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Wealth inequality in South Africa: Evidence from survey and tax data

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Abstract

This paper assesses two sources of information on the South African wealth distribution: a survey conducted among almost 36,000 South Africans in 2010-2011, and a novel sample of almost 1.2 million personal income tax records for the 2010-2011 tax year. Since both sources cover different sub-populations, I propose an approach to scale the results by fitting and drawing from censored distributions. Despite the differences in the coverage of each dataset, I find that both sources yield similar results for overall inequality once appropriate censoring rules and parametrizations are defined. In particular, I find robust evidence that wealth is much more unequally distributed than incomes: 10 percent of the population own at least 90-95 percent of all wealth, compared to 55-60 percent of all labour incomes. With a Gini coefficient of about 0.95 (compared to 0.7 for incomes), the South African wealth distribution is as unequal as that of the world as a whole.

KEYWORDS: Saving; Wealth; Income and wealth distribution
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Wealth Inequality in South Africa: Insights from Survey and Tax Data

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1 Introduction

The Global Financial Crisis, the Great Recession and the increase in economic inequality have brought considerable attention to the issues of wealth distribution and redistribution (see, e.g. Piketty, 2014; IMF 2014; OECD, 2015). In many countries, however, the debates are ahead of the evidence. One such country is South Africa.

Despite the concern about the persisting economic disparities since the end of apartheid, existing research has focused almost exclusively on income inequality (see, e.g., Leibbrandt et al., 2010; Van der Berg, 2010; Alvaredo and Atkinson, 2010). Even though South Africa was one of the first countries to publish a large-scale wealth survey in 2012, this data was given much less attention than the income data collected in the same survey.[1] This is particularly surprising given that capital receives almost 40 percent of total output in South Africa, suggesting that wealth inequality plays an important role in shaping overall inequality (Orthofer, 2015).

Without trusted domestic data, recent proposals on tax reform have been based on findings from other countries, primarily Thomas Piketty's work on the major advanced economies (Davis Tax Committee, 2015). In this paper I re-evaluate the available survey data by combining it with novel tax records and the official household sector balance sheets. I not only want to shed more light on the distribution of income and wealth in South Africa, but also seek to propose a way in which researchers can integrate multiple data sources to study inequality even in countries in which each individual source is subject to various biases and inaccuracies.

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[1]Two early exceptions are McGrath's (1982) analysis of the wealth distribution in the Natal Province of the 1970s and van Heerden's (1997) thesis on the wealth distribution of the Transvaal in 1985. Both studies use the estate multiplier method to estimate the wealth distribution from estate accounts. Daniels et al.'s (2014) analysis of the quality of the wealth data in the second wave of the National Income Dynamics Study (NIDS) is the only study using the new survey data.

The survey data presented in this paper stem from the second wave of the National Income Dynamics Study (NIDS), which was conducted in 2010-2011 and included a special module on wealth. Surveys are a common source of information on personal wealth, but tend to understate both assets and liabilities due to the social sensitivity and cognitive complexity of the topic. Since rich households are often found to have the lowest response rates, surveys are particularly prone to understate the wealth at the top of the distribution (ECB2013a; Vermeulen, 2014; Daniels et al., 2014).

Tax filing is mandatory for people with incomes above certain thresholds, such that personal tax records are not subject to the same biases as voluntary surveys. In South Africa, however, wealth itself is not liable to taxation, such that taxable investment incomes must hold as a proxy for wealth. In this paper I use a previously unpublished dataset of almost 1.2 million Personal Income Tax (PIT) records for the 2010-2011 tax year. Although the PIT should provide better information on the top of the distribution than the NIDS, the data have other limitations. First, the PIT provides no information on forms of wealth that do not generate taxable investment incomes to the tax filer, such as owner-occupied housing, pension assets or assets held in trusts. Second, the PIT excludes all individuals whose incomes are below the filing thresholds. While non-filers are not of much concern to researchers in advanced economies, they constitute the majority of the population in developing countries. Less than 20 percent of the South African adult population are liable to file income taxes, and less than a tenth of these filers—about one percent of the total adult population—declared any investment incomes at all.

To compare the information from both data sources I treat the PIT as a proxy for the wealth of the tax-filing top tail of the distribution, and "scale" the results by simulating the wealth of non-filers from a bottom-censored lognormal distribution.[2] I also test the NIDS for potential misreporting of top wealth by dropping and re-drawing the richest one percent from a top-censored Pareto distribution. This approach is validated by the finding that the resulting measures of income inequality coincide almost perfectly between the two sources: one percent of the population earns 16-17 percent of all incomes; ten percent earn 56-58 percent.

With regards to wealth inequality, the results coincide less neatly. Tail wealth remains particularly hard to pinpoint, with top one percent shares ranging from 60 percent in the NIDS to almost 90 percent in the PIT. Nevertheless, both sources agree that wealth inequality is extreme: ten percent of the population own more than

[2] Researchers in other countries have estimated the underlying asset holdings by capitalizing incomes using average investment returns for each asset class (Wolff, 1987; Saez and Zucman, 2014). Given the low granularity of the PIT records (split into *interest income* and *other investment income* only) and given the additional sensitivity that would be introduced by making assumptions on the returns of the *other financial assets* category, I use investment incomes directly. This equates to the assumption that all asset classes generate the same average returns.

90 percent of all wealth while 80 percent have no wealth to speak of; a propertied middle class does not exist.

Since neither the NIDS nor the PIT reflects the asset composition in the national accounts, I also combine the estimates using the PIT to measure of the concentration of financial assets, the NIDS to measure the concentration of non-financial assets, and the national accounts to define appropriate weights. The resulting top wealth shares of 67 percent for the top centile and 93 percent for the top decile should provide the most reliable first estimates for wealth inequality in South Africa. With a combined Gini coefficient of 0.95 (compared to 0.7 for income), they suggest that the country itself is as unequal as the world at large.

Age and race can play a role in explaining the high degree of wealth inequality in South Africa. Younger people have had less time to accumulate savings than older ones; non-white citizens were denied access to most forms of capital during the apartheid system (see, e.g., McGrath, 1982). Yet, neither of these factors is found to contribute more than five percent to total wealth inequality. While the age-wealth profiles lend some support for the life-cycle hypothesis among middle class households, inequality *within* generations remains much more important than inter-generational inequality. And while non-white households are still much poorer on average than white households, it stands out that the inequality *within* the African majority population far exceeds the inequality of all other groups. Paradoxical as it sounds, the presence of (disproportionately wealthy) white households *lowers* overall wealth inequality in South Africa. This finding supports existing research on incomes, according to which South Africas highly unequal income distribution is increasingly shaped by growing within-group inequality (Leibbrandt et al., 2010).

To my knowledge, this is the first study that systematically examines private wealth, its distribution and composition in South Africa. It draws on a growing literature on wealth inequality using household wealth surveys (e.g., ECB 2013a,b; Vermeulen 2014) and income tax records (e.g., Saez and Zucman, 2014; Bricker et al., 2016), and extends it to a context in which both surveys and tax records are less reliable. My initial hypothesis was that an integrated view of the two sources would be necessary in a country in which each individual data source is highly incomplete and inaccurate. I was thus surprised to find that the two data sets led to surprisingly similar conclusions on the overall income and wealth distribution (outside the top one percent). Although this paper suggests that more accurate data is necessary for designing concrete policies on wealth redistribution, it should provide some encouragement to practitioners who wish to study the degree of inequality in countries with even scarcer data than South Africa.

2 Household wealth: The aggregate view

The concept and measure of wealth in this paper follows directly from the household sector balance sheets in the South African national accounts. Based on the work of Aron and Muellbauer (2006) and Aron et al. (2008) the definition is consistent with those in the major advanced economies. Wealth is calculated as the residual between the market value of all assets and liabilities – a quantity also known as "net worth". Assets include financial assets (such as cash, stocks, bonds, unit trusts, pension and long-term insurance assets) and non-financial assets (real estate, land and other fixed assets), but exclude durable consumer goods (such as cars). Although the combined assets of the household sector typically exceed its liabilities on the aggregate level, the net worth of individual households can therefore also be negative.

At 255 percent of national income, private wealth plays a much smaller role in South Africa than in the major advanced economies (where it ranged from 400 to 700 percent in 2010; see Piketty, 2014). Two thirds of this wealth is in the form of financial assets, with pension and life-insurance assets being the single most important form of private wealth (36 percent of total assets in 2010).

Despite the relatively low level of private wealth, capital receives an even larger share in South Africa than elsewhere. The net capital share of output is just below 40 percent – significantly higher than the 25-30 percent reported in Piketty's sample of advanced economies.[3] In combination, these figures point to a disproportionately high return on capital in South Africa (Piketty, 2014; Orthofer, 2015).

A high capital share of total income means that wealth inequality plays an important role in determining the structure of overall inequality: almost 40 percent of total income accrues to capital owners, which tend to form a much smaller group than the recipients of labour incomes. To what extent the factor distribution shapes the overall personal income distribution depends on the size of this group as well as on the concentration of investment incomes and wealth relative to labour incomes and employment. The remainder of this paper will attempt to address this question.

3 Wealth distribution: Data sources

There are two main sources for microeconomic data on wealth: large-scale household surveys and administrative records from tax authorities. The main advantage

[3]The methodology of dividing the aggregate compensation of employees through GDP tends to understate the labour share, since incomes of those *not* formally employed in the corporate sector are included in the denominator but not the numerator (Gollin, 2002). An alternative methodology is to divide the *corporate* compensation of employees through *corporate* value added only (Karabarbounis and Neiman, 2014). For South Africa, the corporate sector shares are very similar to the total economy estimates. Using SARB data, the corporate and total capital shares for 2010 are 51 and 50 percent; in Karabarbounis and Neiman' database they are 48 and 46 percent. To obtain net capital shares, I subtract depreciation from the denominator (Karabarbounis and Neiman, 2014).

of surveys is that they allow researchers to pose a large number of questions to a large number of people. The second wave of the biannual National Income Dynamics Study (NIDS)—conducted by the Southern Africa Labour and Development Research Unit (SALDRU) in 2010-2011—included a special module on wealth, and asked almost 9,000 households with 36,000 adult members about the value of all their assets and debts. The main disadvantage of surveys is that the participation is voluntary; surveyed households can refuse to answer certain questions or decline participation altogether. In the case that the willingness to participate differs between poorer and richer people, this introduces a bias in the survey results (Wolff, 1987; Ravallion, 2003; Vermeulen, 2014). The accuracy of wealth survey data also suffers from the social sensitivity and cognitive complexity of the topic, which tends to lead people across the distribution to understate the value of their assets vis-à-vis the interviewer (ECB 2013a; Daniels et al. 2014).

Since taxation is mandatory for people with incomes above certain thresholds, tax records can provide better information on the top of the wealth distribution. In South Africa, however, wealth itself is not liable to taxation, such that taxable investment incomes must hold as a proxy. For this study, the South African Revenue Service (SARS) provided a previously unpublished 20 percent sample of the 2010-2011 Personal Income Tax (PIT) assessment, which consists of almost 1.2 million individual records.[4] Since not all assets produce income streams and since not all income streams can be tracked at the level of the individual, however, the wealth coverage of the PIT records is much narrower than can be achieved by household surveys.[5] The following sections discuss the South African survey and tax data in greater detail.

3.1 Wealth concepts in the NIDS and the PIT

3.1.1 What is included in the NIDS?

In theory, the wealth concept of the NIDS is closely comparable to the national accounts. A household questionnaire asks the oldest woman in the household about the value of the household's non-financial assets and mortgages, while an adult questionnaire asks each household member about their financial assets and liabilities. Both questionnaires also contain a "one-shot" question on wealth. This question asks whether the respondent would be in debt, break even or have something left over if they would sell all assets and repay all debts, and asks them to quantify

[4] The 2011 assessment covers the tax year from March 2010 to February 2011. SARS also provided a 20% sample of the 2014 assessment for the 2013-2014 tax year, which is briefly discussed in Appendix B.4.

[5] A third type of data, also administrative, comes from estate tax records. When combined with mortality tables, these can be used to estimate the underlying wealth distribution (Wolff, 1987; Piketty and Saez, 2006). The first analyses on the South African wealth distribution were based on estate tax records from Natal (McGrath, 1982).

this amount. From these four sources one can (in theory) construct comprehensive estimates of household and individual wealth.

To generate such a wealth variable, I first aggregate all asset-level data from the adult and household questionnaires into pension and life-insurance assets, other financial assets/liabilities, real estate assets/liabilities and other non-financial assets. I do not impute missing values, unless the answer is given in preceding or subsequent questions. I then aggregate the individual-level assets and liabilities across household members to arrive at the bottom-up estimate for household-level wealth. Analogous to this, I break down household-level assets and liabilities to arrive at individual wealth estimates.[6]

In certain cases, the answer to the one-shot wealth question might provide a more reliable indicator than the bottom-up estimates. I substitute valid, non-zero one-shot results for the bottom-up estimate if these estimates are missing or zero. I also substitute one-shot results in cases in which these exceed the bottom-up estimate in absolute terms due to item non responses on the category level (i.e., the household does not have valid responses for all classes of assets and liabilities), or due to unit non-responses within households.[7]

If all questions are answered accurately, this procedure should provide a comprehensive estimate of private wealth. In practice, however, it is unlikely that survey respondents disclose their entire wealth. Although half of all formal-sector employees are covered by occupational pension schemes, for instance (National Treasury, 2012), only five percent of adults reported owning a pension or retirement annuity, and only a third of these were able or willing to provide a quantification. While pension and long-term insurance assets thus constitute more than 30 percent of assets in the national accounts, they only account for 10 percent of assets in the NIDS. For non-pension financial assets, the under-statement is even more pronounced.[8] If financial assets are more concentrated than non-financial assets (see, e.g. ECB, 2013b; Saez and Zucman, 2014; OECD, 2015), the under-statement of financial wealth is likely to introduce a downward-bias to our estimates on wealth inequality.[9]

[6]The NIDS asks for up to three home owners. Where available, I use this information to allocate real estate assets and mortgages to household members; otherwise, I allocate these items evenly to all household members.

[7]Appendix A.1 and A.2.2 provide detail on the treatment of missing values and the construction of our wealth aggregates.

[8]Note that the national accounts and the NIDS are not perfectly comparable: The national accounts include non-profit institutions in the household sector, while the NIDS does not survey such institutions. National accounts and surveys also differ in the treatment of business assets and the coverage of land (ECB 2013b). However, the discrepancies seem to large to be explained by conceptual differences. See Appendix A.5 for a Table with the portfolio composition, and Appendix A.6 for a detailed discussion of pension wealth in the NIDS.

[9]Financial assets have also been found to be understated in other countries (see, for example, Sierminska et al., 2008; Andreasch and Lindner, 2014). Apart from general under-reporting, the high concentration of financial assets among very wealthy households (who tend to be under-represented in surveys) can also play a role in explaining the discrepancy.

3.1.2 What is included in the PIT?

Whereas the concept of wealth in the NIDS is at least theoretically comprehensive, the coverage of the PIT is from the outset limited to those assets that generate taxable incomes in the name of the individual tax filer (see also Table 1). It therefore provides no information whatsoever on assets that do not generate investment incomes (such as owner-occupied housing), assets whose incomes are exempt from taxation, or assets whose incomes accrue to a different entity (such as in the case of pension funds or trusts).

In countries with more comprehensive (or better integrated) wealth-related tax systems, researchers usually estimate underlying asset holdings before analyzing the wealth distribution (Wolff, 1987; Saez and Zucman, 2014; Bricker et al., 2016). This capitalization technique makes assumptions on the average investment returns for each asset class, and uses these returns to convert flows into stocks. Given the low granularity of the PIT records provided by SARS (split into *interest income* and *other investment income* only in order to protect anonymity) and given the additional sensitivity that would be introduced by making assumptions on the average return of the *other financial assets* category, the analyses presented in this paper are based on investment incomes directly. Compared to the income capitalization methodology, this simplification equates to the assumption that all asset classes generate the same average returns.

The following provides an overview about all forms of wealth that are missing in the PIT:

Tax exemptions: Local interest up to R22,300 is exempt from taxation, and local dividends are liable to the dividend withholding tax rather than the PIT. While these incomes are reported for informational purposes in the PIT files, they are not verified by the tax authorities. If recipients of interest incomes below the tax threshold don't bother to report their earnings, this could lead us to *overstate* the degree of inequality.[10]

Owner-occupied housing: For most lower and middle income households, their homes constitute a large share of their wealth. Since owner-occupied houses do not generate incomes, these assets are not reflected in the PIT – an omission that is likely to further *overstate* the degree of inequality, and that we cannot correct for with the available data.

Pension assets: Interests in pension funds and long-term insurers are an even more important asset class for South African households than housing. However, pension and insurance assets are only taxable through the PIT when paid out to

[10] I impute non-reported interest incomes based on draws from a fitted distribution, which should provide a lower bound for the inequality of local interest incomes. See Section 3.3.1 for details on the imputation of interest incomes under the filing threshold.

the beneficiary (as an annuity or lump-sum withdrawal), which would lead us to *overstate* inequality significantly. I propose to impute the value of pension assets from current pension and retirement annuity contributions, which are reported as deductions in the PIT. However, the lack of information on individual contribution periods and pre-retirement withdrawals limits the accuracy of this correction and likely leads us to *understate* the degree of inequality.[11]

Private trusts: While the investment incomes of trusts are liable to taxation, the PIT does not link the tax files of private trusts to individual beneficiaries. Since private trusts are widely used among wealthy South Africans, their omission is likely to *understate* the degree of inequality further.

Business assets: Although the PIT includes profits of unincorporated businesses, these are likely to include a significant labour component. Since the estimation on the basis of investment returns is highly sensitive (R100,000 in entrepreneurial income would be interpreted as one million Rand worth of business assets under a rate of return of 10 percent), I decide to exclude business profits from our measure of investment income. Since real business assets are among the most highly concentrated forms of wealth, this exclusion will further contribute to *understate* the degree of inequality.

Capital gains: In addition to regular income streams, many assets generate capital gains or losses when the current value differs from the purchase price. However, these paper gains or losses only become liable to PIT filing when they are sold, donated, bequeathed or otherwise disposed of. If the data spanned several decades, the distribution of reported capital gains and losses could provide very valuable insight on the underlying wealth distribution. Due to the irregularity of asset disposals, however, the inclusion of realized capital gains and losses in a cross-sectional study would bias our findings. I therefore exclude capital gains and losses from the investment income data, despite the fact that this also contributes to *understate* inequality.[12]

Tax evasion: Although PIT filings are verified in tax inspections, it is likely that a non-negligible portion of investment incomes bypasses the tax system due to tax evasion – particularly through offshore assets. As with private trusts, offshore portfolios are more common among the wealthy, thus constituting another omission that biases our estimates downwards.

[11]See Appendix B.2 for details on the imputation of pension assets.

[12]While I exclude local capital gains, I cannot exclude foreign capital gains since these series were not provided for confidentiality reasons. Foreign capital gains are relatively small – in 2011, 2,024 individuals reported foreign capital gains of R73,361 on average (compared to 54,050 individuals reporting local capital gains of R105,730 and 190,318 individuals reporting interest incomes of R55,537 on average) (South African Revenue Service, 2012). Nevertheless, the failure to exclude individuals with high foreign once-off capital gains is likely to increase measured inequality significantly.

Liabilities: The PIT provides no information on liabilities. This could lead us to either over- or understate the degree of inequality: On the one hand, we implicitly treat indebted people as if they had zero or even positive wealth; on the other, we also overstate the wealth of highly leveraged investors. Since assets are distributed very similarly to wealth in the NIDS, this indicates that the bias should only be moderate.

Whether our estimates of wealth inequality from the PIT investment incomes are over- or understated (relative to the NIDS and relative to the true level of inequality) will depend on the relative magnitude of the individual biases.

3.2 Coverage of the NIDS and the PIT

3.2.1 *Who is included in the NIDS?*

One of the main advantages of the NIDS dataset is its scope. As one of South Africa's largest household surveys, it covers roughly 9,000 households with 36,000 adult members. Despite a relatively high non-response rate on wealth-related questions, it still contains 18,820 observations on individual wealth – thus covering a larger share of the population than some of the American and European wealth surveys.

Despite the comparably large size of the NIDS, the survey is unlikely to provide an unbiased representation of the South African wealth distribution. It is commonly found that higher-income households are less likely to be successfully interviewed in surveys (Wolff, 1987; Ravallion, 2003; Vermeulen, 2014). SALDRU provides two sets of weights to correct for systematic differences in the probability that a household is interviewed in the initial and subsequent waves of the survey, as well as to calibrate the dataset to national, provincial and sex-race-age group population totals.[13] While these weights help to correct for the under-representation of middle-class households relative to poorer ones, they cannot correct for the fact that a survey with roughly 9,000 households is unlikely to include one of the few thousand ultra-high-net worth households that tend to control a significant proportion of wealth in any country. Of the 10 South Africans on the African *Forbes* ranking, the poorest had a net worth of more than R3 billion (US$400 million). With a net worth of "only" R300 million, the richest person in the NIDS is thus well below this cut-off of the ultra-wealthy.[14]

3.2.2 *Who is included in the PIT?*

South African residents are liable to file income taxes as soon as their income exceeds a certain filing threshold. In 2011, 5.9 individuals filed their taxes; about 17 percent

[13] I use SALDRU's post-stratified weights in all analyses of the NIDS. Appendix A.2.1 provides details on these weights.

[14] Even when rich households are included and interviewed in the survey, they might be less likely to respond to wealth-related questions than others (Vermeulen, 2014). In the NIDS we do not find that item non-response rates differ systematically between income deciles – if anything, non-respondents have higher incomes than non-respondents once we impute the one-shot wealth estimates. See Appendix A.2.1 and A.2.2 for details on sampling and response biases.

of the adult population of 34.5 million.[15] Filing thresholds imply that our data is *censored* for the bottom 83 percent of the distribution: We have no other information on the incomes of the non-filing majority than that their labour income must have been less than R120,000 and their local interest income below R22,300 in 2010.

In addition to being bottom-censored, the PIT data is effectively top-coded for individuals with taxable incomes above R10 million (602 individuals in 2010-11). For confidentiality reasons, SARS provides only aggregate statistics for this group of people.[16] Even with top-coding, the richest person in the PIT reports interest incomes of R22 million – in line with assets of R2-4 billion at a rate of return of 5-10 percent and a 20 percent share of interest-bearing assets. Although the *Forbes* rankings report even wealthier South Africans, this suggests that the coverage of the top tail is indeed much better than in the PIT than in the survey data.

3.3 Scaling and resampling

3.3.1 Scaling the bottom tail of the PIT

Since the PIT only includes the sub-population of tax filers, we have to make assumptions on the incomes of non-filers before calculating distributional metrics for the overall population. A standard assumption on the shape of the income distribution is a leptokurtic lognormal distribution: While the thick upper tail of the income distribution are described through a power law, the majority of incomes follow a lognormal distribution (Pareto, 1897; Lydall, 1976; Montroll and Shlesinger, 1982; Battistin et al., 2009). To "scale" the distributional estimates from the 5.9 million tax filers to the total adult population of 34.5 million, I simulate the incomes of non-filers by fitting a censored lognormal distribution to the data.

I first add 5.7 million observations ($5.7 = 0.2 \times (34.5 - 5.9)$) to the dataset, and set their incomes equal to the filing thresholds. I take logarithms and use a Tobit model to estimate the mean $\hat{\mu}$ and variance $\hat{\sigma}^2$ of the censored distribution. I then impute the missing data as random draws from a normal distribution $ln(y^*) \sim N(\hat{\mu}, \hat{\sigma})$, conditional on the data being below the threshold b. The conditional mean

[15] For labour incomes, the 2011 threshold is R120,000 (one employer) or R60,000 (more than one employer). With regards to investment income, the filing threshold is R22,300 for local interest and R3,700 for foreign interest or dividends – an amount consistent with financial assets of more than R300,000 at 2010 deposit interest rates of 6-8 percent (see Appendix B.1). The exception to this overlap are non-compliant high-income individuals (who do not file tax returns for the purpose of tax evasion) and low-income individuals who do file tax returns in order to claim deductions. Voluntary filing is common: In the 2011 assessment sample, 25 percent of filers have labour incomes below R60,000 and 50 percent below R120,000, and 98 percent of filers have interest incomes below the filing threshold of R22,300.

[16] While this top-coding does not bias our results on top wealth shares for the larger population, it does introduce a minor downward bias to some distributional metrics (such as Gini coefficients). It has been proposed to correct for right-censoring by simulating the topcoded values from a censored distribution (see e.g. Jenkins et al., 2011). Given the small number of top-coded observations (120 individuals in a sample of almost 1.2 million) and the complications arising from top-coding on the basis of a third variable (taxable income), I proceed with the imputation of averages.

and variance for bottom-censored observations are derived as

$$E(y|y \leq b) = \hat{\mu} - \hat{\sigma}\frac{\phi(\beta)}{\Phi(\beta)} \tag{1}$$

$$Var(y|y \leq b) = \hat{\sigma}^2\Big[1 - \beta\frac{\phi(\beta)}{\Phi(\beta)} - \Big(\frac{\phi(\beta)}{\Phi(\beta)}\Big)^2\Big] \tag{2}$$

where b is the lower censoring value, $\hat{\mu}$ and $\hat{\sigma}$ the estimated mean and standard deviation of the censored distribution, ϕ the standard normal density, Φ the cumulative standard normal density, and $\beta = \frac{b-\hat{\mu}}{\hat{\sigma}}$ (see Greene, 2012, Ch.19).

Even among filers, individual data points might be censored because of tax exemptions on investment incomes. A person with a labour income of R200,000 and interest incomes of R10,000 is liable to file taxes because he or she exceeds the filing threshold on employment incomes, but might decide to omit his or her interest income as it is irrelevant to the bottom line. Applying the scaling approach to these non-reporters (zero entries among filers) should correct for any such bias.

3.3.2 Resampling the top tail of the NIDS

While the PIT excludes the bottom 83 percent of the population, the NIDS runs the risk of under-representing the very top. While there are some very wealthy individuals in the NIDS, Daniels et al. (2014) suggest that these observations may just be the result of measurement error rather than of genuinely rich respondents. Indeed, a detailed analysis of the wealthiest people in the survey reveals some irregularities regarding the composition of assets and the associated income streams, supporting the measurement error hypothesis. Since it would be imprudent to discard all "too-rich-to-be-true" observations without replacement, I test the sensitivity of the results by dropping the wealthiest one percent of respondents from the dataset (therefore artificially truncating the sample to the right) and re-drawing them from a power-law distribution.

A variable x follows a power law if all $x > x_{min}$ are drawn from a probability distribution $p(x) = Cx^{-\alpha}$, where x_{min} is the lower bound on power law behaviour, the tail index α determines the weight of the tail (with lower α indicating a fatter tail), and C is a normalization constant that ensures that the total probability sums to one. I follow the procedure proposed by Clauset et al. (2009) to estimate α under different levels of x_{min}. In the NIDS, our estimates cluster around $\alpha \approx 1.0$ for the top 1-5 percent of the wealth distribution, although the fit of the distribution is poor. In the PIT, we are more successful at fitting a Pareto distribution for the top one percent of tax filers, and estimate a tail index of $\alpha \approx 1.5$. This estimate is closer to Pareto's original findings (Pareto, 1897), as well as to recent findings on the wealth distribution of advanced economies (Klass et al., 2006; Gabaix, 2009; Vermeulen, 2014). I resample the richest one percent of respondents (all individuals with more than one million Rand) using both the fitted ($\alpha = 1.0$) and "theoretical" ($\alpha = 1.5$) distributions, averaging the distributional results from 100 inverse random draws.[17]

3.4 Summary: Biases in NIDS and PIT

The main limitation of the NIDS is its coverage of the top tail of the wealth distribution and the quality of its responses across the distribution. Targeted wealth surveys such as the Eurosystem HFCS or the American SCF are specifically designed to reduce the sampling and response biases, and to ensure a high level of accuracy of responses by using a detailed questionnaire and extensive consistency checks during and after the computer-assisted interviews.[18] Nevertheless, the HCFS understates aggregate household wealth (and particularly financial wealth) compared to the national accounts (ECB 2013b), and understates wealth inequality compared to results from rich lists (Vermeulen, 2014). Given the fact that wealth was just a "special theme" in the second Wave in the NIDS, the biases that are associated with wealth surveys are thus likely to be much more severe in the South African case.

Being mandatory and cross-checked in tax inspections, the PIT is not subject to the same biases as the NIDS. However, the main weakness of the PIT is the limited coverage of investment incomes and the challenges in drawing conclusions about the distribution of the underlying assets and liabilities. Table 2 provides an overview over the coverage and biases in the survey data and the tax records.

4 Wealth distribution: Results

4.1 Individual results

Despite the differences in the two data sources, their results on *income inequality* coincide almost perfectly. One percent of the population receives 16-17 percent of all incomes; together, the top decile receives 56-58 percent. Overall inequality is high, with a Gini coefficient of 0.70 in the PIT and 0.72 in the NIDS. Although these figures reflect poorly on the South African labour market, their comparability supports the validity of our scaling approach.

[17] Appendix A.4 provides details on the resampling methodology and summarizes results on the fitted distribution.

[18] In the U.S. SCF and the French and Spanish HFCS surveys, information from tax records is used to create a separate sampling frame of wealthy individuals (Saez and Zucman, 2014; Vermeulen, 2014). In other countries, the HCFS attempts to oversample wealthy households on the basis of regional incomes (Vermeulen, 2014). In some European countries, the HFCS attempts to increase the sampling and response rates of wealthy households by providing incentives against the selection of "easier" households by interviewers. (see, e.g., Albacete et al., 2012). The survey design also contains measures to increase the accuracy of responses. For instance, households are not asked about the value of their life insurance, but about the inception date, contract duration, frequency and amount of contributions. In addition to over 150 internal checks, all survey responses are then analysed by experts, and inconsistent or unusual responses are confirmed or corrected in follow-up interviews (Albacete et al., 2012; ECB 2013a).

Table 1: PIT – Measure of "wealth"

Asset class	% of total	Income	Concentration	Covered in PIT?
Pension and long-term insurance assets	35	Various	Medium	Partly†
Other financial assets				
Cash equivalents	11	Interest	Medium	Yes‡
Other securities*	22	Interest and dividends	High	Yes‡
Real estate assets	26			
Owner-occupied		Implied rent	Low	No
Rented out		Rental income	High	Yes
Other non-financial assets (e.g., agricultural land, livestock, business assets)	6	Business and rental income	High	Yes
Liabilities	20	Interest	Low	No

Note: Portfolio composition in the national accounts and coverage in the PIT. The distribution of total assets is estimated from the balance sheets for households and financial institutions. The degree of concentration is based on Piketty (2014) and Saez and Zucman (2014). *Other securities includes government securities, stocks, debentures, preference shares and ordinary shares. †Current contributions to pension and retirement annuity funds only. ‡Local interest below the threshold of R22,300 and local dividend income in its entirety is exempt from the PIT, and the accuracy of exempt incomes is not verified in the tax inspection process.

Table 2: NIDS vs PIT – Coverage and biases

	NIDS	PIT
Coverage		
Pension and long-term insurance assets	Good in theory, poor in practice: many n/a	Good coverage of current contributions, but no information on total assets
Other financial assets	Good in theory, poor in practice: many n/a	Good for most assets except domestic equities and assets held through trusts
Real estate assets	Good	Rented out real estate only
Other non-financial assets	Business wealth as one-shot question only	Good, although business income includes labour component
Biases		
Sampling bias	Severe	n/a
Response bias	Limited	n/a
Recall bias	Severe	Limited (false responses for tax evasion reasons only)

Note: Comparison of coverage and biases in the NIDS and PIT data.

With regards to investment incomes and wealth, the results coincide less neatly. Particularly top inequality is much higher in the tax records than in the survey data: one percent of the population owns about 60 percent of wealth in the NIDS, but receives almost 90 percent of investment incomes in the PIT. Yet both sources agree on the extent of overall wealth inequality – likely because they are so close to the upper bound: ten percent of the population own almost all wealth (95 percent) and receive almost all investment incomes (99 percent); in both sources, the Gini coefficient approaches unity (see Table 3 and Figure 1 for the NIDS, and Table 4 and Figure 2 for the PIT). If these figures are in the vicinity of the truth, South Africa as a country is as unequal as the world as a whole (see Davies et al., 2016).[19]

4.2 Concepts of wealth and combined estimates

The comparison between the NIDS and the PIT is, in theory, a comparison between total wealth on the one hand and investment incomes on the other. The coverage of the PIT is much more limited than the NIDS, but neither of the two measures is representative of the portfolio composition in the national accounts: The NIDS over-states the share of non-financial assets by a factor of 2, the PIT does not include non-financial assets at all; the NIDS under-states the share of pension assets by a factor of 3, the PIT provides only information on current contributions.

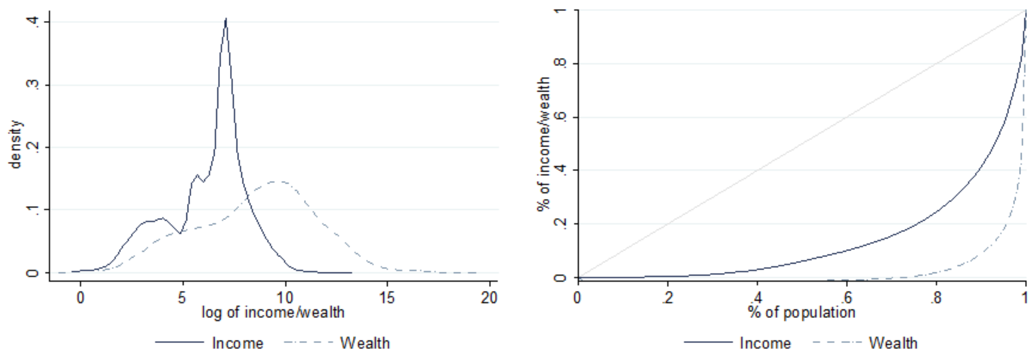
When we use the information on current contributions to adjust the PIT for investment incomes on pension assets, the top wealth shares in the PIT start to coincide almost perfectly with those in the NIDS. The share of the top percentile drops from 90 to "only" 60 percent; that of the top decile adjusts from 99 to 96 percent.[20] Since pension assets constitute the most important asset class for South African households, this measure seems more meaningful than the unadjusted measure from the PIT (and maybe even the NIDS). However, it is likely that it constitutes a lower bound for true pension inequality, since neither dataset provides information on interruptions to contribution periods and pre-retirement withdrawals from pension funds – both of which are possible under the South African system, and are likely to be more common among lower-income households (National Treasury, 2012).[21]

[19] Davies et al. (2016) estimate the global wealth distribution by estimating a relationship between income and wealth inequality (based on 31 countries with micro-level wealth data, not including South Africa). They estimate the global Gini coefficient at 0.91, the top 10 percent wealth share at 87 percent and the top 1 percent wealth share at 48 percent.

[20] If we were to replace reported pensions in the NIDS with comparable imputations (using a fixed share of labour incomes as current contributions), the wealth share of the top one percent would drop to only 50 percent and re-introduce a wedge between results from the two datasets. However, the pension adjustment has much less impact on the wealth share of the top 10 percent (91 compared to 95 percent).

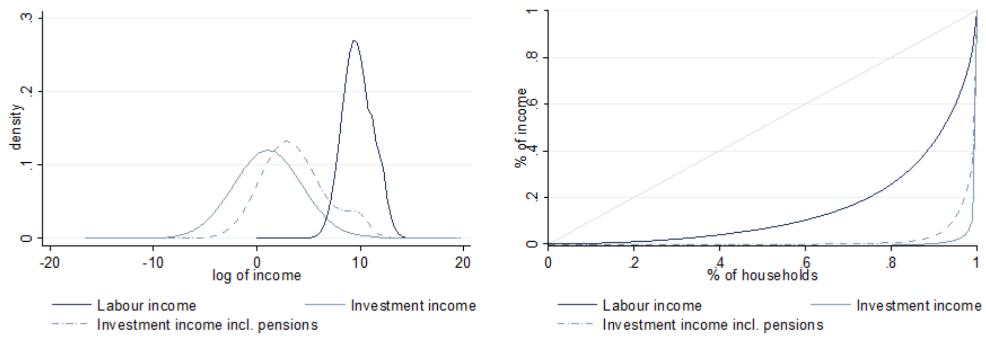
[21] To estimate the value of pension assets in the PIT, I assumed a price inflation of 6 percent, wage inflation of 8 percent, investment returns of 10 percent and a starting age of 25 to calculate the current value of all pension and retirement fund contributions. To account for pre-retirement withdrawals, I also applied a uniform 50 percent discount to the current value of these assets

Figure 1: NIDS – Income and wealth distribution



Note: Income distribution, NIDS, 2010. Calculations based on weighted sample using household-level data and post-stratified weights. Left panel: Kernel density curves of logged incomes; right panel: Lorenz curves.

Figure 2: PIT – Income and wealth distribution



Note: Income distribution, PIT, 2010. Results scaled to the total adult population (see Section 3.3.1). Left panel: Kernel density curves of logged incomes; right panel: Lorenz curves.

Since the PIT provides no information from which to make a comparable adjustment for owner-occupied housing and other non-financial assets, we instead "impute" the estimates of inequality from the NIDS by calculating a weighted average of the individual distributional metrics. With a Gini coefficient of at least 0.96 for pension assets (PIT), 0.99 for other financial assets (PIT) and 0.90 for non-financial assets (NIDS), and with portfolio shares of 36, 32 and 32 percent in the national accounts, we find a combined Gini coefficient of 0.95 and top wealth shares of at least 67 and 93 percent for the richest centile and decile.

While the findings on tail wealth are thus highly sensitive with regards to the concept of wealth under study, our finding that 10 percent of the population owns at least 90-95 percent of all wealth remains robust across all specifications.[22]

4.3 Resampling of tail wealth

The fact that top income wealth shares in the NIDS are comparable to the PIT is surprising given that survey data tends to understate the very top of the distribution. Given the relatively small number of observations on wealth in the NIDS (18,820 observations, of which only half are non-zero), our results risk being determined by a few (potentially erroneous) outliers rather than by the appropriate representation of genuinely wealthy people. To test the robustness of our estimates to such potential outliers, we can re-sample the top tail from a fitted or a theoretical distribution.

I drop and re-draw all individuals with a net worth of more than one million Rand (the top one percent of the wealth distribution in the NIDS) from the distributions described in section 3.3. While the fitted parametrization ($\alpha = 1.0$) results in even higher top wealth shares than the original data, the top one percent share drops to 45 percent when using the "theoretical" tail index of $\alpha = 1.5$. Since all other data in this paper suggest that inequality is higher in South Africa than in the developed economies for which the tail index of 1.5 was derived, these results should be interpreted as a lower bound. For the top 10 percent wealth share, our lower bound remains robust at 90-95 percent under all parametrizations.[23]

(although not for assets in retirement annuities). Appendices A.6 and B.2 give more details on the methodology.

[22] Instead of broadening the coverage of assets in the PIT, we could also focus on a more limited concept of wealth in the NIDS. Looking at financial assets only, the degree of inequality in the NIDS surpasses even the unadjusted measure of inequality in the PIT; with regards to investment incomes, we find that inequality is somewhat lower. Note, however, that only 430 individuals reported non-zero investment incomes (compared to 13,505 individuals with non-zero wealth).

[23] As a further sensitivity analysis, I also attempt to resample only those individuals that were identified as "outliers" in a multivariate outlier analysis (see Appendix A.3), and find that the results remain robust. For income, the findings are robust to resampling the top one percent from a fitted distribution with $\alpha = 2.0$.

Table 3: NIDS – Income and wealth distribution

	Top 1%	*Top 10%*	*Middle 40%*	*Bottom 50%*	*Gini*
Wealth					
Full sample	61	95	6	-1	0.98
Top 1% resampled, $\alpha = 1.0$	69	96	5	-1	0.93
Top 1% resampled, $\alpha = 1.5$	45	92	9	-1	0.87
Income					
Full sample	17	58	35	7	0.72

Note: Quantile shares, NIDS, 2010, in percent. Calculations based on weighted sample using adult-level data and post-stratified weights.

Table 4: PIT – Income and wealth distribution

	Top 1%	*Top 10%*	*Gini*
Investment income			
Local interest*	84	98	0.98
Total investment*	88	99	0.99
Total investment & pensions*	61	96	0.96
Income			
Employment income	16	56	0.70

Note: Quantile shares, PIT, 2010. Results scaled to the total adult population (see Section 3.3.1). *Adjusted for tax-exempt interest income.

Table 5: NIDS – Wealth distribution by asset class

	Full sample		*Trimmed sample*	
	Top 1 %	Top 10 %	Top 1 %	Top 10 %
Wealth	61	95	47	92
Total assets	62	95	50	92
Total liabilities	51	99	42	99
One-shot wealth	63	97	60	97
Pension and life assets	99	100	97	100
Non-pension financial assets	96	99	96	99
Real estate assets	54	80	32	71
Capital income	70	100	58	100

Note: Quantile shares, NIDS, 2010, in percent. Calculations based on weighted sample using adult-level data and post-stratified weights. "Trimmed sample" excludes outliers (see Appendix A.3).

4.4 Comparison with rich lists

For the wealthiest of all people, "rich lists" can provide additional information. According to the *Forbes Africa's 50 Richest* list, 10 South Africans had a combined net worth of $25 billion (R390 billion at year-end exchange rates) in 2015, almost five percent of the entire wealth of all 54 million citizens. New World Wealth, a consultancy, estimates that there were 46,800 high net worth individuals with a combined wealth of $184 billion (R2,140 billion) in the country in 2014. When compared with the aggregate data from the household sector balance sheets, this suggests that 0.1 percent of the South African population owns a quarter of total household wealth. This high share lends some support to the very high top wealth shares presented in this paper. If anything, our top wealth shares could be understated due to the failure to capture the very top of the distribution (NIDS) or their assets in complex ownership structures (PIT).

4.5 The equalizing effect of households

Wealth surveys typically use households rather than individuals as the main unit of analysis (see, for example, ECB 2013a; 2013b). As with income and consumption, household-level data on wealth is understood to better reflect the fact that many assets and debts tend to owned or guaranteed jointly by members of the household (such as the family house and mortgage, joint bank accounts, or even through the contingent division of property in the case of bereavement or divorce).

If we consider household instead of individual-level data, the degree of inequality softens somewhat: The income and wealth shares of the top 10 percent drop by 6-8 percentage points; the shares of the middle 40 percent increase by almost as much.[24] This reflects the fact that the pooling of wealth within households smoothes out some of the spikes in income and wealth, while the distribution for the bottom half of the population is largely unaffected. Although the PIT provides no information on household membership, we would expect to find a similar pattern in the tax database.

5 Other analyses on the wealth distribution

5.1 Wealth distribution and demography

One advantage of surveys is that they contain questions on a wide range of topics other than personal finance, which allows researchers to analyse the wealth distribution by any number demographic, geographic or other characteristics. Tax records contain much less demographic information; in the case of the PIT we can infer only

[24] Detailed results for the household-level income and wealth distribution are provided in Appendix A.7.

age and gender of the tax filer. In this section, I use these data for an overview of the wealth distribution by demographic characteristics.

5.1.1 Wealth and age

From a theoretical perspective, the most interesting link between wealth distribution and demography is that between wealth and age. According to the life-cycle hypothesis of consumption and saving, individuals save during their work-life and dis-save during retirement (Modigliani and Brumberg, 1954; Ando and Modigliani, 1963). This implies that very young and very old people should be asset poor, while people at their transition to retirement should be the wealthiest group.

Indeed, Figure 3 confirms this theory in the NIDS: Among individuals with non-zero wealth, median wealth increases steadily from less than R5,000 for youths to around R15,000 for the pre-retirement cohort, before declining back to R10,000 for the 75+ group. However, it would be incorrect to deduce that wealth inequality is explained entirely by the demographic pyramid: For all age groups < 55, within-group wealth inequality is as least as high as overall wealth inequality. A decomposition based on the Theil index suggests that less than one percent of total wealth inequality is explained by the inequality between age groups.

Inter-generational inequality is even less pronounced in the PIT. While there is a slight hump-shaped curve between ages 30 and 70—particular for lower-income people—, people under 30 and over 70 constitute the wealthiest age groups in the tax database. This discrepancy between the NIDS and the PIT could suggest that inheritances and bequests play a more important role among relatively well-to-do tax filers than among the larger population in the NIDS.[25]

5.1.2 Wealth, race and gender

Although there is no economic reason to expect a correlation between wealth and race or gender, the survey data confirms the suspicion that the degree of inequality remains high between racial groups – a legacy of the system of apartheid, which denied non-white citizens the access to most forms of capital until 1994 (see, e.g., McGrath, 1982). However, the NIDS also shows that the degree of inequality *within* the African group exceeds that for the overall population, being much higher than the level of inequality within any other racial group (see Figure 4). The decomposition based on the Theil index suggests that less than five percent of total wealth inequality and less than 15 percent ot total income inequality is explained by between-group inequality. This is consistent with earlier findings on the South African income dis-

[25] In theory, the observed pattern could also point to a selection bias: Since very young and very old people are not generally employed, only those with high *investment* incomes become subject to tax filing requirements. However, the pattern persists when calculating the age-wealth profiles for recipients of employment incomes only. Since I do not track individuals over time, the life-cycle profile might also be shaped by generational effects (e.g., the greater impact of the financial crisis and economic downturn on younger people). I do not control for these.

tribution, according to which the structure of inequality is increasingly shaped by growing inequality within racial groups (Leibbrandt et al., 2010; Van der Berg, 2010).

With regards to gender, both sources show little difference in the mean and median wealth of men and women, although the larger number of men in the PIT implies that men receive a larger share of total reported investment incomes than female taxpayers (60 percent versus 40 percent). In neither case does the Theil index suggest that inequality between men and women plays a role in explaining total wealth inequality.

Overall, the demographic analyses paint a more favourable picture of the quality of the survey data than the aggregate analyses did earlier: although the NIDS struggles to capture financial assets and very wealthy individuals, it seems to provide robust results on the wealth distribution in the majority population.[26]

5.2 Joint distribution of income and wealth

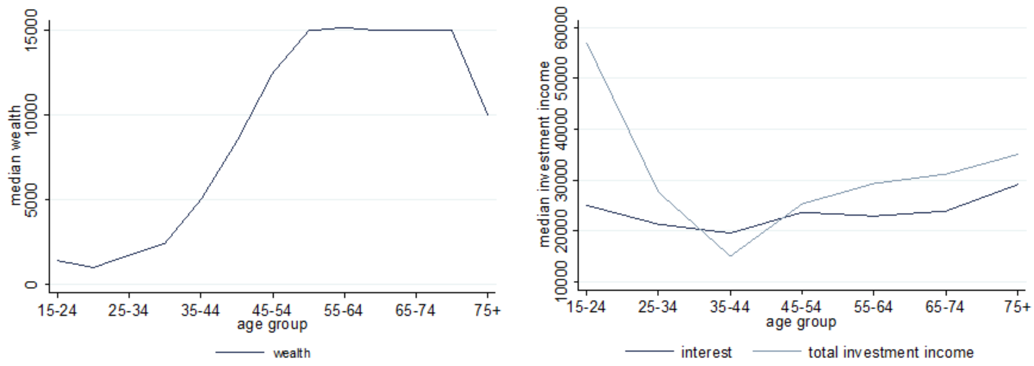
Although wealth generates income in the form of dividends, interest and rents, income and wealth are not generally closely linked. In the NIDS, the rank correlation between total income and wealth is 0.35; in the PIT, the equivalent figure for gross and investment income is 0.5. Both figures are in line with the correlations observed in other countries (0.2-0.6 in the OECD countries, see OECD, 2015).

The correlation between income and wealth is most pronounced in the upper end of the distribution: About 70 percent of people in the top income quintile of the NIDS are also in the top two wealth quintiles (and vice-versa), explaining why the correlation may be higher in the unscaled PIT than in the NIDS. With regards to race, we find a much higher correlation for the (richer and more egalitarian) white sub-population than for the African majority (as seen in the concentration curves presented in Figure 4). This suggests that the wealth of white households corresponds more closely to their incomes than in the African sub-population, where even high-income households often have very little wealth (and vice-versa).

Overall, the relatively low correlation between income and wealth suggests that the taxation of employment incomes targets a different group than the taxation of investment incomes and wealth. Alongside the greater degree of concentration of wealth, this discrepancy highlights the policy importance of studying the wealth distribution in addition to the income distribution.

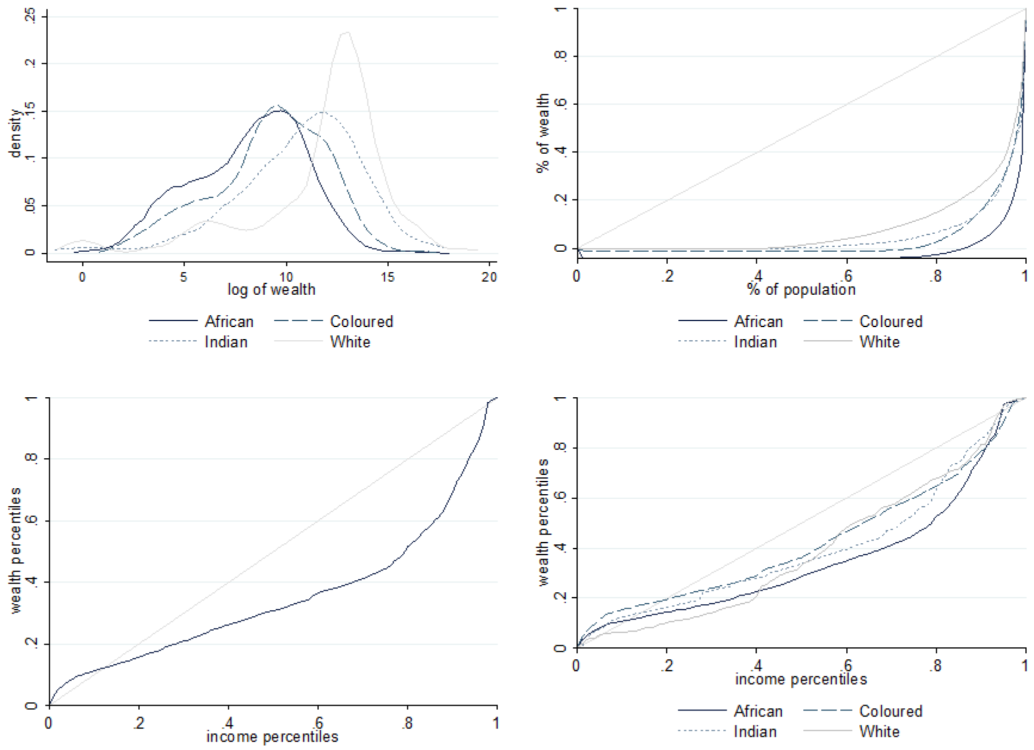
[26]Detailed results for wealth by race and gender in Appendix A.7.

Figure 3: Wealth by age



Note: Median wealth by age, NIDS and PIT, 2010, in Rand. Calculations exclude individuals with zero wealth / investment incomes. Left panel: NIDS, Right panel: PIT.

Figure 4: NIDS – Wealth by race



Note: Wealth distribution by racial group, NIDS, 2010. Calculations based on weighted sample using adult-level data and post-stratified weights. Top left panel: Kernel density curves of logged wealth; top right panel: Lorenz curves of wealth; Bottom panels: Concentration curves for income and wealth.

6 Conclusion

Wealth is much more unequally distributed than incomes. One percent of the South African population owns at least half of all wealth, the top decile together owns more than 90-95 percent. With a Gini coefficient of about 0.95, wealth is as unequally distributed *within* South Africa as it is in the world at large. For incomes, the equivalent figures are 10-20 and 55-60 percent, and the Gini coefficient is close to 0.7.

The fact that a large majority of people are asset-poor is not unique to South Africa: Even in rich countries, the wealth share of the bottom half amounts to only about five percent of total (Piketty, 2014; OECD, 2015). What stands out, however, is the small wealth share of the middle of the distribution, or the virtual absence of a socioeconomic group that Piketty refers to as "patrimonial" or "propertied" middle class – the emergence of which *"was the principal structural transformation of the distribution of wealth in the developed countries in the twentieth century."* (Piketty, 2014, p. 260). Table 6 compares the results for South Africa with other countries.

This paper started with the hypothesis that the two data sets on investment incomes and wealth were incomplete and inaccurate, and needed to be integrated in order to gain robust estimates of the wealth distribution. I expected the survey data to represent only the bottom 95 percent or so of the population, while I knew that the tax data only covered the top 20 percent. I was thus surprised to find that the two data sets led to surprisingly similar conclusions once I defined appropriate censoring rules and parametric assumptions for the underlying distributions. Although the wealth shares for the top one percent of the population ranged from around 50 to just under 100 percent, the wealth share for the top 10 percent remained close to 90-95 percent across a variety of specifications. For labour incomes (whose definition is more comparable between the survey and the tax data), the distributional metrics coincided almost perfectly between the two sources.

The comparability of the scaled estimates could be a result of the extreme degree of concentration: With a top 10 percent wealth share above 90 percent even in the survey that was thought to *understate* wealth inequality, all other estimates were bound to be close. Yet despite its shortcomings, this study concludes on the optimistic note that we can learn a lot about the wealth distribution even if the data are incomplete and inaccurate. This finding should provide some encouragement to researchers practitioners who wish to study wealth inequality in other countries in which the data is even scarcer data than in South Africa.

TABLE 6: TOP WEALTH SHARES ACROSS COUNTRIES AND SOURCES

Country	Top 10%	Top 1%	Data	Reference
South Africa*	≥ 90	≥ 50	Survey	*author's calculations*
South Africa*	≥ 95	≥ 60	PIT	*author's calculations*
South Africa	72	40	Estimated	Stierli et al. (2014)
United States	75	34	Survey	Federal Reserve Bank (2014)
United States	79	37	Survey + Forbes	Vermeulen (2014)
United States	77	58	PIT	Saez and Zucman (2014)
France	50	18	Survey	ECB (2013b)
France	51	19	Survey + Forbes	Vermeulen (2014)
France*	61	21	Estate Tax	Piketty et al. (2006)
Germany	59	24	Survey	ECB (2013b)
Germany	68	33	Survey + Forbes	Vermeulen (2014)
World	87	48	Estimated	Davies et al. (2016)

Note: Comparison of top wealth shares across countries and data sources. *Asterisks denote wealth shares on the level of individuals rather than households.

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Appendices

Appendix A: NIDS

This appendix contains additional information on the wealth data in the second wave of the National Income Dynamics Study (NIDS) and on the methodology used to analyse it (sections A.1 - A.6). It also contains additional tables on some of the results that were discussed only briefly in this paper, notably on the distribution at the level of households and the distribution of wealth within and between demographic groups (section A.7).

A.1 Non-response and imputations

There are two types of missing values in survey data: Unit non-response occurs when a household or individual is not successfully interviewed (because he or she is unavailable or refuses to participate); item non-response occurs when an interviewee does not answer a specific question (because he or she doesn't know the answer or refuses to answer). For the latter case, NIDS/SALRDU provides a set of regression-based imputations (see Brown et al., 2015).

Since imputations run the risk of smoothing out the wealth distribution, I do not use imputed series. However, I treat missing values in three straightforward ways: First, I substitute missing values for zeros when this follows from previous responses on categorical questions (e.g., setting banking assets to zero if the answer to "Do you have a bank account?" was negative). For some variables, the NIDS poses bracket questions ("Would you say the amount was more or less than X Rand?") when respondents don't know the value of their income or wealth. In this case, I substitute missing values on the quantification question for the mid-point of the resulting brackets. Third, I follow SALDRU's approach of substituting valid answers to the one-shot question for missing values on income and wealth, as described in Section 3.1.1. Fourth, I substitute one-shot responses when these exceed the bottom-up estimate in absolute terms due to item non-responses on category level (i.e, the individual or household does not have valid responses for all classes of assets and liabilities).[27] Table 7 provides an overview of this process for four selected variables, while Table 8 summarizes the process of construction the final wealth aggregates.[28]

[27] The results from the one-shot wealth question are an imperfect substitute for bottom-up data: On the adult level, the correlation between bottom-up and one-shot wealth is 14 percent, on the household level it is 42 percent.

[28] The NIDS also includes durable goods, informal loans from family or friends and unpaid service bills or taxes. For consistency with the national accounts, I do not consider these items as assets and liabilities. Although housing is included in the household questionnaire, the individual questionnaire contains a question on outstanding home loans. I use these data to impute missing values on the household level.

Table 7: Treatment of missing values: Selected variables

	Adult Questionnaire			*Household*
	Labour income	Banking assets	One-shot wealth	One-shot wealth
Questionnaires	23 846	23 846	23 846	8986
Entries for question	17 601	16 869	16 872	6196
% of total	74	71	71	69
% of total, weighted	86	82	82	91
Categorical questions ("yes/no" or "zero/non-zero")				
Don't know (%)	0	0	44	37
Refused (%)	0	2	5	6
Answered no/zero (%)	77	66	36	36
Answered yes/non-zero (%)	23	32	15	21
"Quantifiable" responses	4018	5449	2469	1326
% of total	17	23	10	15
Quantification questions				
Missing (%)	0	1	4	0
Don't know (%)	3	14	18	26
Refused (%)	8	20	1	1
Quantified (%)	88	65	77	73
"Raw" observations	3541	3559	1910	964
% of total	15	15	8	11
Data imputations				
Drop 'unjustified' zeros	0	−1302	−2	0
Include missing zeros*	13 515	11 101	6038	2227
Values from brackets*	511		461	321
Used observations	17 567	13 358	8407	3512
% of total	74	56	35	39
% of total, weighted		60	45	55

Note: Treatment of missing values, selected variables, NIDS, 2010. Un-weighted counts. *Replacement of missing values with data from categorical questions (zero values for "no"/"zero"-answers). **Replacement of missing values with data from bracket questions (e.g., R2500 for the bracket R0-5000).

Table 8: Derivation of total wealth

	Item	Survey	Response rate (%) *Total*	*Non-zero*	Notes
	Private pension	A	78	1	
+	Life insurance	A	77	5	
=	*Assets: pension/life*		80	2	(1)
	Cash on hand	A	76	19	
+	Bank account	A	60	15	
+	Trusts, stocks, shares	A	81	0	
=	*Assets: other financial*		66	27	(1)
	Personal loan	A	81	2	
+	Study loan	A	82	0	
+	Vehicle finance	A	81	1	
+	Hire purchase	A	82	2	
+	Credit card	A	81	2	
+	Store card	A	81	6	
+	Mashonisa loan	A	82	1	
+	Micro loan	A	82	0	
=	*Liabilities: non-mortgage*		82	11	(1)
	Net business wealth	A	29	1	(2)
⇒	*Individual-level wealth (bottom-up)*		81	31	(3)
	Assets: real estate	H	70	57	
+	Assets: livestock	H	85	4	
−	Liabilities: mortgages	H	95	7	
⇒	*Household-level wealth (bottom-up)*		94	59	(4)
⇒	*Total individual wealth (bottom-up)*		81	31	(5)
	One-shot wealth	A	45	17	(2)
⇒	*Total individual wealth*		93	55	(6)

Note: Derivation of household-level wealth data, NIDS, 2010. Calculations based on weighted sample using post-stratified weights. Specific notes: (1) Aggregation of above items; (2) From one-shot question; (3) Aggregation of financial assets, financial liabilities (−), net business wealth; (4) Aggregation of real estate assets, mortgage liabilities (−), livestock assets; (5) Allocation of real estate wealth evenly to co-owners (where available) or household members, allocation of livestock assets evenly to household members; (6) Imputation of valid, non-zero one-shot question for missing values or zero values in bottom-up estimate or when one-shot response exceeds bottom-up estimate in absolute terms due to item non-responses on category level (not all asset/liability classes with valid responses).

A.2 Sampling and response biases

A.2.1 Sampling bias and survey weights

A sampling bias arises when a survey systematically under-samples specific groups. SALDRU provides two sets of weights to correct for sampling biases in the NIDS. *Design weights* correct for biases in the probability that a household is included and interviewed in the survey. *Post-stratified weights* further adjust the weights to reflect the national, provincial and sex-race-age group population totals as given by current population estimates in each wave. Since income, expenditure and wealth variables tend to be correlated with sex, race and age, SALDRU recommends the use of these weights to reduce the sampling bias for cross-sectional analyses (Leibbrandt et al., 2009; Wittenberg, 2009; Brown et al., 2015).

As Table 9 shows, the use of post-stratified weights has little impact on the estimates of income inequality, but lowers our estimate for (top one percent) wealth inequality significantly.

A.2.2 Response bias

A response bias arises if respondents to the survey or certain questions within the survey differ systematically from non-respondents. The typical finding is that better-off households are less likely to participate in surveys.

Figure 5 depicts non-response rates by income deciles. It suggests that non-response rates do not differ strongly between income deciles, and are actually higher among higher-income individuals once we impute one-shot questions for non-responses. This finding is confirmed in a formal F-test on the null hypothesis of equal income between respondents and non-respondents (see Table 10). One reason for the positive gradient between derived response rates and incomes could be that a "break-even" response to the one-shot wealth question is counted as zero wealth, while the response that the individual would have "something left over" needs to be quantified to count as non-missing.

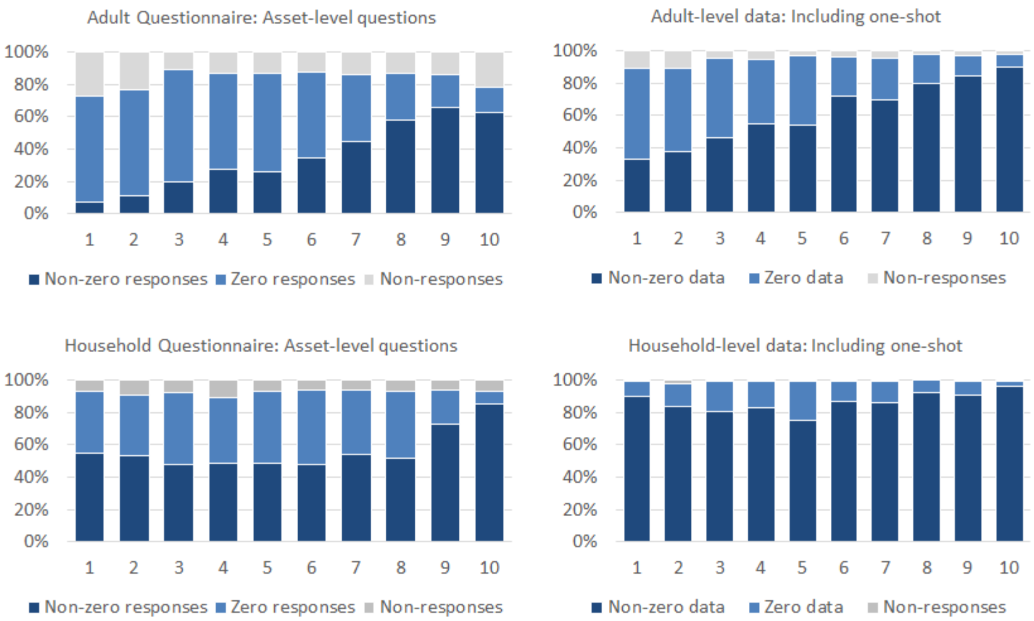
In contrast to the finding that non-respondents have equal (bottom-up) or lower (derived wealth) incomes, the same tests suggest that non-respondents are more highly educated than respondents. Although we also find that non-respondents to the bottom-up wealth questions are more likely to be white and female than respondents, the results are inconclusive for age, race and gender at the level of derived wealth.

Table 9: Distributional implications of survey weights

	No weights	Design weights	Calibrated weights
Wealth			
Top 1 %	79	66	61
Top 10 %	98	97	95
Middle 40%	4	4	6
Bottom 50%	−2	−1	−1
Total (%)	100	100	100
Income			
Top 1 %	20	20	17
Top 10 %	56	60	59
Middle 40%	37	34	35
Bottom 50%	7	6	6
Total (%)	100	100	100

Note: Quantile shares, NIDS, 2010, in percent. Calculations using adult-level data.

Figure 5: Response rates by income quintile



Note: Response rate by income quintile, NIDS, 2010. Left column shows response rates (including split between zero and non-zero quantifications) for asset-level questions; right column shows availability of data once asset-level questions from individual and household survey are combined with one-shot responses.

Table 10: Test for response bias

	Share of total (%)		Mean income (R)		F-Test
	Resp.	*Non-Resp.*	*Resp.*	*Non-Resp.*	
Bottom-up					
Individual	81	19	2 850	3 253	0.75
Household	92	8	6 506	5 872	0.39
Derived wealth					
Individual	94	7	2 988	1 518	12.7***
Household	99	1	6 457	6 647	0.00

Note: Comparison of survey means of monthly income by respondent status on wealth questions, NIDS, 2010. "Bottom-up" refers to the completion of the wealth-related questions in the adult- or household questionnaire, "Derived wealth" includes one-shot wealth alongside results from both adult questionnaires. Column "F-Test" reports the value of the F-statistic and indicates the p-value ($^{***}: p < 0.01$, $^{**}: 0.01 \leq p < 0.05$, $^{*}: 0.05 \leq p < 0.1$). Calculations based on weighted sample using adult-level data and post-stratified weights.

A.3 Outliers

I attempt to systematically identify outliers using the multivariate approach proposed by Billor et al. (2000) and implemented in STATA by Weber (2010). This algorithm starts with the subset with the smallest Mahalabonis distance from the whole sample, and iteratively adds all observations with a distance smaller than some threshold, defined as a percentile of the χ^2-distribution (Billor et al., 2000; Weber, 2010). One challenge when using this method is therefore the specification of the relevant variables, the other is the definition of the threshold: Which characteristics plausibly predict a household's wealth, and how far shall we allow them to deviate from the predicted levels before we dismiss the household as an outlier?

Ideally, we would like to determine the outliers based on a broad set of predictive variables. Since wealth generates income in the form of interest, dividends or rents, I include the person's income from capital sources (interests, dividends, rents and private pension incomes), alongside his or her total income and an indicator whether or not he or she receives government grants (which, being means-tested, should be inversely related to wealth). In line with the life-cycle hypothesis of savings and wealth, I also include the age and squared age of the individual. I include level of education of as a proxy of lifetime income as well as financial acumen. Finally, I include an indicator of whether a person uses sophisticated financial products – either a private pension, life insurance or trusts, stocks and shares, and whether he or she is a co-owner of the house.

Table 11 summarizes the results of the multivariate outlier detection model. As soon as we exclude about 20 people, the wealth share of the richest 10 percent starts to stabilize at around 90 percent. The analysis of these outliers suggests that we are excluding primarily the wealthiest people in the survey, although we also drop several people whose wealth is low compared to their incomes. The mean and median wealth and incomes of the outlier population are much larger than that of the full sample.

Table 11: NIDS – Multivariate outlier analysis

		Wealth		*Income*	
Threshold	Outliers	Top 10%	Top 1%	Top 10%	Top 1%
0.01%	24/13 497	92	47	57	17
0.05%	32/13 497	92	47	56	16
0.10%	374/13 497	90	33	56	16
0.50%	388/13 497	89	29	55	15
1%	402/13 497	89	28	55	15
5%	438/13 497	88	23	53	11
10%	454/13 497	88	24	52	11
Full sample	0/19 436	95	61	58	17

Note: Multivariate outlier detection based on the household's income (total and capital income), age/squared age and education level, as well as indicator variables for the ownership of a home, a bank account, pension annuity, trusts, stocks or shares, and of receipt of a government grant. "Threshold" denotes the 1-x^{th} percentile of the χ^2-distribution; "Outliers" gives the number of outliers identified under this threshold. Calculations based on weighted sample using adult-level data and post-stratified weights.

A.4 Re-sampling of the top tail

A variable follows a power law if it is drawn from a probability distribution

$$p(x) = Cx^{-\alpha} \quad \text{if } x \geq x_{min} \tag{3}$$

where x_{min} is the lower bound on power law behaviour, the “tail index” α determines the “weight” of the tail, and C is a normalization constant that ensures that the total probability sums up to one. Taking logarithms, this means that $\ln p(x) = \alpha \ln x + \text{constant}$, so a power law distribution is consistent with a linearly downward-sloping histogram on a log-log chart (Mitzenmacher, 2001; Clauset et al., 2009). The break-point between the concave and straight portion of the histogram then provides an indication for the value of x_{min}.

Figure 6 shows the log-log histogram (empirical complementary cumulative distribution function) for income and wealth in the NIDS. For incomes, the chart indicates power-law behaviour within the top 1% of the distribution; for wealth, the threshold seems to be closer to 0.25% (which could point to under-sampling or under-reporting at the top of the distribution).

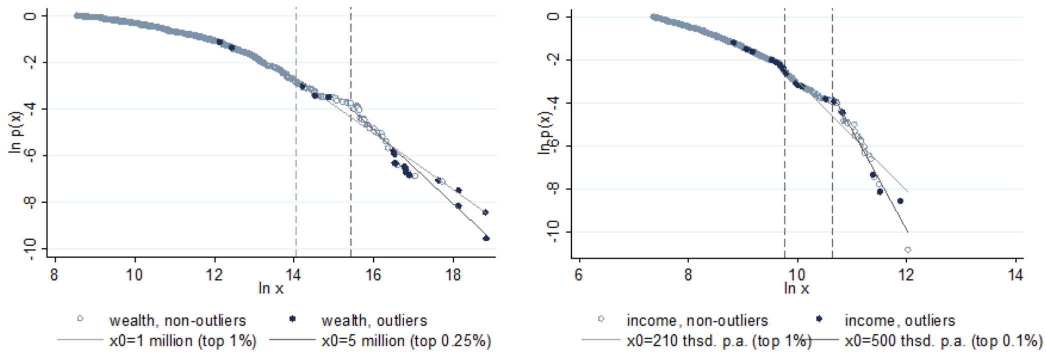
I follow the procedure proposed by Clauset et al. (2009) to fit and test a power law distribution under different levels of x_{min}.[29] Table 12 and Table 13 summarize the results for the NIDS and the PIT. With estimates for x_{min} and α, we can make conditional draws from the distribution using inverse random sampling,

$$x = \frac{x_{min}}{U^{1/\alpha}} \tag{4}$$

where U denotes uniformly distributed random number over the interval [0,1). Since I only re-sample a limited number of observations, I use a bootstrapping approach to increase the robustness. I run 100 draws with replacement for each resampled individual, and average the resulting top-wealth shares and Gini coefficients over these draws.

[29] Clauset et al. (2009) suggest to chose the threshold at which the Kolmogorov-Smirnov statistic (which measures the distance between the density functions of the actual and fitted data) is minimized.

Figure 6: NIDS – Power-law distribution



Note: Empirical complementary cumulative distribution function (CCDF) on a log-log chart, NIDS, 2010. Plots of unweighted adult-level data.

Table 12: NIDS – Power law distribution

w_{min}	Observations	% of total	KS	α
500 000	383	2.0	0.12***	1.0 (0.05)
750 000	267	1.4	0.10***	1.0 (0.06)
1 000 000	209	1.1	0.13***	1.1 (0.07)
1 250 000	160	0.8	0.15***	1.0 (0.08)
2 500 000	83	0.4	0.26***	1.0 (0.11)
5 000 000	61	0.3	0.24***	1.8 (0.23)

Note: Fitting the power law distribution for wealth $> w_{min}$, NIDS, 2010. Column "KS" reports the value of the (combined) Kolmogorov-Smirnov statistic and indicates the p-value ($^{***}: p < 0.01$, $^{**}: 0.01 \leq p < 0.05$, $^{*}: 0.05 \leq p < 0.1$). Column "α" reports standard errors in parentheses. Calculations based on weighted sample using adult-level data and post-stratified weights.

Table 13: PIT – Power law distribution

w_{min}	Observations	% of total	KS	α
50 000	89 857	7.7	0.01***	1.4 (0.01)
75 000	50 446	4.3	0.02***	1.4 (0.01)
100 000	34 239	2.9	0.02***	1.5 (0.01)
125 000	25 124	2.1	0.03***	1.5 (0.01)
250 000	9331	0.8	0.01	1.6 (0.02)
500 000	2968	0.3	0.02*	1.6 (0.03)

Note: Fitting the power law distribution for total investment income $> w_{min}$, PIT, 2010. Column "KS" reports the value of the (combined) Kolmogorov-Smirnov statistic and indicates the p-value ($^{***}: p < 0.01$, $^{**}: 0.01 \leq p < 0.05$, $^{*}: 0.05 \leq p < 0.1$). Column "α" reports standard errors in parentheses. Calculations based on unadjusted, unscaled PIT data.

A.5 Portfolio composition

Table 14 compares the portfolio composition in the NIDS data to the national accounts. One salient feature in this comparison is the understatement if financial assets relative to the non-financial assets in the survey. Pension and non-pension financial assets each constitute a third of total assets in the national accounts, but only 10 percent of total assets in the NIDS. While the composition of liabilities matches the national accounts more closely, the debt-asset ratio shows that liabilities are understated to an even greater extent than assets. This finding is largely robust to the removal of outliers (as identified in Appendix A.7).

Table 5 reports the wealth distribution by asset class. It shows that the distribution of total assets is very similar to the distribution of net wealth, which justifies the comparison between wealth in the NIDS and assets in the PIT.

Table 14: NIDS – Portfolio composition

	Full NIDS sample	*Trimmed sample*	*Pension adjusted*	*National accounts*
Pension/life assets	11	16	47	36
Non-pension financial assets	9	13	5	32
Real estate assets	76	67	45	26
Other non-financial assets	4	4	2	6
Total assets	100	100	100	100
Mortgage debt	52	76	52	57
Other debt	48	24	48	43
Total liabilities	100	100	100	100
Liabilities/assets (%)	11	6	7	20
Wealth/income (%)	538	426	774	231

Note: Portfolio composition, NIDS, 2010, in percent of total assets (liabilities). "Trimmed sample" excludes outliers (see Appendix A.3). "Pension adjusted sample" includes adjustment for pensions (see Appendix A.6). Calculations based on weighted sample using adult-level data and post-stratified weights, using complete observations only (i.e. individuals without missing values on the level of any asset class: $n = 4,917$ in full sample; $n = 4,275$ in trimmed sample).

A.6 Pensions in the NIDS

Despite the fact that half of private- and public-sector employees are covered by occupational pension schemes (National Treasury, 2012), only five percent of adults reported owning a pension or retirement annuity in the NIDS, and only a third of these were able or willing to provide a quantification. I attempt to correct for this by imputing pension assets for all employed individuals with zero- or non-responses regarding the current value of these assets.

Under the assumption of consumer price inflation (π_p) of 6%, wage inflation (π_w) of 8% (including promotional effects), nominal investment returns (r) of 10%, a constant contribution rate of 15% of the annual labour market income (y) and a starting age of 25 years, we can estimate the current value of a person's pension from his or her age and current contributions ($c_{curr} = 0.15 \times y$). Since pension funds allow people to withdraw their pension assets when switching between jobs, I also apply a 50% withdrawal discount (w) on the estimated assets in pension funds.[30]

I first estimate the initial pension and retirement fund contribution at age 25 (c_{ini}) per Equation 5, and then calculate the current value of previous contributions per Equation 6, where n denotes the number of years between 25 and the current age:

$$c_{ini} = \frac{c_{curr}}{(1+r)^n} \tag{5}$$

$$p_{assets} = c_{ini} \times \frac{(1+r)^n - (1+\pi_w)^n}{(r - \pi_w)} \times (1-w) \tag{6}$$

This imputation raises the share of pension assets from just above 10 to to just below 50 percent of assets – considerably higher than in the national accounts (see Table 14). Since withdrawal rates are likely higher for low-income people (who switch jobs more often and have greater need to use their pensions to support consumption between jobs), this estimation likely understates true inequality (National Treasury, 2012).

[30] The author acknowledges the advice of Davy Corobulo and Natalie Van Zyl with regards to realistic assumptions on retirement saving dynamics in South Africa.

A.7 Additional results

Table 15 summarizes income and wealth shares on the level of households. Compared to the results on the level of individuals, the income and wealth shares of the top 10 percent drop by 6-8 percentage points; the shares of the middle 40 percent increase by almost as much. This reflects the fact that the pooling of wealth within households smoothes out some of the spikes in income and wealth, while the distribution for the bottom half of the population is largely unaffected.

Tables 16 and 17 contain detailed results for the wealth distribution by racial group and gender. With regards to race, Table 16 shows that between-group inequality remains very high, but also shows that within-group inequality of the African group exceeds that for the overall population, being much higher than the level of inequality within any other racial group. With regards to gender, Table 17 shows little difference in the mean and median wealth of men and women.

Table 15: NIDS – Individual vs. household-level distribution

	Wealth		*Income*	
	Individual	Household	Individual	Household
Top 1%	61	47	17	10
Top 10%	95	89	35	51
Middle 40%	6	12	35	39
Bottom 50%	−1	−1	7	10
Gini	0.98	0.89	0.72	0.62

Note: Quantile shares, NIDS, 2010, in percent. Calculations based on weighted sample using post-stratified weights.

Table 16: Wealth and race: Within- and between-group inequality

	African	Coloured	Indian	White
Median wealth ('000 R)	0	0	10	200
Average wealth ('000 R)	32	68	994	1 810
Top 10% wealth share (%)	98	84	84	72
Middle 40% (%)	6	17	16	27
Bottom 50% (%)	-4	-1	0	1
Total (%)	100	100	100	100
Observations	15 321	2 547	218	585

Note: Wealth by racial group, NIDS, 2010. Calculations based on weighted sample using adult-level data and post-stratified weights.

Table 17: Wealth and gender: Within- and between-group inequality

	NIDS		*PIT (unscaled)*	
	Male	Female	Male	Female
Median wealth ('000 R)	0	0	0	3
Average wealth ('000 R)	105	103	18	15
Top 10% wealth share (%)	95	94	73	60
Middle 40% (%)	7	7	28	41
Bottom 50% (%)	-2	-1	-1	-1
Total (%)	100	100	100	100
Observations	8 004	10 667	668 369	493 397

Note: Wealth by gender, NIDS and PIT, 2010. NIDS calculations based on weighted sample using adult-level data and post-stratified weights. PIT calculations based on total investment incomes, with adjustments for tax-exempt interest income and pensions (unscaled, relative to the tax-filing sub-population).

Appendix B: PIT

This appendix contains additional information on the data in the second wave of the Personal Income Tax (PIT) assessment sample of 2011 (section B.1), on the imputation of pension assets (section B.2) and on the results before scaling to non-filers (section B.3). It also provides an overview of the assessment sample of 2014, which was made available by SARS but which was not analysed in this paper (section B.4).

B.1 PIT Data and Sample

B.1.1 PIT assessment sample

The South African Revenue Services gave us access to a 20 percent sample of the 2011 income tax assessment. Table 18 provides an overview over the *series* provided in the assessment sample, and the derivations of the variables used in this paper. Table 19 then provides an overview over the *observations* in the 20 percent sample.

B.1.2 PIT filing thresholds

Whether or not someone is included in the PIT database depends on their liability to file income taxes. In 2011, South African residents were liable to file personal income taxes if their incomes exceeded the following thresholds (SARS, 2011):

- income from a single employer exceeds R120,000 for the year, and/or
- income from more than one employer exceeds R60,000, and/or
- local interest income in excess of R22,300 for taxpayers below the age of 65 or R32,000 for taxpayers aged 65 and older and/or
- foreign interest or dividend income in excess of R3,700, and/or
- income from own business, irrespective of the amount.

According to the NIDS, the labour income threshold should be exceeded by only 3-7 percent of employees, while the investment income threshold should be exceeded by about one third of recipients of investment incomes. In reality, about 95 percent of tax filers (16 percent of the population) declared incomes from employment in the PIT, while only 7 percent (1 percent of the population) declared incomes from investments.

Table 18: PIT – Data Overview

	Item	Code	Notes
	Local interest	4201	Local interest earned†
+	Local capital gains	4250	Excludes the basic exemption for capital gains (exclusion rate in 2010-11: 75%)
−	Local capital losses	4251	
+	Other gains	42*	Local dividends†; rental profits/losses; income from building societies; income from fixed period shares and deposits; royalties; foreign investment income (interest, dividends, capital gains/losses); gambling gains/losses
−	Other losses	42*	
=	*Investment income incl. capital gains*	Derived	
+	Business profits	01-34*	Profits/losses from unincorporated businesses or trades
−	Business losses	01-34*	
=	*Business income*		
+	Normal income	36	Local and foreign labour and pension income
+	Fringe benefits	38	
+	Lump sum income	39	Local and foreign lump-sump income, including special remuneration and pension/ provident fund lump-sums
=	*Labour income*‡		
=	*Gross income*		All incomes received by the individual
−	Deductions	40	E.g., Taxes paid under pay-as-you-earn; pension, provident or medical fund contributions
−	Exemptions		The exempted portion of interest income, all local dividends
=	*Taxable income*		Taxable income used to determine the normal tax due (before any rebates and tax credits)

Note: Overview over the data in the PIT assessment sample. *Asterisks refer to the subset of items under the respective SARS Code that not mentioned separately in the table. † Local interest below the threshold of R22,300 and local dividend income in its entirety is exempt from the PIT, and the accuracy of exempt incomes is not verified in the tax inspection process. ‡Employment income derived from taxable normal and lump sum income (only taxable portion of normal and lump sum income provided by SARS).

Table 19: PIT – Sample Overview

	2010-2011	2013-2014	Notes
Total population	49 991 300	52 982 000	
Of which aged 15+	34 487 100	37 527 258	
Submitted tax records	5 876 889	5 149 506	
Implausible/null values	956	1 516	Implausible or null values excluded by SARS
Remaining tax records	5 875 933	5 147 990	
Of which high-earners	602	1 259	"High earners" with taxable incomes > $R10$ million to be considered separately for confidentiality reasons
20% sample excluding high-earners	1 175 187	1 029 598	Assessment sample as made available by SARS to the author
Ages 15+ only	1 173 469	1 027 289	
20% sample of high-earners	120	252	Summary statistics on all 602/1259 high earners made available to the author (mean, standard deviation, minimum, maximum, 25^{th}, 50^{th} and 75^{th} percentiles)

Note: Overview over the observations in the PIT assessment sample. Population totals from StatsSA mid-year population estimates for 2010 and 2013.

B.2 Pensions in the PIT

The PIT provides no information on investment incomes on pension assets. However, the PIT contains data on current contributions to pension or retirement annuity funds, which allow us to estimate the current value of pension assets in analogy to the procedure described for the NIDS (see Appendix A.6). The main difference is that we can read current contributions directly from the data (as opposed to estimating it at 15% of current earnings), and that we can distinguish contributions to pension funds and from contributions to retirement annuity funds. Since assets in the latter cannot be withdrawn before retirement, I apply the 50% discount to the assets in pension funds only.

Since the PIT works records investment incomes rather than the underlying assets, the annual investment income on pension assets needs to be estimated per Equation 7:

$$p_{income} = p_{assets} \times r \tag{7}$$

I set the investment income from pension assets to zero for people below 25, and to missing for people above 65.[31] When calculating distributional statistics for pension assets (or total investment income including pension assets), we work on the population below 65 years only.

When estimating investment incomes on pension assets with this approach, we find that they constitute almost 80 percent of total investment incomes. As in the case of the NIDS, our estimates likely understate the true inequality of pension wealth significantly (since withdrawal rates and interruptions to contribution times are likely higher for low-income people).

[31] Ideally, we would set only retirees to missing, while keeping zero pension wealth for people who above 65, do not receive a pension and do not contribute to pension or retirement annuity funds. However, the current SARS dataset does not distinguish between labour and pension incomes under employment income.

B.3 PIT Unscaled results

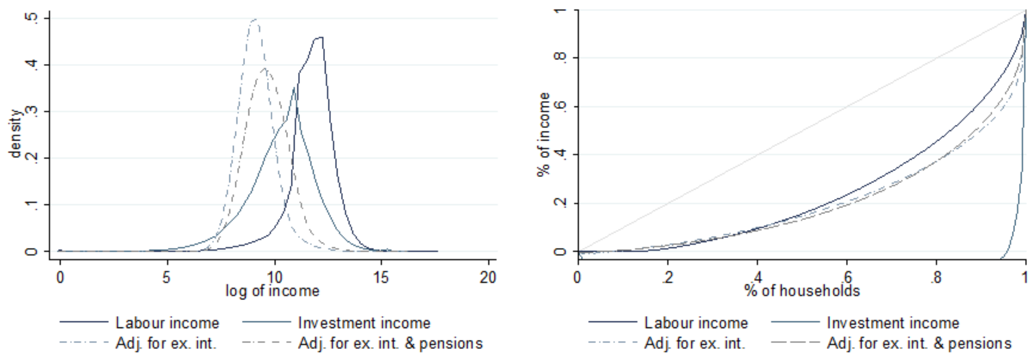
Table 20 and Figure 7 provide results on the wealth distribution within the tax-filing sub-population (prior to scaling), and show the importance of the adjustments made to the measure of wealth. The imputation of interest incomes below the filing threshold via a bottom-censored log-normal distribution is the most important adjustment in the unscaled sample. In the scaled sample, the imputation of interest incomes below the filing threshold has a much smaller impact.

Table 20: PIT – In-sample (unscaled) distribution

Income source	Share $\neq 0$	Top 10%	Top 1%	Gini
Employment	91	38	10	0.52
Local interest	3	100	77	0.99
Other investment	5	105	82	1.09
Total investment	7	104	68	1.05
Pensions†	52	62	22	0.79
Local interest, adjusted for tax-exempt omissions*	100	36	12	0.46
Total investment, adjusted for tax-exempt interest*	100	50	24	0.59
Total investment, adjusted for tax-exempt interest & pensions‡	100	47	19	0.59

Note: Quantile shares, PIT, 2010. Results relative to the tax-filing population (not scaled to non-filers). Second column contains share of non-zero observations. *Adjustment for omissions of tax-exempt interest income described in Section 3.3.1. †Adjustment for investment income on pension assets described in Appendix B.2; Distributional metrics for the population < 65 years only. ‡Distributional metrics for the total population (results for the population < 65 years only marginally lower). Note that in the presence of individuals with negative investment incomes, the Gini coefficient is no longer bounded to one (see also OECD, 2015).

Figure 7: PIT – In-sample (unscaled) distribution



Note: Income distribution, PIT, 2010. Unscaled results. Left panel: Kernel density curves of logged incomes; right panel: Lorenz curves.

B.4 PIT 2014: Main results

SARS also provided us with a 20 percent sample of the 2014 tax assessment for 2013-2014 tax year. Table 21 summarizes the results for the within-sample distribution. It suggests that inequality is slightly lower than in the 2010-2011 tax year, although this is likely due to higher filing rates.

TABLE 21: PIT – 2010-2011 VS 2013-2014

Income source	Share $\neq 0$	Top 10%	Top 1%	Gini
2011				
Employment	91	38	10	0.52
Local interest	3	100	77	0.99
Other investment	5	105	82	1.09
Total investment	7	104	68	1.05
2014				
Employment	94	36	10	0.49
Local interest	4	100	78	0.99
Other investment	7	102	81	1.02
Total investment	9	102	71	1.01

Note: Quantile shares, PIT, 2010 and 2013. Results relative to the tax-filing population (not scaled to non-filers). Second column contains share of non-zero observations. Note that in the presence of individuals with negative investment incomes, the Gini coefficient is no longer bounded to one (see also OECD, 2015).

The **Research Project on Employment, Income Distribution and Inclusive Growth (REDI3x3)** is a multi-year collaborative national research initiative. The project seeks to address South Africa's unemployment, inequality and poverty challenges.

It is aimed at deepening understanding of the dynamics of employment, incomes and economic growth trends, in particular by focusing on the interconnections between these three areas.

The project is designed to promote dialogue across disciplines and paradigms and to forge a stronger engagement between research and policy making. By generating an independent, rich and nuanced knowledge base and expert network, it intends to contribute to integrated and consistent policies and development strategies that will address these three critical problem areas effectively.

Collaboration with researchers at universities and research entities and fostering engagement between researchers and policymakers are key objectives of the initiative.

The project is based at SALDRU at the University of Cape Town and supported by the National Treasury.

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Research Project on Employment, Income Distribution & Inclusive Growth

Towards an integrated response to unemployment, inequality and poverty