that very little deleveraging took place in the South African vehicle finance market. We also find a sharp increase in the other consumer debt-to-income ratio at the end of 2009 as households sought alternative credit sources, due to, in part, stricter lending criteria from banks.

Most of our variables behaved similarly across the different financial cycles, except for mortgage debt and other consumer credit, which shows the extent to which households were under credit pressure. Mortgage debt reacted differently, largely due to the house price bubble in the most recent crisis. South Africa has a unique housing market and funding system with variable interest rates, increasing the elasticity between mortgages and interest rates. The deflation in house prices is what most likely caused households to deleverage more in their mortgage bonds following the financial cycle peak.

We were able to draw stylised conclusions about the behaviour of economic variables in South Africa, on average, over the financial downward phase, and how they compared to the most recent downward phase. We found that on average during financial crises in South Africa, real house prices fall by 30%, while in the recent financial crisis, real house prices only fell by 15%. Stock prices fell by 20%, also not as much as the average over all financial downswings. The mortgage debt-to-income ratio was 10.7 percentage points higher than the average over all the downward phases, as mortgage credit grew at a much faster pace than income over this period. Vehicle debt-to-income was also 5.2 percentage points above the average, while other consumer credit registered 6.2 percentage points above the average over all downward phases.

In an attempt to gain a deeper understanding of the deleveraging of households in South Africa, we turned to micro data analysis, as aggregate level data potentially conceals relevant information about the distribution of debt and deleveraging. At an aggregate level, information can mask the ability of households to repay loans; which is dependent on the distribution of debt and income across households (André, 2016). With high income-inequality, as is the case for South Africa, these distributions could be highly skewed, resulting in the macroeconomic aggregate being a poor proxy for individual households.

We used the first four waves of the NIDS data, i.e. 2008, 2010/2011, 2012 and 2014/2015. A benefit of using NIDS in this thesis is that its timing overlaps with the period directly following the May 2007 South African financial cycle peak. A characteristic feature of survey data on financial questions to households is the high incidence of missing data. NIDS tries to determine if households have assets or debt by asking further questions on ownership. We combine these binary responses (e.g., yes, we have debt) with additional survey data to impute missing values (e.g., the amount of debt we have). We made use of MICE, which is a useful method for dealing with missing data. We make use of a combination of nearest neighbour, predictive mean matching and multiple imputation to impute logical missing values for the NIDS survey. We also compare our results to the publically provided NIDS data, where regression imputation is used. By imputing the individual debt variables for those who responded that they were debt participants, we increased the total number of observations for all debt types by 43.8% in Wave 1, 35.4% in Wave 2, 26.3% in Wave 3 and 13.4% in Wave 4. We also increased the household income response rate from 75% to 81% in Wave 1, 84% to 94% in Wave 2, 90% to 97% in Wave 3 and 95% to 98% in Wave 4.

After increasing our observations through imputation, we utilised the revised data to create a household panel to explore household deleveraging. Consistent with the debt groupings that we used in chapter 2, we group the different debt types into mortgage debt, vehicle debt and other consumer debt. We further include a category for other debt, included in the NIDS questionnaire, but likely not included in chapter 2's definitions of debt at the aggregate level, as macroeconomic measures are more associated with formal credit from banks.

We exploit the micro data to gain further insights into who deleveraged in South Africa after the recent financial cycle peak. Most other studies usually only observe the drivers of debt or high leverage (see Coletta et al., 2014; Dynan and Kohn, 2007; Bhutta, 2012; Wildauer, 2016). In order to measure household deleveraging over the different waves, we constructed a unique household identifier. We specify that a household representative had to be at least 18 years old and be the household head or key decision maker over all household expenditure. When still uncertain, we follow the adult who joins the new household that contained most of the baseline household members. In the end there are 7 263 households in the 1st wave, 5 652 households in the 2nd wave, 5 691 in the 3rd wave, and 5 402 in the 4th wave.

To explore whether households deleveraged, following the financial cycle peak of May 2007, we utilised the panel data, following households to determine if they decreased their debt between Wave 1 and subsequent waves, respectively. We estimated a probit model for deleveraging, conditioned on Wave 1 characteristics. We controlled for both individual and household characteristics. We followed McCarthy and McQuinn (2017a) and further controlled for income and mortgage leverage in Wave 1 (this is represented by the loan-to-value ratio). We also included leverage measures for each debt type. In the last equation we added a further control, mortgage repayment to income ratio, introduced by McCarthy and McQuinn (2011) as a measure for household liquidity. This is a useful measure as a large part of South Africa's difficulty resulted from the mortgage market.

Although there have been many studies on debt and debt determinants in South Africa, little is known about who suffers the most when debt levels are high and who deleverages. By analysing household debt positions, from a micro economic perspective, we were able to show that deleveraging after the recent financial cycle peak was mostly driven by married households in urban areas. We also identified that while deleveraging occurred at an aggregate level, it was mainly those with the financial resources (top income quintile), who had higher mortgage and consumer credit, that deleveraged. There is no indication that lower income quintile households are able to deleverage. We further show that employment, usually a major factor in obtaining debt, was not a major driver of deleveraging. This suggests that even an economic recovery and increased employment opportunities may not translate into significant deleveraging. Having a job, in itself, does not necessary provide adequate financial resources for households to deleverage.

Although growth rates in mortgage, consumer and other debt have decelerated, debt-to-income levels across all these debt types remain high, compared to the period leading up to the latest financial cycle peak. This suggests that consumers are still in a more vulnerable state than in the period leading up to May 2007. As such, any major negative income shocks, either caused by external factors, domestic economic or political conditions, could prolong the financial downward phase. This could stop any consumer-led recovery and the uptake of new credit. We also showed that deleveraging had a small, but statistically significant negative impact on consumption.

All studies have limitations. Limitations of this study include not being able to optimise on the gains from the distributional benefit of multiple imputations, as we aggregated debt to the household level. Furthermore, deleveraging can be impacted by various factors over different time periods. We show results only for the period directly following the financial cycle peak (2008-2015). Between periods, other factors, such as the hosting of the 2010 Soccer World Cup tournament in South Africa could have boosted incomes. It could also be that the economic environment at the time, specifically high unemployment, could have had an impact on the results; these could be different in a period of strong economic growth and high employment creation. It is also important to note that results can only be seen as associations, as it is possible that there are unobservable factors that are correlated with the control variables, and therefore these results cannot be seen as causal.

Apart from exploring other estimation methods, for determining who deleveraged and dealing with possible selection bias in our NIDS data, future research should aim to establish to what extent important financial decisions regarding wealth effects could have on deleveraging, consumption and the economic recovery. Furthermore, research should aim to establish other deleveraging channels through which the financial cycle downward phase could impact the economic recovery.

BIBLIOGRAPHY

Adarov, A. (2018). Financial Cycles Around the World. wiiw Working Papers 145, The Vienna Institute for International Economic Studies, wiiw.

Aikman, D., Haldane, A. G., and Nelson, B. D. (2015). Curbing the Credit Cycle. *Economic Journal*, 125(585):1072–1109.

Alessi, L. and Detken, C. (2009a). 'real time' early warning indicators for costly asset price boom/bust cycle: A role for global liquidity. *European Central Bank, Working Paper Series No. 1039*.

Alessi, L. and Detken, C. (2009b). 'Real time'early warning indicators for costly asset price boom/bust cycles: a role for global liquidity. Working Paper Series 1039, European Central Bank.

Allison, P. D. (2000). Multiple Imputation for Missing Data: A Cautionary Tale. *Sociological Methods and Research*, 28:301–309.

Allison, P. D. (2002). Missing Data. *Quantitative Applications in the Social Sciences*, 136:104.

André, C. (2016). Household debt in OECD countries. OECD Economics Department Working Papers 1277, OECD Publishing, Paris, Paris.

Andridge, R. R. and Little, R. J. A. (2010). A review of hot deck imputation for survey non-response. *International Statistical Review*, 78(1):40–64.

Aye, G. C., Balcilar, M., Bosch, A., and Gupta, R. (2014). Housing and the business cycle in South Africa. *Journal of Policy Modeling*, 36(3):471–491.

Azur, M., Stuart, E., Frangakis, C., and Leaf, P. (2011). Multiple imputation by chained equations: What is it and how does it work? *International Journal of Methods in Psychiatric Research*, 20(1):40–49.

Baker, S. R. (2014). Debt and the Consumption Response to Household Income Shocks. Technical report.

Balcilar, M., Gupta, R., Jooste, C., and Wohar, M. E. (2016a). Periodically collapsing bubbles in the South African stock market. *Research in International Business and Finance*, 38(C):191–201.

Balcilar, M., Gupta, R., van Eyden, R., Thompson, K., and Majumdar, A. (2018). Comparing the forecasting ability of financial conditions indices: The case of South Africa. *The Quarterly Review of Economics and Finance*, 69:245–259.

Balcilar, M., Thompson, K., Gupta, R., and van Eyden, R. (2016b). Testing the asymmetric effects of financial conditions in South Africa: A nonlinear vector autoregression approach. *Journal of International Financial Markets, Institutions and Money*, 43:30–43.

BASA (2017). The Banking Association South Africa.

Baxter, M. and King, R. G. (1999). Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series. *Review of Economics and Statistics*, 81(4):575–593.

Baxter, R. (2009). The global economic crisis and its impact on South Africa and the country's mining industry. Technical report, Challenges for Monetary Policy-makers in Emerging Markets.

Bech, M. L., Gambacorta, L., and Kharroubi, E. (2014). Monetary policy in a downturn: Are financial crises special? *International Finance*, 17(1):99–119.

Bernanke, B. S. (2012). The Great Moderation. In Koenig, E. F., Leeson, R., and Kahn, G. A., editors, *The Taylor Rule and the Transformation of Monetary Policy*, Book Chapters, chapter 6. Hoover Institution, Stanford University.

Besomi, D. (2006). Tendency to equilibrium, the possibility of crisis, and the history of business cycle theories. *History of Economic Ideas*, 14(2):53–104.

Bhutta, N. (2012). Mortgage Debt and Household Deleveraging: Accounting for the Decline in Mortgage Debt Using Consumer Credit Record Data. Feds working paper no. 2012-14, Available at SSRN: https://ssrn.com/abstract=2051020 or http://dx.doi.org/10.2139/ssrn.2051020.

Blanchard, O. J., Simon, J., Blanchard, O., and Simon, J. (2001). The Long and Large Decline in U.S. Output Volatility. *Brookings Papers on Economic Activity*, 32(1):135–174.

Boonzaaier, W. (2018). Residential Property Price Indicators in South Africa: Current and Future Developments.

Borio, C. (2014). The financial cycle and macroeconomics: What have we learnt? *Journal of Banking and Finance*, 45(1):182–198.

Borio, C., Disyatat, P., and Juselius, M. (2014). A Parsimonious Approach to Incorporating Economic Information in Measures of Potential Output. *BIS Working Papers*, (442):1–41.

Borio, C., Disyatat, P., and Juselius, M. (2017). Rethinking potential output: embedding information about the financial cycle. *Oxford Economic Papers*, 69(3):655–677.

Borio, C. and Drehmann, M. (2009). Assessing the risk of banking crises - revisited. *BIS Quarterly Review*.

Borio, C., Drehmann, M., and Xia, D. (2018). The financial cycle and recession risk. *BIS Quarterly Review*.

Borio, C., Furfine, C., and Lowe, P. (2001). Procyclicality of the financial system and financial stability: issues and policy options. In *in Settlements, Bank for International eds., Marrying the macro- and micro-prudential dimensions of financial stability*, volume 01, pages 1–57.

Borio, C., Kennedy, N., and Prowse, S. (1994). Exploring Aggregate Asset Price Fluctuations Across Countries: Measurement, Determinants and Monetary Policy Implications. *BIS Economic papers*, 40.

Borio, C., Vale, B., and von Peter, G. (2010). Resolving the financial crisis: are we heeding the lessons from the Nordics? BIS Working Papers 311, Bank for International Settlements.

Boschan, C. and Ebanks, W. (1978). *The Phase-average Trend: A New Way of Measuring Economic Growth*.

Boshoff, W. (2005). The properties of cycles in South African financial variables and their relation to the business cycle. *The South African Journal of Economics*, 73(4):694–709.

Boshoff, W. (2010). Band-pass filters and business cycle analysis: Highfrequency and medium-term deviation cycles in South Africa and what they measure. ERSA working paper series 200, Economic Research Southern Africa.

Bricker, J., Bucks, B. K., Kennickell, A. B., Mach, T. L., and Moore, K. B. (2011). Surveying the aftermath of the storm: changes in family finances from 2007 to 2009. Finance and Economics working paper Series 2011-17, Board of Governors of the Federal Reserve System (U.S.).

Brown, M., Haughwout, A., Lee, D., and van der Klaauw, W. (2011). Do We Know What We Owe? A Comparison of Borrower- and Lender-Reported Consumer Debt. Economic policy review, Federal Reserve Bank of New York.

Brown, S., Garino, G., Taylor, K., and Price, S. W. (2005). Debt and Financial Expectations: An Individual- and Household-Level Analysis. *Economic Inquiry*, 43(1):100–120.

Brunet, O. (2000). Calculation of Composite Leading Indicators: A Comparison of Two Different Methods. In *Twenty-Fifth CIRET Conference*, Paris.

Bry, G. and Boschan, C. (1971). Cyclical Analysis of Time Series: Selected Procedures and Computer Programs. NBER Technical Paper, National Bureau of Economic Research, Inc.

Bunn, P. and Rostom, M. (2014). Household debt and spending. *Bank of England Quarterly Bulletin*, 54(3):304–315.

Burns, A. F. and Mitchell, W. C. (1946). Measuring Business Cycles. In *NBER Book Series Studies in Business Cycles*. National Bureau of Economic Research, Inc.

Casale, D. (2004). What has the feminisation of the labour market bought women in South Africa? Trends in labour force participation, employment and earnings, 1995–2001. *Journal of Interdisciplinary Economics*, 15(3-4):251–275.

Chinhema, M., Brophy, T., Brown, M., Leibbrandt, M., Mlatsheni, C., and Woolard, I. (2016). National Income Dynamics Study Panel User Manual. Technical report, Southern Africa Labour and Development Research Unit, Cape Town.

Choonoo, S. (2016). Developments in the South African Credit Market and Analysis on Indebted Consumers Using NIDS Data. Master's thesis, University of Capetown.

Christelis, D. (2011). Imputation of Missing Data in Waves 1 and 2 of SHARE. CSEF Working Papers 278, Centre for Studies in Economics and Finance (CSEF), University of Naples, Italy.

Christelis, D., Georgarakos, D., and Jappelli, T. (2015). Wealth shocks, unemployment shocks and consumption in the wake of the Great Recession. *Journal of Monetary Economics*, 72:21–41.

Christiano, L. J. and Fitzgerald, T. J. (2003). The Band Pass Filter. *International Economic Review*, 44(2):435–465.

Cichello, P., Leibbrandt, M., and Woolard, I. (2012). *Southern Africa Labour and Development Research Unit Education: Analysis of the NIDS Wave 1 and 2 Datasets*. Number 78.

Claessens, S., Kose, M. A., and Terrones, M. E. (2011). Financial Cycles: What? How? When? *NBER International Seminar on Macroeconomics*, 7(1):303–344.

Claessens, S., Kose, M. A., and Terrones, M. E. (2012). How do business and financial cycles interact? *Journal of International Economics*, 87(1):178–190.

Coletta, M., Bonis, R. D., and Piermattei, S. (2014). The determinants of household debt: a cross-country analysis. Temi di discussione (Economic working papers) 989, Bank of Italy, Economic Research and International Relations Area.

Cooper, D. (2012). U.S. Household Deleveraging: What Do the Aggregate and Household-Level Data Tell Us? Research department public policy briefs, Federal Reserve Bank of Boston, Research Department Public Policy Briefs.

Cooper, D. and Dynan, K. (2016). Wealth shocks and macroeconomic dynamics. *Journal of Economic Surveys*, 30(1):34–55.

Cull, R. and Scott, K. (2010). Measuring household usage of financial services: Does it matter how or whom you ask? *World Bank Economic Review*, 24(2):199–233.

Daniell, H. (2009). The use of sample weights in hot deck imputation. *National Instittute of Health*, 76(October 2009):211–220.

Daniels, R. C. and Augustine, T. (2016). The measurement and distribution of household wealth in South Africa using the National Income Dynamics Study (NIDS) Wave 4. Working paper 183, Southern Africa Labour and Development Research Unit.

Daniels, R. C., Finn, A., and Musundwa, S. (2014). Wealth data quality in the national income dynamics study wave 2. *Development Southern Africa*, 31(1):31–50.

De Wet, S., Botha, I., and Booyens, M. (2015). Measuring the effect of the National Credit Act on indebtedness in South Africa. *Journal of Economic and Financial Sciences*, 8(1):83–104.

Dell'ariccia, G., Igan, D., Laeven, L., Tong, H., Vandenbussche, J., and Bakker, B. (2012). Policies for Macrofinancial Stability: How to Deal with Credit Booms. Technical report, IMF Staff Discussion Note 12/06.

DeMaio, T. J. (1980). Refusals: Who, where and why. *Public Opinion Quarterly*, 44(2):223–233.

Drehmann, M., Borio, C., and Tsatsaronis, K. (2012). Characterising the Financial Cycle: Don't Lose Sight of the Medium Term! *BIS Working Papers*, (380):1–38.

Drehmann, M., Borio, C. E. V., Gambacorta, L., Jiménez, G., and Trucharte, C. (2010). Countercyclical Capital Buffers: Exploring Options. BIS Working Paper 317, Bank for International Settlements.

Drehmann, M. and Juselius, M. (2014). Evaluating early warning indicators of banking crises: Satisfying policy requirements. *International Journal of Forecasting*, 30(3):759–780.

du Toit, L. (2008). Optimal HP filtering for South Africa. Working Papers 07/2008, Stellenbosch University, Department of Economics.

Durrant, G. B. (2005). Imputation Methods for Handling Item- Nonresponse in the Social Sciences. ESRC National Centre for Research Methods and Southampton Statistical Sciences Research Institute. *NCRM Methods Review Papers*, NCRM/002.

Dynan, K. (2012a). Is a Household Debt Overhang Holding Back Consumption. *Brookings Papers on Economic Activity*, 43(1 (Spring):299–362.

Dynan, K. (2012b). Is a Household Debt Overhang Holding Back Consumption. *Brookings Papers on Economic Activity*, 43(1 (Spring):299–362.

Dynan, K. and Edelberg, W. (2013). The relationship between leverage and household spending behavior: Evidence from the 2007-2009 survey of consumer finances. *Federal Reserve Bank of St. Louis Review*, 95(5):425–48.

Dynan, K. E. and Kohn, D. L. (2007). The Rise in US Household Indebtedness: Causes and Consequences. In Kent, C. and Lawson, J., editors, *The Structure and Resilience of the Financial System*, RBA Annual Conference Volume. Reserve Bank of Australia.

Einarsson, B. G., Gunnlaugsson, K., Ólafsson, T. T., and Pétursson, T. G. (2015). The long history of financial boom-bust cycles in Iceland - Part I: Financial crises. Economics wp 68, Department of Economics, Central bank of Iceland.

Einarsson, B. G., Gunnlaugsson, K., Ólafsson, T. T., and Pétursson, T. G. (2016). The long history of financial boom-bust cycles in Iceland - Part II: Financial cycles. Economics, Department of Economics, Central bank of Iceland.

Ellis, L. (2010). The Housing Meltdown: Why Did It Happen in the United States? *International Real Estate Review*, 13(3):351–394.

Farrell, G. and Kemp, E. (2018). Measuring the Financial Cycle in South Africa. Ersa working paper series, Economic Research Southern Africa.

Ferber, R. (1966). Item nonresponse in a consumer survey. *Public Opinion Quarterly*, 30(3):399–415.

Fondeville, N., Özdemir, E., and Ward, T. (2010). Over-indebtedness New evidence from the EU-SILC special module. Technical report.

Gelman, A. and Hill, J. (2007). *Data analysis using regression and multilevel/hierarchical models*. Cambridge University Press.

Gelman, A. and Rubin, D. B. (1992). Inference from Iterative Simulation Using Multiple Sequences. *Statistical Science*, 7(4):457–472.

Gerdrup, K., Kvinlog, B. A., and Schaanning, E. (2013). Key indicators for a countercyclical capital buffer in Norway - Trends and uncertainty. *Norges Bank Staff Memo*, No 13/2013.

Glick, R. and Lansing, K. J. (2009). U.S. Household Deleveraging and Future Consumption Growth. *Federal Reserve Bank of San Francisco Economic Letter No. 01*.

Gomez-Salvador, R., Lojschova, A., and Westermann, T. (2011). Household Sector Borrowing in the Euro Area: A Micro Data Persective. BCL working papers 58, Central Bank of Luxembourg.

Gonzalez, R. B., Lima, J., and Marinho, L. (2015). Business and Financial Cycles: an estimation of cycles' length focusing on Macroprudential Policy. Banco central do brasil working paper 385, Central Bank of Brazil, Research Department.

Goodhart, C. and Hofmann, B. (2008). House prices, money, credit, and the macroeconomy. *Oxford Review of Economic Policy*, 24(1):180–205.

Graham, J. W. (2009). Missing Data Analysis: Making It Work in the Real World. *Annual Review of Psychology*, 60(1):549–576.

Granados, J. (2012). Does investment call the tune? empirical evidence and endogenous theories of the business cycle. *Research in Political Economy*, 28.

Greenland, S. and Finkle, W. D. (1995). A Critical Look at Methods for Handling Missing Covariates in Epidemiologic Regression Analyses. *American Journal of Epidemiology*, 142(12):1255–1264.

Hamilton, J. D. (2018). Why you should never use the Hodrick-Prescott filter. *Review of Economics and Statistics*, 100(5):831–843.

Harding, D. and Pagan, A. (2002). Dissecting the cycle: A methodological investigation. *Journal of Monetary Economics*, 49(2):365–381.

Hiebert, P., Jaccard, I., and Schüler, Y. (2018). Contrasting financial and business cycles: Stylized facts and candidate explanations. *Journal of Financial Stability*, 38:72–80.

Hiebert, P., Klaus, B., Peltonen, T. A., Schüler, Y. S., and Welz, P. (2014). Capturing the Financial Cycle in Euro Area Countries. *Financial Stability Review*, 2.

Hiebert, P., Peltonen, T. A., and Schüler, Y. S. (2015). Characterising the financial cycle: a multivariate and time-varying approach. Working Paper Series 1846, European Central Bank.

Hodrick, R. J. and Prescott, E. C. (1997). Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit and Banking*, 29(1):1–16.

Hurd, M. D. (1999). Anchoring and Acquiescence Bias in Measuring Assets in Household Surveys. *Journal of Risk and Uncertainty*, 19(1-3):111–136.

Jorda, O., Schularick, M., and Taylor, A. (2011). Financial Crises, Credit Booms, and External Imbalances: 140 Years of Lessons. *IMF Economic Review*, 59(2):340–378.

Jordà, Ò., Schularick, M., and Taylor, A. M. (2015). Leveraged bubbles. *Journal of Monetary Economics*, 76:S1–S20.

Jourdan, B. and Ellyne, M. (2015). Did the National Credit Act of 2005 facilitate a credit boom and bust In South Africa? In *Economic Society of South Africa*.

Juster, F., Cao, H., Couper, M., Hill, D., Hurd, M., Lupton, J., Perry, M., and Smith, J. (2007). Enhancing the quality of data on the measurement of income and wealth. Working papers, University of Michigan, Michigan Retirement Research Center.

Kabundi, A. and Mbelu, A. (2017). Estimating a time-varying financial conditions index for South Africa. Working Paper 17/02 8008, South African Reserve Bank.

Kamada, K. and Nasu, K. (2011). The Financial Cycle Indexes for Early Warning Exercise. Working paper series wp 11-E-1, Bank of Japan, Japan.

Kemp, H. (2018). Ten years after the Lehman collapse: SA's post-crisis performance in perspective. Technical report, Bureau of Economic Research (BER).

Kindleberger, C. P. and Aliber, R. Z. (2005). *Manias, Panics and Crashes: A History of Financial Crises*. Fifth edit edition.

Klein, P. A. and Moore, G. H. (1985). Monitoring Growth Cycles in Market-Oriented Countries: Developing and Using International Economic Indicators. In *National Bureau of Economic Research*, pages 3–27. Published for the National Bureau of Economic Research by Ballinger Pub. Co.

Kondratieff, N. D. (1922). The world economy and its trends during and after war. Technical report.

Kondratieff, N. D. (1925). The big cycles of conjuncture. *The problems of conjuncture*, 1(1):28–79.

Kondratieff, N. D. (1926). Die langen Wellen der Konjunktur. *Archiv fuer Sozialwissenschaft und Sozialpolitik*, 56(3):573–609.

Kondratieff, N. D. (1928). The big cycles of conjuncture. *Institute of Economics RANION Moscow Russian Federation*.

Koo, R. C. (2013). Central Banks in Balance Sheet Recessions: A Search for Correct Response. Technical report, Nomura Research Institute.

Kwak, D. W. (2010). Tests of MCAR and estimation methods for missing data: An application to the effect of class size reduction on SAT score for grades in K-3. Michigan State University. Job market paper.

Laidler, D. (1999). The Quantity of Money and Monetary Policy. Staff Working Papers 99-5, Bank of Canada.

Laubscher, P. (forthcoming). A history of South Africa's modern business cycle. In *Business cycles and structural change in South Africa: An integrated view*.

Lillard, L., Smith, J. P., and Welch, F. (1986). What Do We Really Know about Wages? The Importance of Nonreporting and Census Imputation. *Journal of Political Economy*, 94(3, Part 1):489–506.

Little, R. J. A. (1988). Missing-Data Adjustments in Large Surveys. *Journal of Business and Economic Statistics*, 6(3):287–296.

Little, R. J. A. and Rubin, D. B. (1986). *Statistical Analysis with Missing Data*. John Wiley & Sons, Inc., New York, NY, USA.

Lo, S. and Rogoff, K. (2015). Secular stagnation, debt overhang and other rationales for sluggish growth, six years on. Technical report, BIS.

Lowe, P. and Borio, C. (2002). Asset prices, financial and monetary stability: exploring the nexus. BIS Working Papers 114, Bank for International Settlements.

Lucas, R. E. (2003). Macroeconomic Priorities. *American Economic Review*, 93(1):1–14.

Luüs, C. (2005). The Absa residential property market database for South Africa - key data trends and implications. In for International Settlements, B., editor, *Real estate indicators and financial stability*, volume 21 of *BIS Papers chapters*, pages 149–70. Bank for International Settlements.

Matsebula, V. and Yu, D. (2017). Financial inclusion in South Africa: a NIDS data analysis of household access and the usage of financial services and products. Technical report, Department of Economics, University of the Western Cape. Presented at the 2017 ESSA conference.

McCarthy, Y. and McQuinn, K. (2011). How are Irish households coping with their mortgage repayments? Information from the survey on income and living conditions. *Economic and Social Review*, 42(1):71–94.

McCarthy, Y. and McQuinn, K. (2017a). Deleveraging in a Highly Indebted Property Market: Who does it and are there Implications for Household Consumption? *Review of Income and Wealth*, 63(1):95–117.

McCarthy, Y. and McQuinn, K. (2017b). Price Expectations, Distressed Mortgage Markets and the Housing Wealth Effect. *Real Estate Economics*, 45(2):478–513.

Mian, A., Rao, K., and Sufi, A. (2013). Household balance sheets, consumption, and the economic slump. *Quarterly Journal of Economics*, 128(4):1687–1726.

Mian, A. R. and Sufi, A. (2010). Household leverage and the recession of 2007-09. *IMF Economic Review*, 58(1):74–117.

Minsky, H. P. (1992). The Financial Instability Hypothesis. Working paper no. 74, The Jerome Levy Economics Institute.

Mintz, I. (1969). Dating Postwar Business Cycles: Methods and Their Application to Western Germany, 1950–67. In *National Bureau of Economic Research*, pages 55–111. National Bureau of Economic Research, Inc.

Mintz, I. (1972). Dating American Growth Cycles. In *Economic Research: Retrospect and Prospect, Volume 1, The Business Cycle Today*, pages 39–88. National Bureau of Economic Research, Inc.

Miranda, M. R. (2017). The Debate over the Origin of the Great Recession in the United States. *Norteamérica*, 12(1):79–103.

Mongardini, J. and Saadi-Sedik, T. (2003). Estimating Indexes of Coincident and Leading Indicators; An Application to Jordan. IMF Working Papers 03/170, International Monetary Fund.

Moolman, H. (2004). *The South African stock market and the economic environment*. PhD thesis, Pretoria: University of Pretoria.

Moore, G. H. (1983). The forty-second anniversary of the leading indicators. In *Business Cycles, Inflation, and Forecasting, 2nd edition*, pages 369–400. Ballinger.

Moore, J. C. and Loomis, L. S. (2001). Using alternative question strategies to reduce income nonresponse. Statistical Research Division U.S. Bureau of the Census Washington D.C. 20233. Research report series.

Naicker, B. V. and Md. Kabir, H. (2013). Implementation of South African National Credit Act and its impact on home loans market: the case of First National Bank. *Risk governance & control: financial markets & institutions*, 3(2):18–29.

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A., and Giovannini, E. (2008). *Handbook on Constructing Composite Indicators and User Guide*, volume 2005.

National Credit Regulator (2018). Credit Bureau Monitor data. Quarterly consumer credit market report, NCR, South Africa.

Nicoletti, C. and Peracchi, F. (2006). The effects of income imputation on microanalyses: evidence from the european community household panel. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 169(3):625–646.

NIDS (2018). Frequently asked questions about NIDS. [Available:] `http://www.nids.uct.ac.za/nids-data/documentation/faqs/data-about-nids`.

Ntsalaze, L. and Ikhide, S. (2016). Household Over-indebtedness: Understanding its Extent and Characteristics of those Affected. *Journal of Social Sciences*, 48(1-2):79–93.

Nwanzu, G. (2010). Factors , Preventions and Correction Methods for Non-Response in Sample Surveys. *Journal of Applied Statistics*, 1(1):79–89.

Paile, K. (2013). The Impact of the National Credit Act on Household Debt Levels in South Africa. Technical report, Wits Business School.

Patterson, C. and Steenkamp, S. (2017). Identifying a housing bubble in South Africa. Unpublished, Department of Economics, Stellenbosch University, South Africa.

Pedersen, A., Mikkelsen, E., Cronin-Fenton, D., Kristensen, N., Pham, T. M., Pedersen, L., and Petersen, I. (2017). Missing data and multiple imputation in clinical epidemiological research. *Clinical Epidemiology*, Volume 9:157–166.

Pistaferri, L. (2016). Why Has Consumption Remained Moderate after the Great Recession? Conference paper: The elusive "great" recovery: Causes and implications for future business cycle dynamics.

Posel, D. and Casale, D. (2005). Who replies in brackets and what are the implications for earnings estimates? An analysis of earnings data from South Africa. Working Papers 07, Economic Research Southern Africa.

Raghunathan, T. E., Lepkowski, J. M., Van Hoewyk, J., and Solenberger, P. (2001). A multivariate technique for multiply imputing missing values using a sequence of regression models. *Survey Methodology*, 27(1):85–95.

Ravn, M. O. and Uhlig, H. (2002). On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations. *Review of Economics and Statistics*, 84(2):371–376.

Reinhart, C. M. and Rogoff, K. S. (2009). The aftermath of financial crises. *American Economic Review*, 99(2):466–472.

Riphahn, R. T. and Serfling, O. (2005). Item non-response on income and wealth questions. *Empirical Economics*, 30(2):521–538.

Rubin, D. B. (1987). *Multiple Imputation for Nonresponse in Surveys*. New York: Wiley.

Rünstler, G. and Vlekke, M. (2018). Business, housing, and credit cycles. *Journal of Applied Econometrics*, 33(2):212–226.

SARB (2011). Business cycles in South Africa during the period 2007 to 2009. In *Quarterly Bulletin No 260. June 2011. Pretoria: South African Reserve Bank*, pages 61–66.

SARB (2015). Revisions to the composite leading and coincident business cycle indicators. In *Quarterly Bulletin No 276. June 2015. Pretoria: South African Reserve Bank*, pages 15–17.

SARB (2016). Business cycles in South Africa from 2009 to 2013. In *Quarterly Bulletin No 279. March 2016. Pretoria: South African Reserve Bank*, pages 102–1012.

Schafer, J. L. and Graham, J. W. (2002). Missing data: our view of the state of the art. *Psychological methods*, 7 2:147–77.

Schularick, M. and Taylor, A. M. (2012). Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008. *American Economic Review*, 102(2):1029–1061.

Schüler, Y. S. (2018). *On the cyclical properties of Hamilton's regression filter*. Deutsche Bundesbank.

Schüler, Y. S., Hiebert, P. P., and Peltonen, T. A. (2017). Coherent financial cycles for G-7 countries: Why extending credit can be an asset. ESRB Working Paper Series 43, European Systemic Risk Board.

Schumpeter, J. A. (1939). *Business Cycles: A Theoretical, Historical, and Statistical Analysis of the Capitalist Process. Originally published: 1st ed. New York : McGraw-Hill Book Co.* vol 2 edition.

Simo-Kengne, B. D., Gupta, R., and Aye, G. C. (2014). Macro shocks and house prices in south africa. *The Journal of Real Estate Portfolio Management*, 20(3):179–194.

Smit, D. and van der Walt, B. (1982). Growth trends and business cycles in the South African economy, 1972 to 1981. In *Quarterly Bulletin No 144. June 1982. Pretoria: South African Reserve Bank*, pages 41–57.

Southern Africa Labour and Development Research Unit (2016a). National Income Dynamics Study 2008, Wave 1. [Available:] `http://www.nids.uct.ac.za/nids-data/data-access`.

Southern Africa Labour and Development Research Unit (2016b). National Income Dynamics Study 2010-2011, Wave 2. [Available:] `http://www.nids.uct.ac.za/nids-data/data-access`.

Southern Africa Labour and Development Research Unit (2016c). National Income Dynamics Study 2012, Wave 3. [Available:] `http://www.nids.uct.ac.za/nids-data/data-access`.

Southern Africa Labour and Development Research Unit (2016d). National Income Dynamics Study 2014 - 2015, Wave 4. [Available:] `http://www.nids.uct.ac.za/nids-data/data-access`.

Southern Africa Labour and Development Research Unit (2016e). National Income Dynamics Study Panel User Manual.

Statistics South Africa (2015). Mid-year population estimates – 2015. [Available:] `http://www.statssa.gov.za/publications/P0302/P03022015.pdf`.

Statistics South Africa (2017). Poverty trends in South Africa: An examination of absolute poverty between 2006 and 2015. [Available:] `http://www.statssa.gov.za/publications/Report-03-10-06/Report-03-10-062015.pdf`.

Stremmel, H. (2015). Capturing the financial cycle in Europe. Working Paper Series 1811, European Central Bank.

Strohsal, T., Proano, C., and Wolters, J. (2017). Characterizing the financial cycle: evidence from a frequency domain analysis. IMK Working Paper 189-2017, IMK at the Hans Boeckler Foundation, Macroeconomic Policy Institute.

Su, Y.-S., Gelman, A., Hill, J., and Yajima, M. (2011). Multiple Imputation with Diagnostics in R : Opening Windows into the Black Box. *Journal of Statistical Software*, 45(2):1–31.

Sudman, S., Bradburn, N. M., and Schwarz, N. (1996). *Thinking about answers : the application of cognitive processes to survey methodology*. Jossey-Bass Publishers.

The Conference Board (2001). *Business Cycle Indicators Handbook*. The Conference Board.

Thompson, K., Van Eyden, R., and Gupta, R. (2015a). Identifying an index of financial conditions for South Africa. *Studies in Economics and Finance*, 32(2):256–274.

Thompson, K., van Eyden, R., and Gupta, R. (2015b). Testing the Out-of-Sample Forecasting Ability of a Financial Conditions Index for South Africa. *Emerging Markets Finance and Trade*, 51(3):486–501.

Tourangeau, R. (1984). Cognitive science and survey methods. In *Cognitive aspects of survey methodology: Building a bridge between disciplines*, pages p 73–100.

Tourangeau, R., Rips, L. J., and Rasinski, K. (2000). *The Psychology of Survey Response*. Cambridge University Press, Cambridge.

Van Buuren, S., Brand, J. P., Groothuis-Oudshoorn, C. G., and Rubin, D. B. (2006). Fully conditional specification in multivariate imputation. *Journal of Statistical Computation and Simulation*, 76(12):1049–1064.

Van Buuren, S. and Groothuis-Oudshoorn, K. (2011). Mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software*, 45(3):1–67.

Van der Walt, B.E. (1989). Business cycles in South Africa during the period 1981 to 1987. In *Quarterly Bulletin No 171. March 1989. Pretoria: South African Reserve Bank*.

Van der Walt, B.E. and Prinsloo, J W. (1993). Consumer credit in South Africa. In *Quarterly Bulletin No 189. September 1993. Pretoria: South African Reserve Bank*.

Venter, J. (2009). Business cycles in South Africa during the period 1999 to 2007. In *Quarterly Bulletin No 253. September 2009. Pretoria: South African Reserve Bank*, pages 61–69.

Venter, J. C. (2019a). A brief history of business cycle measurement in South Africa. In Smirnov, S., Ozyildirim, A., and Picchetti, P., editors, *Business Cycles in BRICS*, pages 185–211. Springer International Publishing, Cham.

Venter, J. C. (2019b). The SARB's Composite Business Cycle Indicators. In Smirnov, S., Ozyildirim, A., and Picchetti, P., editors, *Business Cycles in BRICS*, pages 425–446. Springer International Publishing, Cham.

Vermaak, C. (2012). Tracking poverty with coarse data: evidence from South Africa. *The Journal of Economic Inequality*, 10(2):239–265.

Vink, G., Frank, L. E., Pannekoek, J., and van Buuren, S. (2014). Predictive mean matching imputation of semicontinuous variables. *Statistica Neerlandica*, 68(1):61–90.

Von Fintel, D. (2007). Dealing with earnings bracket responses in household surveys? How sharp are midpoint imputations? *The South African Journal of Economics*, 75(2):293–312.

Wayman, J. C. (2003). Multiple Imputation For Missing Data: What Is It And How Can I Use It? Paper presented at the annual meeting of the american educational research association, Chicago.

Wildauer, R. (2016). Determinants of US household debt: New evidence from the SCF. Working Papers PKWP1608, Post Keynesian Economics Society (PKES).

Wittenberg, M. (2008). Nonparametric estimation when income is reported in bands and at points. Working Paper 94, Economic Research Southern Africa.

Wittenberg, M. (2014). Wages and wage inequality in South Africa 1994-2011: The evidence from household survey data. SALDRU Working Paper 135, Southern Africa Labour and Development Research Unit, University of Cape Town.

Wong, R., Orozco-Rocha, K., Zhang, D., Michaels-Obregon, A., and Gonzalez-Gonzalez, C. (2016). Imputation of Non-Response on Economic Variables in the Mexican Health and Aging Study (MHAS/ENASEM) 2012. Project report.

Wood, J. A. (2016). What are the interest rates on store accounts?

Yu, D. (2013). Some factors influencing the comparability and reliability of poverty estimates across household surveys. *Stellenbosch Economic Working Papers*, 03/13.

Zarnowitz, V. (1992). How Trends and Fluctuations Are Observed, Modeled, and Simulated: An Introduction. In *Business Cycles: Theory, History, Indicators, and Forecasting*, NBER Chapters, pages 181–202. National Bureau of Economic Research, Inc.

Zarnowitz, V. and Ozyildirim, A. (2006). Time series decomposition and measurement of business cycles, trends and growth cycles. *Journal of Monetary Economics*, 53(7):1717–1739.

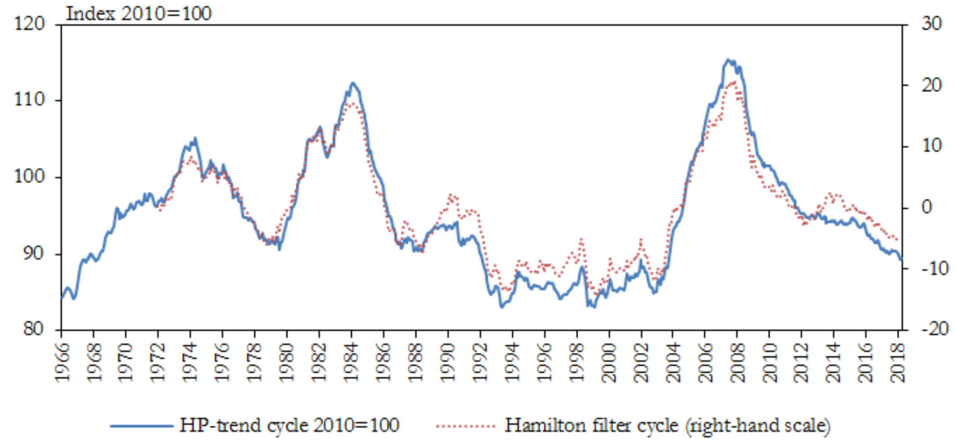
APPENDIX

A

APPENDIX FOR THE COMPOSITE INDEX CALCULATIONS AND ADDITIONAL INFORMATION

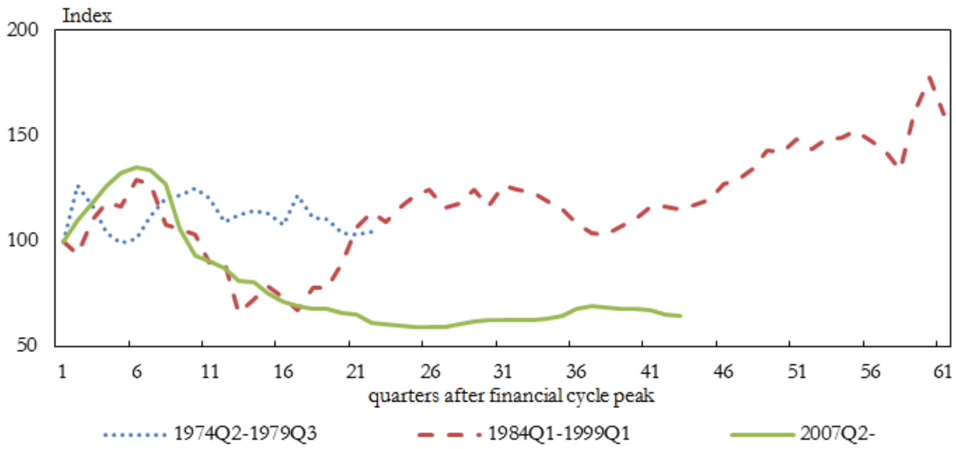
A.1 Additional graphs

Figure A.2.1: HP filter versus Hamilton regression



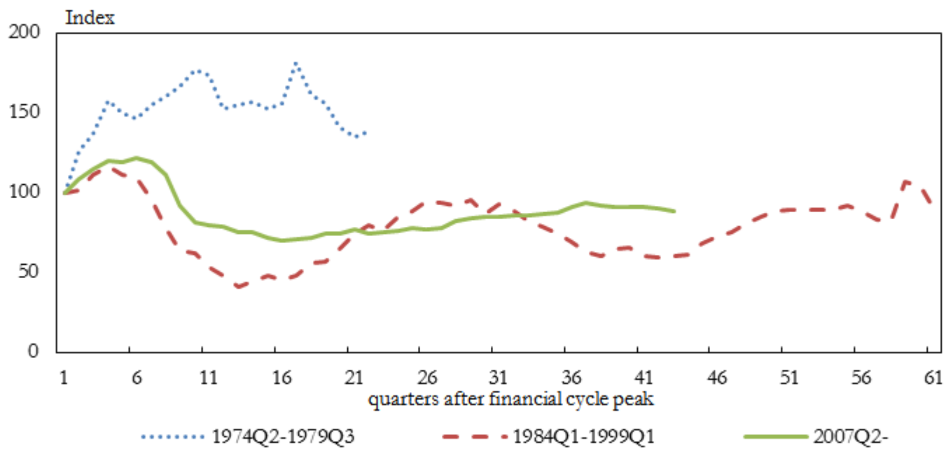
Source: Own calculations, SARB

Figure A.2.2: Financial cycle phase comparisons: Mortgage finance cost-to-income ratio



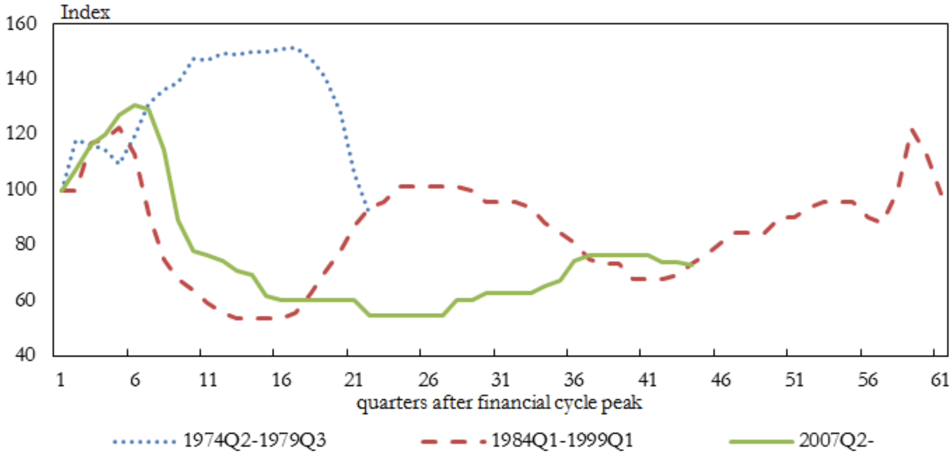
Source: Own calculations, SARB

Figure A.2.3: Financial cycle phase comparisons: Consumer finance cost to income ratio



Source: Own calculations, SARB

Figure A.2.4: Financial cycle phase comparisons: Reserve bank policy rate

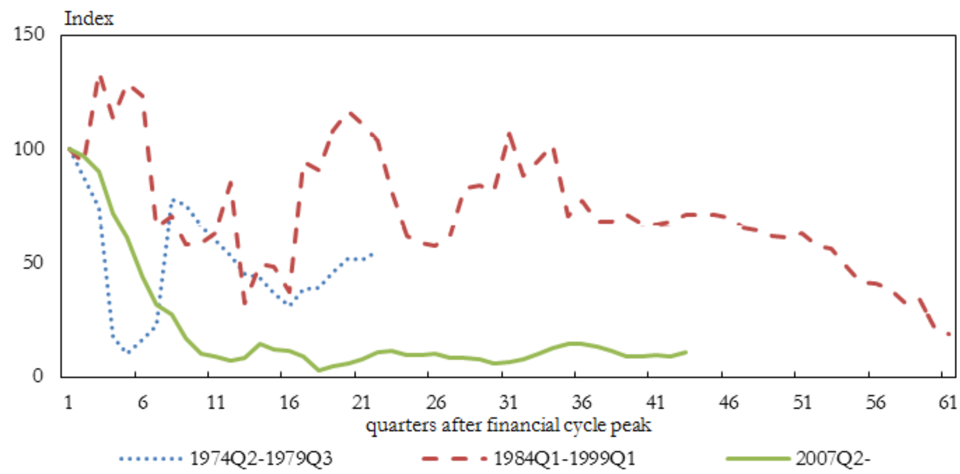


Source: Own calculations, SARB

We also looked at debt financing cost to income ratios of the three debt variables over the phases (results are shown in figure A.2.2 to figure A.2.4). The debt financing cost of mortgage-to-income ratios initially continued to increase, up to 6 quarters after the upper turning point of the financial cycle was reached, before it came down sharply during the recent downward phase. This was similar to the previous financial downward phase. It is important to note that inflation targeting as a monetary policy framework was only fully implemented in 2001 in South Africa, and therefore interest rate policy may have reacted differently to the cycle historically. This is likely also the reason why the financing cost in the 1974 financial downswing was different from the current phase for all the debt categories. The ratio of mortgage finance cost to income also came down initially in the previous financial cycle; however, the decline was quickly reversed after 13 quarters.

Unfortunately we do not have sufficient historical vehicle financing cost data, so we include this with the consumer credit cost. The ratio of consumer cost to income (including vehicle cost that is only available from January 1995), did not fall as much as the ratio of mortgage finance cost to income. Similar to the previous cycle, policy rates (figure A.2.4) only started to fall 4 to 5 quarters after the upper turning point was reached in the financial upward phase. However, in the current financial downswing interest rates remained lower for much long, compared to the other phases.

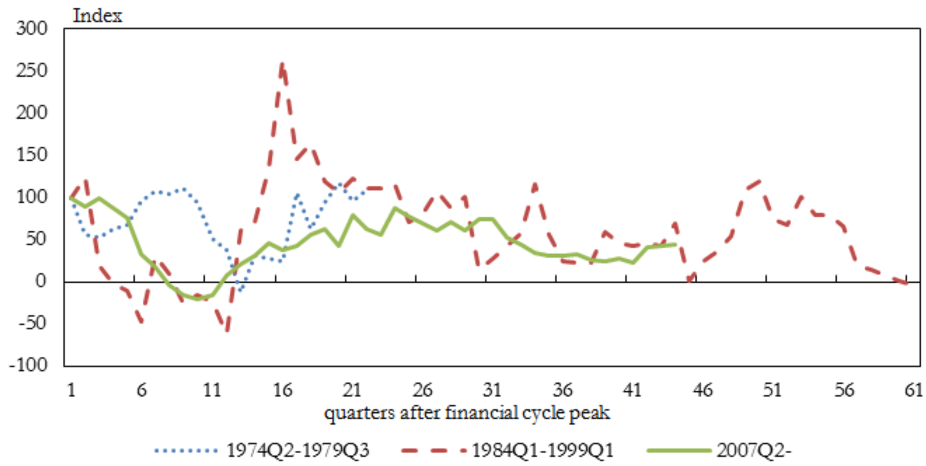
Figure A.2.5: Financial cycle phase comparisons: Mortgage debt growth over 4 quarters



Source: Own calculations, SARB

Year-on-year growth in mortgage debt in the current downward phase of the financial cycle did not fall as sharply as it did after the 1974 peak. Although it did decline further than in any of the two previous downward phases and has remained at this low level ever since (figure A.2.5). Supporting this view that most of South Africas deleveraging likely happened in the mortgage sector, year-on-year growth in mortgage debt outstanding fell sharply in the current downward phase of the financial cycle, probably due to a combination of factors. Firstly, it is possible that households repaid capital faster (postponed new purchases and repaid their current mortgages) or that they defaulted on their properties, resulting in write offs, or that their debt was consolidated into another account. Furthermore, banks tightened their lending criteria, making it more difficult for households to actually get new loans. These include measures such as higher interest rates and bigger deposit requirements.

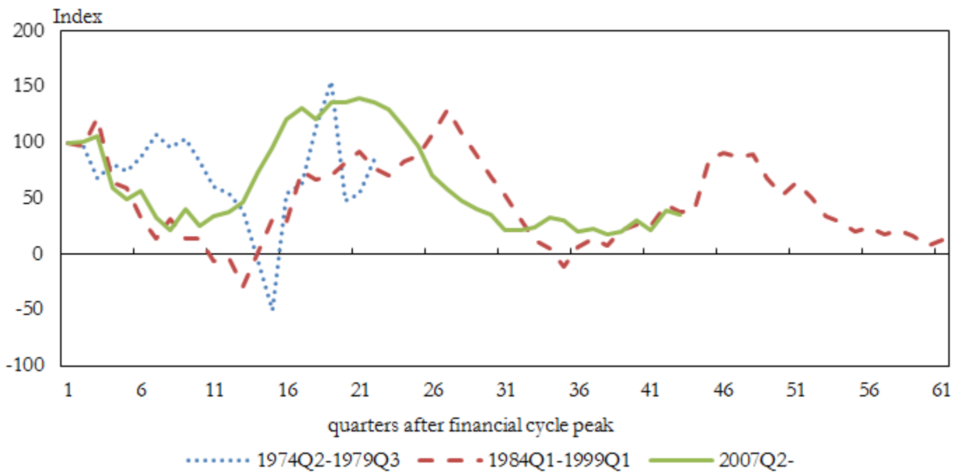
Figure A.2.6: Financial cycle phase comparisons: Vehicle debt growth over 4 quarters



Source: Own calculations, SARB

Although year-on-year growth in vehicle credit also fell sharply after the peak was reached in 2007, growth in vehicle credit recovered only 10 quarters after the financial peak was reached, before falling anew after another 21 quarters. It is clear that growth in the vehicle finance sector recovers soon after the financial cycle peak was reached, whereas growth in mortgage credit continues to remain weak even 42 quarters after the peak in the financial cycle was reached (figure A.2.6).

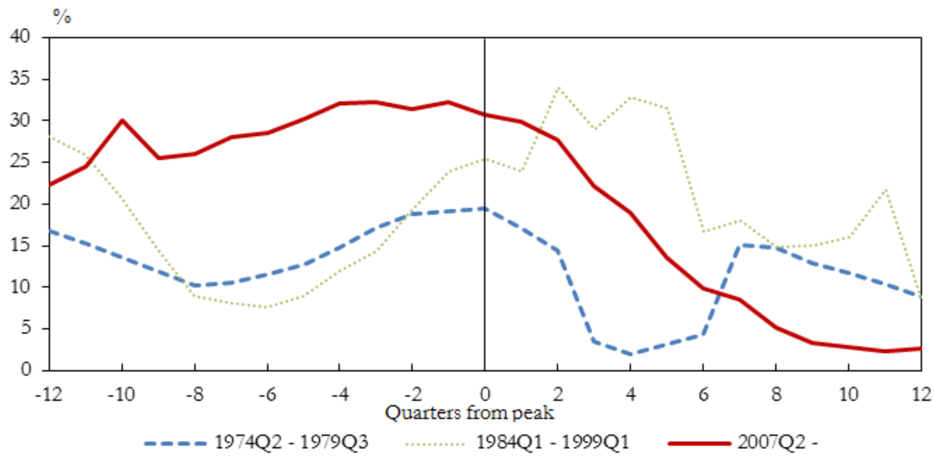
Figure A.2.7: Financial cycle phase comparisons: Other consumer debt growth over 4 quarters



Source: Own calculations, SARB

Year-on-year growth in other consumer credit also fell sharply after the peak was reached in May 2007, growth in other consumer credit recovered only 8 quarters after the financial peak was reached, before falling anew after another 10 quarters (figure A.2.7). Consumer credit however likely relates more to the business cycle than to the financial cycle. It is clear that the financial woes initially did have an impact on the other consumer market; however it recovered soon afterwards, whereas mortgage credit did not. This is also in line with South Africa entering a business cycle downward phase in December 2013 (SARB, 2016).

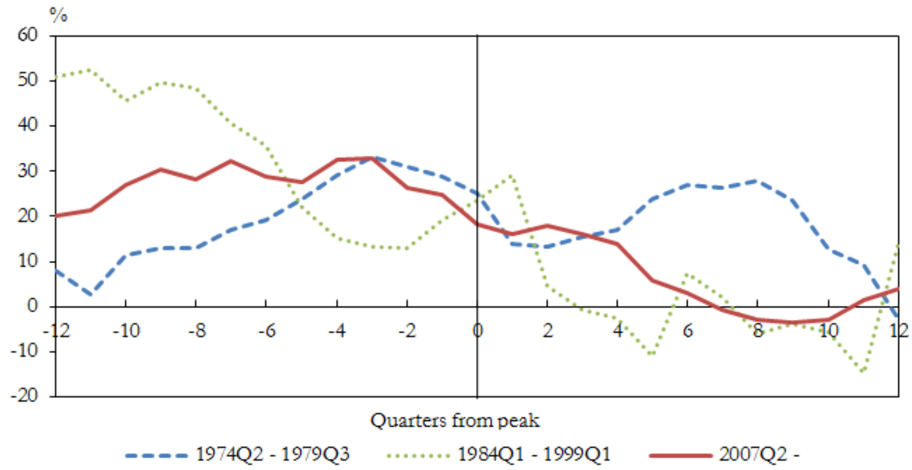
Figure A.2.8: Average phase comparison: Mortgage debt growth over 4 quarters



Source: Own calculations, SARB

We also assessed the year-on-year rate of growth in mortgage debt (see figure A.2.8) where we see a sharp acceleration in the growth about 8 quarters before the upper turning point of a financial cycle in the two previous downward phases. During the current downward phase there was a slow and gradual increase, from already high levels, in mortgage debt growth, which peaked around one quarter before the financial cycle peak. This long sustained increase in mortgage debt growth during the phase leading up to the peak is likely responsible for the debt overhang observed in the high mortgage debt-to-income ratio.

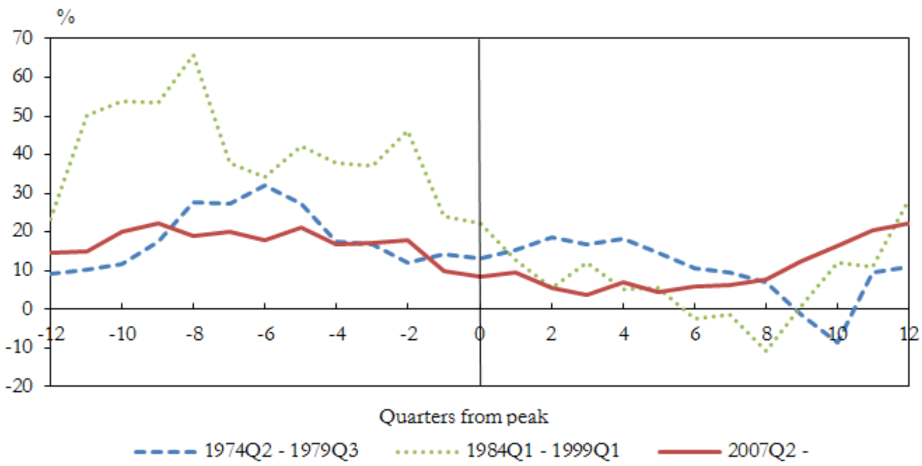
Figure A.2.9: Phase comparison around turning point: Vehicle debt growth over 4 quarters



Source: Own calculations, SARB

The year-on-year growth in vehicle credit (figure A.2.9) is an early indicator of turning points (especially in the business cycle literature). We see that vehicle credit growth peaked 3 quarters before the start of the recent financial downswing, and then falls sharply afterwards. After 10 to 12 quarters vehicle credit in the current financial downward phase reached a lower turning point, suggesting that it turned faster than mortgage credit growth.

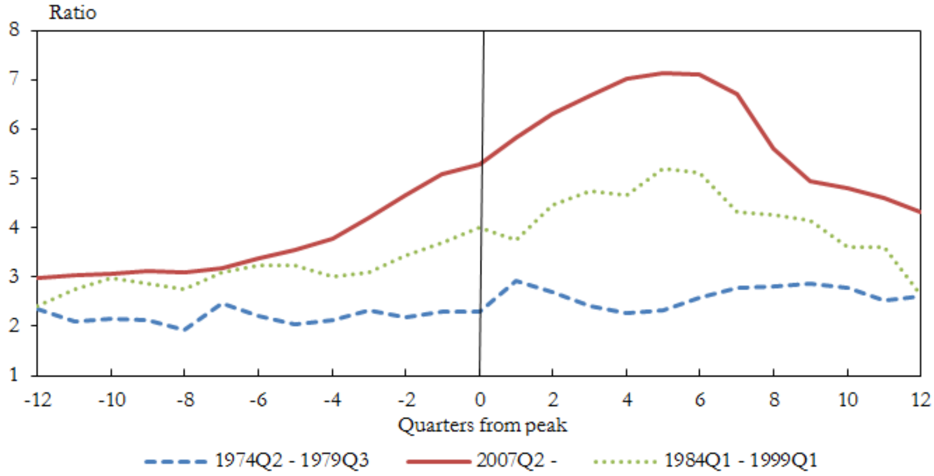
Figure A.2.10: Phase comparison around turning point: All other consumer debt growth over 4 quarters



Source: Own calculations, SARB

The year-on-year growth in all other consumer credit remained relatively stable over the period, gradually declining over 11 quarters to the current financial cycle peak. During the previous two downward phases, other consumer credit growth only picked up 8 to 10 quarters after the peak was reached, while in the current phase, other consumer credit growth already started to increase 3 quarters after the financial peak. This is a result of tight credit access and households making use of other means of accessing credit or because daily consumption became tight and more households had to rely on other consumer credit to get by (see figure A.2.10).

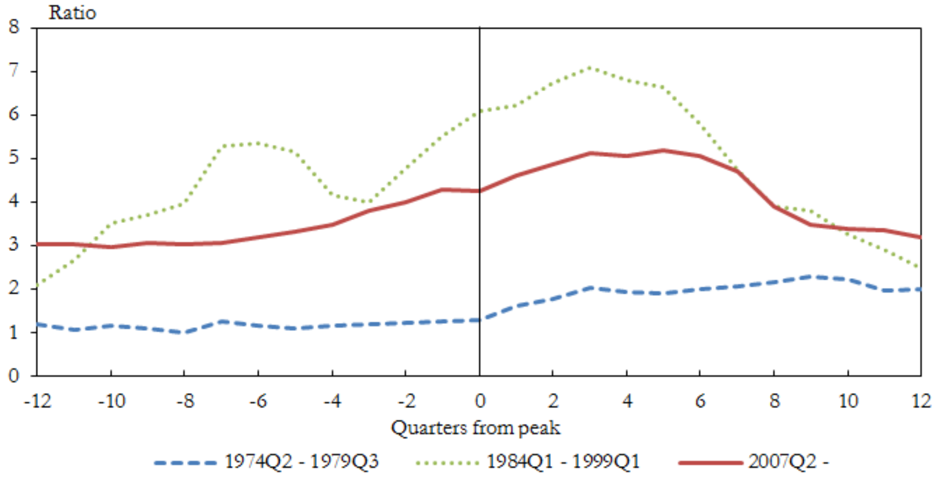
Figure A.2.11: Phase comparison around turning point: Mortgage finance cost-to-income ratio



Source: Own calculations, SARB

For completeness, we also looked at the financing cost to income ratios of our three debt variables. The mortgage finance cost to income ratio only peaks 5 to 6 quarters after a upper turning point is reached in a financial cycle, after which the ratio declines sharply as interest rates starts to fall (figure A.2.11). Mortgage finance cost to income in the current financial downward phase was also much higher compared to the previous two phases. Although mortgage finance cost as a ratio of income came down, it remains higher than in the previous two financial downward phases.

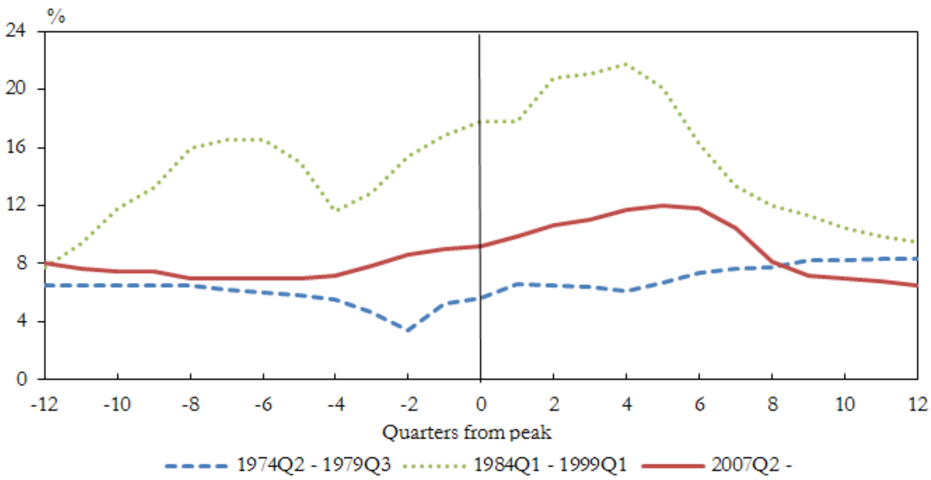
Figure A.2.12: Phase comparison around turning point: Consumer finance cost to income



Source: Own calculations, SARB

Similarly, consumer financing cost (we include vehicle financing cost here) to income also peaks after the upper turning point, at about 5 quarters, after which it falls to pre-peak levels (figure A.2.12). The ratio of consumer financing cost to income follows the repo rate (figure A.2.13); peaking 6 quarters after a financial cycle peak. Compared to the previous phase, consumer finance cost to income did not increase to such a high level likely, in-part, due to the introduction of the national credit act of 2007 which capped interest rates charges on consumer credit[86]

Figure A.2.13: Phase comparison around turning point: Reserve bank policy rate



Source: Own calculations, SARB

Although we analyse the policy rate, we should note that inflation targeting was only adopted in 2000, so policy rate regimes are not strictly comparable over the phases. The higher policy rate

[86] It is difficult to determine the impact of the national credit act on consumer debt costs

during the previous financial downward phase was in a substantially higher domestic inflation environment (12.2% on average over the period, compared to 6.1% over the most recent downward phase.

APPENDIX B

APPENDIX FOR DETAILS ON THE DEBT PARTICIPATION QUESTIONS

B.1 Debt participation question details

Table B.1: Question on debt participation

Description of variables
Household level
Does a household member own this dwelling?
What is the amount of the bond still owing on this property?
Individual level
Do you personally have a [...]? Personal loan from a bank
Personal loan from a micro-lender
Study loan with a bank
Study loan with an institution other than a bank
Credit card
Store card (For example, Edgars, Foschini or Woolworths store card)
Hire purchase agreement
Loan from a family member
Loans from friends
Loan with a Mashonisa/informal money lender
What is the remaining outstanding balance on your [...]?
Personal loan from a bank
Personal loan from a micro-lender
Study loan with a bank
Study loan with an institution other than a bank
Credit card
Store card (For example, Edgars, Foschini or Woolworths store card)
Hire purchase agreement
Loan from a family member
Loans from friends
Loan with a Mashonisa/informal money lender

Source: NIDS

APPENDIX

C

APPENDIX FOR ADDITIONAL DESCRIPTIVES AND ESTIMATION OUTPUT OF DELEVERAGING

C.1 Debt descriptive statistics by debt type and income quintiles

Table C.1.1: Median and mean debt oustanding by debt type and income quintiles

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Mortgage debt					
Wave 1	R 58 593 [R 89 035]	R 37 927 [R 41 800]	R 109 954 [R 101 000]	R 74 306 [R 115 527]	R 295 352 [R 442 671]
Wave 2	R 186 295 [R 249 948]	R 215 520 [R 189 262]	R 129 880 [R 222 414]	R 188 050 [R 306 414]	R 288 343 [R 417 748]
Wave 3	R 329 608 [R 280 012]	R 67 728 [R 91 941]	R 163 509 [R 1 189 086]	R 77 013 [R 236 851]	R 206 138 [R 327 967]
Wave 4	R 195 351 [R 188 337]	R 68 000 [R 90 565]	R 229 813 [R 160 017]	R 137 093 [R 159542]	R 250 451 [R 612 617]
Vehicle debt					-
Wave 1	R 107 891 [R 196 696]	R 44 303 [R 45 618]	R 4 282 [R 4 282]	R 50 759 [R 72 407]	R 114 721 [R 127 489]
Wave 2	R 790 025 [R 466 190]	R 82 993 [R 105 126]	R 73 291 [R 158 948]	R 112 830 [R 139 896]	R 75 220 [R 167 371]
Wave 3		R 84 975 [R 82 360]	R 90 701 [R 87 818]	R 74 439 [R 92 696]	R 97 370 [R 163 119]
Wave 4	R 27 149 [R 59 181]	R 140 252 [R 120 355]	R 5 810 [R 2 850 563]	R 58 992 [R 59 699]	R 85 854 [R 139 736]
Consumer					
Wave 1	R 4 917 [R 9 562]	R 5 525 [R 9 617]	R 4 401 [R 6 882]	R 7 479 [R 13 553]	R 10 653 [R 21 765]
Wave 2	R 10 029 [R 13 244]	R 5 767 [R 8 310]	R 5 639 [R 13 901]	R 7 835 [R 14 196]	R 11 283 [R 20 507]
Wave 3	R 3 779 [R 7 641]	R 6 140 [R 10 058]	R 6 808 [R 8 845]	R 9 124 [R 14 664]	R 17 658 [R 30 992]
Wave 4	R 5 009 [R 10 989]	R 4 436 [R 13 621]	R 5 653 [R 17 327]	R 7 025 [R 14 905]	R 22 961 [R 146 162]
Other					
Wave 1	R 999 [R 2 449]	R 2 347 [R 3 752]	R 1 756 [R 2 671]	R 2 054 [R 3 507]	R 2 569 [R 5 356]
Wave 2	R 758 [R 3 691]	R 1 116 [R 4 758]	R 1 755 [R 3 479]	R 2 006 [R 3 944]	R 3 409 [R 6 183]
Wave 3	R 1 137 [R 1 894]	R 1 819 [R 3 301]	R 2 281 [R 27 022]	R 2 249 [R 4 381]	R 3 411 [R 5 057]
Wave 4	R 973 [R 3 248]	R 1 300 [R 2 750]	R 1 703 [R 3 440]	R 2 000 [R 4 371]	R 2 950 [R 7 181]
Total					
Wave 1	R 2 877 [R 38 013]	R 2 892 [R 14 734]	R 2 954 [R 18 594]	R 6 675 [R 35 261]	R 63 521 [R 240 229]
Wave 2	R 4 378 [R 107 324]	R 3800 [R 46 058]	R 4 674 [R 45 449]	R 8 149 [R 86 137]	R 77 727 [R 261 800]
Wave 3	R 2 290 [R 47 298]	R 3 791 [R 14 845]	R 3 486 [R 118 644]	R 6 413 [R 37 513]	R 53 458 [R 200 687]
Wave 4	R 1 613 [R 17 845]	R 2 004 [R 14 910]	R 2 950 [R 57 658]	R 4 107 [R 19 266]	R 42 026 [R 341 718]

All values reported are in real terms. Medians and [means] are reported.

Source: Own calculations, NIDS

Table C.1.2: Share of debt types held by income quintiles by wave, for those who had debt

Quintile 1	Mortgage debt	Vehicle debt	Consumer debt	Other debt	Total
Wave 1	24.7%	3.0%	28.9%	63.9%	14.2%
Wave 2	33.1%	2.8%	22.7%	60.8%	16.8%
Wave 3	8.9%	0.0%	30.5%	72.3%	18.3%
Wave 4	4.8%	2.5%	30.6%	77.5%	33.4%
Quintile 2	Mortgage debt	Vehicle debt	Consumer debt	Other debt	Total
Wave 1	15.3%	1.6%	30.1%	71.0%	16.5%
Wave 2	22.7%	1.7%	28.2%	65.2%	17.0%
Wave 3	5.7%	0.8%	42.0%	68.2%	23.0%
Wave 4	2.9%	1.4%	36.3%	78.3%	39.4%
Quintile 3	Mortgage debt	Vehicle debt	Consumer debt	Other debt	Total
Wave 1	12.7%	0.3%	37.1%	72.2%	25.7%
Wave 2	15.3%	1.3%	38.0%	66.8%	21.9%
Wave 3	5.4%	0.9%	50.7%	69.0%	29.8%
Wave 4	3.0%	1.0%	40.3%	78.7%	47.7%
Quintile4	Mortgage debt	Vehicle debt	Consumer debt	Other debt	Total
Wave 1	18.4%	4.0%	50.4%	70.7%	37.3%
Wave 2	18.4%	2.7%	44.3%	66.6%	31.4%
Wave 3	8.9%	2.9%	52.9%	68.8%	45.7%
Wave 4	4.8%	3.5%	48.4%	80.3%	61.8%
Quintile5	Mortgage debt	Vehicle debt	Consumer debt	Other debt	Total
Wave 1	41.0%	29.7%	61.9%	61.9%	74.1%
Wave 2	40.7%	20.3%	52.4%	57.0%	59.6%
Wave 3	32.7%	21.0%	63.9%	67.5%	68.5%
Wave 4	25.6%	24.8%	68.3%	71.1%	80.9%

Total refers to the share of respondents who had debt in that wave and quintile.

Source: Own calculations, NIDS

C.2 Debt deleveraging by income quintiles

Table C.2.1: Change in debt outstanding over waves by debt type and income quintile

Total debt	Wave 1 - 2	Wave 1 - 3	Wave 1 - 4
Quintile 1	R 856 [R 21 911]	R 1 410 [R -19 984]	R 1 573 [R 15 396]
Quintile 2	R 419 [R 119 165]	R -587 [R 38 736]	R 1 467 [R 5 228]
Quintile 3	R 1 285 [R 4 846]	R -781 [R -8 105]	R 120 [R 1 312]
Quintile 4	R 1 003 [R 16 741]	R 2 660 [R 15 258]	R 1 604 [R 15 088]
Quintile 5	R -10 873 [R 32 004]	R -6 783 [R -11 337]	R -7 037 [R 150 872]
Total mortgage debt			
Quintile 1	R 58 343 [R 125 275]	R 25 503 [R 18 642]	R 189 869 [R 92 684]
Quintile 2	R -360 746 [R -360 746]	R 202 713 [R 165 552]	-
Quintile 3	R 311 208 [R 171 657]	R -190 262 [R -71 651]	R 413 017 [R 413 017]
Quintile 4	R -42 671 [R -12 283]	R -21 626 [R 43 979]	R -59 175 [R 2 699]
Quintile 5	R -35 604 [R 14 561]	R -49 670 [R 21 938]	R -94 257 [R -118 846]
Total vehicle debt			
Quintile 1	-	-	R 249 961 [R 96 945]
Quintile 2	-	-	-
Quintile 3	-	-	-
Quintile 4	R -59 782 [R -81 907]	R 83 508 [R 335]	R 13 435 [R 13 435]
Quintile 5	R -38 261 [R 7 346]	R 1 796 [R 21 081]	R 8 696 [R 48 950]
Total consumer debt			
Quintile 1	R 9 110 [R 13 574]	R 11 294 [R -1 367]	R 15 545 [R 57 084]
Quintile 2	R 2 575 [R 5 796]	R -2 917 [R -3 581]	R -1 486 [R 1 596]
Quintile 3	R 8 [R -451]	R -1 728 [R -1 167]	R 2 106 [R 6 556]
Quintile 4	R 4 734 [R 7 756]	R -539 [R 3 509]	R 466 [R 8 211]
Quintile 5	R -1 760 [R -2 376]	R 2 605 [R 11 542]	R 5 610 [R 82 153]
Total other debt			
Quintile 1	R 41 [R 38]	R 297 [R -1 013]	R 305 [R 694]
Quintile 2	R -85 [R -508]	R -211 [R 1 414]	R 96 [R 913]
Quintile 3	R 684 [R -331]	R 205 [R 661]	R 120 [R 105]
Quintile 4	R 154 [R 2 193]	R 531 [R 348]	R 980 [R 2 647]
Quintile 5	R 1 036 [R -1 274]	R 661 [R 1 118]	R 319 [R 11 292]

All values reported are in real terms. Medians are reported and means in [ ]. For vehicle debt in quintile 1 - 3, we had no matched respondents who reported vehicle debt in Wave 1 and respectively in subsequent waves 2 and 3.

Source: Own calculations, NIDS

C.3 Additional probit results for deleveraging

Table C.3.1: Probit results for deleveraging for Wave 1 - 2

	Wave 1 - 2				
	(1)	(2)	(3)	(4)	(5)
At least one adult employed in the household	-0.028 (-0.39)	-0.007 (-0.10)	0.018 (0.26)	0.017 (0.25)	0.012 (0.16)
Household who receive at least one welfare grant	-0.109* (-1.73)	-0.108* (-1.69)	-0.080 (-1.32)	-0.079 (-1.30)	-0.078 (-1.29)
Children Share	0.023 (0.20)	0.001 (0.01)	-0.018 (-0.16)	-0.026 (-0.23)	-0.012 (-0.10)
Female	-0.032 (-0.61)	-0.050 (-0.92)	-0.067 (-1.31)	-0.064 (-1.26)	-0.075 (-1.42)
Married	-0.033 (-0.61)	-0.034 (-0.60)	-0.030 (-0.57)	-0.030 (-0.57)	-0.040 (-0.74)
Coloured	-0.046 (-0.60)	-0.027 (-0.31)	-0.021 (-0.25)	-0.020 (-0.24)	-0.018 (-0.22)
Asian/Indian	0.109 (0.74)	0.153 (1.06)	0.138 (1.02)	0.139 (1.02)	0.137 (1.02)
White	-0.048 (-0.59)	-0.003 (-0.04)	-0.009 (-0.12)	-0.015 (-0.19)	-0.015 (-0.19)
Education	-0.008 (-0.99)	-0.004 (-0.42)	-0.000 (-0.00)	0.000 (0.03)	-0.000 (-0.00)
Age	0.019 (1.56)	0.022* (1.72)	0.021 (1.57)	0.021 (1.56)	0.021 (1.60)
Age squared	-0.000* (-1.66)	-0.000* (-1.81)	-0.000(-1.61)	-0.000 (-1.60)	-0.000 (-1.64)
Live in a traditional area	0.185* (1.65)	0.208* (1.86)	0.206** (1.98)	0.205** (1.98)	0.209** (2.02)
Live in an urban area	0.168* (1.76)	0.195** (2.08)	0.160* (1.82)	0.159* (1.81)	0.165* (1.88)
Ln(Income)	0.082*** (3.05)				
Loan-to-value ratio	-0.001 (-0.22)	-0.001 (-0.30)	-0.003 (-0.75)	-0.003 (-0.84)	-0.003 (-0.86)
Income quintile 2		0.017 (0.11)	0.148 (1.19)	0.144 (1.16)	0.143 (1.16)
Income quintile 3		0.011 (0.09)	0.249** (2.20)	0.246** (2.17)	0.243** (2.16)
Income quintile 4		0.044 (0.39)	0.253** (2.27)	0.251** (2.24)	0.249** (2.26)
Income quintile 5		0.141 (1.29)	0.388*** (3.52)	0.384*** (3.48)	0.390*** (3.58)
Mortgage debt-to-income ratio			0.037** (2.21)	0.036** (2.18)	0.036** (2.18)
Vehicle debt-to-income ratio			-0.057** (-2.26)	-0.059** (-2.46)	-0.059** (-2.44)
Consumer debt-to-income ratio			0.400*** (3.37)	0.398*** (3.35)	0.389*** (3.28)
Other debt-to-income ratio			0.327** (2.22)	0.326** (2.20)	0.338** (2.26)
Mortgage repayment-to-income ratio				0.003 (0.71)	0.003 (0.63)
Future uncertainty (worse off)					-0.070 (-0.77)
Observations	747	747	747	747	747

t statistics in parenthese.

* p<0.10 ** p<0.05 *** p<0.01

Due to the small size in the Asian/Indian sample these results should be read with caution. Results are marginal effects. Results are weighted using post-stratification weights. Exclusion categories are: male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future. Future uncertainty refers to in 2 years time for Wave 1 - 2. All respondents had to have reported debt in Wave 1 and Wave 2, respectively.

Source: Own calculations, NIDS

Table C.3.2: Probit results for deleveraging for Wave 1 - 3

	Wave 1 - 3				
	(1)	(2)	(3)	(4)	(5)
At least one adult employed in the household	-0.045 (-0.58)	-0.026 (-0.33)	-0.016 (-0.20)	-0.012 (-0.16)	-0.048 (-0.60)
Household who receive at least one welfare grant	0.014 (0.23)	-0.007 (-0.11)	-0.005 (-0.08)	-0.006 (-0.10)	-0.016 (-0.27)
Children Share	0.066 (0.56)	0.060 (0.52)	-0.004 (-0.04)	0.001 (0.01)	0.041 (0.37)
Female	-0.038 (-0.71)	-0.040 (-0.76)	-0.054 (-1.08)	-0.056 (-1.12)	-0.091* (-1.82)
Married	0.047 (0.89)	0.046 (0.88)	-0.002 (-0.03)	-0.003 (-0.06)	-0.054 (-1.05)
Coloured	0.022 (0.26)	0.016 (0.20)	0.028 (0.40)	0.029 (0.41)	0.022 (0.32)
Asian/Indian	-0.051 (-0.35)	-0.019 (-0.14)	-0.049 (-0.36)	-0.051 (-0.38)	-0.043 (-0.31)
White	-0.088 (-1.07)	-0.057 (-0.72)	-0.014 (-0.19)	-0.010 (-0.13)	0.011 (0.15)
Education	-0.007 (-0.82)	-0.007 (-0.82)	-0.014* (-1.68)	-0.014* (-1.73)	-0.016** (-2.05)
Age	0.014 (1.09)	0.015 (1.23)	0.013 (1.15)	0.014 (1.18)	0.015 (1.36)
Age squared	-0.000 (-0.59)	-0.000 (-0.76)	-0.000 (-0.72)	-0.000 (-0.75)	-0.000 (-0.93)
Live in a traditional area	-0.208 (-1.62)	-0.198* (-1.71)	-0.192* (-1.82)	-0.192* (-1.82)	-0.181* (-1.72)
Live in an urban area	-0.083 (-0.69)	-0.058 (-0.55)	-0.100 (-1.06)	-0.099 (-1.05)	-0.092 (-0.97)
Ln(Income)	0.056* (1.81)				
Loan-to-value ratio	0.866** (2.45)	0.852** (2.57)	0.369* (1.78)	0.374* (1.79)	0.357* (1.72)
Income quintile 2		0.226* (1.75)	0.377*** (3.46)	0.378*** (3.47)	0.359*** (3.36)
Income quintile 3		0.264** (2.45)	0.391*** (4.45)	0.393*** (4.46)	0.380*** (4.36)
Income quintile 4		0.086 (0.86)	0.195** (2.51)	0.196** (2.51)	0.196*** (2.58)
Income quintile 5		0.257** (2.46)	0.374*** (4.52)	0.376*** (4.55)	0.394*** (4.94)
Mortgage debt-to-income ratio			0.103*** (4.22)	0.105*** (4.17)	0.107*** (4.26)
Vehicle debt-to-income ratio			0.145 (1.41)	0.146 (1.42)	0.170* (1.87)
Consumer debt-to-income ratio			0.150** (2.05)	0.153** (2.05)	0.139** (2.00)
Other debt-to-income ratio			-0.090* (-1.66)	-0.092* (-1.67)	-0.077 (-1.50)
Mortgage repayment-to-income ratio				-0.011 (-0.99)	-0.014 (-1.29)
Future uncertainty (worse off)					-0.228*** (-2.60)
Observations	859	859	859	859	859

t statistics in parenthese.

* p<0.10 ** p<0.05 *** p<0.01

Due to the small size in the Asian/Indian sample these results should be read with caution. Results are marginal effects. Results are weighted using post-stratification weights. Exclusion categories are: male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future. Future uncertainty refers to in 5 years time for Wave 1 - 3. All respondents had to have reported debt in Wave 1 and Wave 3, respectively.

Source: Own calculations, NIDS

C.4 Additional probit results for deleveraging with interactions for high debt-to-income ratios and income

Table C.4.1: Probit model for deleveraging when controlling for the interaction between income and various debt-to-income ratios for Wave 1 - 2

	Deleveraging over Wave 1 - 2			
Deleveraging	(1)	(2)	(3)	(4)
At least one adult employed in the household	-0.103 (-0.51)	-0.187 (-0.95)	-0.067 (-0.35)	-0.058 (-0.31)
Household who receive at least one welfare grant	-0.162 (-0.97)	-0.367** (-2.15)	-0.333** (-1.96)	-0.340** (-2.06)
Children Share	-0.177 (-0.56)	0.083 (0.26)	0.171 (0.54)	0.052 (0.16)
Female	-0.180 (-1.19)	-0.079 (-0.53)	-0.100 (-0.68)	-0.096 (-0.67)
Married	-0.152 (-0.99)	-0.234 (-1.56)	-0.162 (-1.10)	-0.130 (-0.88)
Coloured	-0.105 (-0.49)	0.005 (0.03)	-0.141 (-0.65)	-0.116 (-0.58)
Asian/Indian	-0.073 (-0.19)	0.279 (0.64)	0.342 (0.83)	0.296 (0.75)
White	-0.253 (-1.07)	-0.070 (-0.32)	-0.211 (-0.95)	-0.196 (-0.89)
Education	-0.034 (-1.49)	-0.034 (-1.45)	-0.017 (-0.76)	-0.029 (-1.28)
Age	0.065* (1.91)	0.055* (1.69)	0.043 (1.15)	0.050 (1.49)
Age squared	-0.001* (-1.93)	-0.001* (-1.86)	-0.001 (-1.22)	-0.001(-1.56)
Live in a traditional area	0.452 (1.43)	0.601* (1.72)	0.583* (1.86)	0.435 (1.36)
Live in an urban area	0.277 (1.01)	0.547* (1.77)	0.462* (1.74)	0.441 (1.60)
Loan-to-value ratio	-0.006 (-0.37)	-0.009 (-0.71)	-0.000 (-0.03)	-0.002 (-0.15)
Mortgage repayment-to-income ratio	0.003 (0.51)	0.033* (1.79)	0.002 (0.61)	0.003 (1.12)
Future uncertainty (worse off)	-0.345 (-1.40)	-0.379* (-1.73)	-0.193 (-0.83)	-0.322 (-1.41)
Ln(Income)	0.192** (2.23)	0.151* (1.75)	0.300*** (3.48)	0.323*** (3.78)
Mortgage debt-to-income ratio	-1.272*** (-3.66)			
Ln(Income) # Mortgage debt-to-income ratio	0.143*** (4.17)			
Vehicle debt-to-income ratio		-10.69*** (-3.13)		
Ln(Income) # Vehicle debt-to-income ratio		0.980*** (3.28)		
Consumer debt-to-income ratio			-1.149*** (-3.16)	
Ln(Income) # Consumer debt-to-income ratio			0.244*** (3.52)	
Other debt-to-income ratio				10.42* (1.66)
Ln(Income) # Other debt-to-income ratio				-0.894 (-1.41)
Constant	-3.309*** (-2.88)	-2.669** (-2.41)	-4.408*** (-3.92)	-4.569*** (-4.02)
Observations	747	747	747	747

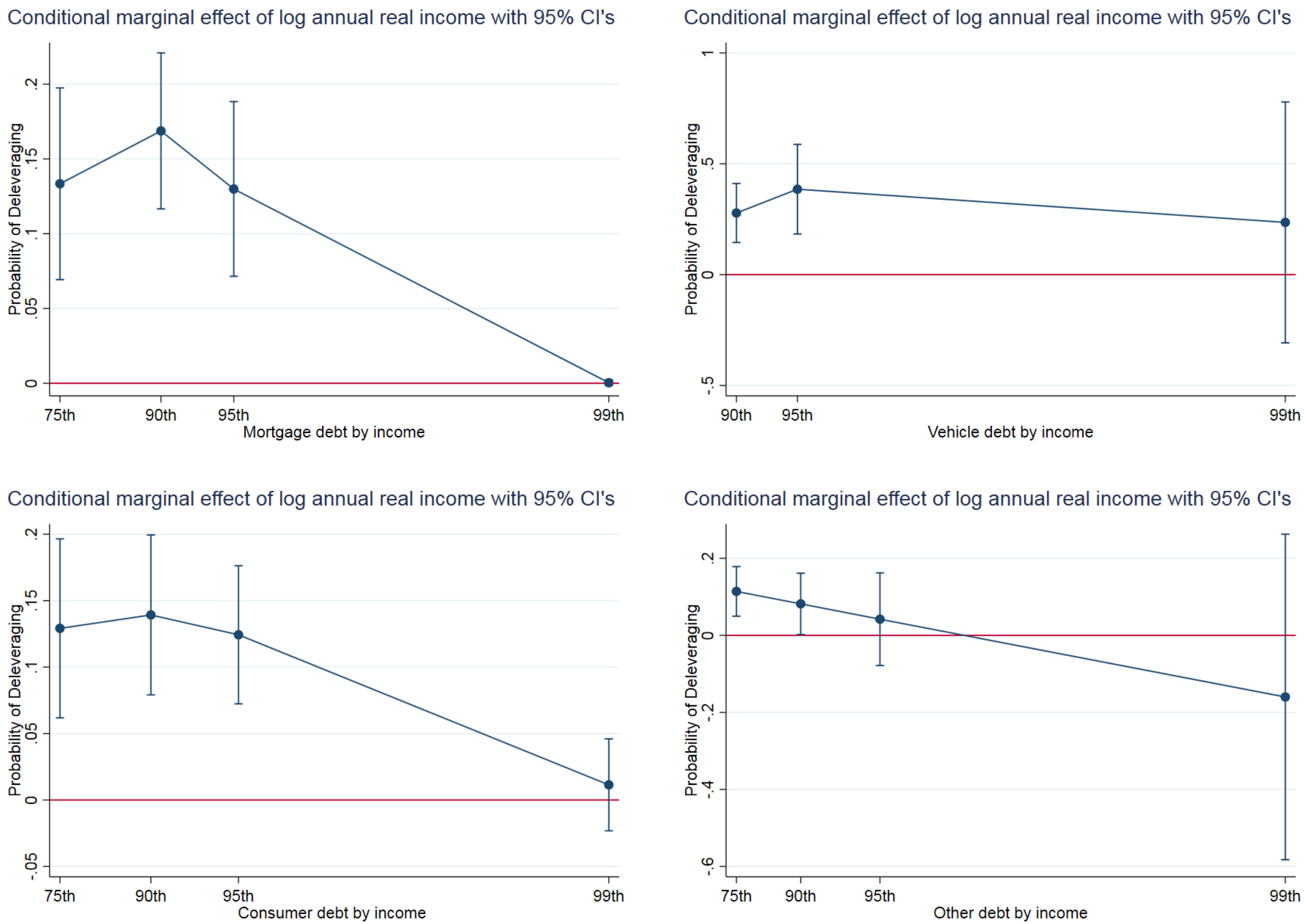
t statistics in parentheses

* p<0.10 ** p<0.05 *** p<0.01

Due to the small size in the Asian/Indian sample these results should be read with caution. Results are not in marginal effects. Results are weighted using post-stratification weights. Exclusion categories are: male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future. Future uncertainty refers to in 2 years time for Wave 1 - 2. All respondents had to have reported debt in Wave 1 and Wave 2 respectively.

Source: Own calculations, NIDS

Figure C.4.1: Effect of a change in log income on deleveraging at selected points in the debt-to-income distribtion for Wave 1 - 2



CI - Confidence interval. Results are shown at the 75th, 90th, 95th and 99th percentile of debt-to-income and income (while keeping all other variables at the mean), except for vehicle debt-to-income, that is zero at the 75th percentile and therefore excluded. Results are weighted using post-stratification weights. All respondents had to have reported debt in both Wave 1 and Wave 2. Non-weighted results are similar, except for mortgage debt where the probability of deleveraging continue to increase at the 95th percentile.

Source: Own calculations, NIDS

Table C.4.2: Probit model for deleveraging when controlling for the interaction between income and various debt-to-income ratios for Wave 1 - 3

	Deleveraging over Wave 1 - 3			
Deleveraging	(1)	(2)	(3)	(4)
At least one adult employed in the household	-0.210 (-0.88)	-0.237 (-1.10)	-0.195 (-0.90)	-0.205 (-0.96)
Household who receive at least one welfare grant	0.149 (0.89)	-0.025 (-0.15)	0.045 (0.27)	0.020 (0.12)
Children Share	-0.040 (-0.12)	0.321 (1.00)	0.280 (0.86)	0.353 (1.10)
Female	-0.274* (-1.80)	-0.178 (-1.19)	-0.137 (-0.92)	-0.181 (-1.23)
Married	-0.078 (-0.50)	-0.061 (-0.40)	0.011 (0.07)	-0.007 (-0.04)
Coloured	-0.008 (-0.04)	0.044 (0.20)	0.069 (0.30)	0.077 (0.34)
Asian/Indian	-0.509 (-1.23)	-0.094 (-0.23)	-0.108 (-0.27)	-0.204 (-0.51)
White	-0.343 (-1.48)	-0.197 (-0.83)	-0.255 (-1.09)	-0.280 (-1.21)
Education	-0.041* (-1.69)	-0.038 (-1.64)	-0.024 (-1.03)	-0.023 (-0.97)
Age	0.036 (1.06)	0.034 (0.98)	0.036 (1.05)	0.023 (0.68)
Age squared	-0.000 (-0.60)	-0.000 (-0.50)	-0.000 (-0.51)	-0.000 (-0.13)
Live in a traditional area	-0.668* (-1.92)	-0.525 (-1.42)	-0.653* (-1.72)	-0.452 (-1.46)
Live in an urban area	-0.451 (-1.41)	-0.189 (-0.55)	-0.330 (-0.94)	-0.148 (-0.53)
Loan-to-value ratio	0.830 (1.33)	2.346** (2.40)	2.446** (2.42)	2.472** (2.47)
Mortgage repayment-to-income ratio	-0.016 (-0.39)	-0.003 (-0.07)	-0.008 (-0.20)	0.003 (0.08)
Future uncertainty (worse off)	-0.486* (-1.92)	-0.559** (-2.30)	-0.348 (-1.41)	-0.424* (-1.74)
Ln(Income)	0.299*** (3.19)	0.194** (2.09)	0.241*** (2.68)	0.296*** (3.26)
Mortgage debt-to-income ratio	-0.010 (-0.04)			
Ln(Income) # Mortgage debt-to-income ratio	0.031 (1.26)			
Vehicle debt-to-income ratio		-0.715** (-2.30)		
Ln(Income) # Vehicle debt-to-income ratio		0.116** (2.37)		
Consumer debt-to-income ratio			-1.302*** (-2.92)	
Ln(Income) # Consumer debt-to-income ratio			0.211*** (2.98)	
Other debt-to-income ratio				-3.213*** (-2.79)
Ln(Income) # Other debt-to-income ratio				0.528*** (2.92)
Constant	-3.391*** (-2.76)	-2.472** (-2.09)	-3.265*** (-2.74)	-3.772*** (-3.34)
Observations	859	859	859	859

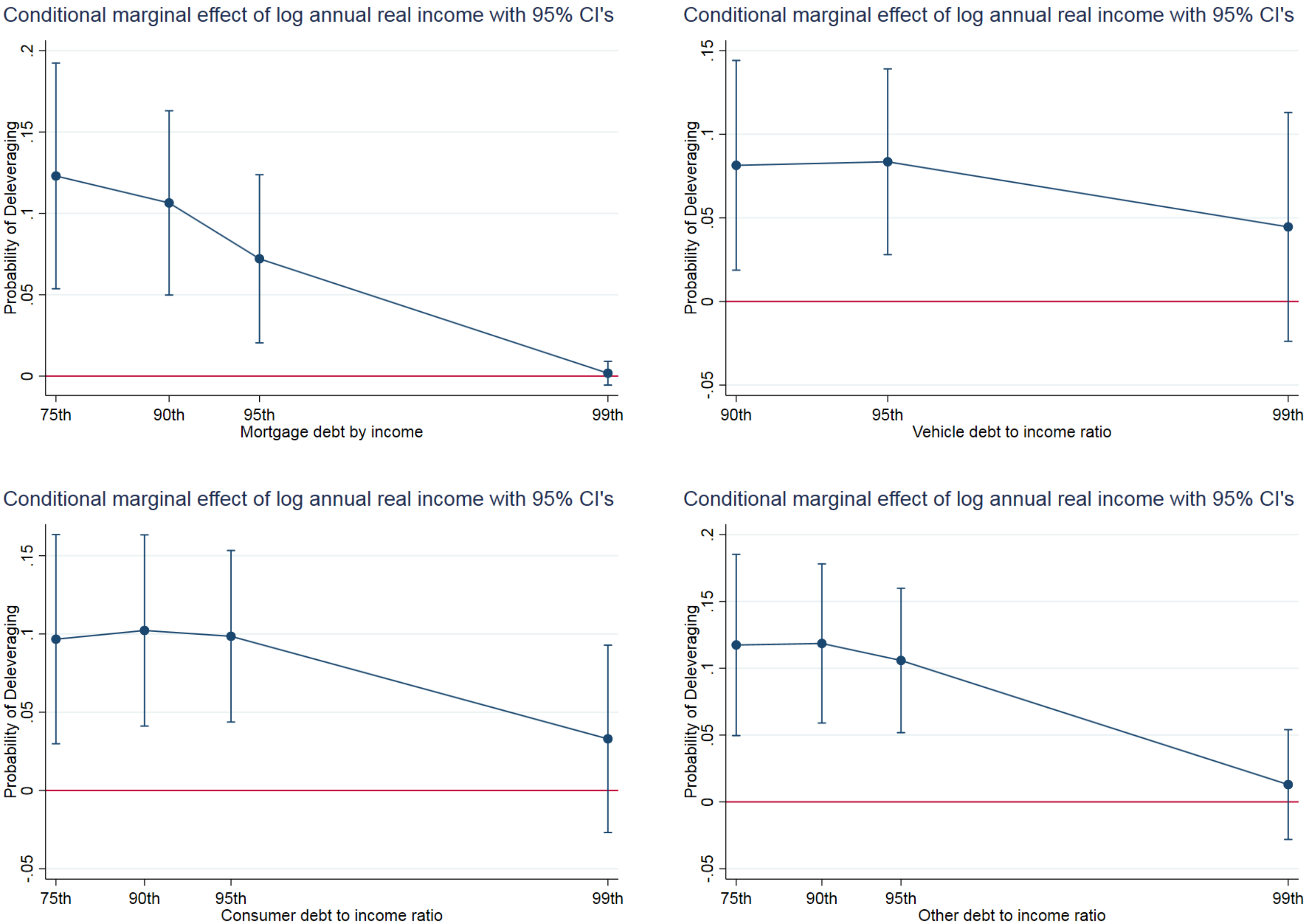
t statistics in parentheses

* p<0.10 ** p<0.05 *** p<0.01

Due to the small size in the Asian/Indian sample these results should be read with caution. Results are not in marginal effects. Results are weighted using post-stratification weights. Exclusion categories are: male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future. Future uncertainty refers to in 5 years time for Wave 1 - 3. All respondents had to have reported debt in Wave 1 and Wave 3 respectively.

Source: Own calculations, NIDS

Figure C.4.2: Effect of a change in log income on deleveraging at selected points in the debt-to-income distribtion for Wave 1 - 3



CI - Confidence interval. Results are shown at the 75th, 90th, 95th and 99th percentile of debt-to-income and income (while keeping all other variables at the mean), except for vehicle debt-to-income, that is zero at the 75th percentile and therefore excluded. Results are weighted using post-stratification weights. All respondents had to have reported debt in both Wave 1 and Wave 3. Non-weighted results are similar.

Source: Own calculations, NIDS

C.5 Probit results for the probability of attrition between Wave 1 and subsequent waves

Table C.5.1: Marginal effects of the probability of reporting debt in Wave 1 and not the subsequent waves

	Wave 1 - 2	Wave 1 - 3	Wave 1 - 4
At least one adult employed in the household	0.077*** (3.07)	0.046** (1.99)	0.050*** (2.62)
Household who receive at least one welfare grant	0.074*** (3.05)	0.040* (1.74)	-0.010 (-0.52)
Children Share	-0.150*** (-3.36)	-0.128*** (-3.05)	-0.108*** (-3.17)
Female	-0.012 (-0.56)	-0.027 (-1.30)	-0.024 (-1.37)
Married	-0.041* (-1.85)	-0.019 (-0.90)	-0.020 (-1.14)
Coloured	-0.003 (-0.09)	-0.082*** (-3.15)	0.013 (0.54)
Asian/Indian	0.114 (1.52)	0.003 (0.04)	0.090 (1.38)
White	0.230*** (6.73)	0.119*** (3.25)	0.258*** (7.15)
Education	-0.001 (-0.25)	-0.003 (-1.07)	-0.000 (-0.14)
Age	-0.002* (-1.77)	0.000 (0.33)	-0.000 (-0.17)
Live in a traditional area	-0.000 (-0.00)	0.017 (0.48)	0.014 (0.45)
Live in an urban area	-0.019 (-0.51)	0.076** (2.35)	0.018 (0.66)
Loan-to-value ratio	0.046 (1.13)	0.038 (1.02)	0.071** (2.57)
Income quintile 2	0.079** (2.12)	0.044 (1.28)	0.097*** (3.74)
Income quintile 3	0.065* (1.76)	-0.009 (-0.26)	0.078*** (3.09)
Income quintile 4	0.029 (0.75)	0.067* (1.83)	0.163*** (5.57)
Income quintile 5	0.001 (0.92)	0.001 (1.49)	0.003 (0.85)
Mortgage debt-to-income ratio	0.007** (2.08)	0.011*** (2.58)	0.009** (2.55)
Vehicle debt-to-income ratio	-0.003** (-2.28)	-0.004** (-2.15)	-0.003** (-2.44)
Consumer debt-to-income ratio	0.045* (1.79)	-0.005 (-0.64)	0.010* (1.73)
Other debt-to-income ratio	-0.025 (-1.11)	0.012 (0.65)	-0.008 (-0.78)
Mortgage repayment-to-income ratio	-0.009** (-2.02)	0.003 (1.29)	-0.008** (-2.18)
Future uncertainty (worse off)	-0.068* (-1.85)	0.007 (0.19)	-0.029 (-0.99)
Observations	2 545	2 752	3 222

t statistics in parenthese.
* p<0.10 ** p<0.05 *** p<0.01
Due to the small size in the Asian/Indian sample these results should be read with caution. Results are marginal effects. Results are not weighted. Exclusion categories are: male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future. Future uncertainty refers to in 5 years time for Wave 1 - 3 and Wave 1 - 4, as compared to 2 years time in Wave 1 - 2.

Source: Own calculations, NIDS

C.6 Non-weighted results

Table C.6.1: Probit results for deleveraging for Wave 1 - 2, non-weighted

	Wave 1 - 2				
	(1)	(2)	(3)	(4)	(5)
At least one adult employed in the household	0.033 (0.62)	0.042 (0.77)	0.026 (0.49)	0.026 (0.49)	0.022 (0.40)
Household who receive at least one welfare grant	-0.058 (-1.23)	-0.062 (-1.30)	-0.028 (-0.59)	-0.028 (-0.60)	-0.029 (-0.62)
Children Share	0.126 (1.48)	0.126 (1.47)	0.129 (1.56)	0.130 (1.58)	0.139* (1.68)
Female	-0.015 (-0.38)	-0.020 (-0.50)	-0.030 (-0.79)	-0.031 (-0.80)	-0.040 (-1.03)
Married	-0.009 (-0.23)	-0.006 (-0.14)	-0.006 (-0.15)	-0.006 (-0.15)	-0.016 (-0.41)
Coloured	-0.050 (-1.01)	-0.049 (-0.97)	-0.047 (-0.97)	-0.047 (-0.97)	-0.047 (-0.98)
Asian/Indian	0.005 (0.04)	0.024 (0.20)	0.040 (0.35)	0.039 (0.35)	0.035 (0.31)
White	-0.061 (-0.96)	-0.042 (-0.68)	-0.025 (-0.42)	-0.024 (-0.41)	-0.022 (-0.38)
Education	0.004 (0.62)	0.006 (0.95)	0.005 (0.88)	0.005 (0.87)	0.005 (0.81)
Age	0.002 (0.26)	0.003 (0.36)	0.004 (0.38)	0.004 (0.38)	0.004 (0.43)
Age squared	-0.000 (-0.16)	-0.000 (-0.23)	-0.000 (-0.31)	-0.000 (-0.32)	-0.000 (-0.36)
Live in a traditional area	0.012 (0.12)	0.014 (0.15)	0.046 (0.52)	0.046 (0.52)	0.044 (0.50)
Live in an urban area	0.049 (0.62)	0.057 (0.72)	0.050 (0.68)	0.050 (0.68)	0.049 (0.67)
Ln(Income)	0.025 (1.15)				
Loan-to-value ratio	0.003 (0.86)	0.003 (0.88)	0.001 (0.53)	0.002 (0.56)	0.001 (0.53)
Income quintile 2		-0.028 (-0.25)	0.113 (1.02)	0.116 (1.05)	0.116 (1.05)
Income quintile 3		-0.016 (-0.17)	0.187** (1.97)	0.189** (1.99)	0.188** (1.99)
Income quintile 4		-0.017 (-0.19)	0.199** (2.19)	0.200** (2.21)	0.199** (2.21)
Income quintile 5		-0.004 (-0.05)	0.247*** (2.72)	0.249*** (2.75)	0.254*** (2.82)
Mortgage debt-to-income ratio			0.036** (2.22)	0.036** (2.21)	0.036** (2.20)
Vehicle debt-to-income ratio			-0.054** (-2.26)	-0.054** (-2.23)	-0.054** (-2.22)
Consumer debt-to-income ratio			0.436*** (4.42)	0.441*** (4.45)	0.434*** (4.41)
Other debt-to-income ratio			0.345** (2.55)	0.346** (2.54)	0.353*** (2.59)
Mortgage repayment-to-income ratio				-0.001 (-0.83)	-0.001 (-0.89)
Future uncertainty (worse off)					-0.064 (-1.09)
Observations	747	747	747	747	747

t statistics in parenthese.
* p<0.10 ** p<0.05 *** p<0.01
Due to the small size in the Asian/Indian sample these results should be read with caution. Results are marginal effects and non-weighted.
Exclusion categories are: male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future.
Future uncertainty refers to in 2 years time for Wave 1 - 2.

Source: Own calculations, NIDS

Table C.6.2: Probit results for deleveraging for Wave 1 - 3, non-weighted

	Wave 1 - 3				
	(1)	(2)	(3)	(4)	(5)
At least one adult employed in the household	0.059 (1.17)	0.069 (1.34)	0.069 (1.41)	0.071 (1.43)	0.052 (1.04)
Household who receive at least one welfare grant	0.036 (0.85)	0.026 (0.60)	0.039 (0.92)	0.038 (0.89)	0.035 (0.83)
Children Share	0.033 (0.42)	0.036 (0.46)	0.006 (0.08)	0.011 (0.14)	0.022 (0.28)
Female	-0.012 (-0.33)	-0.016 (-0.42)	-0.021 (-0.58)	-0.023 (-0.63)	-0.043 (-1.18)
Married	0.078** (2.03)	0.084** (2.21)	0.052 (1.43)	0.052 (1.43)	0.026 (0.67)
Coloured	0.031 (0.70)	0.028 (0.61)	0.032 (0.73)	0.033 (0.75)	0.032 (0.73)
Asian/Indian	0.018 (0.17)	0.033 (0.32)	0.003 (0.03)	-0.001 (-0.01)	-0.002 (-0.02)
White	-0.038 (-0.63)	-0.026 (-0.45)	-0.014 (-0.26)	-0.014 (-0.25)	-0.008 (-0.15)
Education	-0.000 (-0.02)	0.002 (0.29)	-0.006 (-1.01)	-0.006 (-1.01)	-0.006 (-1.17)
Age	0.013 (1.53)	0.013 (1.59)	0.011 (1.39)	0.011 (1.41)	0.012 (1.60)
Age squared	-0.000 (-1.17)	-0.000 (-1.20)	-0.000 (-1.03)	-0.000 (-1.05)	-0.000 (-1.22)
Live in a traditional area	-0.025 (-0.32)	-0.029 (-0.36)	-0.028 (-0.37)	-0.027 (-0.37)	-0.029 (-0.39)
Live in an urban area	0.066 (1.01)	0.074 (1.13)	0.037 (0.60)	0.038 (0.61)	0.037 (0.60)
Ln(Income)	0.022 (1.02)				
Loan-to-value ratio	0.498* (1.87)	0.501* (1.90)	0.236 (1.46)	0.234 (1.44)	0.220 (1.38)
Income quintile 2		-0.019 (-0.19)	0.078 (0.75)	0.079 (0.76)	0.069 (0.67)
Income quintile 3		0.128 (1.41)	0.226** (2.44)	0.227** (2.45)	0.228** (2.50)
Income quintile 4		0.017 (0.20)	0.111 (1.24)	0.111 (1.24)	0.111 (1.27)
Income quintile 5		0.051 (0.57)	0.147 (1.58)	0.150 (1.61)	0.163* (1.78)
Mortgage debt-to-income ratio			0.101*** (5.18)	0.105*** (5.11)	0.107*** (5.16)
Vehicle debt-to-income ratio			0.155** (2.24)	0.154** (2.23)	0.157** (2.40)
Consumer debt-to-income ratio			0.090* (1.71)	0.093* (1.71)	0.090* (1.68)
Other debt-to-income ratio			-0.063 (-1.64)	-0.064 (-1.64)	-0.060 (-1.53)
Mortgage repayment-to-income ratio				-0.010 (-1.22)	-0.011 (-1.32)
Future uncertainty (worse off)					-0.136** (-2.30)
Observations	859	859	859	859	859

t statistics in parenthese.

* p<0.10 ** p<0.05 *** p<0.01

Due to the small size in the Asian/Indian sample these results should be read with caution. Results are marginal effects and non-weighted.
Exclusion categories are: male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future.
Future uncertainty refers to in 5 years time for Wave 1 - 3.

Source: Own calculations, NIDS

Table C.6.3: Probit results for deleveraging for Wave 1 - 4, non-weighted

	Wave 1 - 4				
	(1)	(2)	(3)	(4)	(5)
At least one adult employed in the household	0.016 (0.37)	0.014(0.31)	0.028 (0.62)	0.028 (0.62)	0.025 (0.57)
Household who receive at least one welfare grant	-0.007 (-0.18)	-0.009 (-0.22)	0.004 (0.11)	0.004 (0.11)	0.003 (0.07)
Children Share	-0.060 (-0.84)	-0.061 (-0.86)	-0.067 (-0.94)	-0.067 (-0.94)	-0.063 (-0.88)
Female	0.010 (0.30)	0.010 (0.31)	0.007 (0.21)	0.007 (0.21)	0.003 (0.08)
Married	0.075** (2.15)	0.079** (2.27)	0.077** (2.23)	0.077** (2.23)	0.070** (1.97)
Coloured	-0.039 (-0.92)	-0.043 (-1.01)	-0.041 (-0.98)	-0.041 (-0.98)	-0.040 (-0.96)
Asian/Indian	-0.028 (-0.25)	-0.012 (-0.11)	-0.026 (-0.24)	-0.026 (-0.24)	-0.027 (-0.25)
White	-0.036 (-0.60)	-0.008 (-0.14)	-0.005 (-0.08)	-0.005(-0.08)	-0.001 (-0.02)
Education	-0.011** (-2.16)	-0.010** (-2.11)	-0.011** (-2.27)	-0.011** (-2.27)	-0.011** (-2.30)
Age	0.002 (0.22)	0.002 (0.26)	0.003 (0.35)	0.003 (0.35)	0.003 (0.37)
Age squared	-0.000 (-0.10)	-0.000 (-0.17)	-0.000 (-0.26)	-0.000 (-0.26)	-0.000 (-0.27)
Live in a traditional area	0.046 (0.66)	0.049 (0.71)	0.055 (0.79)	0.055 (0.79)	0.057 (0.82)
Live in an urban area	0.124** (2.09)	0.128** (2.15)	0.105* (1.78)	0.105* (1.78)	0.106* (1.81)
Ln(Income)	0.052*** (2.87)				
Loan-to-value ratio	-0.005*** (-2.80)	-0.005*** (-2.70)	-0.009 (-0.99)	-0.009 (-0.99)	-0.008 (-1.43)
Income quintile 2		0.076 (1.02)	0.130* (1.76)	0.130* (1.75)	0.129* (1.74)
Income quintile 3		0.095 (1.47)	0.134** (2.08)	0.134** (2.08)	0.135** (2.09)
Income quintile 4		0.103* (1.68)	0.139** (2.25)	0.139** (2.25)	0.139** (2.25)
Income quintile 5		0.175*** (2.80)	0.221*** (3.43)	0.221*** (3.43)	0.224*** (3.47)
Mortgage debt-to-income ratio			0.040*** (4.03)	0.040*** (4.00)	0.040*** (3.95)
Vehicle debt-to-income ratio			-0.061*** (-4.05)	-0.061*** (-4.04)	-0.062*** (-3.99)
Consumer debt-to-income ratio			0.106** (2.09)	0.106** (2.07)	0.105** (2.01)
Other debt-to-income ratio			-0.067* (-1.76)	-0.067* (-1.74)	-0.065* (-1.67)
Mortgage repayment-to-income ratio				0.000 (0.01)	-0.000 (-0.01)
Future uncertainty (worse off)					-0.046 (-0.81)
Observations	1 042	1 042	1 042	1 042	1 042

t statistics in parenthese.

* p<0.10 ** p<0.05 *** p<0.01

Due to the small size in the Asian/Indian sample these results should be read with caution. Results are marginal effects and non-weighted. Exclusion categories are: male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future. Future uncertainty refers to in 5 years time for Wave 1 - 4.

Source: Own calculations, NIDS

Table C.6.4: Probit model for deleveraging when controlling for the interaction between income and various debt-to-income ratios for Wave 1 - 2

	Deleveraging over Wave 1 - 2, non-weighted			
Deleveraging	(1)	(2)	(3)	(4)
At least one adult employed in the household	0.090 (0.64)	0.012 (0.09)	0.034 (0.24)	0.050 (0.36)
Household who receive at least one welfare grant	-0.084 (-0.68)	-0.213* (-1.70)	-0.132 (-1.05)	-0.132 (-1.08)
Children Share	0.218 (0.95)	0.307 (1.36)	0.425* (1.88)	0.309 (1.39)
Female	-0.105 (-0.99)	-0.030 (-0.28)	-0.070 (-0.66)	-0.056 (-0.53)
Married	-0.079 (-0.72)	-0.121 (-1.11)	-0.078 (-0.72)	-0.078 (-0.73)
Coloured	-0.174 (-1.34)	-0.083 (-0.64)	-0.145 (-1.10)	-0.123 (-0.96)
Asian/Indian	-0.073 (-0.23)	-0.114 (-0.34)	0.005 (0.02)	-0.046 (-0.15)
White	-0.252 (-1.49)	-0.118 (-0.70)	-0.180 (-1.08)	-0.179 (-1.08)
Education	-0.000 (-0.02)	-0.000 (-0.01)	0.008 (0.46)	0.003 (0.20)
Age	0.012 (0.50)	0.007 (0.27)	-0.005 (-0.18)	0.011 (0.45)
Age squared	-0.000 (-0.35)	-0.000 (-0.20)	0.000 (0.21)	-0.000 (-0.39)
Live in a traditional area	0.036 (0.15)	-0.039 (-0.16)	0.109 (0.45)	-0.054 (-0.22)
Live in an urban area	0.010 (0.05)	0.072 (0.35)	0.152 (0.75)	0.080 (0.39)
Loan-to-value ratio	0.004 (0.39)	0.006 (0.71)	0.007 (0.76)	0.007 (0.83)
Mortgage repayment-to-income ratio	0.000 (0.15)	0.018 (1.13)	-0.002 (-0.72)	0.002 (0.89)
Future uncertainty (worse off)	-0.290* (-1.74)	-0.188 (-1.13)	-0.156 (-0.95)	-0.257 (-1.58)
Ln(Income)	0.014 (0.21)	0.011 (0.18)	0.130** (2.02)	0.162** (2.50)
Mortgage debt-to-income ratio	-1.208*** (-3.61)			
Ln(Income) # Mortgage debt-to-income ratio	0.137*** (4.26)			
Vehicle debt-to-income ratio		-4.955* (-1.76)		
Ln(Income) # Vehicle debt-to-income ratio		0.488** (2.01)		
Consumer debt-to-income ratio			-1.069*** (-4.10)	
Ln(Income) # Consumer debt-to-income ratio			0.231*** (4.56)	
Other debt-to-income ratio				2.307 (0.53)
Ln(Income) # Other debt-to-income ratio				-0.118 (-0.27)
Constant	-0.690 (-0.85)	-0.402 (-0.51)	-1.770** (-2.17)	-2.247*** (-2.71)
Observations	747	747	747	747

t statistics in parenthese.

* p<0.10 ** p<0.05 *** p<0.01

Due to the small size in the Asian/Indian sample these results should be read with caution. Results are not marginal effects. Results are non-weighted. Exclusion categories are: male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future. Future uncertainty refers to 2 years time in Wave 1 - 2.

Source: Own calculations, NIDS

Table C.6.5: Probit model for deleveraging when controlling for the interaction between income and various debt-to-income ratios for Wave 1 - 3, non-weighted

	Deleveraging over Wave 1 - 3			
Deleveraging	(1)	(2)	(3)	(4)
At least one adult employed in the household	0.154 (1.10)	0.085 (0.63)	0.092 (0.67)	0.106 (0.77)
Household who receive at least one welfare grant	0.134 (1.17)	0.082 (0.72)	0.128 (1.14)	0.064 (0.56)
Children Share	-0.020 (-0.09)	0.131 (0.62)	0.209 (1.00)	0.140 (0.67)
Female	-0.137 (-1.33)	-0.061 (-0.60)	-0.034 (-0.34)	-0.065 (-0.64)
Married	0.086 (0.79)	0.093 (0.88)	0.135 (1.29)	0.121 (1.16)
Coloured	0.101 (0.83)	0.094 (0.78)	0.082 (0.68)	0.152 (1.26)
Asian/Indian	-0.131 (-0.42)	0.043 (0.16)	0.049 (0.17)	0.042 (0.15)
White	-0.149 (-0.92)	-0.085 (-0.52)	-0.091 (-0.56)	-0.038 (-0.23)
Education	-0.017 (-1.08)	-0.010 (-0.65)	-0.007 (-0.47)	-0.004 (-0.24)
Age	0.034 (1.55)	0.033 (1.49)	0.033 (1.48)	0.029 (1.30)
Age squared	-0.000 (-1.17)	-0.000 (-1.13)	-0.000 (-1.12)	-0.000 (-0.94)
Live in a traditional area	-0.061 (-0.29)	-0.073 (-0.35)	-0.080 (-0.38)	-0.046 (-0.22)
Live in an urban area	0.063 (0.36)	0.175 (1.03)	0.138 (0.80)	0.152 (0.88)
Loan-to-value ratio	0.508 (1.16)	1.299* (1.84)	1.353* (1.89)	1.387* (1.91)
Mortgage repayment-to-income ratio	-0.024 (-1.12)	0.002 (0.07)	-0.009 (-0.36)	-0.000 (-0.02)
Future uncertainty (worse off)	-0.383** (-2.26)	-0.279 (-1.62)	-0.226 (-1.33)	-0.242 (-1.44)
Ln(Income)	0.114* (1.88)	0.074 (1.23)	0.123** (1.96)	0.127** (2.02)
Mortgage debt-to-income ratio	-0.106 (-0.69)			
Ln(Income) # Mortgage debt-to-income ratio	0.039** (2.40)			
Vehicle debt-to-income ratio		-0.590*** (-2.81)		
Ln(Income) # Vehicle debt-to-income ratio		0.096*** (2.90)		
Consumer debt-to-income ratio			-1.085** (-2.44)	
Ln(Income) # Consumer debt-to-income ratio			0.175** (2.47)	
Other debt-to-income ratio				-2.948** (-2.35)
Ln(Income) # Other debt-to-income ratio				0.488*** (3.13)
Constant	-2.404*** (-3.23)	-2.009*** (-2.76)	-2.694*** (-3.54)	-2.665*** (-3.55)
Observations	859	859	859	859

t statistics in parenthese.

* p<0.10 ** p<0.05 *** p<0.01

Due to the small size in the Asian/Indian sample these results should be read with caution. Results are not marginal effects and non-weighted. Exclusion categories are: male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future. Future uncertainty refers to in 5 years time for Wave 1 - 3.

Source: Own calculations, NIDS

Table C.6.6: Probit model for deleveraging when controlling for the interaction between income and various debt-to-income ratios for Wave 1 - 4

	Deleveraging over Wave 1 - 4, non-weighted			
Deleveraging	(1)	(2)	(3)	(4)
At least one adult employed in the household	0.123 (1.03)	0.024 (0.21)	0.015 (0.12)	0.033 (0.28)
Household who receive at least one welfare grant	0.045 (0.45)	-0.013 (-0.13)	0.016 (0.16)	-0.017 (-0.17)
Children Share	-0.289 (-1.50)	-0.182 (-0.97)	-0.048 (-0.26)	-0.155 (-0.84)
Female	-0.002 (-0.03)	0.032 (0.37)	0.039 (0.44)	0.021 (0.23)
Married	0.133 (1.39)	0.119 (1.27)	0.157* (1.68)	0.173* (1.88)
Coloured	-0.108 (-0.96)	-0.067 (-0.61)	-0.108 (-0.97)	-0.100 (-0.92)
Asian/Indian	-0.309 (-0.99)	-0.060 (-0.21)	0.020 (0.07)	-0.078 (-0.27)
White	-0.125 (-0.80)	-0.028 (-0.18)	-0.034 (-0.21)	-0.091 (-0.58)
Education	-0.035*** (-2.68)	-0.033*** (-2.59)	-0.032** (-2.49)	-0.028** (-2.19)
Age	0.002 (0.12)	0.003 (0.14)	0.002 (0.08)	0.005 (0.28)
Age squared	0.000 (0.05)	-0.000 (-0.04)	-0.000 (-0.03)	-0.000 (-0.15)
Live in a traditional area	0.119 (0.64)	0.138 (0.74)	0.194 (1.04)	0.113 (0.61)
Live in an urban area	0.211 (1.34)	0.339** (2.14)	0.371** (2.32)	0.317** (2.00)
Loan-to-value ratio	-0.079* (-1.67)	-0.012*** (-2.69)	-0.016*** (-3.46)	-0.013*** (-2.87)
Mortgage repayment-to-income ratio	-0.002 (-0.85)	0.014 (0.63)	-0.001 (-0.59)	0.002 (0.80)
Future uncertainty (worse off)	-0.175 (-1.16)	-0.124 (-0.84)	-0.061 (-0.40)	-0.121 (-0.83)
Ln(Income)	0.125** (2.39)	0.096* (1.89)	0.118** (2.18)	0.143*** (2.81)
Mortgage debt-to-income ratio	-0.455*** (-3.85)			
Ln(Income) # Mortgage debt-to-income ratio	0.070*** (5.08)			
Vehicle debt-to-income ratio		-1.388** (-2.43)		
Ln(Income) # Vehicle debt-to-income ratio		0.178*** (2.97)		
Consumer debt-to-income ratio			-4.407*** (-3.27)	
Ln(Income) # Consumer debt-to-income ratio			0.532*** (3.54)	
Other debt-to-income ratio				-0.631* (-1.65)
Ln(Income) # Other debt-to-income ratio				0.093 (1.59)
Constant	-1.548** (-2.38)	-1.215* (-1.91)	-1.607** (-2.42)	-1.797*** (-2.81)
Observations	1 042	1 042	1 042	1 042

t statistics in parenthese.

* p<0.10 ** p<0.05 *** p<0.01

Due to the small size in the Asian/Indian sample these results should be read with caution. Results are not marginal effects and non-weighted. Exclusion categories are: male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future. Future uncertainty refers to in 5 years time for Wave 1 - 4.

Source: Own calculations, NIDS

Table C.6.7: OLS regression on the impact of deleveraging on consumption between Wave 1 and subsequent waves, non-weighted

	Δ consumption Wave 1 - 2	Δ consumption Wave 1 - 3	Δ consumption Wave 1 - 4
Deleveraged	-2 635 (-0.20)	-14 611 (-1.28)	-27 529** (-2.58)
At least one adult employed in the household	-701 (-0.03)	8 159 (0.49)	-95 (-0.01)
Household who receive at least one welfare grant	12 802 (1.03)	-6185 (-0.53)	-18 351** (-2.18)
Children Share	-12 130 (-0.50)	-2 839 (-0.09)	12 092 (0.57)
Female	-7 828 (-0.39)	-2 756 (-0.22)	16 416 (1.23)
Married	33 27 (0.17)	-4 421 (-0.32)	16 447 (1.14)
Coloured	-104 98 (-1.08)	-5 188 (-0.55)	-4 013 (-0.40)
Asian/Indian	-147 464* (-1.81)	-98 734 (-0.98)	-171 059** (-2.29)
White	41 065 (0.95)	-69 900*** (-2.69)	-39 108 (-1.30)
Education	265 (0.15)	-1 134 (-0.70)	-1 999* (-1.80)
Age	245 (0.09)	-1 062 (-0.34)	1 916 (0.90)
Age squared	-4.165 (-0.15)	9.351 (0.31)	-28 (-1.32)
Live in a traditional area	23 540 (0.82)	-26 408 (-1.58)	-21 596 (-1.34)
Live in an urban area	3 453 (0.13)	-10 017 (-0.83)	-5 230 (-0.37)
Δ income	0.032 (1.37)	0.003 (1.34)	0.206*** (4.07)
Loan-to-value ratio	657 (1.40)	480** (2.21)	584*** (5.54)
Mortgage debt-to-income ratio	2 975 (1.24)	2 053 (1.55)	2 137** (2.32)
Vehicle debt-to-income ratio	-3 944 (-1.12)	568 (0.16)	-3 372** (-2.45)
Consumer debt-to-income ratio	-8 989 (-0.64)	-2 630 (-0.34)	4 642 (1.56)
Other debt-to-income ratio	6 913 (0.71)	264 (0.05)	-3 646 (-1.17)
Mortgage repayment-to-income ratio	-32 (-0.26)	150 (0.08)	-123 (-1.48)
Future uncertainty (worse off)	3 735 (0.24)	27 720 (1.43)	14 555 (1.01)
Constant	-9 672 (-0.14)	58 362 (0.75)	5 334 (0.10)
Observations	702	820	1 002

t statistics in parenthese.

* p<0.10 ** p<0.05 *** p<0.01

Due to the small size in the Asian/Indian sample these results should be read with caution. Results are non-weighted. Exclusion categories are: non-deleveraging, male, non-married, African, living in a Farm area, income quintile 1 and those expecting to be better off in future. Future uncertainty refers to in 5 years time for Wave 1 - 3 and Wave 1 - 4, as compared to 2 years time in Wave 1 - 2.

Source: Own calculations, NIDS