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Household Debt and Consumption Dynamics: A Non-Developed World View following the Financial Crisis

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Household debt and consumption dynamics

A non-developed world view following the financial crisis

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Abstract

According to recent macroeconomic evidence (Bosch and Koch 2020b; Farrell and Kemp 2020), the global financial crisis is still impacting the South African financial landscape more than 10 years later. In an effort to better understand the effect of the financial crisis, we examine household debt dynamics, with particular attention to deleveraging, following the financial cycle peak. Our analysis is predicated on the National Income Dynamics Study, the first wave of which was conducted adjacent to the beginning of the crisis. We apply standard regression analysis finding heterogeneity in debt and deleveraging at the household level, with both an uptick in short-term debt in the early stages of the crisis and a reduction in long-term debt, primarily mortgage debt, since. Overall, deleveraging was greatest amongst higher income households with relatively larger mortgage debt-to-income ratios, although that was partially offset in households with higher mortgage repayment costs relative to income. Long-term deleveraging was also more likely amongst households with higher vehicle debt-to-income ratios, but lower consumer debt-to-income ratios.

1 Introduction

This research makes use of the first four waves of the National Income Dynamics Study (NIDS), and, in part, exploits the panel structure to determine the drivers of household deleveraging after the South African financial cycle peak and its association with household consumption. A benefit of the timing of the NIDS study is that the first wave was collected nearly coincident to the start of the financial downswing in 2007. Although we are not the first to look at debt using NIDS – Choonoo (2016) looks at determinants of debt servicing cost and Ntsalaze and Ikhide (2016) look at the prevalence of over-indebtedness – however, we are the first to take advantage of the timing of the survey to examine the fallout from the financial crisis and its association with South African household debt, deleveraging and consumption.

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Of particular interest in the following analysis is potential heterogeneity in debt and deleveraging across different sections of the population. If all households reacted the same way, when facing economic challenges, the aggregate data would sufficiently reflect this (Dynan 2012; Cooper and Dynan 2016). However, the literature suggests that deleveraging is heterogeneous. In the UK, for example, highly leveraged households deleverage more, due to disproportionally less access to new credit (Bunn and Rostom 2014). However, Bhutta (2012) argues that deleveraging in the US mortgage market is driven by a sharp decline in debt accumulation arising from tighter credit, as well as a decline in the number of borrowers. Our results, on the other hand, suggest that the limited degree of deleveraging uncovered at the macroeconomic level (Bosch and Koch 2020b) arose from deleveraging in upper income quintile households. Furthermore, we find that deleveraging is associated with reduced household consumption, although the direct reduction is not economically substantial.

2 Literature Review

A set of recent papers has examined the effect of exogenous changes in long-term debt (Ganong and Noel 2020), liquidity (Ganong and Noel 2020) interest rates (Di Maggio et al. 2017) and income (Cookson, Gilje, and Heimer 2020) on household consumption and debt repayment. Ganong and Noel (2020) focus on the US Government's Home Affordable Modification Plan along with private sector offerings, separating the effect of liquidity increases (maturity extensions that do not change wealth) from debt reduction (without affecting short-term payments). They find that (i) the relaxation of the liquidity constraint reduces the probability of default and is associated with consumption increases and (ii) the reduction in debt does not have any meaningful effect. Di Maggio et al. (2017) used adjustable rate mortgages originating in the US well before the financial crisis to gauge the effect of unexpected interest rate decreases that arose following the crisis; they find that the reduction in rates led to increases in consumption, some further voluntary mortgage repayments and extensive heterogeneity in the response. In particular, poorer households, as measured by either high loan-to-value ratios or low incomes, consumed more, and, therefore, did not develerage much. Similarly, Cookson, Gilje, and Heimer (2020) examine the marginal propensity to repay debt out of mineral royalty cash flow shocks, as well as its effect on consumption spending. They find the marginal propensity to repay to be 0.33 on average, but nearer 0.23 for sub-prime lenders. Sub-prime lenders are likely liquidity constrained (and thus poor), as suggested by their further findings that many of them had been denied credit, when attempting to make a car purchase.

These recent papers are an improvement over previous literature, because they offer insights into causal household balance sheet effects on the economy, as well as heterogeneity in those effects.[1] Much of the previous literature has been primarily descriptive or associative. For example, Dynan and Edelberg (2013) show that US household debt ratios remain high, with some households above pre-crisis levels, while consumption spending for households with high mortgage debt-to-income ratios is especially weak. Mian, Rao, and Sufi (2013) suggest that US household consumption is very responsive to shocks in housing net worth, and that poorer and more leveraged households decrease their spending significantly more. Dynan (2012) agrees, finding that elevated leverage is associated with weak consumption growth. Although this negative relationship existed before the financial crisis, there are more households under higher leverage, and, thus, the post-crisis effect on consumption is larger (Cooper 2012). Similar results hold in Ireland (McCarthy and McQuinn 2017a): when controlling for wealth effects, deleveraging and consumption are negatively and statistically significantly related, although economically small.

Although some of the previous research might not be causal, it does suggest explanations for these balance sheet effects. Dynan (2012) and McCarthy and McQuinn (2017a) suggest that wealth loss, especially since the post-crisis period was characterised by a sharp fall in house prices, is an important contributor to weak consumption growth. Similarly, Baker (2018) suggests that the US consumption decrease can be attributed to higher debt levels and liquidity constraints, as well as a need for highly indebted households to attain a more controllable debt level, which they can only achieve if they hold down their consumption. Pistaferri (2016), however, attributes the drag on consumption 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, as well as the deleveraging process. In both the US and UK, highly indebted households could have become more concerned about their balance sheet positions and future incomes; therefore, they may have cut back more on consumption and leverage (Benigno, Eggertsson, and Romei 2020; Baker 2018; Bunn and Rostom 2014).

Theoretical suggestions also abound. For example, Benigno, Eggertsson, and Romei (2020) offer a macroeconomic model with heterogeneous consumers, savers and debtors to examine the effect of a Minsky moment on households and the setting of optimal monetary policy. Their model yields dynamic deleveraging, which can worsen the economy and have deleterious welfare implications, especially for borrowers, such that monetary policy should be more aggressive: a stronger commitment to higher inflation, at least in the short term. A zero lower bound increases the pace of deleveraging, as well as output and inflation, relative to a non-binding lower bound on inflation. They further suggest that the debt effects are stronger, if labour

[1] Albuquerque and Krustev (2018) offer a fixed effects estimate of state-level aggregates of these balance sheet effects on consumption. The results suggest that excessive indebtedness is a drag on consumption, while the drag is strongest amongst states with relatively large debt imbalances.

markets are not flexible enough to allow for increased labour supply. Even in a simple precautionary savings model, where home ownership offers a source of liquidity of last resort, slow deleveraging might arise from a dynamic version of Keynes' paradox of thrift (Guerrieri, Lorenzoni, and Prato 2020): debt repayments reduce consumption, which reduce income and beget further debt repayments.

Given the high levels of unemployment in many developing countries, limited fiscal space (due to high levels of government debt) and potential credibility issues associated with the relaxation of inflation targets, the preceding research suggests an explanation for evidence that the global financial crisis is still impacting the South African financial landscape more than 10 years later (Bosch and Koch 2020b; Farrell and Kemp 2020). The previous research also highlights the importance of further analysis of balance sheets, regardless of the ability to uncover causal effects, the continued focus on micro-data to understand household balance sheets and the need for insight from countries not in the developed world.

Although micro-data studies analysing household debt have gained prominence in recent years (Mian and Sufi 2010; Mian, Rao, and Sufi 2013; Dynan 2012; Dynan and Edelberg 2013; McCarthy and McQuinn 2017b; Di Maggio et al. 2017; Ganong and Noel 2020; Cookson, Gilje, and Heimer 2020), that literature has ignored the developing world. Therefore, in this study, we contribute to the literature by offering a non-developed country perspective. We build on related macroeconomic analysis (Bosch and Koch 2020b), but, rather, exploit household survey data to gain insights into the household debt distribution, with specific focus on households that were able to deleverage after the financial cycle peak in May 2007. Previous debt focused studies have examined the drivers of debt or high leverage (Coletta, Bonis, and Piermattei 2014; Dynan and Kohn 2007; Bhutta 2012; Wildauer 2016). Thus, we also contribute through the examination of the drivers of debt dynamics. The use of micro data will assist us in accounting for the heterogeneous responses of households to financial shocks. Since South Africa, the country we are able to examine, is a developing economy with high income- and wealth-inequality (Leibbrandt, Finn, and Oosthuizen 2016), debt, as well as opportunities to deleverage, are also expected to be unevenly distributed.

3 South African household debt landscape

South Africa has a unique debt landscape, given its high level of income inequality and exclusion from formal financial services, largely among poor individuals and households (Matsebula and Yu 2020). To offer some insight into this landscape, we would like to highlight relevant aspects of the household side of this landscape transpiring since the beginning of the financial crisis. To do so, we use data collected from the National Credit Regulator (NCR) and the South African Reserve Bank. For information related to aggregate debt data following the global crisis, please, see Bosch and Koch (2020b) and Farrell and Kemp (2020).

Data from the NCR shows that consumers struggled to meet their debt obligations at the start of the financial crisis (in this case we use 2007Q4, as this is the start of the NCR data). Figure 1 illustrates the share of account holders who were in arrears for 90 days or more, separating mortgage debt from other debt. 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, suggesting that mortgage holders were initially hit harder than other debt holders during the global financial crisis. The mortgage arrears 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 (Naicker and Kabir 2013), were forced to sell their property or had their property repossessed by the financial institution to whom the debt was owed. Arrears in total non-mortgage debt (other debt in the figure), however, increased gradually, only reaching a peak in 2014Q2, when 16.9% of account holders were behind by 90 days or more in repayments.

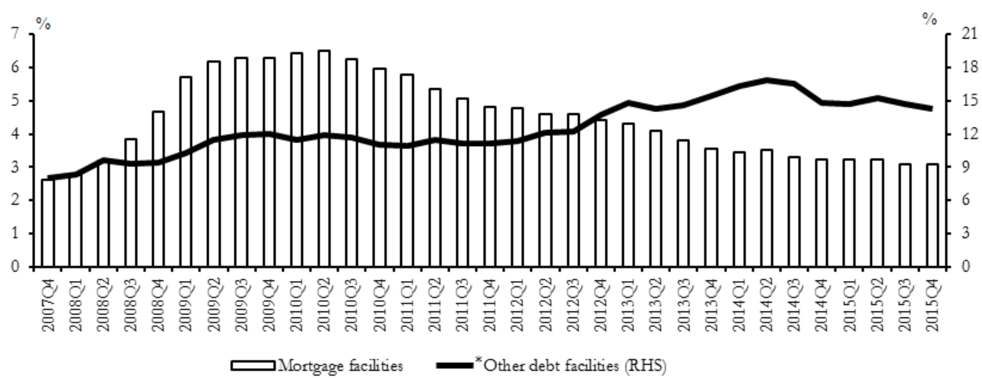


Figure 1: Percent account holders in arrears for 90 days or more. Other debt includes secured and unsecured credit, credit facilities and short-term credit. Source: National Credit Regulator (2018).

We also take data from the South African Reserve Bank related to interest rates charged on various credit products over the same time period to get an indication of the interest rate path during the great recession. In Table 1 we report the average interest rates by debt category as reported by banks (we matched the periods 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.[2] We match debt types from our NIDS sample, described below, to the interest rates reported by banks for comparative purposes. The data suggests that interest rates were highest at the beginning of the crisis (which we relate to wave 1, which was collected in 2008, so not immediately at the start of the crisis), fell and increased at the time of the collection of wave 4 of the data (2014/15).

[2]Although the interest rate on loan shark loans are not reported, we assume that interest on these loans are at least as high as those levied on micro loans by banks.

Table 1 about here

4 Empirical strategy

4.1 Deleveraging

To explore the determinants of household deleveraging after the financial cycle peak of May 2007, we utilise NIDS panel data to determine if households decreased their debt between waves 1 - 2, waves 1 - 3 and waves 1 - 4. The dichotomous outcome is defined from wave 1 to any of the other $j = \{2, 3, 4\}$ waves

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

Given that $Y_{i,j}$ is a dummy variable equal to one if a household's debt decreased over waves 1 - j, and zero otherwise, we apply a standard binary probit model. We also considered linear probability models; however, they predicted relatively large numbers of probabilities outside the unit interval, and, therefore, we did not continue with them. We follow McCarthy and McQuinn (2017a) and Dynan (2012) by controlling for household characteristics ($X_{i,1}$) and other measures of income and debt ($Z_{i,1}$).

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

We condition our controls on wave 1 characteristics postulating 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-linearities in the income response; it also offers a glimpse into potential inequality effects. In South Africa, inequalities are ethnically driven (Leibbrandt, Finn, and Oosthuizen 2016), and, therefore, we include the four main population groups in South Africa. Given the high number of social grant recipients in South Africa (around 45% of households representatives in wave 4), we include a dummy for grant receipt by at least someone in the household.

We also include a dummy variable for employment, which accounts for whether or not at least someone in the household is employed to account 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. It is further possible that married households have shared or dual income and debt, which could allow them to pool resources for deleveraging. Additionally, we control for other traditional demographic variables, such as the share of children in the household, gender, age, age squared (of our household representative, see below) and the geographical area where households reside.

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, although it should be noted that real house prices fell by 15% from May 2007, on average, resulting in lost housing stock values. To account for this loss in value, we include additional controls for highly leveraged households by including ratios, such as mortgage-debt-outstanding-to-income, as well as vehicle-, consumer- and other-debt-to-income ratios. We further proxy household liquidity, relying on McCarthy and McQuinn (2011), whereby liquidity is measured by the mortgage-repayment-to-income ratio. It was especially pertinent in the Irish economy at the time, as many Irish households were experiencing mortgage repayment difficulties. Due in large part to South Africa's slow financial cycle recovery (Bosch and Koch 2020b; Farrell and Kemp 2020), we also included this measure in our model.

Brown et al. (2005), Christelis, Georgarakos, and Jappelli (2015) and McCarthy and McQuinn (2017b) find a positive relationship between optimistic financial expectations and the amount of debt. We see if that might also affect debt reductions. Future income uncertainty relating to economic variables, such as income and unemployment rates, could increase financial uncertainty and impact the deleveraging process. Households who have an adverse view of their future financial position may opt to save towards what they see as an adequate liquidity buffer, to cover future expenditure in difficult times. Furthermore, if a household's expectation of being in worse position 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 using a dummy variable related to negative expectations about the future household,s position: in 2 years' time for wave 1 - 2 and 5 years from now for wave 1 - 3 and wave 1 - 4.

4.2 Consumption

In addition to understanding deleveraging for its own sake, we aim to determine whether or not their is a relationship between household deleveraging and consumption. Dynan (2012) shows that high leverage has a noticeable (but small) negative impact on consumption, with wide confidence bands. Similarly, McCarthy and McQuinn (2017a) find a negligibly small negative, but statistically significant, impact of deleveraging on consumption. Our methodology for this component of the research follows a similar strategy as above, with deleveraging.

$$\Delta C_{i,j} = \alpha_j + \tau_j Y_{i,j} + \beta_j X_{i,1} + \lambda \Delta I_{i,j} + \gamma Z_{i,1} + \varepsilon_{i,j}. \tag{3}$$

We estimate equation (3) using a linear model where our dependent variable is the change in consumption between wave 1 and all subsequent j waves ($\Delta C_{i,j}$), which could be positive or negative. We control for the same variables as in our equation 2 (including wave 1 household characteristics ($X_{i,1}$) and debt ($Z_{i,1}$), except that we use the change in income between wave 1 and all subsequent j waves ($\Delta I_{i,j}$). Our primary variable of interest is whether or not a household i deleveraged between wave 1 and the j^{th} wave; we label this as $Y_{i,j}$, as it was described in equation (1). Thus, our main interest is in τ_j, the association between deleveraging and consumption from wave 1 to wave j.

5 The data

5.1 Creating a household panel

NIDS is a South African panel that follows individuals, and is designed to be representative of the South African population. For our analysis, we use the first four waves of the survey, which were conducted in 2008, 2010/2011, 2012, and 2014/2015 (Southern Africa Labour and Development Research Unit 2016a, 2016b, 2016c, 2016d). 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; however, only 5 115 households were successfully interviewed in all four waves (Southern Africa Labour and Development Research Unit 2016e). For the analysis, we use the calibrated (post-stratification) weights to match the mid-year population estimates released by Statistics South Africa in 2015 (Chinhema et al. 2016; Southern Africa Labour and Development Research Unit 2016e).

Although there are many benefits to longitudinal data, the fact that NIDS has been designed to follow individuals makes it rather difficult to follow households across waves – households are not directly identifiable across waves, except where they contain the same individuals (Southern Africa Labour and Development Research Unit 2016e). One way around this 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.

Therefore, we construct a unique household identifier. We select one person in each household and aggregate all household-level variables to that respondent, setting a number of conditions for that person. First, the household representative needs to be at least 18 years old and have successfully completed the adult questionnaire. In South Africa, 18 is the minimum age to obtain a loan. 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. Second, to ensure this person is a good representative of the household (Cull and Scott 2010), we require the selected person to be the household head or the key decision maker over all household expenditure. 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. Lastly, when there is still uncertainty, we follow the adult who joins the new household that contains most of the baseline household members.[3] Our constructed identifier captures 7 263 households in wave 1, 5 652 households in wave 2, 5 691 in wave 3, and 5 402 in wave 4.

5.2 Capturing debt

Our primary aim is the measurement of household deleveraging, relative to the start of the financial crisis, which hit just before wave 1 went to the field. Thus, the analysis requires measures of household debt, which we categorize as mortgage debt, vehicle debt, other consumer debt and informal/other credit. 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. To make the data comparable across waves, we remove the price effect; 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.

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. In NIDS for example, there are bracketed options for pension cash values, like "is the cash value of pension/annuity more than or less than R50 000?"; response options include: don't know, refuse, more than, about equal to or less than. These quantitative ranges are

[3]The authors would like to thank Manuela Gunther for her help in defining and constructing the unique identifier.

called unfolding brackets, and they represent a survey innovation that substitutes range data for completely missing data (Juster et al. 2007). In order to capture as much debt data as possible, we imputed. Where possible, imputations were supported by unfolding brackets. 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 imputation error. For some variables, however, unfolding brackets were not available, and, therefore, other methods were used; see Bosch and Koch (2020a) for further details regarding the imputation and its performance, which was very good. For this analysis, we use the imputed data described in Bosch and Koch (2020a).

6 Data description

We describe the data that we use in the following subsection, however, for summary purposes, we provide a table of variable definitions in Table A.1.

6.1 Sociodemographics

Table 2 presents the weighted sample statistics for each survey year, focusing on non-financial characteristics. The average age of the household representative at the start of the survey is 43 years, while nearly 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 representatives are African, about 48% of representatives are female, and 67% of households reside in urban areas. We detect some compositional changes; for instance the share of white representatives 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, representatives have attained nine years of education.[4] 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, while about 45% of the households received government grants in 2014/2015.[5] Lastly, the average household consists of approximately four members (approximately one quarter of those are under 18 years old).

Table 2 about here

We summarise the income, expenditure and debt data in Table 3. In the following subsection, we present more detail on the debt data. This table includes both the mean and the median values of debt and its

[4]In the 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.

[5]There are numerous - 900 - missing values over employment status; thus, we use a household dummy variable indicating if there is at least one employed household member.

changes (in the deleveraging section) to examine the possibility of extreme values that may affect means, especially where the reported debt sample is small, as in our case, even after imputations (also see Dynan (2012)). We find that 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. 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 requiring the difference between income and consumption to be covered by borrowing, especially if households drew on their home/mortgage equity for consumption purposes. 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 high income inequality, we disaggregate debt and income across income quintiles. 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].[6]

Table 3 about here

We further note that the median debt outstanding among indebted households has decreased relative to 2008. 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 had dropped to R 11 542 [R 126 089] before decreasing [increasing] to R 6 925 [R 164 316] in wave 4.

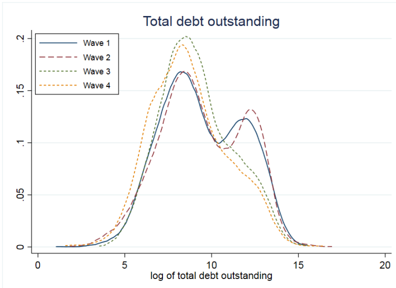
6.2 Debt

We plot kernel densities for our fully imputed debt data in Figure 2. For the plot, we used the average of the imputations - we imputed five times - although imputations were at the individual level, all debt was aggregated to the household. 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, as might be expected.[7]

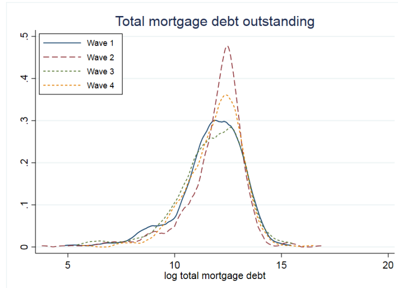
In Figure 3 we illustrate the share of the different debt types as a percentage of total household debt outstanding. Apart from showing that mortgage debt made up the largest share of outstanding debt, followed by vehicle and consumer debt, we also show that, after initially increasing in wave 2, the share of mortgage

[6] We find (but do not report) that the lowest income quintile households mainly hold 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 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].

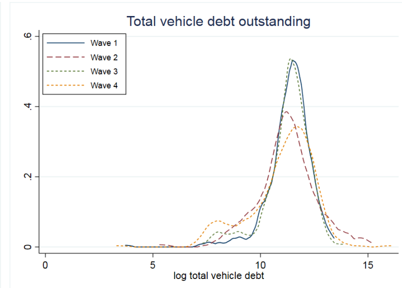
[7] For more detail related to debt across the waves see Table A.2. We further separate them by income quintile in Table A.3.



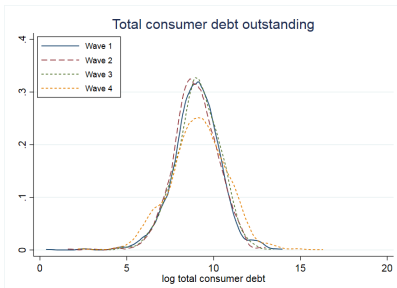
(a) Total Debt



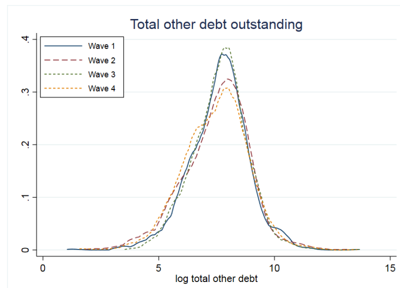
(b) Mortgage Debt



(c) Vehicle Debt



(d) Consumption Debt



(e) Other Debt

Figure 2: Kernel densities of debt for different debt types by NIDS wave.

debt outstanding was the only debt category that decreased substantially in subsequent waves, confirming the aggregate results (Bosch and Koch 2020b). The share of consumer debt to total debt increased noticeably in wave 4, from 9.1% to 30.4%, which may have arisen from distressed borrowing.

7 Results

7.1 Deleveraging description

The preceding debt information is used to determine deleveraging, which we measure in terms of total debt outstanding for those who reported debt in both the first and the relevant subsequent wave. 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. Since we limit our attention to those who had debt across the waves, selection bias may arise, since those who do not report debt in subsequent waves may not be random.[8]

[8]We are possibly ignoring people who have paid off their debt in full. The authors would like to thank Yvonne McCarthy for pointing this out. Unfortunately we only had pay-off information for those who had mortgage debt. When including these respondents, the estimation sample (for those who had debt in wave 1) increased by 57 observations between wave 1 and wave 4; 79 between wave 1 and wave 2 and 69 between wave 1 and wave 3. We, therefore, included this group of people and re-examined the following analysis. We found no important changes to the main relationships of interest. Thus, we do not think selection bias is a serious problem.

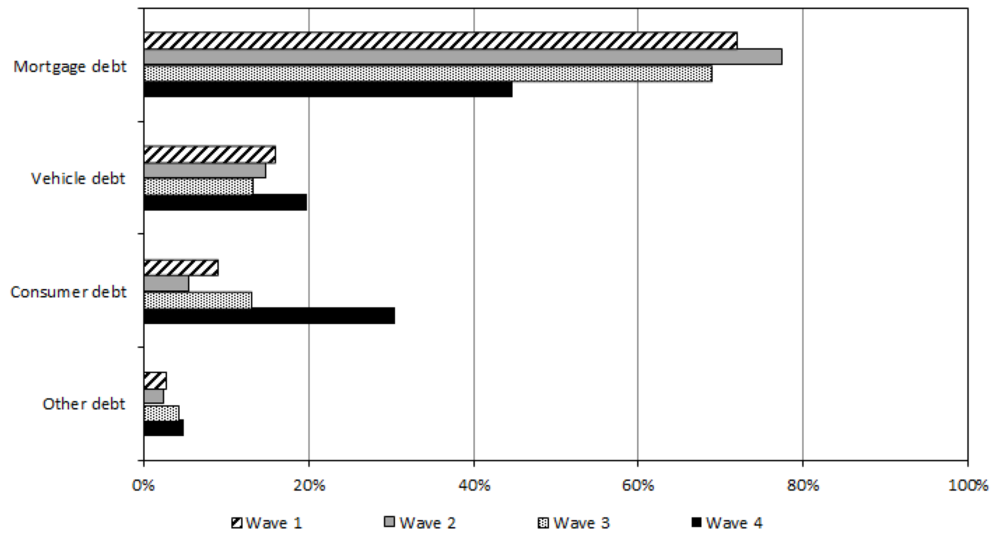


Figure 3: Percent of total debt outstanding by wave and debt type for those who had debt.

We follow Bhutta (2012) and define deleveraging as a reduction in the absolute value of outstanding debt.[9] We compare all deleveraging against the initial period (wave 1) to establish how household initial conditions impacted the ability to deleverage. Thus, we take the difference from wave 1 to wave 2, which constitutes a short-run effect, as well as wave 1 to wave 3 and wave 1 to wave 4 which gives a longer run view; the latter is our primary focus. For clarity, households whose debt increased from wave 1 are seen as 'not deleveraging.'

We show in Table 4 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. From wave 1 - 4, both the median and the mean mortgage debt declined. From wave 1 - 2 a decline in vehicle debt also supported total deleveraging.

Table 4 about here

At the median, we find that deleveraging took place between all waves (Table 4) compared to wave 1. As noted above, we limit the sample to households that were successfully interviewed in wave 1, and in which at least one adult successfully completed the survey; however, we allow for households to drop in and out of the survey in subsequent waves.[10]

[9] McCarthy and McQuinn (2017a) have a custom household survey commissioned by the Central Bank of Ireland, which included a direct question regarding actions taken to deal with debt concerns and was used to capture deleveraging. We do not have such data available to us.

[10] NIDS differentiates between the 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, while dropping in might mean that the household was subsequently located or that the household questionnaire was successfully completed.

7.2 Deleveraging demographics

Because we want to understand differences between those that deleveraged and those that did not, we present a final summary of the characteristics in Table 5, differentiating between these households. In that table, we find that the average age of the household representative in a household 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 representative age is two years older. The majority of those representatives 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 social grant recipients. The majority of the household representatives are male and African.

Table 5 about here

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 earnings 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, which is similar to McCarthy and McQuinn (2017a). As was true for total debt, the medians [means] for all other debt types were higher for the deleveraging group than for the non-deleveraging group.

7.3 Deleveraging model results

The above discussion suggests some differences, but does not account for multivariate effects. For that reason, we applied a binary probit model to understand the determinants of deleveraging. For the analysis, we applied post-stratification weights in all models, unless otherwise specified.[11] We begin with Table 6, which presents probit marginal effects from our deleveraging models estimated across the different combinations of survey waves, as outlined in equation (2). In the base model (column 1), we find only statistically significant positive urban and income effects. Similar to McCarthy and McQuinn (2017a), we do not find the loan-to-value ratio to be important in our base equation for wave 1 - 4.

Table 6 about here

[11] Non-weighted results and additional detailed results for waves 1 - 2 and waves 1 - 3 are available from the authors.

In column 2 we report on a model that allows for simple non-linear income effects, using the bottom 20% of households as the baseline. We find deleveraging over the wave 1-4 period to be 16.5% higher in the upper income category compared to the lowest, while we find no statistically significant effects in other categories. Columns 3-5, which report results for models that include additional controls, offer a qualitatively similar conclusion, although the estimated marginal top income quintile effect is 19.1%. For the wave 1-2 and wave 1-3 period, columns 6 and 7 respectively, we see larger deleverage marginal effects in the upper quintiles, near 40%, as well as lower income quintile effects, 24% to 38% more deleveraging than the poorest households.

We include a number of additional controls to capture potential effects related to highly leveraged households, such as ratios for mortgage, vehicle, consumer and other debt outstanding to income (columns 3-7). Our results suggest that larger mortgage- and consumer-debt-to-income ratios were associated with an increased probability of deleveraging across all wave periods. A one unit increase in the mortgage-debt-to-income ratio led to a 4.6% increase in the probability of deleveraging over waves 1-4, a slightly lower 3.6% over waves 1-2 and more than four times over waves 1-3 (1.1%). For consumer-debt-to-income, the increased probability ranged from 13.1% to 38.9%, where the effects were larger in the shorter intervals. On the other hand, higher other-debt-to-income was associated with a decreased deleveraging probability, except in the short-run (waves 1-2), during which it increased the probability. Vehicle-debt-to-income was also associated with a decreased deleverage probability, except over the medium term (waves 1-3), wherein the deleveraging probability was higher.

Columns 4 through 7 also include a measure of liquidity, the mortgage-repayment-to-income ratio, however, it is not a statistically significant determinant of deleveraging, at least in our sample. In addition to liquidity, we also included a control for uncertainty (columns 5-7), as suggested by Brown et al. (2005), Christelis, Georgarakos, and Jappelli (2015) and McCarthy and McQuinn (2017b). We find suggestive, but not substantive, evidence that the deleveraging probability over the medium term was lower for those more uncertain about their future.

7.4 Income interactions

The preceding results suggest that income is an important determinant of deleveraging, and, the relationship is nonlinear. Furthermore, we uncovered evidence that debt-to-income ratios also mattered. Thus, we extended the analysis to explore further sources of nonlinearities that might be related to these two sets of controls. The results are reported in Appendix Tables A.4 - A.6. However, rather than discussing those results, we provide an illustrative perspective, focusing on the period covering all four waves. Specifically, the interaction effects are illustrated for each of the debt-to-income distributions, using the 75^{th}, 90^{th}, 95^{th}

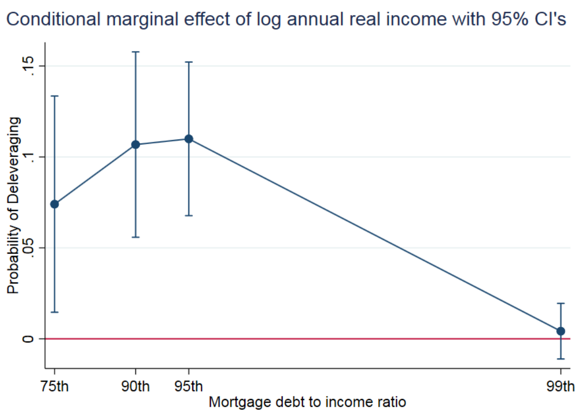
and 99^{th} percentile of the distribution, except for the vehicle debt-to-income ratio, where the 75^{th} percentile is zero. We plot these results in Figure 4 for wave 1 - 4. To interpret the illustration, note that we are considering an increase in the log of real annual income. Thus, given a log scale increase in real income, the illustration shows the probability of deleveraging at that particular percentile of the debt-to-income ratio. The log scale increase in real annual income increases the probability of deleveraging by approximately 7.4%, 10.7%, 11.0% and 0.4%, at the 75^{th}, 90^{th}, 95^{th} and 99^{th} percentile of the mortgage debt-to-income ratio. 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 ratios, not needing to deleverage. In other words, they likely have the means to manage their debt levels. The trend is, however, different for other-debt-to-income. Perhaps other-debt-to-income is higher cost, such that it is in the interest of all households, including the top 99th percentile, to reduce this type of debt.

7.5 Deleveraging and household consumption

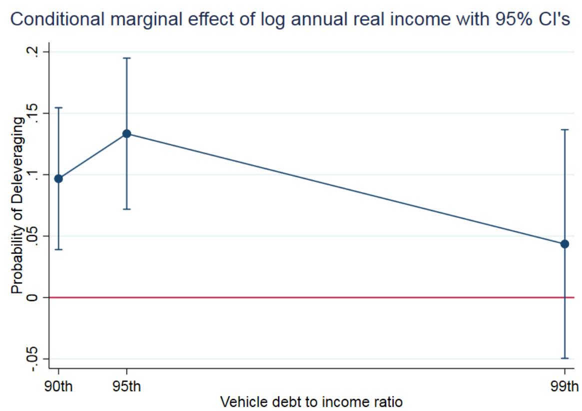
Having high debt in itself does not necessarily impact consumption (Dynan 2012). Pistaferri (2016) suggests that households face a number of different shocks at the same time when an asset bubble bursts. The first of these is a wealth loss. For example, when house prices fell sharply, households who 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. We examine these possibilities, focussing our discussion on wave 1 - 4 (see Table 7), although results for the other periods are also presented in the table.

Table 7 about here

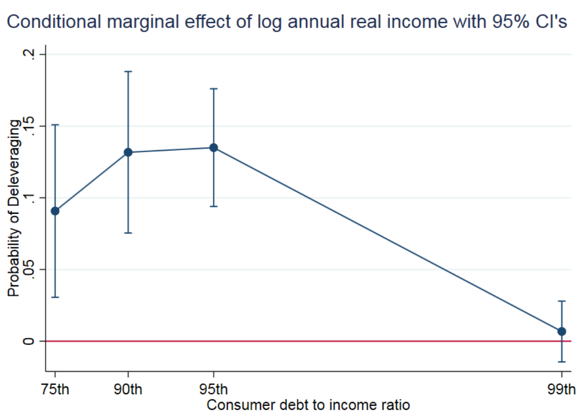
As our main focus is leverage, we begin there. We find that in the immediate period (wave 1 - 2) deleveraging had no significant association with consumption and the sign was, in fact, positive. In the longer run, however, for both wave 1 - 3 and wave 1 - 4, the sign of the coefficient is negative, and in wave 1 - 4 it is statistically significant. Similar to Dynan (2012), however, we have a wide confidence interval, and similar to both Dynan (2012) and McCarthy and McQuinn (2017a), when adjusted for the period (2008-2015/wave 1 - 4 covers 8



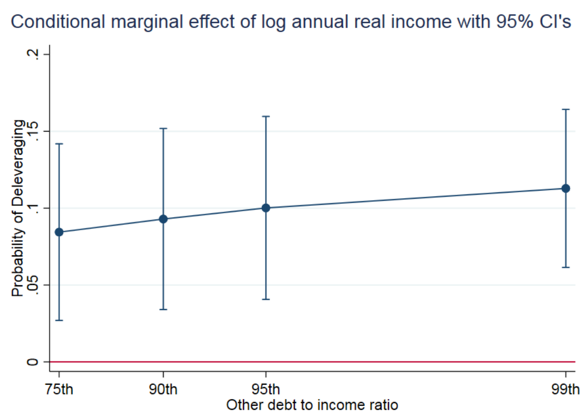
(a) Mortgage Debt



(b) Vehicle Debt



(c) Consumption Debt



(d) Other Debt

Figure 4: Marginal 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. Results are weighted using post-stratification weights. All respondents had to have reported debt in both wave 1 and wave 4.

years), we find that households who deleveraged had lower average consumption each year: approximately R 3 415 per year (R 27 320/8 years). This is 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)). Their results roughly translate to R 10 330 between May 2012 and February 2013 (assuming an average €/ZAR exchange rate of 10.93 over the period), which, according to McCarthy and McQuinn (2017a) is economically insignificant, even though it is statistically significant. Thus, our main findings offer additional support for the conjecture that deleveraging has a very small negative direct impact on household consumption.

We offer more insight by including separate measures of debt. Over the wave 1-4 period, higher mortgage and consumer debt-to-income was positively and significantly correlated with consumption, while the vehicle and other debt association was negative. 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, and, therefore, households view and use these credit lines differently.

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 had statistically and significantly greater consumption. Similarly, we see that changes in income are positively associated with changes in consumption. Therefore, as household income increases it should increase its consumption and, indirectly, economic growth through the consumption channel, but only in the longer run (wave 1 - 4). However, as opposed to McCarthy and McQuinn (2017a), we find that education is negatively related to changes in consumption, once we account for all of the other controls. Possibly, this is because highly educated households have a more prudent approach to finances, due to better financial literacy; maybe, this reflects broader consumption smoothing associated with their schooling decisions, i.e. taking on higher debt earlier in their lives with an expectation of higher future income (Dynan 2012).

7.6 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. 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 8. 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.

Table 8 about here

By creating a matched household debt deleveraging panel, we lose many households who reported debt in wave 1 and not in the subsequent waves: we lose 630 observation over wave 1 - 2; 1 361 over wave 1 - 3 and 1 634 over wave 1 - 4. 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. Over 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; 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. 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 (2012) 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 (2012), other data transformation methods can be explored in future work.

8 Discussion

Results from our base model, Table 6 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 with at least one person employed is not significant, it is positive, which one would expect; households with 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 important for deleveraging. However, when restricting our sample to mortgage holders, we find that households with at least one person employed are more likely to deleverage in all waves, significantly so over the entire period: wave 1 - 4. In column 3, we show that households with a married representative have a higher probability of deleveraging. It could be that this represents dual incomes, which could assist in deleveraging.

Although only significant in our restricted sample for mortgage holders, higher education and age have negative coefficients over wave 1 - 4, suggesting that neither age nor education 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 over 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 over wave 1 - 3, compared to the lowest income quintile.

Households with higher leverage in mortgage and consumer debt were more likely to deleverage. 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 need to deleverage to restore their credit access or gain access to new credit (Bunn and Rostom 2014).

Households with high mortgage debt deleverage more, possibly because mortgage debt is highly sensitive to interest rate changes or because of repossession. The sensitivity to changes in interest rates can, however, change over time, as lenders become more or less conservative (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 National Credit Act (NCA) in 2007 (see De Wet, Botha, and Booyens (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. The NCA also allowed lenders to have better access to information regarding customers' credit scores with the aim to avoid consumers becoming highly indebted.

Having higher vehicle and other debt-to-income ratios resulted in a lower probability to deleverage. Although over 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. 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. 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. Our findings are similar in our mortgage debt sample. When we further control for liquidity (mortgage repayment to income ratio), we see that it is not significant (see column 4), which reinforces the notion that it is the ability to pay (income/liquidity) rather than the amount outstanding that drives deleveraging (Ganong and Noel 2020).

Although it was only significant for the wave 1 - 3 period (for both the base model and the restricted sample), we find that households who expected their financial position to worsen 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 be driven by two factors; firstly, if households see themselves worse off in future, they may look to save 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. 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.

9 Conclusion

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. We made use of a panel data set (NIDS) to explore changes in debt and consumption following this event. Our comparison of deleveraging versus non-deleveraging households shows that deleveraging tended to driven by households with higher income, real debt and house values than our non-deleveraging sample. By analysing household debt positions from a micro economic perspective, we confirm that deleveraging after the recent financial cycle peak was driven by married households in urban areas and those in the highest income quintile.

We also identified that even though deleveraging was observed at the aggregate level, it is mostly the higher income households with mortgage and consumer credit contributing to the aggregate evidence. 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.

We should, however, acknowledge that there may be some bias when interpreting our results, due to selection. Furthermore, the results can only be seen as associations and not causal, as it is not possible to account for unobservable factors that could be correlated with the control variables. In future research, we plan to explore ways to account for selection and other endogeneity issues.

After the global financial crisis, policy makers were searching for clarity related to the timing and impact household deleveraging might have on the South African economy. They were especially interested in the uptake of new credit and the anticipated increase in consumption and economic growth since this directly impacts inflation and monetary policy. With respect to those policy concerns, one conclusion to draw from our results is that individuals with the means to deleverage do so, and primarily through 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.

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Table 1: 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.

Table 2: 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 includes those who had debt (which includ zero) outstanding in each respective wave.

Table 3: 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. The sample covers those who had debt (including zero) outstanding in each respective wave.

Table 4: 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 with means in [ ]. Results are weighted using the post-stratification weights. A breakdown of the changes in debt type, income quintiles and waves are available from the authors. Totals will not add up as respondents can have more than one debt type.

Table 5: 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).

Table 6: Probit marginal effects at the mean on deleveraging probability

	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. Excluded 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 is 5 years into the future for Wave 1 - 3 and Wave 1 - 4, or 2 years time in Wave 1 - 2. Full results for Wave 1 - 2 and 1 - 3 are available from the authors. All respondents had to have reported debt in Wave 1 and in the *j* wave.

Table 7: 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

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 available from the authors.

Table 8: Probit marginal effects (at the mean) on probability of reporting debt in Wave 1 and not 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 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 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.

Appendix

Table A.1: 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.

Table A.2: 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.

Table A.3: 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.

Table A.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			
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.

Table A.5: 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.

Table A.6: Probit estimates of the probablity of 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. Full results for Wave 1 - 2 and 1 - 3 are available from the authors.