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Household Balance Sheets in South Africa

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Abstract

This paper evaluates the composition of household portfolios including assets, liabilities and net worth in the National Income Dynamics Study (NIDS) wave 5 (SALDRU, 2018). The inclusion of a top up sample of 1005 households made the sample more representative of the South African population – particularly the higher end of the wealth distribution, which was previously under-represented because of panel attrition between Waves 1-4. This resulted in an increase in the estimates of real total household assets and liabilities (after the removal of outliers), bringing the distribution closer to the macroeconomic household balance sheet estimates of assets and liabilities provided by the SA Reserve Bank (SARB), which implies that the top-up sample also improved the external validity of the wealth data. We find that household balance sheets are dominated by real estate and vehicular assets and debts, with notable exceptions in different covariate domains. In terms of inequality between waves 4 and 5 of NIDS, there has been a slight decrease in the Gini coefficient on net-worth despite the top-up sample, but an increase in the Gini coefficient on financial assets. The overall conclusion of the paper is that the NIDS Wave 5 wealth module is fit for purpose and researchers can conduct a wide range of analyses with the data, but researchers still need to conduct their own outlier detection checks before commencing analyses.

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1. Introduction

This paper conducts an analysis of the distribution and determinants of household wealth using the fifth wave of the NIDS (SALDRU, 2018). The paper consists of two main parts: (1) an description of the process used for identifying outliers in all components of household assets, liabilities and net worth; and (2) an assessment of the univariate distributions of components of household net worth, as well as assessing the internal and external validity of the data.

NIDS included a wealth module in its second, fourth and fifth waves, conducted in 2010, 2014-2015, and 2017 respectively. Wealth is defined as the value of household assets minus liabilities, known as net worth. Since household membership and composition changes over time, longitudinal analysis of the wealth module across survey waves is impossible. Instead, the stock of wealth at each point must be analysed cross-sectionally. Nonetheless, this paper presents changes in the measurement of wealth over the last two NIDS waves in which wealth is measured.

The wealth questionnaire module used to measure assets, liabilities and net worth in wave 5 is the same as in NIDS wave 4 (see Daniels & Augustine, 2016). That is, it includes household durable assets in the measure of wealth, and, importantly allows for home ownership to be differentiated from land ownership with a land tenure variable identifying private or communal property rights.

As with previous NIDS wealth modules, a measure for one-shot net worth is present in the data, whereby survey respondents are asked what their net worth is inclusive of household possessions. A second "derived" variable for net worth is then constructed as the difference between components of a household's assets and liabilities. If a substantial subset of these questions are missing, the one-shot net worth variable value is substituted for the derived net worth value. The derived net worth variable is thus a richer measurement of net worth than the one-shot net worth measure.

Each wave of the NIDS data was subject to greater levels of attrition, most frequently at the top end of the income distribution. In wave five the sample was refreshed with a top-up sample that was specifically targeted to include higher net worth individuals and households (see Nicola Branson's 2018 wave 5 paper for more details). This has created substantively different estimates of household net worth compared to wave 4.

The rest of this paper proceeds as follows. Firstly, we present a brief review of the wealth literature. This is followed by a discussion of the measurement of household wealth in NIDS wave five, and the process we followed for identifying outliers in the public use data. We then evaluate the distribution of assets, liabilities and net worth, drawing comparisons with previous waves where necessary. Here the impact of the top-up sample on the internal validity of the data is also analysed. The external validity of data is then evaluated using data from the South African Reserve Bank (SARB) on household balance sheets. Household portfolio composition is then discussed. A brief discussion on land tenure arrangements and home ownership and its impact on wealth is also presented highlighting prospects for future research. This is followed by a conclusion.

2. Literature Review

Wealth is a stock variable that reflects the net financial position of a household or individual at a given point in time. It is measured by the concept of net worth, defined as the difference between material assets and liabilities (Davies & Shorrocks, 2000). Material assets broadly comprise financial assets, real assets, and retirement annuities. Assets provide for future consumption and are a source of security against negative shocks to the individual or household. As investments, they can generate returns that generally increase aggregate lifetime consumption and improve a household's well-being over an extended time horizon. Debts, on the other hand, consist of a range of liabilities that can be used for the acquisition of assets (e.g. housing bonds / mortgages), consumption smoothing (e.g. credit cards) or for business purposes.

It should be noted that collecting data on components of individual and household wealth is a socially sensitive exercise, implying that individuals can often be reluctant to disclose this information. This kind of high cognitive burden can lead to recall bias, which may result in measurement error or non-response in the data. However, NIDS has built up high levels of trust with respondents in the survey due to repeated interactions across Waves 1-5, which improves expected data quality. Despite this, it has been shown that high income earners are the most likely to drop out of the sample (SALDRU, 2018), which makes estimating parameters of the wealth distribution particularly sensitive to attrition and outliers (see Daniels, Finn & Musundwa, 2014; Daniels & Augustine, 2016).

The distribution of assets and liabilities as summarized by the net worth measure are traditionally framed theoretically by the lifecycle-permanent income hypothesis in economics. Empirically, it has been shown that household lifecycle portfolio allocations differ between country and household characteristics. McCarthy (2004) shows that there are three stylised facts that emerge from an empirical analysis of household portfolios. That is, portfolios differ by wealth, by the country in which the household lives, and by various household characteristics – such as the age, education, and family size. Secondly, the author finds that the average household's portfolio is typically invested mainly in safe or in only slightly risky assets, once residential housing is excluded. These low-risk assets might include bank accounts, such as savings and checking accounts, time deposits, and life insurance. Finally, most households appear to keep their portfolios very simple, with fewer than five different assets or accounts (McCarthy, 2004).

Understanding the distribution of net worth and wealth is imperative to understanding inequality, as wealth extends out of the labour market, and is sensitive to generational transfers and behavior over time. A report by the OECD (2018) shows that across developed countries the top decile of the net worth distribution hold 52 percent of countries' wealth (OECD, 2018). Further, countries with low net worth are not necessarily poor, since some of them are located high up in the income distribution. The post-recession era has affected net wealth in these countries, with high proportions of real estate debt that exceeds the property value of assets leading to negative net worth estimates. Finally, a panel data analysis of households in the OECD shows that net worth inequality has increased over time, reinforcing the importance of analysing the evolution of the wealth distribution over time.

Researching gender gaps in wealth in developed economies using OLS and non-parametric decomposition techniques, Sierminska, et al. (2010) found a gender wealth gap in Germany. Similarly, in a study of Australian households, Austen, et al. (2014) using a quantile regression adjusted decomposition, found a wealth gap at the top of the distribution. This is shown to be largely associated with single male households holding a larger proportion of retirement, business, and financial assets than single female households.. A wealth gap for married American couples is identified by Schmidt and Sevak (2008) using both an OLS and quantile regression in which lifecycle effects were a prominent determinant. This gap was similarly evident in research in 15 European countries in which a "wealth glass ceiling" was shown to exist for single female households as a result of labour market discrimination (Schneebaum *et al,* 2014).

Gender wealth gaps have also been investigated in developing economies. For example, based on a sample of bottom income quintile Thai households, and using a likelihood probit and tobit analysis, Antonopoulos and Floro (2005) found males have assets of a higher value than the assets held by females, thus increasing the relative net worth of their households. Muyanga, et al. (2013) similarly found that in Kenya female headship is associated with a 13% reduction in household asset wealth, with age and household size strong determining factors. In research by Deere and Leon (2003) in Latin America females were found to hold less than one-quarter of land by which is similar to findings by Kossoudji and Mueller (1983) in Botswana that women were disproportionately asset poor and dependent on remittances for survival. Highlighting the prevalence of the gender wealth gap in the developing world, Filmer (1999) found that in all countries in North, Western and Central Africa and South Asia, gender wealth gaps were large. and thought to be the result of unequal investment in human capital. The study shows a 34-percentage point difference in education investment in boys and girls in households in India.

Racial gaps in the wealth distribution have also been well documented. In a study from the late 1990's Wolff (1998) shows that not only has wealth fallen for the median American household over time, but also that wealth inequality is increasing and racial gaps in wealth inequality have widened. These effects have also been documented by Davern and Fisher (1995).

In the analysis below we disaggregate portfolio composition by relevant covariates such as race and gender and also explicitly investigate inequality in the wealth distribution. However, before doing so we discuss how outliers are treated because they can have a dramatic effect on estimates of inequality, becoming a source of potential bias in those estimates.

3. Measuring Household Wealth in NIDS over time

Time series evaluations of the wealth distribution of the NIDS sample is not directly possible due to changes in household composition over the course of the panel. This section briefly discusses how the NIDS wealth instrument is constructed. It should be noted that the instrument used to measure wealth in the NIDS survey changed between the second and the fourth waves of NIDS, with the change including a new question on household possessions and assets, as well as distinct questions for land and home ownership (See Daniels & Augustine, 2016). Between waves four and five, the questions have remained the same. The changes between the initial two waves measuring wealth need to be borne in mind when conducting analyses over time using the NIDS data.

The measure of total assets in wave five is the same as for wave four and is made up of the sum of real estate assets (including houses and other properties), business assets, vehicles, financial assets (which constitute a bank account and stocks), retirement annuities, and the value of livestock and household durable assets (or household possessions). The measure of total debt is constructed as the sum of real estate debt (and other properties), business debt, vehicle finance and financial debt (or loans). Net worth is defined as the difference between total assets and total debts for each household (for a diagrammatic representation of this, see Daniels and Augustine (2016)).

An underestimation of wealth in consumer surveys can be attributed to an under-sampling of wealthy households, which are believed to hold disproportionately higher shares of larger, more valuable assets (Avery, et al., 1986). A consequence of this is that population estimates based on these assets may be biased downward. In the context of NIDS wave five, a special top-up sample was introduced to enrich the data with a larger number of high income and wealthier households.

3.1 Outliers in components of assets, liabilities and net worth

SALDRU (2018) discuss their rigorous process of outlier identification for the NIDS wealth module in the data collection process of wave 5, which included a multivariate outlier detection algorithm followed up by telephonic interviews of identified respondents in order to verify whether the values were in fact accurate or not. This represents global best practice in terms of survey methodology and implies that researchers can have a high degree of confidence in the data.

However, SALDRU (2018: 63) also note that where telephonic attempts to contact potential outlier respondents were unsuccessful, the outlier values of those respondents *were left in the data*. This implies that researchers still have to conduct their own checks on the influence of outliers in components of assets, liabilities and net worth.

Following the statistical methodology utilized by the NIDS team (SALDRU, 2018), in this paper we also use the blocked adaptive computationally efficient outlier nominators (BACON) (BACON) algorithm of Weber (2010) to identify outliers in every asset, liability and net worth question of NIDS Wave 5. We specify the algorithm in a relatively standard way, using the 15th percentile of the chi square distribution as an initial threshold to separate outliers from non-outliers. Covariates used in the specification include individual characteristics of the household head and more general household characteristics, including age, race, marital status, household size, employment status, education, household income, geographical location, and whether the household owns their home. This algorithm is implemented separately on the following variables:

- Derived net worth;
- One-shot net worth;
- Total assets;
- Real estate assets;

- Business assets;
- Vehicle assets;
- Financial assets;
- Retirement (superannuation) assets;
- Livestock assets;
- Possessions assets;
- Total debt;
- Real estate debt;
- Business debt;
- Vehicle debt; and
- Financial debt.

This resulted in the following five households being omitted from the data for the final sample with which we conduct the analysis: hhid 507716, 511225, 508090, 503496, 510870.

4. The distribution of assets, liabilities and net worth

This section presents an overview of the responses to wealth questions and measures of wealth in the NIDS wave five sample. It evaluates the responses to the one-shot measure of wealth and compares this measure to the derived measure. It then evaluates the univariate distributions of the components of wealth, looks at inequality measures of the components of wealth and further evaluates the distribution of assets and debts in NIDS wave five.

Table 1: Household level response for one-shot wealth

	Frequency	Percent	Cumulative
Don't know	2,304	21.6	21.6
Refused	123	1.2	22.7
Missing	10	0.1	22.8
Something left over	5,195	48.6	71.4
Break even	2,678	25.1	96.5
Debt	378	3.5	100
Total	10,688	100	

Table 1 presents the distribution of responses for the one-shot wealth question in the wave five data. The response shows that just over one fifth of respondents do not know what they would have left over in the event of selling all their assets, whilst just 1.2 percent of respondents refused to answer the question. This refusal rate is similar to the refusal rate in wave four (1.1 percent). The number of respondents who perceive they will have something left over is just less than half (48.6 percent). At the same time, a quarter of the sample stated that they would break even. This response should be interpreted carefully because of the bias associated with rounding responses in questionnaires. Surprisingly, only 3.5 percent of households stated that they would be in debt after they sold all their assets. Once again, this number should be interpreted with caution because of the social sensitivity associated with being perceived as being in a financially precarious situation. The responses presented above are distributed similarly to the responses from wave four (see: Daniels & Augustine, 2016), boding well for the internal validity of the data.

The second household net worth variable is the derived variable. This is the value of assets less liabilities providing a measure of household net worth that allows one to compare with the one-shot variable. The distribution of both measures of net worth, weighted and unweighted, are presented in Table 2.

Table 2: Distribution of two measures of household net worth

Variable	Min	P10	P25	P50	Mean	P75	P95	Max	N
					Weighted				
Derived net worth	-1 363 544	5 608	20 516	90 850	665 705	377 394	2 450 500	3.44E+08	10,689
One shot net worth	-991 460	0	0	15 106	434 482	119 439	1 955 590	7.93E+07	7,932
					Unweighted				
Derived net worth	-1 363 544	6 890	24 249	84 340	597 476	288 945	2 048 881	3.44E+08	10,689
One shot net worth	-991 460	0	0	15 012	332 196	99 688	1 007 098	7.93E+07	7 933

The table shows the differences between the raw data in the sample and the weighted data that represents the population. The first thing to note is the large differences in the unweighted data between one-shot net worth and derived net worth, with one-shot net worth estimates across percentiles being much lower than derived net worth. This difference is most apparent at the median, where derived net worth (which is a more reliable measure) is 5.62 times higher than the estimate from one-shot net worth. Similarly, at the higher percentiles of the distribution net worth from the derived estimate is generally much higher than from the one-shot estimate.

In terms of the weighted estimates, the extremes of the distribution remain unchanged with weights. The bottom of the distribution also remains relatively unchanged, but the impact of the weights is seen from the median upwards for both the derived and one-shot measures of net worth. This shows that wealthier households are still under-represented in the data despite the top-up sample. Henceforth, we proceed by analysing only weighted estimates of the variables. The univariate distributions of the components of wealth are analysed next.

Table 3 shows the distributions of the components of assets and liabilities. The table alludes to the inequality in the distribution of both assets and debts. This can be seen by looking at the differences between the medians and means of each variable. For instance, the median of total debt in the weighted sample is R7005 while the mean is R115 049. This is a mean to median ratio of 16.42, illustrating that the observations at the top end of the debt distribution skew the mean radically. For total assets, the ratio of the mean to median (6.99) is less stark, but still illustrates the extent of the inequality.

Table 3: Distribution of components of assets and liabilities – weighted

Variable	Min	P10	P25	P50	Mean	P75	P95	Max	CV	N
Total assets	401	9 064	25 642	100 456	702 621	396 811	2 515 425	344 000 000	5.36	10066
Real Estate	1	5 004	24 922	79 750	570 927	344 337	1 982 919	98 300 000	4.39	8192
Business	70	1 301	5 004	25 177	220 426	99 223	983 821	10 000 000	3.00	411
Vehicle	20	24 577	40 284	79 750	133 889	169 192	398 129	8 385 535	1.28	1894
Financial	1	90	300	1 032	52 633	4 359	49 844	344 000 000	64.07	5567
Retirement	55	12 653	43 000	150 061	681 529	496 115	3 021 294	32 500 000	2.99	1048
Livestock	9	420	1 593	13 745	40 944	57 520	154 460	689 064	1.64	676
Possessions	9	4 668	9 969	25 020	98 729	60 047	400 314	24 600 000	5.15	10065
Total debt	2	496	1 856	7 005	115 049	45 268	569 816	17 000 000	4.65	4893
Real Estate	149	59 029	105 904	225 550	548 765	547 428	1 554 438	16 700 000	2.34	517
Business	300	1 991	2 518	6 043	34 392	20 000	99 223	545 727	3.09	29
Vehicle	100	9 869	41 674	90 000	140 667	193 093	467 802	983 064	1.09	551
Financial	2	400	1 496	5 000	23 239	17 314	99 146	2 541 220	3.25	4653

Table 4 presents the Gini coefficients of various financial measures in the data related to wealth from NIDS wave four and wave five. Focusing on the wave five estimates, we see that household income inequality (0.61) is much lower than wealth inequality (0.83) in South Africa. Further inequality for financial assets is exceptionally high, at 0.97, implying an almost completely unequal dispersion of financial assets in the country.

Table 4: Gini coefficients of financial measures

Assets/Debts/Income	Gini Wave 4	Gini Wave 5
Total Assets	0.87	0.83
Total Debts	0.90	0.87
Net Worth	0.90	0.83
Household Income	0.61	0.61
Real Estate Assets	0.88	0.83
Retirement Annuities	0.87	0.79
Financial Assets	0.92	0.97
Real Estate Debt	-	0.64

Note: The Gini coefficient on net worth was only calculated based on positive (non-zero) values, it is thus not an adequate reflection of inequality in the net worth distribution.

Comparing the estimates of Gini coefficients between wave four (2014/15) and wave five (2017/18) we see that, on average, asset and debt based inequality have declined by four and three percentage points each. Inequality in real estate assets and retirement annuities has also declined. A good measure of the internal validity of this data is reflected in the household income Gini coefficient which remained at 0.61 for both years.

Before discussing household portfolio composition, we look at the aggregated components of net worth individually by their respective deciles. Table 5 and Table 6 present the asset and debt shares by asset and debt decile, respectively, to provide further insight into the univariate distributions of these variables.

Table 5: Asset shares and value by asset decile

Decile	Share (%)	Median Value (Rands)
1	0.07	ZAR 5 100
2	0.20	ZAR 13 397
3	0.45	ZAR 25 678
4	0.93	ZAR 49 769
5	1.61	ZAR 78 949
6	2.16	ZAR 122 983
7	3.58	ZAR 202 659
8	5.88	ZAR 396 892
9	12.40	ZAR 852 668
10	72.71	ZAR 2 534 540

Table 5 shows that the share of assets held by asset decile is considerably unequal in South Africa. The bottom 10 percent of asset holders own 0.07 percent of total assets, with a median value of R5 100. The middle ten percent (the fifth decile) owns only 1.61 percent of total assets, with a median value 15.5 times larger than the bottom decile at R78 949. Unsurprisingly, the top decile owns the largest share of assets in the country at 72.7 percent, with a median asset value of R2 534 540, which is 29.8 times the median asset value of the fifth decile and an astounding 461.7 times larger than the median value of assets in the bottom decile. This points to the extent of asset-based inequality in South Africa. Further, the median value of assets by asset decile increases almost exponentially at an increasing rate.

Like Table 5, Table 6 shows the median value of debt and share of debt by debt decile. The inequality presented in this figure is also stark, but less so than in the case of assets. The bottom 10 percent of debt holders account for 0.03 percent of total debt, with a median debt value of R66 942. The middle ten percent of the distribution accounts for merely 0.64 percent of total debt, with a median debt value of R101 367, which is 1.5 times higher than the median value of debt for the bottom decile. The top decile of debt owners account for a large 76.97 percent of total debt in the country and the median value of debt in this decile is R1 851 596. This is 18.2 times the size of the median debt for the fifth decile and 27.6 times the median value of debt for the bottom decile.

Table 6: Debt shares and value by debt decile

Decile	Share	Median Value (Rands)
1	0.03	ZAR 66 942
2	0.13	ZAR 69 673
3	0.23	ZAR 71 054
4	0.39	ZAR 108 977
5	0.64	ZAR 101 367
6	1.06	ZAR 124 598
7	1.86	ZAR 170 200
8	5.18	ZAR 303 265
9	13.50	ZAR 756 129
10	76.97	ZAR 1 851 596

5. Internal and External validity of the data

To analyse the internal validity of the data, we start by looking at the change in the components of net worth before the top-up sample was added to the data, and the changes in these components post top-up. Table 7 shows the minimum, maximum, and mean values of each variable. The pre-top-up sample was weighted by the weights designed for the initial data and the post top-up sample was reweighted taking into account the addition of 1005 new observations of higher income households.

The table shows that the addition of the top-up sample has increased the mean values of almost all the components of assets and debts, but the extent of this increase varies across variables.

The weighted mean value of total assets increased by a factor of 1.1 from R629 886 to R702 621. The mean values of real estate, business, and vehicle assets also increased after the top-up sample was introduced. The mean value of financial assets decreased from R 53 328 to R52 633 (by 2 percent), indicating that perhaps some wealthier households have fewer financial assets and more other assets. As expected, the mean values of livestock and possessions did not increase by much with the addition of the new households.

What is interesting is that the mean value of retirement annuities decreased from R709 168 to R681 529, which is a decrease of four percent. One potential explanation for this is that the top-up sample may include a higher proportion of individuals already in the retirement stage of the lifecycle, implying that the value of their retirement annuities are on average lower.

In terms of debts, the mean value of total debt increased by a factor of 1.32 from R87 369 to R115 049, again pointing to the fact that the internal validity of the data is now stronger. Unlike the mean value of assets, where some values decreased, for the components of debt all mean values increased. The largest difference was for business debts, which increased by a factor of 2.97 from R11 570 to R34 392. What this shows is that higher income households have higher value business debts. The increase in the value of real estate debt by a factor of 1.25 from R438 955 to R548 765 is also indicative of the fact that higher income households have more real estate debt.

Overall, however, the increase in mean total asset and debt value post top-up implies that the internal validity of the data is now stronger because of the addition of higher net worth households. This is confirmed by evaluating the mean value of derived net worth, which has increased by a factor of 1.15 from R578 168 to R665 699. Interestingly, the mean value of one-shot net worth increased by a factor of 1.55 from R279 798 to R434 482, showing increased trust of higher income households in divulging their financial status to interviewers. This is also an indicator of increased internal validity of the wealth data in NIDS.

Table 7: Comparison of wealth variables before and after top-up sample

	Sample without top up – weighted				Sample Including top up – weighted			
Variable	**Min**	**Mean**	**Max**	**N**	**Min**	**Mean**	**Max**	**N**
Total assets	401	629 886	344 000 000	9 297	401	702 621	344 000 000	10 066
Real Estate	9	487 093	55 500 000	7 529	1	570 927	98 300 000	8 192
Business	70	154 077	10 000 000	350	70	220 426	10 000 000	411
Vehicle	20	120 326	8 385 535	1 362	20	133 889	8 385 535	1 894
Financial	1	53 328	344 000 000	4 939	1	52 633	344 000 000	5 567
Retirement	55	709 168	32 500 000	805	55	681 529	32 500 000	1 048
Livestock	9	40 169	689 064	674	9	40 944	689 064	676
Possessions	9	96 362	14 900 000	9 296	9	98 729	24 600 000	10 065
Total debt	2	87 369	9 919 851	4 439	2	115 049	17 000 000	4 893
Real Estate	149	438 955	9 914 894	282	149	548 765	16 700 000	517
Business	300	11 570	99 688	26	300	34 392	545 727	29
Vehicle	100	135 251	805 678	417	100	140 667	983 064	551
Financial	2	21 957	2 541 220	4 298	2	23 239	2 541 220	4 653
Net worth Derived	-964 966	578 168	344 000 000	9 684	-1 363 544	665 699	344 000 000	10 688
Net worth One Shot	-500 392	279 798	79 300 000	7 148	-991 460	434 482	79 300 000	7 932

We now turn to examining the external validity of the data. To determine the external validity of the data we evaluate whether the NIDS estimates of assets and liabilities compare well with estimates from national balance sheets from the SARB. Since the SARB uses tax-based data to calculate these figures they are likely to differ substantially from the ones collected using the NIDS instrument. Nonetheless, a comparison between the two is drawn below.

Table 8: Rand value of components of assets and liabilities in NIDS and SARB

	NIDS 2017/18	SARB 2017	NIDS/SARB
Financial Assets	542 000 000 000	8 576 000 000 000	0.06
Non-financial assets	11 600 000 000 000	4 298 000 000 000	2.70
Total assets	12 100 000 000 000	12 874 000 000 000	0.94
Real-estate debt	642 000 000 000	983 000 000 000	0.65
Other debt	363 000 000 000	1 054 000 000 000	0.34
Total debt	1 000 000 000 000	2 036 000 000 000	0.49
Net worth	12 300 000 000 000	10 838 000 000 000	1.13

Source: SARB online statistical query, 2018

Table 8 shows the difference between the values of assets and liabilities between the NIDS and the SARB data. The first interesting finding and the most staggering is the extent to which financial assets are not captured well enough by the NIDS instrument. The table shows that NIDS only captures about 6 percent of the financial asset values reported by SARB. Conversely, NIDS is more efficient at collecting data on non-financial assets, as is shown in row two of the table. It should be borne in mind that non-financial assets include household possessions, which are not captured by SARB, so this may be inflating the NIDS estimates, albeit only slightly. Total assets captured by NIDS and SARB are quite close in proximity to each other, as is net worth. This indicates that the external validity of NIDS regarding assets and net worth, on aggregate, is quite strong.

With respect to debt, the external validity of the NIDS instrument is not as strong. The discrepancies between real estate debt, other debt, and total debt are all quite large. Recalling Table 1, only 3.5 percent of the sample indicated that they would be in debt in response to the one-shot measure of net worth. This is clearly underestimated, as is evident from the SARB data, and further work needs to be carried out to motivate respondents to let go of the social sensitivity surrounding perceptions of being "in debt".

Compared to wave four of NIDS (See: Daniels and Augustine, 2016), the external validity of wave five is better for total assets and its components. For financial assets, external validity improved from a NIDS/SARB ratio of 0.03 to 0.06. The external validity of non-financial assets also improved, with a decline in the NIDS/SARB ratio from 4.34 in wave four to 2.7 in wave five. The estimate for total assets for wave five is also closer to the estimates presented by SARB, with a ratio of 0.94 in wave five compared to the overestimate of 1.27 in NIDS wave four (ibid, 2016). As a result of this, the total estimate for net worth has also improved vis-à-vis wave four, with a NIDS/SARB ratio of 1.13 now compared to 1.42 in wave four.

6. Household Portfolio Composition

We now turn to household portfolio composition across assets and debts analysed across the asset, debt, net worth, age, income and geolocation distributions. This section provides insight as to the composition of household portfolios across these covariates, allowing an overview of how wealth is distributed in South Africa.

Figure 1: Asset portfolio composition by asset decile

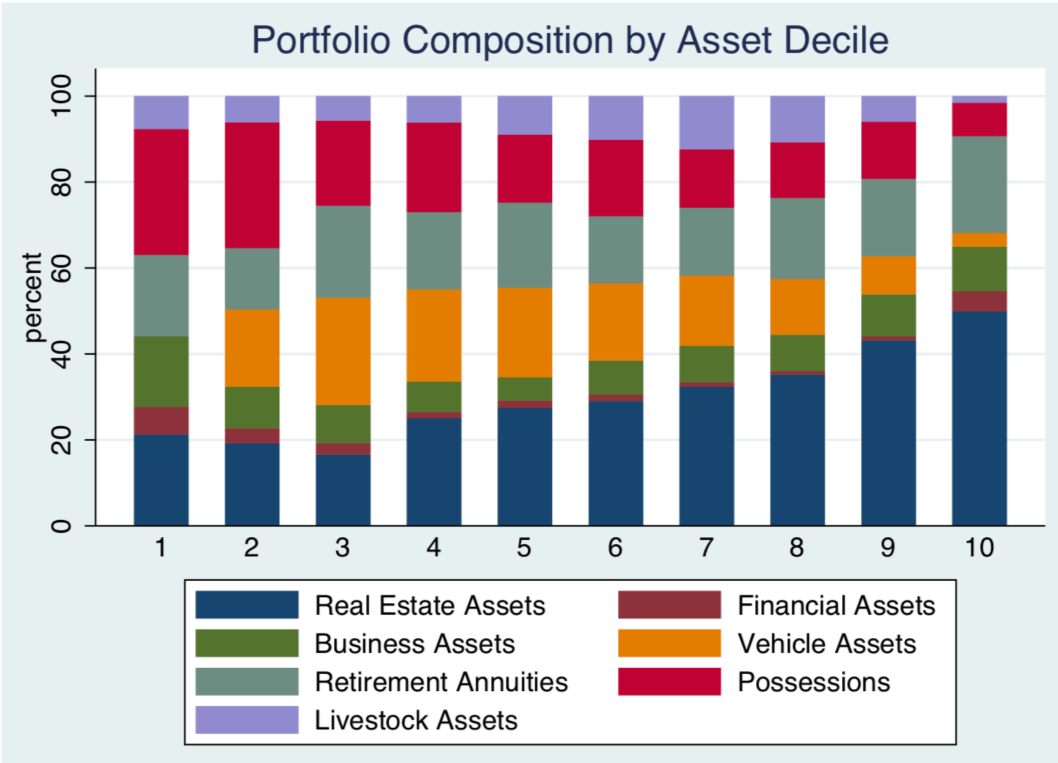


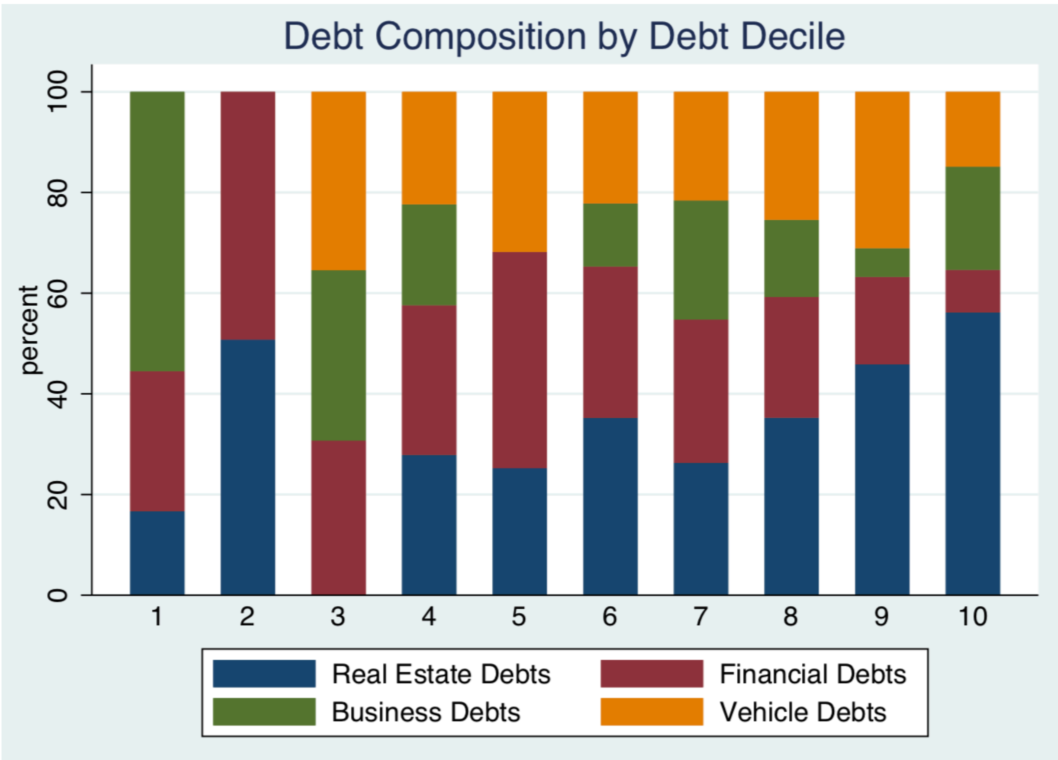
Figure 3 presents asset portfolio composition by asset deciles. The first thing to note in the figure is the larger share possessions comprise at the bottom deciles of the asset distribution, indicating that households in South Africa, especially at the bottom deciles acquire more small assets. Real estate assets are a small share (just over a fifth) in the bottom decile of the asset distribution but this steadily increases to just about half by the tenth decile of the distribution. The share of real estate assets, however, decreases from the first to third decile by five percentage points. Thereafter, the share of real estate assets increases steadily from 25.1 percent in decile four to 43.2 percent of the household asset portfolio in the tenth decile. The share of retirement annuity assets fluctuates across the asset distribution, with those in the bottom decile holding 19 percent of retirement annuities as part of their asset portfolio. This decreases to 15.7 percent in the sixth decile, then increases to just under a quarter of the asset portfolio of those in the tenth decile of the asset distribution. This pattern shows that throughout the distribution of assets the share of retirement annuities as asset holdings fluctuates, but those at the top have a higher share of labour market savings for retirement.

The share of vehicles as an asset is non-existent at the bottom decile of the asset distribution. The share of vehicle assets increases to under a fifth (18 percent) of the asset portfolio of those at the second decile of the distribution. However, there is a decrease in the share of vehicle assets as the asset distribution increases. For instance, at the median 20.9 percent of the asset portfolio of households consists of vehicles, but this decreases to 8.9 percent in decile nine, and drops even further to 3.2 percent at the tenth decile of the asset distribution. What this indicates, is that as households acquire more assets, vehicles become a smaller share of their asset portfolios.

Financial assets are a small share of household assets in South Africa, as are livestock assets. The small share of financial assets may point to liquidity constraints in South African households. This is particularly the case in the middle of the income distribution, alluding to the "missing middle" where real earnings growth is constrained (Bhorat and Khan, 2018) and households have to depend on debt. Looking at the absolute rand values of the median value of financial assets at the median of the asset distribution, we see that households at the median only have financial assets worth R500 (See: Appendix Table A 1) or 1.7 percent of their total asset portfolio share.

Interestingly, business assets make up a noticeable share of the asset distribution, especially for those in the bottom decile (16.4 percent). This could be because households at the bottom end of the asset distribution are more likely to be self-employed, and to manage micro and small enterprises from home. It is important to note that because assets are a stock, this distribution has not changed significantly since wave four (See: Daniels & Augustine, 2016).

Figure 2: Debt composition by debt decile



We now turn to the distribution of debt in households in South Africa. Figure 4 shows debt composition in South Africa by debt decile. The first striking thing about the above figure is that business debt makes up the largest proportion of debt in the bottom decile of the debt distribution (55 percent). This reinforces the pattern we saw in the asset distribution where those in the bottom decile have a high share of business assets. In the first and second deciles of the debt distribution there are no vehicle debts. In contrast to the first decile of the debt distribution, the second decile does not have any business debts either. The next striking thing about the figure is that in the third decile of the debt distribution there is no real estate debt. These findings suggest that there are diverse ways in which poorer households source and use finance.

An interesting thing to note at this point is that the figure above only presents shares. Looking at the absolute values of mean and median debt (Appendix Table A 2) shows that, while the first decile has a large proportion of business debt, this only amounts to R496.00 at the median and mean. This indicates that at the lower deciles of the debt distribution the size of debt and access to debt are limited to smaller amounts.

Vehicle debts appear in the third decile of the debt distribution, indicating that those in the bottom twenty percent of the debt distribution in South Africa may have challenges accessing vehicle finance. The size of vehicle debt as a proportion of the South African household debt portfolio fluctuates between decile three and decile ten, from 35 percent in decile three to 15 percent in decile ten. The size of household business debt also fluctuates across the distribution, not making an appearance at the median.

Real estate debts make up 17 percent of debt at the bottom decile of the debt distribution and this increases to over half (51 percent) of the debt portfolio composition at the second decile. As mentioned earlier, the third decile of the debt distribution does not exhibit any real estate debt, which is cause for further investigation. From the fourth decile on real estate debt generally increases, with 56 percent of household portfolio debt at the tenth decile made up of real estate debt.

Once again, the magnitude of real estate debt changes as we move along the debt distribution. At the first decile, while real estate debt accounts for 17 percent of the debt portfolio in absolute rand terms, it is only valued at R149 at the median and mean (See: Appendix Table A 2). As expected, this is much smaller than the value of real estate debt at the median for the tenth decile of the debt distribution, which is valued at R500 000. The median value of real estate debt along the debt distribution in South Africa is R 4077. This is 122 times smaller than the value of real estate debt at the tenth decile and 27 times larger than the value of real estate debt at the bottom decile of the debt distribution.

Figure 3: Asset portfolio composition by income decile

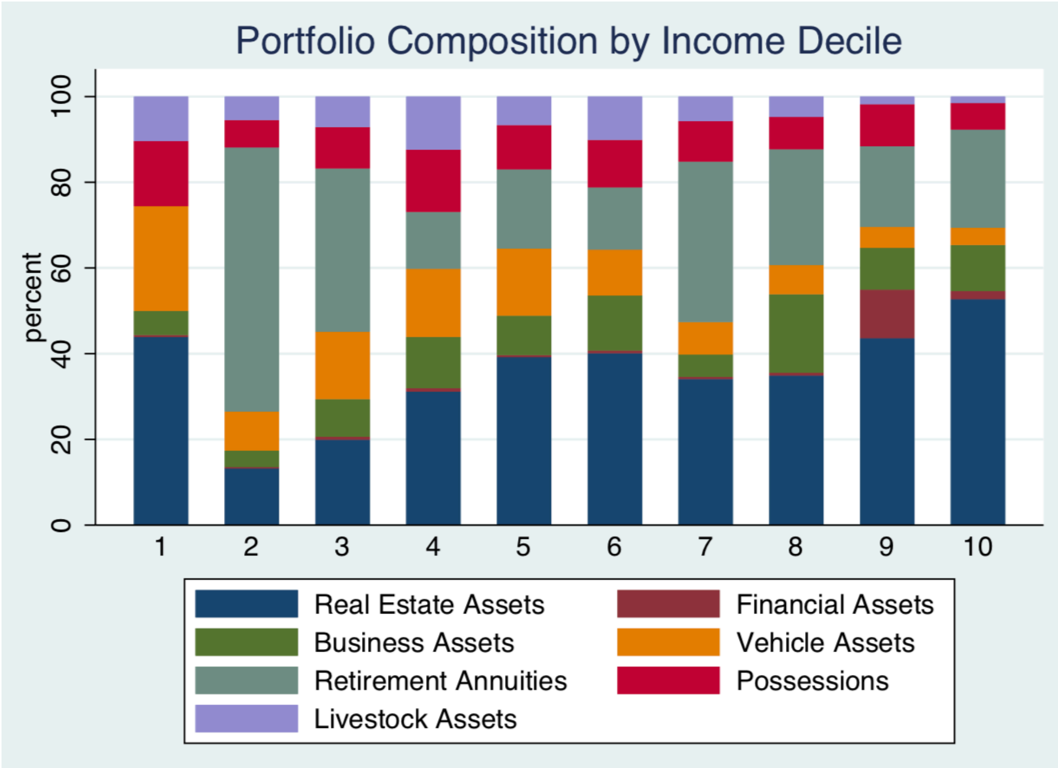


Figure 5 shows the distribution of assets across the income distribution. Income is closely related to wealth, in that those with a higher income have a higher probability of accessing wealth through asset acquisition and access to finance. Ranking income from the smallest ten percent to the top ten percent shows that real estate assets are by far the most common type of assets. Real estate assets make up between 13 and 53 percent of the asset composition across all the deciles of the income distribution. The share of real estate debt at the bottom decile of the distribution is 44 percent, but this is associated with a median value of just R19 938 (See: Appendix Table A 3) Even though the share of real estate assets decreases to 13 percent at the second decile of the income distribution, the median value is higher than at the bottom decile (it is R37 339). At the median of the income distribution the share of real estate assets is 39 percent, and this is associated with a median value of real estate of R53 457. Finally, the share of real estate assets increases between the second and tenth deciles of the income distribution (from 13 percent to 53 percent), with the median value of real estate assets at the tenth decile equal to R1 244 154. This shows that from the second decile onwards, the share of real estate assets increases, but so does the median value of real estate assets held.

The second most prominent asset type held over household income deciles is retirement annuities. Retirement annuities are not present in the bottom decile of the income distribution, showing that households at this decile are not saving for retirement at all. This share increases dramatically at the second decile to 62 percent of the asset portfolio. The median value of retirement annuities at this decile is R503 549, indicative of strong savings behavior at this part of the distribution. This could be associated with mandatory savings arrangements with employers, especially since the share of retirement annuities drops in the deciles following the second. It is worth noting that retirement annuities in the middle of the distribution (fourth, fifth and sixth deciles) comprise relatively small shares (13, 19 and 15 percent) of the asset portfolio of these deciles. This shows that households at the middle of the income distribution are squeezed in terms of their portfolio and are saving a relatively small proportion of their income.

Business assets, livestock assets and possessions all comprise relatively small shares of the household asset portfolio across income decile. For instance, at the median of the household income distribution business assets make up 9 percent of the household asset portfolio, with livestock and possession assets making up 7 and 10 percent respectively.

Across the income distribution, financial assets make up the smallest share of the household asset portfolio composition. This share is less than two percent of the household asset portfolio for all deciles except the ninth, where the share of financial assets is 11 percent. Once again this points to liquidity constraints in South African households, now across the income distribution.

Figure 4: Debt composition by income decile

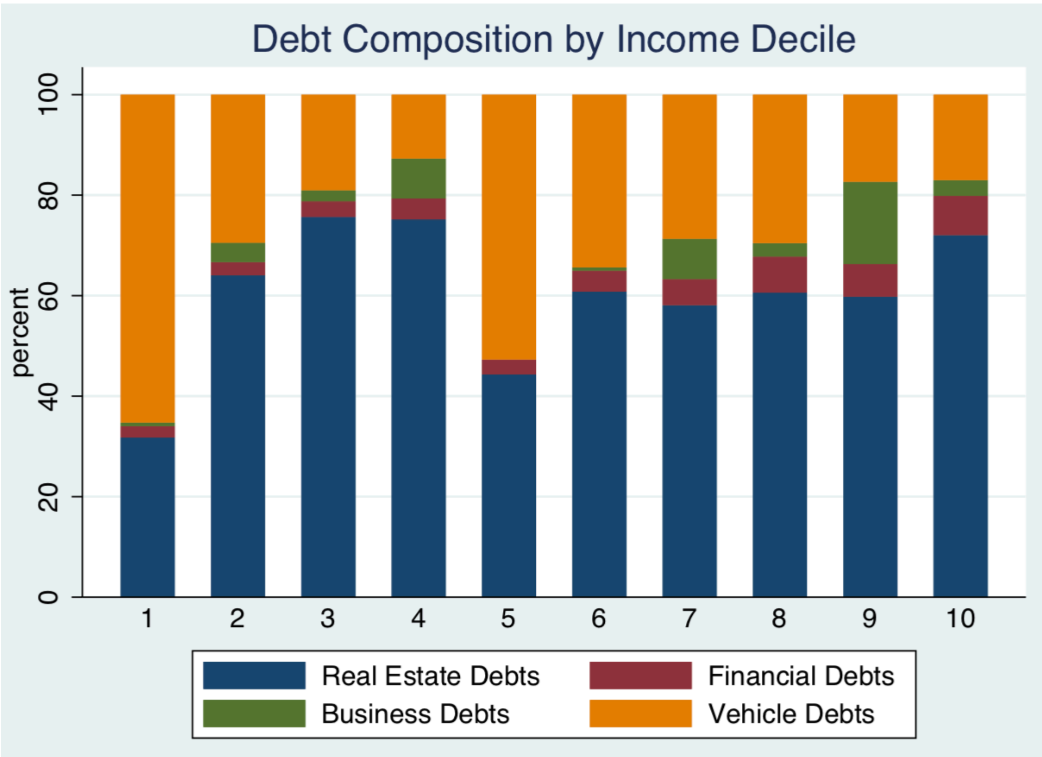
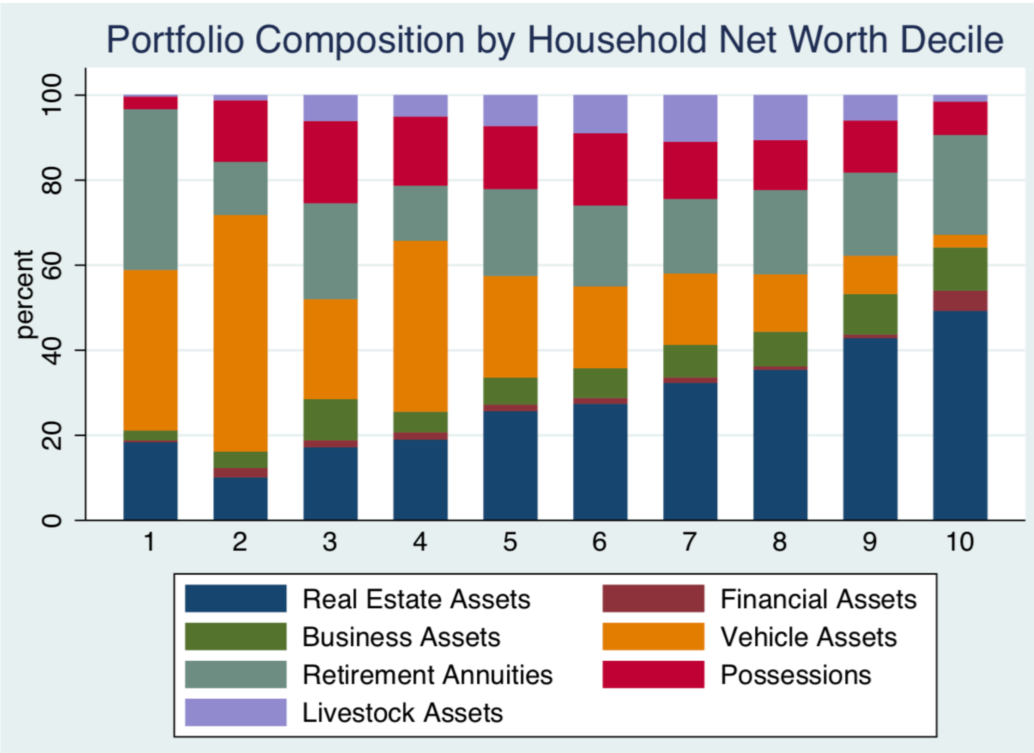


Figure 6 shows that real estate debts make up the largest share of debt composition across most of the income deciles of the income distribution in South Africa. The share of real estate debt fluctuates from 32 percent of the debt portfolio at the bottom decile of the income distribution to a maximum of 75 percent of the debt portfolio at the fourth decile of the income distribution. The median values of real estate debts (See: Appendix Table A 4) also fluctuate across the distribution, starting at a value of R123 811 at the bottom decile, increasing to R151 556 at the median and ending at a median value of R493 599 at the top decile.

After financial debt, vehicle debts are the second most common type of debt across the income distribution in South Africa. The share of vehicle debts does not follow a set pattern across the income distribution. At the bottom decile it accounts for 65 percent of overall debt, whilst at the median it accounts for just more than half of the debt portfolio (53 percent). At the top decile the share of vehicle debt decreases to 17 percent of the debt portfolio. The median values associated with these shares are R248 831 at the bottom decile, R152 899 at the middle decile and R147 460 at the top decile of the income distribution (See: Appendix Table A 4).

Business debts feature only slightly in the composition of debt across income in South Africa. As with financial assets across income, financial debts do not feature prominently in the asset distribution across income in South Africa.

Figure 5: Asset portfolio composition by household net worth decile

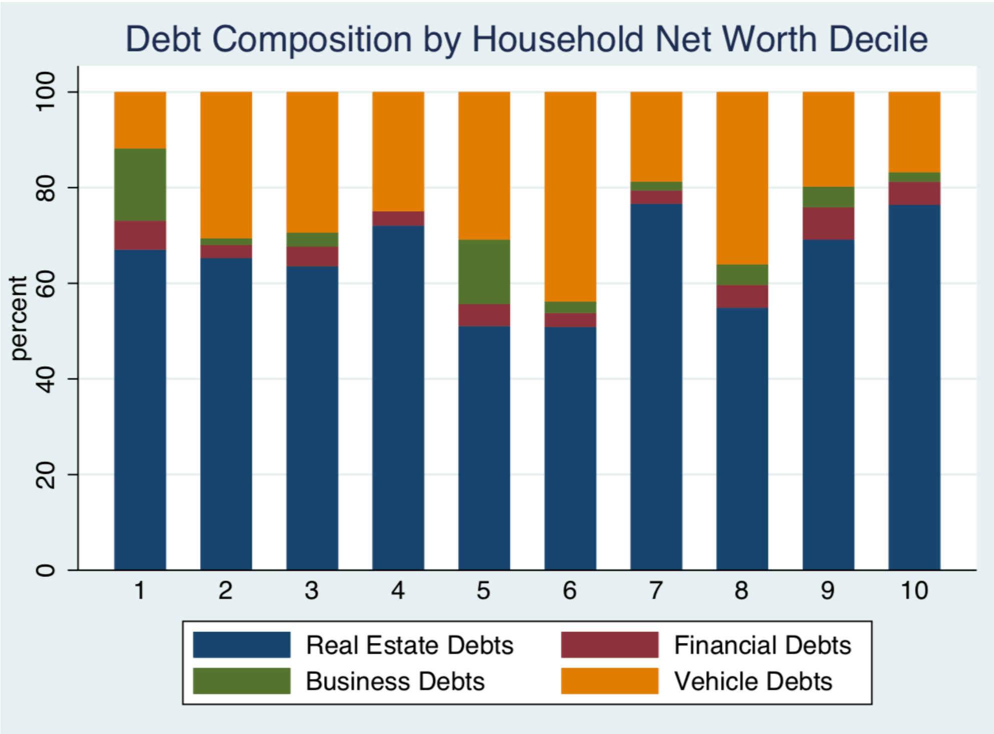


As stated in the discussion above, wealth is a stock, which evolves slowly over time. Figure 7 shows household asset composition across net worth decile in South Africa, providing a snapshot of asset accumulation across the wealth distribution in the country. The patterns observed differ from asset portfolio composition by income, showing that wealth and income, though correlated, result in different behavioural responses by households. An important caveat, before interpreting the above figure, is that because the net worth distribution falls along the negative number line, those in the bottom deciles are not necessarily less wealthy than those at the top. In other words, a household with a large number of assets and liabilities may have a net worth of close to zero placing it in a lower decile. Nonetheless, the figure is interesting as it shows that across the net worth distribution the most prominent assets are real estate assets and household possessions.

The first pattern apparent in the distribution of assets over net worth deciles is that real estate assets make up a small proportion of assets towards the bottom of the distribution of net worth and this increases steadily to the tenth decile. Conversely, the share of vehicle assets – while varying – is generally larger at the bottom of the distribution then decreases in share as net worth decile increases. The share of retirement annuities is largest at the bottom decile, taking on a median value of R3 981 (See: Appendix Table A 5). This share also fluctuates across net worth decile.

The share of business assets fluctuates across the net worth distribution from 2 to 10 percent, with a share of 2 percent at the median of net worth. The share of household possessions also fluctuates from 3 to 19 percent, with a median share of 15 percent. Finally, the share of livestock assets reaches its maximum share at the seventh and eighth decile of the distribution, with a contribution to the asset portfolio of these net worth deciles of 11 percent.

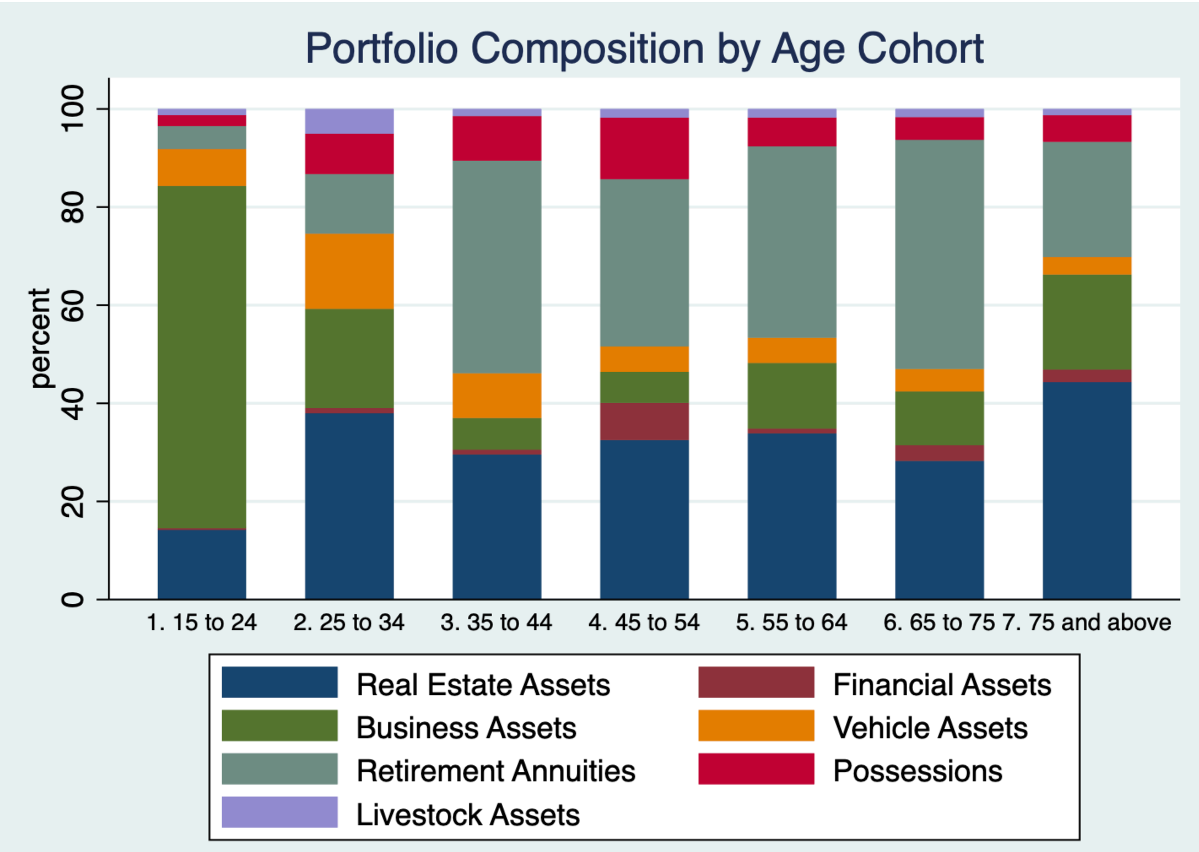
Figure 6: Debt composition by household net worth decile



We now investigate debt composition by household net worth decile. Figure 8 shows that, for the entire net worth distribution, real estate debts make up the largest share of debt by net worth decile. Second to this is vehicle debt, with the share of these fluctuating over the net worth deciles.

Overall financial debts only feature as a very small proportion in the share of household debt by net worth, indicating that households do not seem to take on much financial debt as part of their portfolios. Business debts on the other hand fluctuate by decile, even though they comprise a small share of asset portfolios by net worth. For instance, in the first decile of net worth business debts make up 15 percent of the debt portfolio. This drops to between 1 and 4 percent for all other deciles of the debt distribution except for the median, where business debts make up 14 percent of the debt portfolio at this part of the net worth distribution.

Figure 7: Asset portfolio composition by age cohort



Age is an important determinant of the ability to build wealth, as those at the earlier stages of the lifecycle may have constraints to the acquisition of wealth, both assets and liabilities. Figure 9 shows the asset portfolios of various age cohorts in South Africa. The first notable thing from the figure is the large proportion (70 percent) of business assets for those in the 15 to 24 age cohort. Table A 7 in the appendix, shows that the median value for this asset class is R1 982 919. This is exceptionally high and may be indicative of outliers in this segment of the data. A disaggregation of this statistic by race and education may shed more light on the dynamics underlying the high value of business assets in this age cohort.

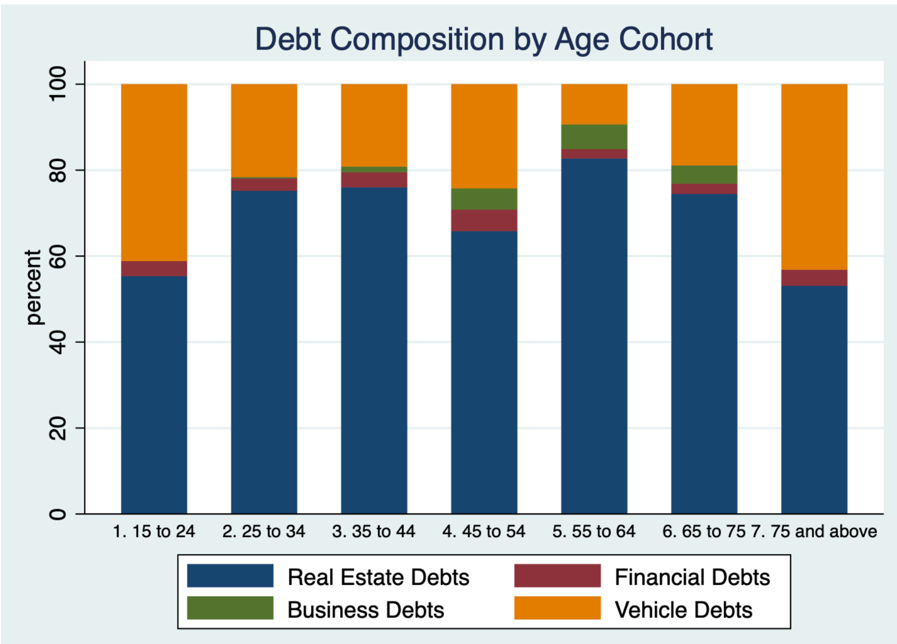
The share of real estate assets varies across age cohort, with the highest share of real estate assets held by those in the age range 75 and above (44 percent, with a median value of R119 439). This makes sense as those towards the end of the life cycle have acquired housing real estate. The second highest share of real estate assets is for those in the 25 – 34 age cohort, with real estate assets making up 38 percent of their asset portfolio. The median value of real estate assets in this age cohort is much lower, at R50 039 (See Appendix Table A 7). In general, Table A 7 shows that the median value of real estate increases by age cohort, from R40 000 for those between 15 and 24 to R119 439 for those above 75.

Throughout the age distribution, household possessions make up a relatively small share of the household asset portfolio, with the largest share of possessions equal to 8 percent for those between 25 and 34. Financial assets make a prominent appearance for those between the ages of 45-54 (9 percent of the household asset portfolio) indicating that this age cohort is likely saving. This is in addition to the large share of retirement annuities that this cohort holds. In general, the share of financial assets makes up a relatively small share of the household asset portfolios across all age cohorts. This is in contrast to retirement annuities which make up a prominent share for those between the ages of 35 to 75. Also worth mentioning is the lack of financial assets and retirement annuities amongst the youth (those under 34), whose inability to save may be hindered by a lack of labour market opportunities and other lifecycle constraints. Conversely, those between the ages of 35 and 75 have a relatively large share of retirement annuities, indicative of the saving phase of the lifecycle.

We now turn to debt composition by age cohort. Figure 10 shows the debt composition by age cohort and some interesting yet expected trends emerge. The first is that the share of real estate debt is the highest contributor to the debt portfolio across all age cohorts. The share of the contribution of real estate debt varies from 55 percent for those between 15 and 24 to 83 percent for those between 55 and 64. Aligning with the lifecycle hypothesis, an investigation of the median values of real estate debt (See: Appendix Table A 8) shows that the median values of real estate debt increase from ages 15 to 64, after which there is a decrease as people exit the labour market.

The second largest debt category across all age cohorts is vehicle debt, with the share of vehicle debt as a proportion of household debt being the largest for households headed by the 15-24 age group (41 percent) and the 75 and above (43 percent) age group. An investigation of the median of vehicle debt by age cohort shows that the value of vehicle debt fluctuates across age categories, not increasing with age.

Figure 8: Debt composition by age cohort



Finally, Figure 10 shows that financial and business debts make up a small proportion of household debt composition across age. In fact, there are no business debts for households headed by those between the ages of 15 and 24, or 75 and above. The proportion of business debt is largest for those in the age range 55-64, with business debts accounting for 6 percent of the debt portfolio.

The share of financial debts ranges from 2 percent for those between 55 and 75 to a maximum of 5 percent of the debt portfolio for those between the ages of 45-54. This relatively high share of financial debt for those in the middle of the age distribution may indicate the existence of some liquidity constraints. At the same time, an investigation of the median value of financial debt by age (Table A 8) shows that the absolute median value of financial debt by age is inverted u-shaped, with those at the tail ends of the distribution borrowing the least and those between the ages of 45-54 borrowing the most (a median value of R7 050).

Access to wealth can be constrained by geo-location, and this is particularly the case for debt, where access to financial institutions can be limited. Similarly, asset acquisition may be hindered by a lack of labour market opportunity based on the location of a household. This section now turns to a review of asset and debt portfolio composition by geo-location. Considered here are the four classifications of geotype in the NIDS data, namely, rural formal areas, urban formal areas, urban informal areas and tribal authority areas (or chiefdoms).

Figure 11 shows asset portfolio allocation by geotype. A good starting point is household in urban formal areas . This group of households comprise an asset portfolio made up mostly of real estate assets (38 percent). This is followed by retirement annuities (34 percent), indicating their close proximity to urban labour markets. The next category that makes up a large share of urban formal household asset portfolios are business assets (12 percent), with a smaller share of vehicle assets (6 percent) and a small share of household possessions (5 percent).

Compared to this group, slightly more than a tenth of of urban informal households' asset portfolios are comprised of real estate assets (13 percent). The largest share of household asset portfolios is made up of retirement annuities (42 percent) then business assets (18 percent), indicating a significant presence of household self-employment. Vehicle assets rank third for those in urban informal areas (17 percent), with a much larger share than was in urban formal households' asset portfolios. Vehicle assets follows retirement annuities for the urban informal category. Most interesting, vis-à-vis urban formal households is the larger share of business assets in this category indicative of a potentially larger pool of self-employed households in urban informal settings. Financial assets make up the smallest share of urban informal household asset portfolios, at a share of 0.5 percent.

Figure 9: Asset portfolio composition by geotype

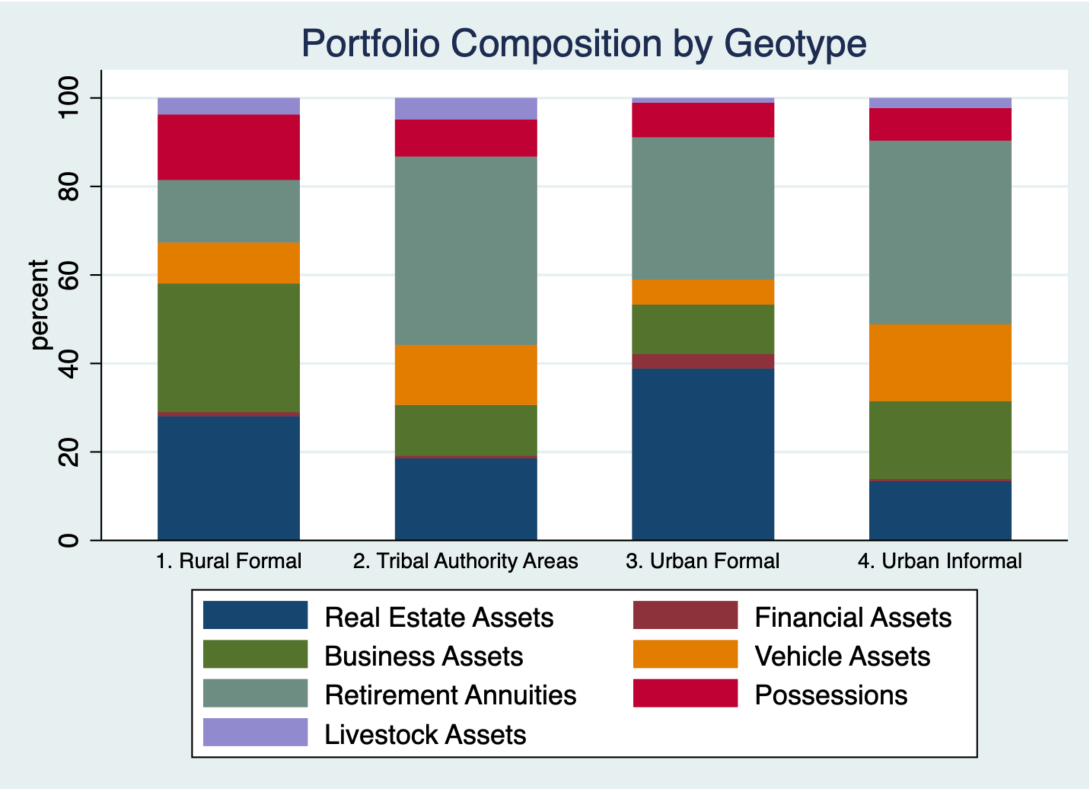


Figure 11 also shows the asset composition of rural formal and tribal authority areas. Business assets comprise the largest share of the asset portfolios of rural formal households, at a share of 29 percent. Following this, real estate assets make up 28 percent of the asset portfolio. Vehicle assets make up slightly less than a tenth (9 percent) of the asset portfolio, higher than in urban formal areas. The share of retirement annuities is the smallest across all geolocations, with this asset contributing 14 percent to the asset portfolio. Rural formal households also have the highest share of household possessions across all geolocations, with a share of 15 percent of the asset portfolio. This is associated with a median value of R19 906 (Table A 9).

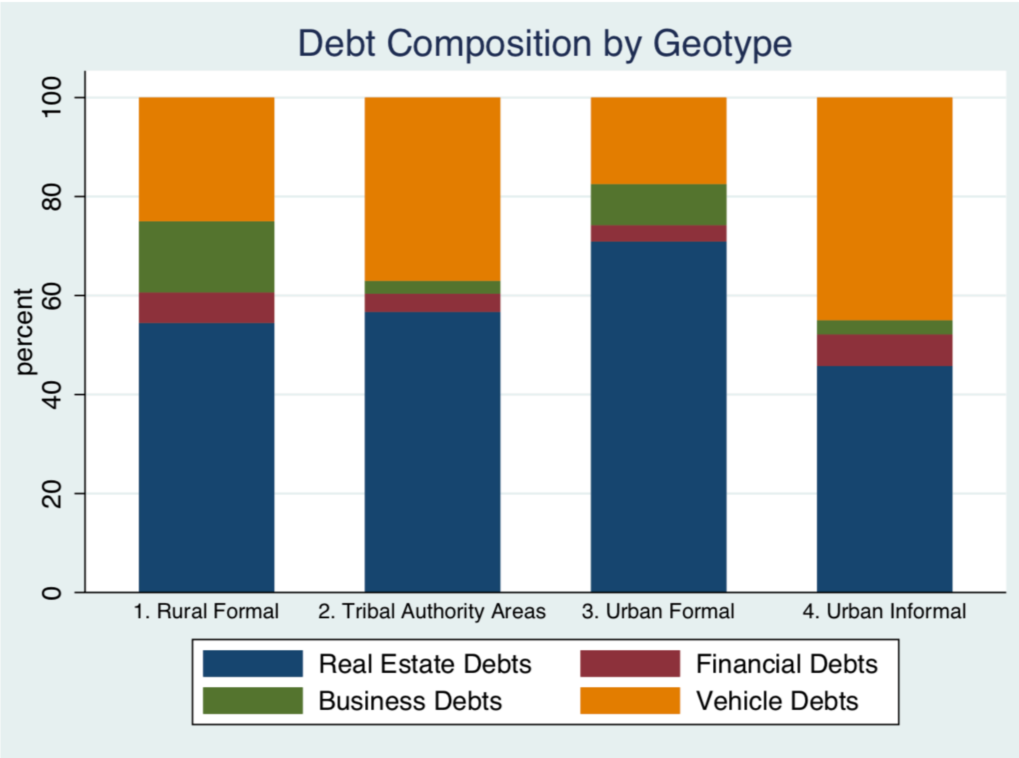
Real estate makes up 18 percent of the average household asset portfolio in Tribal Authority Areas (TAAs). Real estate is the second largest asset class for TAAs, with retirement annuities taking the first place at a share of 43 percent. Business assets make up the smallest share of the asset portfolio in TAAs at 11 percent. On the other hand, livestock assets make up the largest share of the asset portfolio of TAA households, compared to other geolocations, at 5 percent with a median value of R15 000. Comparing the median value of livestock in TAA's to the median value of livestock in rural formal areas shows that the median value of livestock assets is higher in rural formal areas, at R 22 500.

Figure 12 shows the debt composition of households by geotype. The first interesting pattern is the staggering amount of real estate across all geolocations. The share of debt is the highest in urban formal areas, making up 71 percent (with a median value of R245 190[2]) of the debt

[2] See Table A 10

portfolio composition of households in these areas. Following urban formal areas, the share of real estate debt in TAA's is second highest at 57 percent (with a median value of R130 562). The share of real estate debt is third highest in rural formal areas (54 percent), with a median value of R150 600. Finally, the share of real estate debt is smallest in urban informal areas, making up just less than half of the debt portfolio composition, at 46 percent (median value R94 998).

Figure 10: Debt composition by geotype



The second largest share of debt by geolocation is vehicular debt. This is highest in urban informal areas, making up 46 percent of the debt portfolio for the average household in this area. Vehicle debt is then next highest in TAAs, comprising 37 percent of the debt portfolio. Vehicle debt makes up a quarter of the debt portfolio in rural formal areas, and 17 percent of the debt composition in urban formal areas.

Business debts and financial debts make up a relatively small share of debt across all geotypes. However, business debts are largest in rural formal areas, at 14 percent, indicative of entrepreneurial activities taking place at the household level. This ratio drops to 8 percent in urban formal areas and 3 percent in TAA's and urban informal areas, respectively.

Finally, financial debts make up a very small share of debts across all geotypes. This share is 6 percent in urban informal and rural formal areas, 4 percent in TAAs and 3 percent in urban formal areas.

7. Land tenure arrangements and home-ownership

As noted by Daniels and Augustine (2016), the dual land tenure system and its relationship to wealth is often overlooked in the canon of wealth research. NIDS is an excellent tool for bridging this divide as it now accounts for the rights associated with various property types.

Table 9presents the proportion of the sample that own homes but live under different property right regimes. Households either own land privately with a right to sell or are allocated secure rights on tribal land by a reigning chief. This categorisation is split in the table below by geotype. As the table shows, the highest proportion of households with secure rights on tribal land are found in Tribal Authority Areas (TAAs). 38.2 percent of all households in these areas are allocated secure rights. Second to this, secure rights are also found in smaller proportions in rural formal areas, where about one in ten (9.9 percent) of households possess these secure rights through tribal land allocation.

The proportion of households with secure rights on tribal land is much smaller in urban formal and urban informal locations, with 1.6 percent and 4.5 percent of households possessing secure rights, respectively. On a national level, of 4 969 households, 14.2 percent are demarcated as having secure rights through tribal land allocations.

Table 9: Land tenure rights in the NIDS sample

	Private Ownership with right to sell	Secure Rights on tribal land allocation	Other	Total
		Rural Formal		
Frequency	259	29	2	289
%	89.5	9.9	0.6	100
		Tribal Authority Areas		
Frequency	996	617	2	1 616
%	61.7	38.2	0.1	100
		Urban Formal		
Frequency	2 604	43	6	2 660
%	97.9	1.6	0.2	100
		Urban Informal		
Frequency	383	18	4	405
%	94.6	4.5	1	100
		National		
Frequency	4241	707	13	4 969
%	85.4	14.2	0.3	100

Overall, the numbers presented in the table on secure rights are relatively small. For instance, the NIDS data only has 617 households in TAAs. What is interesting, however, is the relationship between land awarded to households on lease by Traditional Councils and household wealth. The descriptive statistics presented above show that in TAAs real estate assets account for more than half the share of the asset portfolio of households whereas real estate finance makes up a small proportion of the share of debt. Understanding how the distribution of wealth interacts with TAA land allocation is imperative to understand how customary land tenure affects the distribution of wealth in the post-Apartheid era.

Table 10: Land tenure rights by asset decile

Asset Decile	Private ownership with right to sell	Secure rights on tribal land allocation	Other	Total
1	90	12	-	102
%	87.80	12.20	-	100
2	160	46	4	211
%	76.02	21.64	2.13	100
3	255	74	0	330
%	77.39	22.57	0.04	100
4	399	111	1	519
%	76.80	21.46	0.23	100
5	533	121	1	655
%	81.45	18.43	0.12	100
6	491	96	5	594
%	82.72	16.23	0.89	100
7	484	110	-	594
%	81.56	18.44	-	100
8	420	66	-	487
%	86.34	13.62	0.04	100
9	476	39	-	515
%	92.47	7.53	-	100
10	561	33	2	596
%	94.11	5.60	0.28	100

Note: Where private ownership with right to sell, secure rights on tribal land allocation and 'other' fail to sum to 100, the remainder is made up of refusals to respond.

Table 14 presents land tenure rights by asset decile. What the table shows is that the largest concentration of households with secure rights on tribal land are found between the second and the seventh deciles of the asset distribution. This implies that there is a varied distribution of asset-based wealth across tribal authority areas and this is a key area for future research. One caveat, however, is the small sample size associated with the number of households represented in TAAs across decile in NIDS

8. Conclusion

The paper shows that estimates of one-shot net worth from the NIDS data with the inclusion of the top-up sample are broadly similar to waves 2 and 4 of NIDS, pointing to the internal validity of the data. At the same time, however, large differences in the weighted distribution of derived net worth and one-shot net worth were present, pointing to the importance of using the derived net worth measure when analysing wealth in this dataset. The importance of the top-up sample for improved external validity was notable compared to wave four, and this is perhaps the biggest difference between the two waves when it comes to data on household wealth distribution in South Africa.

The univariate analysis of components of assets and liabilities demonstrated high levels of inequality in the individual distributions of the components of assets and liabilities, with larger inequality visible in the distribution of total debts, with a mean to median ratio of over 16. This high variance is present in all three waves of NIDS that have a wealth module (waves 2,4 and 5). Further analysis of changes between waves four and five showed evidence that inequality in the distribution of assets, liabilities and net worth has declined, whilst household income inequality has remained about the same. This despite the inclusion of the top-up sample in wave 5, pointing to the fact that sample attrition by wave 4 likely created a few large outliers that skewed the distributions of components of assets, liabilities and net worth. This fascinating relationship between attrition and outlier detection has a profound implication on univariate distributions and is a useful topic for further research.

Importantly, the Gini coefficient on financial assets remains extremely high, and it is at the level of financial assets that NIDS has the greatest external validity discrepancy with the SARB estimates, a fact seen consistently across NIDS waves 2, 4 and now 5 (see also Daniels et al, 2012, Daniels & Augustine, 2016). The inclusion of a top-up sample of 1005 households improved the internal validity of the data in wave 5, where we saw an increase in the median values of the components of wealth subsequent to weighting and the removal of outliers. The overall effect of the top-up sample brought estimates of wealth closer to the macroeconomic estimates provided by South African Reserve Bank (SARB). However, there are still significant differences in some components of the SARB balance sheet estimates, though nowhere near as large as in wave 4.

The brief analysis of tribal authority areas (TAA) showed that 14.2 percent of all households in South Africa are still located there. The distribution of wealth in TAAs is vastly understudied, and this paper opens a window to understanding the relationship between property rights and asset ownership across different land tenure arrangements. We see that there is a varied distribution of asset-based wealth across tribal authority areas, with larger proportions of TAA households residing in the middle of the asset distribution.

Overall, this paper shows that estimates of assets, liabilities and net worth have been dramatically improved by the addition of the top-up sample in wave five. The NIDS data is therefore fit for purpose for comprehensive analytical research on household wealth to support & inform relevant policies.

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Appendix

Table A 1: Asset portfolio composition by asset decile, (R000's)

	Real estate		Business Assets		Vehicle Assets		Financial assets		Retirement Annuities		Livestock Assets		Possessions		Total Assets	
Asset Decile	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50
Decile 1	3	2	2	2	-	-	1	0	2	2	1	0	4	3	5	5
Decile 2	7	5	3	3	6	5	1	0	5	5	2	0	10	10	13	13
Decile 3	13	15	7	5	20	25	2	1	17	20	5	4	16	15	26	26
Decile 4	29	30	8	3	25	23	2	1	20	24	7	6	24	20	49	50
Decile 5	49	50	10	5	37	39	3	1	35	34	16	6	28	25	80	79
Decile 6	72	73	20	18	44	40	4	1	39	28	25	14	44	40	126	123
Decile 7	136	149	36	18	69	60	5	1	67	50	52	47	57	49	210	203
Decile 8	267	272	64	40	98	74	6	1	143	79	81	47	98	59	407	397
Decile 9	560	575	127	50	115	91	12	3	233	181	77	61	172	92	876	853
Decile 10	3 452	1 611	715	298	223	175	326	8	1 556	500	106	36	537	178	5 264	2 535

Table A 2: Debt portfolio composition by debt decile, (R 000's)

	Real Estate Debt		Business Debt		Vehicle Debt		Financial Debt		Total Debt	
Debt Decile	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50
Decile 1	0.1	0.1	0.5	0.5	-	-	0.2	0.3	0.2	0.3
Decile 2	0.9	1.3	-	-	-	-	0.9	0.9	0.9	0.9
Decile 3	-	-	2.0	2.0	2.1	2.1	1.8	1.9	1.8	1.9
Decile 4	2.9	3.0	2.1	2.5	2.4	2.5	3.1	3.0	3.1	3.0
Decile 5	3.2	4.1	-	-	4.0	4.0	5.5	5.3	5.5	5.3
Decile 6	11.6	12.0	4.1	3.5	7.3	6.0	9.9	9.8	10.0	9.8
Decile 7	17.2	18.9	15.4	20.0	14.1	16.7	18.6	18.9	19.5	18.9
Decile 8	56.3	61.0	24.4	17.5	40.6	40.0	38.3	37.0	49.5	45.5
Decile 9	144.0	141.0	17.9	10.0	97.5	90.0	54.6	30.7	150.4	145.3
Decile 10	886.2	500.0	323.1	545.7	234.4	193.1	133.6	62.5	914.8	569.8

Table A 3: Asset portfolio composition by household income decile, (R 000's)

HH Income Decile	Real Estate Assets		Business Assets		Vehicle Assets		Financial Assets		Retirement Annuities		Livestock Assets		Possessions		Total Assets	
	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50
Decile 1	86.3	19.9	11.0	2.5	47.9	26.0	0.8	0.2	-	-	20.3	4.9	29.9	10.0	93.0	21.9
Decile 2	84.9	37.3	24.3	5.0	57.8	60.0	1.1	0.3	390.8	503.5	34.7	7.9	40.5	15.0	113.8	44.2
Decile 3	77.6	41.7	34.3	10.0	61.1	43.5	2.6	0.5	148.3	150.1	27.6	15.0	37.6	15.2	103.4	47.1
Decile 4	99.2	46.4	38.2	10.0	50.7	41.9	2.5	0.5	42.3	50.4	39.4	16.0	46.2	19.8	126.2	50.4
Decile 5	172.5	53.5	40.4	9.9	68.9	47.2	2.2	0.5	81.4	49.6	29.2	13.1	45.4	20.0	193.4	74.1
Decile 6	211.6	72.0	67.5	6.0	56.5	44.6	3.3	0.6	76.6	27.4	53.2	27.6	58.4	24.8	238.7	91.6
Decile 7	350.8	91.6	53.7	24.8	78.2	49.6	4.9	1.0	385.2	59.0	58.7	28.0	97.3	29.9	429.6	130.2
Decile 8	484.2	205.3	254.2	25.2	94.0	63.4	9.0	1.6	375.1	52.5	65.9	29.0	104.4	44.4	650.1	287.2
Decile 9	1 013.8	491.5	226.1	50.4	113.2	79.8	263.3	3.9	437.5	197.9	41.0	9.0	228.6	69.5	1 528.3	670.5
Decile 10	3 055.5	1 244.2	623.8	294.9	232.5	175.3	108.8	10.0	1 328.2	466.9	87.7	84.6	358.0	120.0	4 297.2	1 988.9

Table A 4: Debt portfolio composition by household income decile, (R 000's)

HH Income Decile	Real Estate Debt		Business Debt		Vehicle Debts		Financial Debts		Total Debts	
	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50
Decile 1	90.5	123.8	2.0	2.0	185.9	248.8	6.5	1.7	11.9	1.9
Decile 2	111.5	75.0	6.7	2.5	51.3	4.0	4.6	1.5	8.2	1.8
Decile 3	191.3	218.2	5.5	3.5	48.1	45.5	7.9	2.0	13.7	2.2
Decile 4	128.9	139.4	13.7	10.0	21.8	20.1	7.1	2.1	9.7	2.3
Decile 5	105.4	151.6	-	-	125.3	152.9	7.1	3.6	10.7	3.8
Decile 6	110.5	80.7	1.2	1.0	62.4	35.0	7.6	3.9	11.7	4.0
Decile 7	180.7	97.3	24.9	24.9	89.1	88.5	16.1	5.5	26.5	6.0
Decile 8	178.8	158.4	7.9	6.0	87.2	68.8	21.2	7.9	57.9	19.1
Decile 9	367.8	200.2	100.8	20.0	106.6	75.1	40.0	17.8	150.1	46.9
Decile 10	825.3	493.6	36.0	17.5	194.8	147.5	89.2	28.9	604.5	263.7

Table A 5: Asset portfolio composition by net worth decile, (R 000's)

Net Worth Decile	Real Estate		Business Assets		Vehicle Assets		Financial Assets		Retirement Annuities		Livestock Assets		Possessions		Total Assets	
	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50
Decile 1	57.7	2.5	7.3	2.0	118.5	136.0	1.4	0.5	118.5	4.0	0.8	0.7	9.5	4.0	39.1	5.0
Decile 2	5.9	5.0	2.2	2.5	32.2	34.7	1.3	0.5	7.2	5.0	0.7	0.1	8.4	7.9	12.1	10.6
Decile 3	13.6	10.1	7.6	5.0	18.5	19.8	1.3	0.5	17.8	20.0	4.8	3.5	15.2	15.0	24.7	22.3
Decile 4	27.1	24.8	6.9	3.0	57.5	34.9	2.5	0.6	18.6	20.0	7.2	5.7	23.3	19.9	50.7	44.5
Decile 5	46.5	49.2	11.5	3.1	43.4	39.1	2.8	0.5	37.0	47.3	13.1	5.6	26.8	24.0	76.8	74.3
Decile 6	74.2	73.0	18.8	11.7	52.1	40.0	3.8	0.6	51.6	27.7	24.3	13.7	45.9	39.7	130.3	119.6
Decile 7	141.7	133.1	33.4	18.0	73.6	52.9	5.8	1.0	76.8	50.4	48.0	44.5	59.0	49.8	224.2	200.0
Decile 8	286.2	271.9	66.0	40.0	109.1	80.0	6.3	1.3	160.1	104.3	85.3	62.8	94.8	54.0	434.7	395.3
Decile 9	587.4	543.8	130.5	50.0	123.3	93.4	12.3	2.7	268.2	202.5	81.9	45.8	167.6	89.7	913.7	855.8
Decile 10	3 550.1	1 700.0	732.4	302.2	215.3	148.8	341.3	7.0	1 689.9	527.5	109.3	57.5	564.9	197.4	5 409.2	2 567.1

Table A 6: Debt portfolio composition by household net worth decile, (R 000's)

Net Worth	Real Estate Debt		Business Debt		Vehicle Debt		Financial Debt		Total Debt	
Decile	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50
Decile 1	571.7	155.2	128.7	3.5	100.5	88.5	51.7	8.4	102.3	10.3
Decile 2	116.8	97.3	2.5	2.5	54.8	24.1	4.9	2.0	6.4	2.0
Decile 3	77.8	80.7	3.6	2.5	36.0	3.6	5.0	2.0	9.0	2.2
Decile 4	264.8	210.3	-	-	91.6	90.1	11.1	2.8	22.4	3.0
Decile 5	108.0	105.9	28.6	10.0	65.2	30.0	9.6	3.0	12.2	3.1
Decile 6	216.0	186.9	10.0	10.0	186.0	138.4	12.4	3.6	25.2	4.0
Decile 7	382.1	195.3	9.2	2.0	93.4	72.5	13.9	4.7	52.1	5.9
Decile 8	241.7	181.3	18.9	17.5	158.5	88.5	21.0	6.3	84.5	9.2
Decile 9	372.3	208.0	23.6	20.0	106.3	70.1	36.2	13.6	159.2	38.2
Decile 10	837.8	368.8	21.4	2.0	183.9	129.4	53.4	17.8	485.9	157.1

Table A 7: Asset portfolio composition by age cohort, (R 000's)

	Real Estate		Business Assets		Vehicle Assets		Financial Assets		Retirement Annuities		Livestock Assets		Possessions		Total Assets	
Age Cohort	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50
15 to 24	257.8	40.0	1 244.5	1 982.9	134.1	134.8	1.7	0.4	83.6	18.0	22.0	7.9	40.1	11.3	202.2	21.3
25 to 34	335.1	50.0	178.7	19.9	135.5	98.4	9.4	1.0	106.6	49.8	44.5	31.3	68.5	18.8	333.4	50.5
35 to 44	440.4	73.0	96.8	25.2	135.8	75.5	13.5	1.0	647.6	227.1	21.7	6.0	108.9	25.2	592.5	100.5
45 to 54	643.7	99.7	166.0	15.0	136.7	80.1	200.4	1.6	898.5	277.0	46.5	27.6	92.7	30.0	977.6	154.9
55 to 64	1 000.5	125.2	395.8	59.8	151.9	89.6	28.7	1.8	1 151.5	275.0	51.1	18.5	174.1	39.7	1 370.6	197.4
65 to 75	703.9	136.0	273.4	80.0	114.9	65.7	79.1	1.3	1 163.4	158.0	41.1	15.5	115.4	37.8	979.3	196.0
75 and above	918.2	119.4	401.4	62.8	73.3	48.3	53.2	2.6	487.0	178.7	26.4	7.7	111.8	49.6	1 103.2	181.3

Table A 8: Debt portfolio composition by age cohort, (R 000's)

	Real Estate Debt		Business Debt		Vehicle Debt		Financial Debt		Total Debt	
Age Cohort	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50
1. 15 to 24	192.5	195.6	-	-	143.1	100.0	12.0	1.9	28.1	2.0
2. 25 to 34	584.5	204.1	2.2	2.5	168.2	100.2	22.4	4.0	98.4	5.0
3. 35 to 44	509.6	245.2	8.7	6.0	127.3	65.5	23.3	6.0	131.2	10.9
4. 45 to 54	383.4	225.6	29.0	17.5	141.8	89.2	28.7	7.0	118.7	11.2
5. 55 to 64	1 114.2	297.7	77.9	20.0	125.7	100.6	28.7	6.5	179.2	10.3
6. 65 to 75	422.3	201.4	23.9	10.0	107.2	69.4	13.6	3.6	62.1	4.0
7. 75 and above	94.2	78.0	-	-	76.5	50.4	6.6	2.0	21.3	2.5

Table A 9: Asset portfolio composition by geo-location, (R 000's)

	Real Estate		Business Assets		Vehicle Assets		Financial Assets		Retirement Annuities		Livestock Assets		Possessions		Total Assets	
Geo-location	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50
Rural Formal	325.1	49.2	336.2	50.4	107.3	70.5	10.3	0.8	163.4	49.8	43.0	22.6	171.0	19.9	455.4	53.4
Tribal Authority Areas	160.6	55.0	99.6	19.9	118.2	60.0	5.4	0.6	369.5	70.1	42.0	15.0	72.7	25.0	263.9	90.5
Urban Formal	894.3	155.3	279.9	25.2	140.5	88.5	80.6	1.6	803.4	197.9	25.5	1.0	108.6	29.5	1 023.7	145.6
Urban Informal	78.6	32.9	103.4	5.0	101.6	75.5	2.8	0.6	243.8	272.7	13.2	0.7	43.2	15.0	131.9	39.4

Table A 10: Debt portfolio composition by geo-location, (R 000's)

	Real Estate Debt		Business Debt		Vehicle Debt		Financial Debt		Total Debt	
Geo-location	mean	p50	mean	p50	mean	p50	mean	p50	mean	p50
Rural Formal	226.9	150.6	59.8	59.8	104.0	66.6	25.6	5.0	67.9	7.3
Tribal Authority Areas	223.2	130.6	10.2	2.0	145.6	125.9	14.4	2.5	30.3	3.0
Urban Formal	588.2	245.2	68.8	20.0	144.8	90.0	27.4	6.0	160.0	10.6
Urban Informal	87.8	95.0	5.5	2.5	86.2	78.7	12.3	3.5	16.1	3.5

SALDRU

Southern Africa Labour and
Development Research Unit

The Southern Africa Labour and Development Research Unit (SALDRU) conducts research directed at improving the well-being of South Africa's poor. It was established in 1975. Over the next two decades the unit's research played a central role in documenting the human costs of apartheid. Key projects from this period included the Farm Labour Conference (1976), the Economics of Health Care Conference (1978), and the Second Carnegie Enquiry into Poverty and Development in South Africa (1983-86). At the urging of the African National Congress, from 1992-1994 SALDRU and the World Bank coordinated the Project for Statistics on Living Standards and Development (PSLSD). This project provide baseline data for the implementation of post-apartheid socio-economic policies through South Africa's first non-racial national sample survey.

In the post-apartheid period, SALDRU has continued to gather data and conduct research directed at informing and assessing anti-poverty policy. In line with its historical contribution, SALDRU's researchers continue to conduct research detailing changing patterns of well-being in South Africa and assessing the impact of government policy on the poor. Current research work falls into the following research themes: post-apartheid poverty; employment and migration dynamics; family support structures in an era of rapid social change; public works and public infrastructure programmes, financial strategies of the poor; common property resources and the poor. Key survey projects include the Langeberg Integrated Family Survey (1999), the Khayelitsha/Mitchell's Plain Survey (2000), the ongoing Cape Area Panel Study (2001-) and the Financial Diaries Project.

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