A SERIES OF NATIONAL ACCOUNTS-CONSISTENT ESTIMATES OF POVERTY AND INEQUALITY IN SOUTH AFRICA

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A SERIES OF NATIONAL ACCOUNTS-CONSISTENT ESTIMATES OF POVERTY AND INEQUALITY IN SOUTH AFRICA[1]

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ABSTRACT

This paper makes a unique contribution to the South African literature in combining data from an alternative source of household survey data – the All Media and Product Survey (AMPS) – with national accounts income trends for this country, in the recent tradition of research on the world distribution of income performed by Bhalla (2002), Karshenas (2003), Bourguignon and Morrisson (2002), Sala-i-Martin (2002a; 2002b), and Quah (2002), amongst others. Its usefulness lies in arriving at alternative estimates of post-transition poverty and inequality that are consistent with the story that national accounts and other official data collectively tell us about the path of the South African economy during the post-transition period. While the method of scaling survey distribution data by national accounts means is somewhat controversial, it is not clear that the distributional trends obtained using the post-transition sets of either the IESs or the Population Censuses are more reliable, given serious deficiencies in both sources of data. Adjusted distributions yield lower levels of poverty and a stronger decline in poverty during the second half of the period than the figures obtained from the raw AMPS data. While the levels of poverty obtained using adjusted income distributions are artificially low, the derived downward trend is supported by a number of official data sources.

Keywords: Poverty, Inequality, Income distribution Analysis, South Africa
JEL codes: D6, I32, I38

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A SERIES OF NATIONAL ACCOUNTS-CONSISTENT ESTIMATES OF POVERTY AND INEQUALITY IN SOUTH AFRICA

1. INTRODUCTION

In recent years, the usefulness of survey data for analysing income distributions has been increasingly vocally disputed. In particular, the discrepancy between trends in welfare derived from the national accounts and those derived from household surveys is a primary factor fuelling the debate. In 1987, survey mean income stood at 65.1% of national accounts GDP per capita for developing countries as a whole; by 1998, this proportion had fallen to 54.4% (Bhalla 2002: 109). In South Africa, the inconsistency is more fundamental: some of the trends in the income distributions constructed from official household surveys over the latter half of the 1990s are entirely incompatible with trends in the national accounts concept of household income over the same period. For instance, Leibbrandt, Levinsohn and McCrary (2005) found evidence of a 40% decline in individual per capita incomes between 1995 and 2000, after analysing the Income and Expenditure Surveys (IESs) collected in these years. By contrast, calculations based on the national accounts data show that household income growth was positive throughout this period, with no single year recording an increase measuring less than 2%[3].

This paper makes a unique contribution to the South African literature in combining data from an alternative source of household survey data – the All Media and Product Survey (AMPS) – with national accounts income trends for this country, in the recent tradition of research on the world distribution of income performed by Bhalla (2002), Karshenas (2003), Bourguignon and Morrisson (2002), Sala-i-Martin (2002a; 2002b), and Quah (2002), amongst others. Its usefulness lies in arriving at alternative estimates of post-transition poverty and inequality that are consistent with the story that national accounts and other official data collectively tell us about the path of the South African economy during the post-transition period. Since AMPS data are available annually, it is possible to extend analysis following a similar methodology employed by Van der Berg and Louw (2004) and Van der Berg, Burger, Burger, Louw and Yu (2005). The paper begins with a discussion on the use of national accounts data to adjust survey-based income distributions, including an overview of motivations for adopting this technique and some of its major criticisms. Next, an outline of the adjustment methodology applied to AMPS data is provided, together with descriptive analysis relating to trends in household income during the post-transition period. This provides the foundation for presentation of adjusted AMPS-based estimates of poverty and inequality. The paper closes with a summary and policy conclusions.

[3] This calculation is based on the recently discontinued SARB current income (6244L) series.

2. WHY SCALE HOUSEHOLD SURVEY-BASED INCOME DISTRIBUTIONS BY NATIONAL ACCOUNTS DATA?

The large and growing disparity between average living standards measured on the basis of national accounts data and households surveys, highlighted above, has raised concern amongst analysts the world over. A solution first adopted by the Indian government involves replacing household survey means with national accounts means, while retaining the distribution of welfare yielded by household surveys. While the government of India abandoned use of this technique in 1993 (allegedly due to concerns regarding the quality of their national accounts data – Deaton 2005: 17), it has subsequently routinely been used on Latin American data, where survey distributions have been scaled by individual components of household income (see for instance Szekely and Hilgert 1999). Furthermore, in more recent years the methodology has found wider application, with a number of authors – including Sala-i-Martin, Quah, Bourguignon and Morrison – employing it to investigate topics concerning world poverty. This extension has drawn fresh criticism, and a re-examination of the merits of the approach. Accordingly, a review of the case for national accounts adjustment in the South African scenario is provided next, as well as a discussion on the theoretical benefits and costs accompanying the adoption of this technique.

Delving into the South African data, a comparison of household income captured by national accounts data and aggregate household income derived from two sets of data sources yields two important conclusions. Table 1 below shows the ratio of national accounts current income to estimates of aggregate household income from the IESs of 1995 and 2000 and annual AMPS surveys.

Firstly, the ratio of survey to national accounts income is often highly variable. For instance, the official data sources - namely the October Household Survey (OHS) and the Labour Force Survey (LFS) - capture more than 100% of national accounts remuneration income in 1995, but less than 70% in 2004. Given a steady and relatively stable upward trend in national accounts income – in line with economic growth trends in South Africa, questions regarding the reliability of trends drawn from official survey income aggregates arise. One may also be concerned over the substantially smaller estimate of household income drawn from surveys for most of the period. Analysing the issue from the household expenditure[4] side, Deaton (2005: 4) notes that surveys only capture three quarters of national accounts totals in the OECD – the group of countries for which one would expect data quality to be highest. Secondly, the proportion of national accounts income captured by official surveys seems to be falling over time. In contrast, the AMPS estimates of household income seem to be roughly stable over time, in relation to national accounts. AMPS data may also be considered more reliable if one applies Deaton's (2005: 4) argument that the standard deviation of the ratio between survey and national accounts income provides a measure of the accuracy of a data source.

[4] Expenditure captured in surveys is typically smaller than income, although theoretically they should be equal if saving is included in the definition of expenditure.

Table 1: Proportion of national accounts income captured by various household surveys, 1993-2004

Year	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	Standard deviation
National accounts current income (Rmill)	313 763	352 213	402 256	452 785	508 851	555 002	607 591	677 570	737 206	825 109	898 558	989 290	
IES			96%					62%					
AMPS	66%	62%	60%	60%	57%	59%	56%	60%	59%	58%	60%	57%	2.9%

Which factors are responsible for the observed disparities between estimates of household income drawn from surveys and national accounts data? The most obvious point relates to the different coverage and accounting practices adopted in constructing the two data sources. Surveys often exclude students and some institutions (including hostels), whereas national accounts theoretically account for the whole population. Unlike the measure of household income captured in surveys, the concept of household income in the national accounts includes income accruing to non-incorporated business enterprises as well as non-governmental non-profit organisations (NGOs) that render social and community services to households. Some authors argue that growth in the NGO sector – which could be particularly rapid in developing countries due to a changing production structure – may be driving the increasing gap between national accounts and survey income aggregates (Ravallion 2000). However, Bhalla (2002: 108) points out that this is not likely to be the case.

Even if the accounting unit were the same – namely the household – the definition of household income would remain different across data sources. Current income in the national accounts includes both income in kind and imputed rents accruing to households, while the measure of household income collected by household surveys often excludes or poorly captures these items. Commenting on the discrepancy between national accounts and survey estimates of expenditure, Deaton (2005: 10) remarks: "there are conceptual differences between the two concepts of consumption, but these do not account for the differences in growth rates, so that one or both of the growth rates are incorrect".

A factor that drives level differences between national accounts and survey measures of income, but not necessarily the growing gap between them associated with economic growth, is measurement and sampling error. Household surveys often suffer from incompleteness, *inter alia* as a result of household non-compliance and item non-response. It is well known that more affluent households are both less likely to participate in surveys and more likely to underreport income when they do comply (Ravallion 2000; Bhalla 2002; Korinek et al. 2005). Banerjee and Piketty (2003: 2) estimate that 20-40% of the gap between survey and national accounts based estimates of growth is due to undercounting the very affluent. Further, household survey data for 16 Latin American countries reveal that the 10 richest households participating in household surveys in each country in most cases reported total incomes merely equivalent to the typical salary earned by a manager of a medium to large sized firm in the region (Szekely & Hilgert 1999: 13). Surveys may also incorrectly reflect the population income distribution as a result of flaws in the sampling design: the IES2000 provides a recent South African example in this regard. In addition, they may be less representative of households in remote rural or dangerous areas, as a result of obstacles to fieldwork (Deaton 2005: 15).

National accounts data similarly suffer from a range of defects. Since the household income and expenditure series are typically constructed using survey data, and extrapolated with the aid of other data for time periods in which no survey data are available, the quality of national accounts data varies according to whether the year in question is a benchmark year (i.e. a year for which survey data are available). In South Africa, the benchmarks for national accounts series relating to household income are changed at approximately five-year intervals. A related issue is population weighting: ratios are applied to survey data to achieve representivity with respect to the population. These ratios are generally infrequently revised, and may lead to incorrect estimates if a population is dynamic. Deaton (2005: 15) argues that the use of outdated ratios and correction factors is especially deleterious when economies are developing, given the associated changes in their production structures. Finally, national accounts series may be revised frequently; in South Africa, revisions to household income series were recently undertaken in accordance with the IES2000, resulting in real household expenditure growth rising from an average of 2.6% per annum over 1998-2003, to 2.9% (Mantshimuli 2004: 65. Van Walbeek (2006) provides more detail on South African national accounts revisions.) Bhalla (2002) argues that errors in national accounts data series are more likely to cancel out than those in surveys, as a result of the series being compiled from a range of sources and being subject to cross-checking.

Thirdly, it is likely that the ability of the national accounts to capture income increases as economies develop. In contrast to the two points discussed above, this one directly affects the size of the gap between proportions of household income captured by the different data sources. The value of informal sector activity is notoriously difficult to measure, and can be sizeable in a developing country context. As economies grow and their structures change, many production activities shift from households to the formal sector, as a result of the "increasing marketization, complexity, and roundaboutness of production with economic development" (Deaton 2005: 15). Consequently, economic activity may be increasingly accurately picked up in national accounts data. This implies that in developing countries, the level of national accounts income is understated while growth is overstated. To some extent this phenomenon may explain the apparently widening gap between national accounts and official survey estimates of household income and wages in South Africa during the first post-transition decade: a period of moderate but robust economic growth. However, empirical international research does not support the existence of such a bias during economic expansion[5] (Ravallion 2003: 649). Deaton (2005: 3) is critical of this result, attributing it to large variation across countries in the ratio of survey to national accounts totals.

Despite the shortcomings inherent in national accounts data series, there is practical value to be derived from adjusting income distributions drawn from household surveys with national accounts data for purposes of trend analysis. In addition, the adjusted distributions can be used for time series analysis of macroeconomic data (for instance, investigating the impact of economic growth on poverty and inequality). Several recent distribution studies have yielded results quite at odds with the national accounts and other clues to the state of the South African economy, partly as a result of relying on official

[5] However, Ravallion (2003) does note a large discrepancy between national accounts and survey estimates of growth during times of economic contraction.

household survey data that may not be suitable for purposes of comparative analysis. The Leibbrandt et al. (2005) findings provide an example in this regard. The magnitude of the decline recorded based on the two IESs implies a greater fall in output than the one that occurred during the Great Depression, and is at odds with a number of economic indicators relating to the period. Indeed, it is argued here that the existing post-transition South African official household surveys are plagued by serious deficiencies that render them unsuitable for trend analysis (see section 4). While the quality of national accounts data is called into question in some developing countries (for example India), the evidence below suggests that in South Africa the quality of survey data is a cause for greater concern.

Firstly, one might expect a sharp decline in income to lead to a comparable fall in petrol sales. However, sales of petroleum products increased 9.0% over the period 1995-2000, petrol by 2.4%, and paraffin by 0.8% (SAPIA); note that the low growth in paraffin sales may have been a result of growing access to electricity. Another indicator of economic activity, electricity produced, increased by 12.9% while electricity consumed rose by 15.0%, the difference being accounted for by electricity imports (StatsSA(a)). The volume of goods transported, mainly by road, increased by 12.2% (StatsSA(b)). Audited national revenue figures also provide a real and strong contradiction of the survey trends. Instead of strongly declining, as one would expect in response to a sharp decline in incomes of the magnitude implied by the two IES surveys, overall tax revenue increased 23.9%, largely driven by strong increases in VAT revenues (18.9%), income tax revenues (26.0%) and company tax revenue (32.6%) (SARB). Such revenue increased despite the fact that VAT rates remained unchanged, and that both income tax and company tax rates were adjusted *downwards* during the period. Improved tax administration is acknowledged to have contributed to this rise, but some economists believe GDP growth is under- rather than over-estimated, judged *inter alia* by the buoyancy of tax revenues.

Data from surveys on economic activity conducted by Statistics South Africa that feed into national accounts data series indicate that many of the components of aggregate production and expenditure have grown substantially over the period 1995-2000. Retail and wholesale sales grew by 9.9% and 4.8% respectively, while there were also increases in expenditure on non-durables (4.8%), semi-durables (33.9%) and durables (8.4%). In fact, the only two items that experienced negative growth were car sales (value of vehicles sold declined by 8.5%) and buildings completed (value down 11.2%), both of which are strongly cyclical types of expenditure (own calculations using Statistics South Africa 2004). Taken together, this is fairly compelling evidence that average incomes over 1995-2000 did not follow the negative direction suggested by research comparing distributions drawn from the IES.

In a similar vein, Bhalla (2002: 115-116) demonstrated that national accounts estimates of growth in living standards in India are closer than households survey growth estimates to the improvement suggested by the estimated changing price and income elasticities of staple food items. His argument for continuing to adjust survey means with national accounts data is succinctly summarised as follows:

"The World Bank's reason for not adjusting survey means with national accounts means is that the latter are plagued with measurement problems. Which is true. However, the choice of which estimate is finally chosen should be decided according to which method minimizes errors, especially errors in trends, because that is an important variable of interest. And it is likely that not adjusting survey means introduces a larger error into the trends than adjusting the survey means by national accounts data."

Bhalla (2002: 126)

3. WHAT DOES THE LITERATURE SAY ABOUT SCALING HOUSEHOLD SURVEY MEANS WITH NATIONAL ACCOUNTS DATA?

A number of authors have raised criticisms of the national accounts adjustment methodology. Three major attacks are discussed here. The first argument is that there should be no presumption that economic growth is shared equally – or anything close to it – by the population of a country, assuming that estimates of growth derived from the national accounts are reliable. For instance, in India the national accounts paint a picture of strongly rising consumption mobility during the 1990s, on the back of robust economic growth. However, household surveys yield a less rosy outlook, particularly in terms of the reduction in poverty realised over the period (Deaton & Kozel 2005: 179). Deaton (2005: 17) argues that given the differences in coverage and definition across the two data sources, it is possible for the incomes of the poor (captured in surveys) to increase by less than the national accounts growth rate without any increase in aggregate inequality, as estimated from survey data. Indeed, in a very unequal society such as South Africa's, widespread economic exclusion may seriously inhibit the poor from improving their welfare in any significant way during booms. However, this paper will argue that the rapid expansion of the social grant system in South Africa during the first few years of the twenty first century weakens this argument for at least the latter half of the period under study.

The second argument relates to the consistency with which data sources are used and applied in economic analysis. In this regard, Milanovic (2002) is sceptical of using national accounts data for the mean while retaining use of survey data for the distribution of income, arguing that the use of two fundamentally different data sources interferes with "internal consistency". Problems may also arise from working with two different measures of income, given the differences in coverage and accounting described above. In particular, NGOs may account for a relatively large chunk of income or expenditure in developing countries, particularly those that are heavily reliant on donor aid. As a middle-income country, however, South Africa is not aid-dependent. In general, Ravallion (2000) believes the disparities to be glaring enough to make national accounts and survey measures of household income fundamentally incompatible. Deaton (2005: 17) makes a similar argument, pointing out that "national accounts track money, not people". Bourguignon (2005) does not support the survey purist argument as strongly. He argues that the adjustment to the national accounts mean is only valid if the error captured by household surveys (that is, the random component picked up in addition to the true mean) is unrelated to the true level of welfare (income) across the entire income distribution. If there is a higher degree of misreporting in the upper tail of the income distribution (as is hypothesized), this assumption is violated. However, if the correlation between the survey error and level of income over the range of the income distribution is small, the adjustment may be justified. Nonetheless, to allow for the potential introduction of inconsistency, this paper presents unadjusted estimates of poverty for South African as an alternative to the adjusted estimates, noting that our conclusions remain largely unchanged.

The third argument centres on the way in which survey income distributions are typically adjusted using national accounts data – that is, neutrally. Adjusting survey data with national accounts data involves making two assumptions, one across space and another across time.

Firstly, one typically assumes that the under- or over-estimation of household welfare in surveys is equi-proportional to reported income over the entire range of the income distribution, regardless of potentially relevant factors including geographical location. However, we know that undercapturing of income is often greatest at the upper end of the income distribution, due to underreporting by the rich to avoid tax-related consequences or their reluctance to participate in surveys. This appears to be a particularly severe problem in highly unequal countries, such as South Africa (Deaton 2005: 11). Given the large contribution that rich households make towards aggregate income, this implies that adjusting incomes upwards uniformly (that is, by a constant proportion) could result in great under-estimation of poverty.

Korinek, Mistiaen and Ravallion (2005) explore the distributional consequences of correcting for survey non-compliance using US data (the Current Population Survey). They find that household compliance (i.e. participation in surveys, which need not imply full reporting of income) falls monotonically as income rises, as one might expect. Interestingly, the U.S. Census Bureau's correction for this non-response is almost distribution-neutral; income at any percentile is increased by approximately 20% (Korinek et al. 2005: 19). This accords with Bhalla's (2002: 117) research on Indian data; he argues that "a "constant" multiplier is not only plausible but also likely". The reason advanced for this is that the poor tend to be more likely to underreport food expenditure, while the rich tend to underreport non-food expenditure more; these forms of underreporting appear to balance each other out in proportional terms (Bhalla 2002: 117). While Korinek et al. (2005) find that correcting for non-response results in mean income and inequality rising substantially, the adjustment has little effect on poverty incidence for a broad range of poverty lines[6]. In the analysis contained in this paper, racial distributions are scaled up separately and by different magnitudes. Consequently, both the shape of the aggregate income distribution and its mean are

[6] In fact, the authors find that the U.S. poverty rate tends to be over-estimated in general, as a result of higher survey compliance by less affluent households (Korinek et al. 2005: 19).

affected by the adjustment.

Secondly, the application of national accounts adjustment incorporates an assumption that underreporting of income increases uniformly (in proportional terms) across the population as the economy grows. This is not valid if changes in household behaviour associated with economic growth and development form the driving force behind increasing under-reporting of income in household surveys, as Milanovic (2002) suggests might be the case. For instance, non-compliance with surveys might rise with an overall increase in income levels. Similarly, rising geographic inequality associated with economic growth – as observed in India – would tend to lower the ratio of survey to national accounts income or expenditure means (Deaton 2005: 12-13). However, this effect may be offset by an improvement in the ability of surveys to capture income accruing to the poor as production activities move to the formal sector.

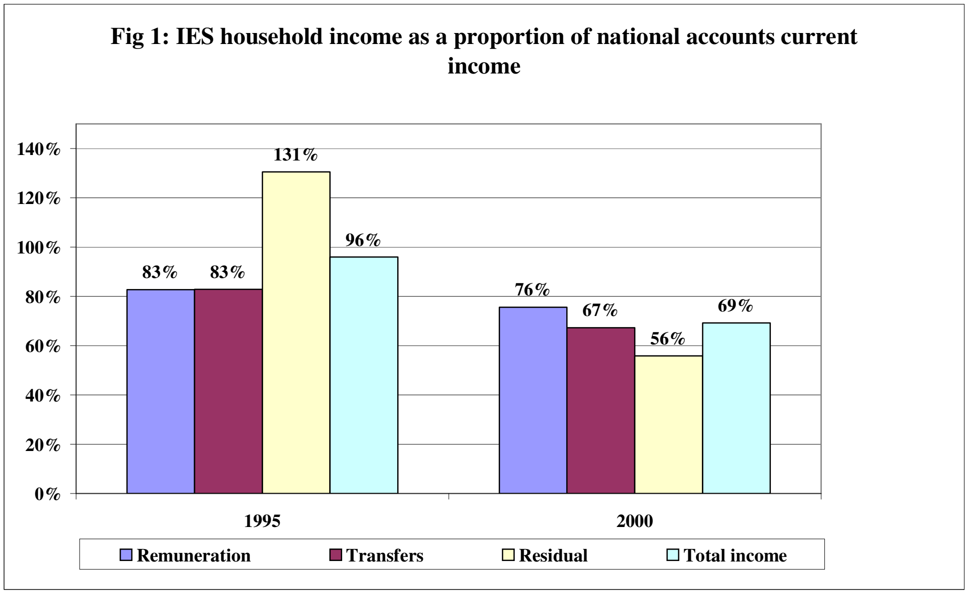
Given the potential difficulties associated with time and space in the undercapturing of income in surveys, Milanovic (2002) suggests that if analysts identify a need to correct survey data, the resulting adjustment should not be uniform. However, the discussion above has highlighted at least two cases for which a careful tailored adjustment of incomes across the range of the distribution has resulted in an almost distribution-neutral correction for survey non-compliance, namely the USA and India. Bhalla (2002: 120) argues that it can generally be assumed that approximately 10% of national accounts expenditure is not captured by household surveys as a result of non-compliance, equivalent to the median consumption shares of the wealthiest 2% of the average developing country population. This proportion may be subtracted from national accounts estimates of household expenditure (or analogously income) before adjustment is applied, if there are concerns for poverty analysis flowing from raising incomes of the poor by too great a factor. Alternatively, one may inflate the poverty line to reflect the incomes of the non-rich potentially being raised artificially much (Bhalla 2002: 120). The same remedy may be applied in cases where compliant affluent households underreport income by a greater proportion than the rest of the population; in the Indian case, the wealthier half of the population understates expenditure by an estimated 3.5% more than the poorer half of the population (Bhalla 2002: 120-121).

In this paper, stochastic dominance testing is applied to show that broad conclusions regarding poverty trends since 1994 are robust to the application of a range of plausible poverty lines. While the *levels* of poverty differ substantially depending on which poverty line is selected, the *trends* remain the same. This is a very important point, since the choice of poverty line is generally considered to be intrinsically a fairly arbitrary one. With respect to the criticism of neutral adjustment across time, at least for AMPS-based analysis – such as the research contained in this paper – this does not appear to be applicable, given the broadly consistent capturing of income demonstrated by the survey. To conclude this section, it is helpful to remember Deaton's (2005: 17) general criticism of welfare data, namely that neither means nor distributions are measured perfectly in either household surveys or the national accounts. The contribution of this paper is to attempt to reconcile the two sources in a way that sheds more light on poverty trends than what is available on the basis of survey data alone.

4. SOUTH AFRICAN INCOME DATA SOURCES: 1993-2004

There are a number of post-transition household surveys on which researchers analysing trends in poverty and inequality may draw. The two most prolifically used sets are the IESs of 1995 and 2000 (linked to the OHS and LFS respectively) and the Population Censuses of 1996 and 2001. The Censuses contain personal and household income, reported in a relatively small number of intervals (14 in 1996 and 12 in 2001). A greater problem stems from the fact that they contain a large – and apparently increasing – number of "zero-income" households: 12.6% in 1996 and 23.2% in 2001 (Simkins 2004: 6). Since it is impossible for households to subsist without any form of income, this is a serious form of misreporting. The problem is no lesser for personal income data from the Censuses: in 1996, 11.8% of households returned missing values for the incomes of one or more members (Simkins 2004: 6), while in 2001 more than a quarter of individuals lived in households where some of the individuals had missing income data (Ardington et al. 2005: 7).

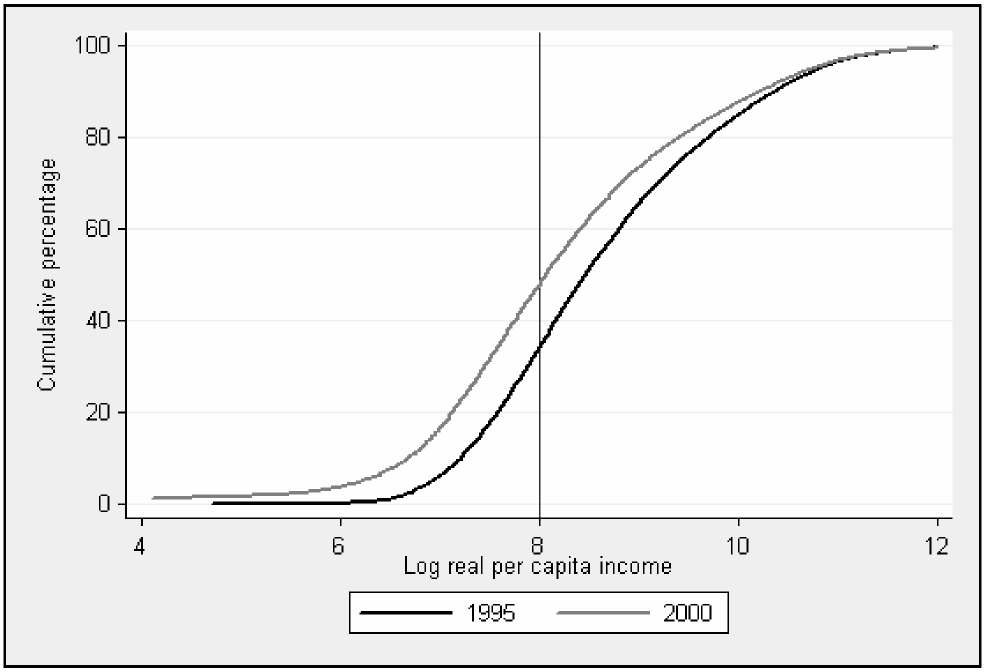
The IESs provide an alternative to the Censuses, and include extensive information on both income and expenditure, some of which is available in point estimate form. However, these surveys have been beset by problems prejudicing their comparability: Statistics South Africa recently admitted that data from the 1995 and 2000 takes cannot reliably be used to derive trends in income. If Census 2001 is used as a yardstick, the IES2000 under-represents the white population while over-representing the black population (Hoogeveen & Özler 2004: 41). This is reflected in IES2000 property income estimates that appear too low to be reliable (Simkins 2004: 4); however, the opposite is true in 1995. Indeed, the consistency with which the IES captures the various components of household income seems to be highly variable. This is further reflected in tax data; in 1995 the IES captured 97% of the personal income tax aggregate reported by SARS, while in 2000 it captured a mere 42% (own calculations using National Treasury). Figure 1 expresses the components of household income captured by the two IES surveys as proportions of the comparable national accounts data series.



Further, data management seems to have been worse in IES2000 than in the previous round: the number of zero responses for food expenditure is substantially higher in the later survey, and there are more cases of large gaps between household income and expenditure[7]. The implications of these deficiencies for distributional analysis are revealed in Figure 2 below, where the two cumulative distribution functions for log per capita household incomes from the two IESs are plotted together. The vertical line represents a poverty line of R3000 per capita per annum in 2000 values (this poverty line is used again in later analysis). Observe the implausibly sharp rise in poverty between 1995 and 2000 yielded by a comparison of the income distributions generated from the two IESs[8].

Fig 2: Cumulative distribution functions, IES1995 and IES2000

[7] These variables are designed to be of equivalent size in the IES.
[8] Some analysts, including Hoogeveen and Özler (2004; 2006) have preferred to work with IES expenditures rather than incomes. Using this measure of welfare does not change the direction or magnitude of the trend in poverty over 1995-2000.



Given the shortcomings associated with both of these data sources and the need for more recent data, this paper utilises a third, non-official data source – the AMPS. This is a household survey run by the South African Advertising Research Foundation, for which income data are available annually for the entire period under study. Comprehensive information regarding the survey is available in Van der Berg et al. (2007).

Finally, a note on the South African national accounts data series used in this paper is in order. The current income series collected by the SARB until very recently is the sum of compensation of employees, property income, and transfers from government, incorporated firms and the rest of the world received by private households, NGOs and non-incorporated firms[9]. In proportional terms, transfers from business and the rest of the world are very small. The discussion below thus focuses on the remaining three components of the current income series.

The compensation of employees series is compiled using StatsSA's Quarterly Employment Survey (the QES excludes the agricultural sector), estimates of wages in the agricultural sector provided by the Department of Agriculture, data from two surveys run by SARB (but not published) on the financial sector and on large and medium firms, and estimates of informal sector wages calculated by StatsSA on the basis of the LFSs. Up until June 2005 the Survey of Employment and Earnings (SEE) provided the official basis of the series, and the SARB makes an attempt to reconcile the more recent wage data from the QES with the data collected using the SEE. Given the variety of data sources available, some

[9] The SARB has recently begun to compile South African national accounts in line with internationally standardised national accounting definitions, and the current income series has fallen away during this change.

crosschecking can be done by the SARB to ensure that the series is relatively consistent and reliable. However, there are quality concerns regarding these data sources, particularly with respect to the QES.

Property income consists of dividends received, net interest received, rent income (net of maintenance costs), mortgage interest, consumption of fixed capital, and the profits of non-incorporated firms. The series is compiled using StatsSA's Economic Activity Survey (which excludes the financial sector) and a variety of SARB data sources relating to banking and insurance. The banks are required by law to disclose a range of information on their assets and liabilities, which enables SARB to gain a good idea of the property owned by bank clients and income accruing to these assets. More difficult to track is property income accruing to assets employed in the informal sector and those owned by unbanked individuals and small business enterprises. For the purposes of this paper, transfers to households from business and the rest of the world are added to property income, collectively forming the residual category.

Government transfers involve the payment of social grants, data for which are sourced by the SARB from the Department of Social Development.

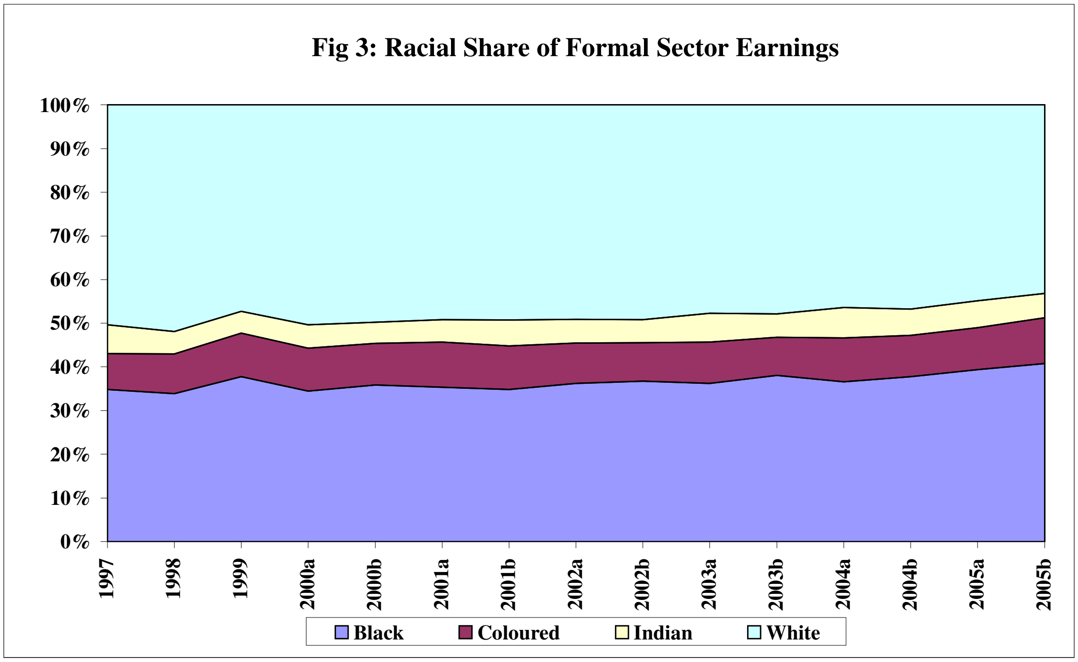
5. NATIONAL ACCOUNTS-CONSISTENT ESTIMATES OF POVERTY AND INEQUALITY FOR SOUTH AFRICA: 1993-2004

5.1 METHODOLOGY

The methodology followed in this paper for scaling survey means with national accounts data is described more fully in Van der Berg et al. (2005). It has remained largely the same, with the exception of small improvements in the technique used to estimate the distribution of wage income. A brief explanation of the methodology follows below.

As mentioned earlier, current income comprises a number of components. Two interesting trends amongst these emerge over the past decade. The first is a surprisingly large rise in the contribution of property income to current income, suggesting that the rich have benefited disproportionately from economic growth since 1994. In South Africa, wealth is far less equally distributed than income is, and there is a stronger racial bias in its distribution. The second trend is a dramatic increase in government transfers from 2002 onwards, contributing towards faster growth in aggregate income. This is predominantly the result of the extension of the child support grant (CSG) to children up to the age of 14, although the increase in the number of people taking up the disability grant – a much larger grant but with far less beneficiaries than the CSG – is also a significant contributor. Any expansion of the social grant system disproportionately benefits the poor, given the application of a means test to potential social grant recipients. Consequently, trends in current income suggest a widening of income inequality over the first post-transition decade, accompanied by a reduction in poverty since 2002 that should also have dampened the recent rise in inequality to some extent.

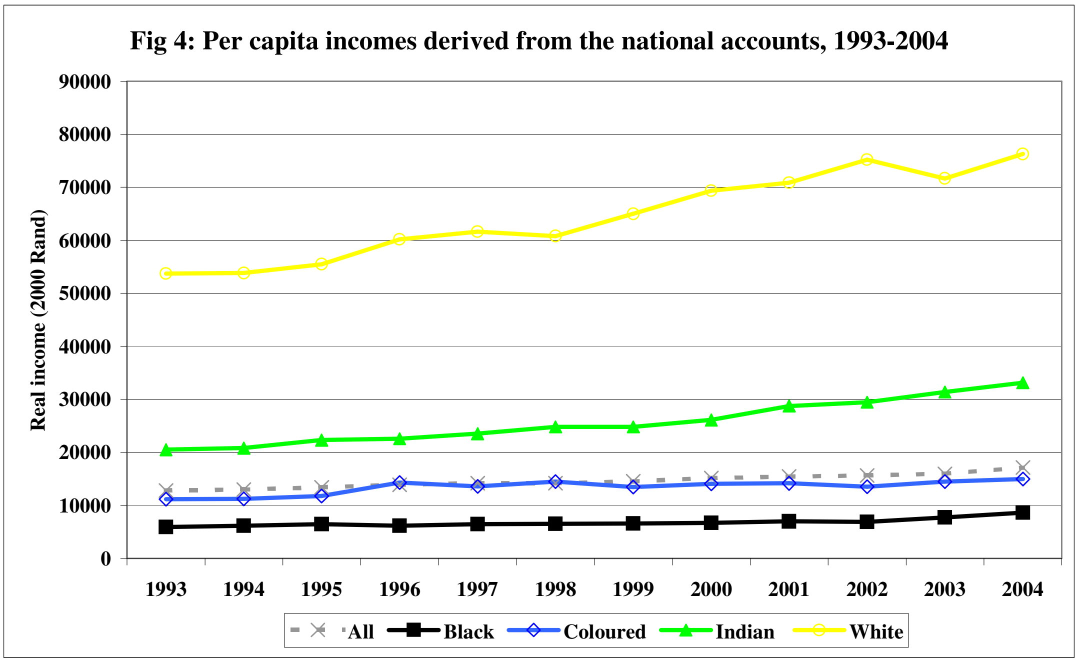
Having noted trends in current income, the next step involved arriving at a distribution of the components of current income for each race group. The distributions of individual components of current income across the population were estimated by race group, using a variety of survey data sources. Once the survey-based distributions of each component of current income had been obtained, each one was adjusted in line with the relevant national accounts mean. To scale wage income in accordance with national accounts data, employee remuneration was divided by racial employment estimates obtained using the Standardised Employment Series (which ended in 1996), the OHS (which ended in 1999) and the LFS (2000-2004). Figure 3 below shows trends in the racial shares of income from main job earned in the formal sector, sourced from the OHS and LFS series. Note the steadily increasing black share of remuneration, which comes predominantly at the expense of the shrinking white share. The coloured and Indian shares of remuneration remained roughly constant over the period.



Arriving at a national-accounts consistent distribution of transfer income required delving into a number of data sources. Under apartheid, the racial distribution of grant payments was available, so this data was utilised for estimating the racial share of transfer income during the early 1990s. Previous fiscal incidence research by Van der Berg (2001) provided the racial shares of transfer income for 1993, 1995 and 1997, while similar more recently conducted research by the same author – based in large part on the IES/OHS1995 and IES/LFS2000 – provided comparable information for 1995 and 2000 (Van der Berg 2005). The General Household Surveys (GHS) collected in 2002, 2003 and 2004 comprised another source of data. Estimates of actual grant income received by each race group were obtained by applying the racial shares of social grants obtained from each GHS to public expenditure on grants obtained from the 2005 Intergovernmental Fiscal Review. For the years where no direct data source was available, shares were interpolated.

Property income is mainly comprised of income earned from assets and business profits. Since the asset (i.e. wealth) distribution is more highly skewed than the income distribution, and assets are accumulated slowly, income flows from assets are slow to change. Given the scanty data on property income, a simplifying assumption is made, namely that the black share of property income grew slowly over the period, increasing by 0.5 percentage points annually from a very low base. This is roughly half the annual increment in the black share of the population in the higher income categories, thus it appears not to be an excessive assumption. Alternative assumptions have little effect on the final distribution and poverty results.

Once the various components of current income had been distributed across race groups, it was possible to extract trends in per capita incomes by race. Figure 4 below shows trends by race group during the post-transition period. Note the upward trend for members of all race groups; in fact, black incomes grew faster than white incomes, although this is somewhat obscured by the very different bases off which growth occurred for the two race groups. Coupled with more rapid population growth amongst blacks than whites, this is reflected in an increasing share of current income accruing to blacks: an estimated 39.1% in 2004 versus 31.5% in 1993. These inter-racial distribution figures are not all that dissimilar from those obtained from AMPS itself, although AMPS shows a slightly more rapid rise in the black share of aggregate income than these estimates do.



In order to be able to conduct income distribution analysis, it was necessary to combine data for intra-group distributions of income with the national accounts-based data for inter-group distributions of income. AMPS datasets were employed for this purpose. Once racial distributions had been obtained using the AMPS data, the per capita survey means for each race group were adjusted in line with inter-racial per capita means obtained as described above.

5.2 ANALYSING POVERTY AND INEQUALITY

Once annual income distributions for 1993-2004 consistent with national accounts data were derived as described above, it became possible to apply standard measures of poverty and inequality. One major purpose of the paper is to establish with as much confidence as possible whether poverty has declined since political transition, so most of the attention focuses on measurement of trends in poverty rather than inequality. The poverty line selected for analysis is R250 monthly per capita household income in 2000 value, or R3 000 per annum. This is higher than the $2 a day line, which converts into R174 per month in 2000 rand, and thus includes both severe and more moderate poverty. However, it is lower than the cost-of-basic-needs measure employed by Hoogeveen and Özler (2006). It is also consistent with earlier distributional analysis in Van der Berg and Louw (2004), Van der Berg et al. (2005) and Van der Berg et al. (2007). To some extent the selection of a poverty line is arbitrary by its very nature; accordingly the findings in this paper are subjected to robustness testing through the estimation of cumulative distribution functions.

The standard Foster-Greer-Thorbecke (FGT) measures of poverty provide the cornerstone for poverty analysis in this paper. The poverty headcount (P_0) reflects the extent of poverty; the poverty gap index (P_1) reflects the depth of poverty; and the squared poverty gap index (P_2) reflects the severity of poverty. In the case of P_0, two figures are presented: the headcount rate (percentage of the population falling below the poverty line) and the headcount itself (the number of people falling below the poverty line). Table 2 below presents each of these measures of poverty for 1993, 1995, 2000 and 2004. Estimates of FGT measures for each year from 1993 to 2004 are presented in the appendix.

Table 2: Poverty trends, 1993-2004

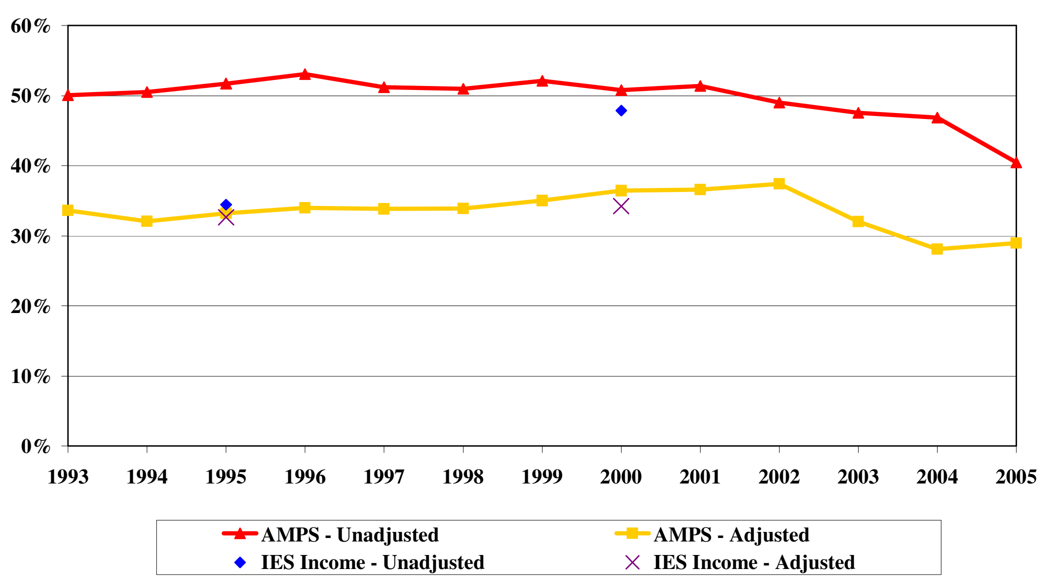
Group	FGT	1993	1995	2000	2004
All	P_0 headcount rate	33.6%	33.2%	36.4%	28.1%
	P_0 headcount	13 426 144	13 724 926	16 287 231	13 063 241
	P_1	0.1491	0.1493	0.1631	0.1128
	P_2	0.0879	0.0889	0.0946	0.0612
Blacks	P_0 headcount rate	41.7%	41.4%	45.3%	34.1%
	P_0 headcount	12 697 247	13 114 982	15 687 471	12 403 318
	P_1	0.1858	0.1885	0.2045	0.1375
	P_2	0.1095	0.1130	0.1189	0.0745
Coloureds	P_0 headcount rate	19.2%	16.4%	14.6%	15.2%
	P_0 headcount	648 524	572 815	547 874	598 543
	P_1	0.0743	0.0553	0.0522	0.0552
	P_2	0.0404	0.0267	0.0269	0.0292
Indians	P_0 headcount rate	4.5%	2.7%	3.3%	3.0%
	P_0 headcount	45 814	27 778	36 256	33 939
	P_1	0.0188	0.0083	0.0117	0.0111
	P_2	0.0123	0.0044	0.0064	0.0064
Whites	P_0 headcount rate	1.0%	0.3%	0.4%	0.6%
	P_0 headcount	48 907	14 479	19 151	31 302
	P_1	0.0072	0.0013	0.0015	0.0038
	P_2	0.0064	0.0009	0.0010	0.0031

The best-known FGT measure – namely the headcount – reflects a moderate rise in poverty between

1995 and 2000, in line with the findings of Leibbrandt et al. (2006). By 2004 the incidence of poverty in South Africa had fallen substantially, with a reduction of eight percentage points – equivalent to three million people – in the number falling below the poverty line. Similar trends prevail in the depth and severity of poverty, which both showed a marked decline after 2000. While population growth can sometimes offset reductions made in the headcount rate (through keeping the headcount number high), it is encouraging to see that despite population growth, the number of people living in poverty in 2004 is slightly lower than the comparator for the pre-transition year of 1993. Observe that the overall trend is driven by trends in the black population, for which poverty showed the greatest improvement after 2000. This is particularly positive given that the black population group is not only the largest but also the least affluent. Poverty amongst coloureds and Indians appears to have been largely stable over the period, while white poverty appears to have increased slightly after 2000, although the numbers remain very small.

To place estimates of the incidence of poverty in South Africa in context, national accounts-scaled AMPS estimates are contrasted with raw AMPS estimates and IES figures, both using raw IES data and IES data that has been scaled in line with the national accounts. The IES estimates are taken from Van der Berg and Louw (2004).

Fig 5: Poverty count, 1993-2004 (poverty line = R3000)



IES-based figures aside, the story told by these figures appears to be largely the same, regardless of which set of estimates is preferred. While the levels of poverty vary widely depending on which data source is used, the trend changes little. During the second half of the 1990s, poverty stabilised or rose slightly, with an improvement visible later in the period under study. Interestingly, the adjusted AMPS figures reflect that poverty continued to rise until as recently as 2002. From this year onwards it declined rapidly until

2004. The fall in poverty implied by raw AMPS data was visibly more gradual although it began earlier, in 2001. Observe how far out of line the trend implied by the raw IES estimates is, contrasted with the patterns implied by estimates of poverty derived from the other data sources. It is clear that at least in the case of the IES datasets for 1995 and 2000, national accounts scaling yields some benefits for poverty trend analysis through making measures based on the two surveys more comparable.

If poverty has declined, has this had positive implications for the notoriously high income inequality level in South Africa? Table 3 below presents a range of inequality indicators for selected years for South Africa, including the commonly used Gini coefficient, which is most sensitive to changes in the middle of the income distribution (Hoogeveen & Özler 2004: 12). The Theil-T and Theil-L indices belong to the class of general entropy inequality measures, which are functions of a parameter α. The lower α is, the more sensitive the index is to income changes at the lower end of the distribution. Setting α equal to zero yields the Theil-L index (also known as the mean logarithmic deviation), a particularly useful measure if an increase in inequality owing to falling incomes amongst the poor is viewed as the most harmful kind. Setting α equal to one yields the more common Theil-T, which weights sub-groups by income share; the Theil-L weights sub-groups by population share. An advantage of the general entropy inequality measures is that they allow for the decomposition of aggregate inequality into between-group and within-group components, allowing one to determine the influence of changing racial inequality. As in the case of poverty, inequality measures for each year from 1993 to 2004 are presented in the appendix.

Table 3: Income inequality measures, 1993-2004

Gini coefficient				
	1993	**1995**	**2000**	**2004**
Blacks	0.547	0.568	0.609	0.598
Coloureds	0.529	0.507	0.537	0.550
Indians	0.465	0.473	0.500	0.542
Whites	0.443	0.438	0.467	0.500
Total	0.678	0.677	0.716	0.700
Theil-T index				
	1993	**1995**	**2000**	**2004**
Blacks	0.584	0.631	0.764	0.740
Coloureds	0.505	0.459	0.525	0.562
Indians	0.374	0.420	0.479	0.608
Whites	0.341	0.334	0.385	0.479
Total	0.938	0.929	1.081	1.066
Within-Race	0.440	0.457	0.530	0.594
Between-Race	0.498	0.472	0.550	0.471
Contribution of within-race component to the total	47%	49%	49%	56%
Theil-L index / Mean logarithmic deviation				
	1993	**1995**	**2000**	**2004**
Blacks	0.559	0.616	0.695	0.666
Coloureds	0.527	0.475	0.545	0.584
Indians	0.421	0.404	0.462	0.552
Whites	0.386	0.345	0.398	0.469
Total	0.935	0.979	1.083	1.000
Within-race	0.530	0.549	0.642	0.635
Between-race	0.405	0.430	0.441	0.366
Contribution of within-race component to the total	57%	56%	59%	63%

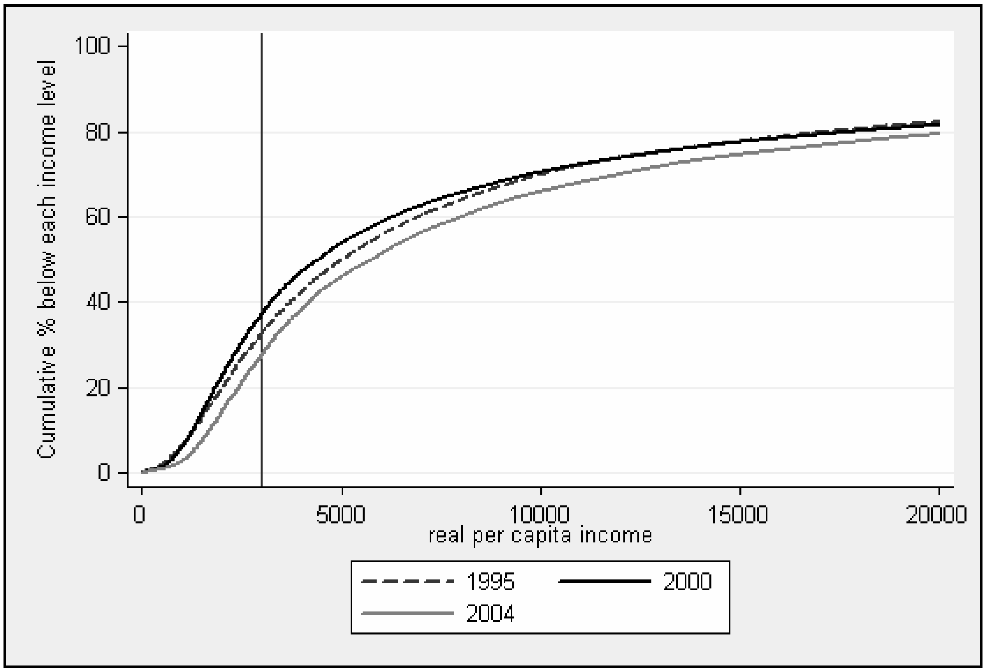
It seems that the improvement in the incomes of the poor since 1994 has not kept track with the increases in affluence experienced by individuals higher up in the income distribution. All measures indicate that inequality increased substantially between 1995 and 2000, moderating after that, probably due to the recent expansion in social grant payments. The massive increase in the Theil-T measure calculated for blacks between 1995 and 2000 suggests that the rise in aggregate inequality over this period was predominantly due to improvement in conditions at the upper end of the income distribution. While black inequality levels stabilised and dropped slightly after 2000, white inequality continued to rise, although off a much lower base. However, levels of inequality within the black population remain the highest amongst all race groups. Estimates of the Theil-T indicate that within-race inequality appears to have risen rapidly in relative importance as a component of aggregate inequality after the turn of the century; the Theil-L reflects a similar pattern although starting earlier and showing a more modest increase in the relative importance of within-race inequality. This is a continuation of a longer term trend, although it appears to have gained further momentum recently. In fact, within-race inequality has now finally overtaken the extreme levels of between-race inequality engineered by apartheid policy as the main driver of income inequality in South Africa.

6. SENSITIVITY TESTING

As analysis of poverty trends is the main focus of this paper, robustness testing is concentrated on determining the robustness of these. Two major issues affecting the robustness of conclusions are the choice of poverty line and the application of the national accounts adjustment methodology. These are dealt with separately below.

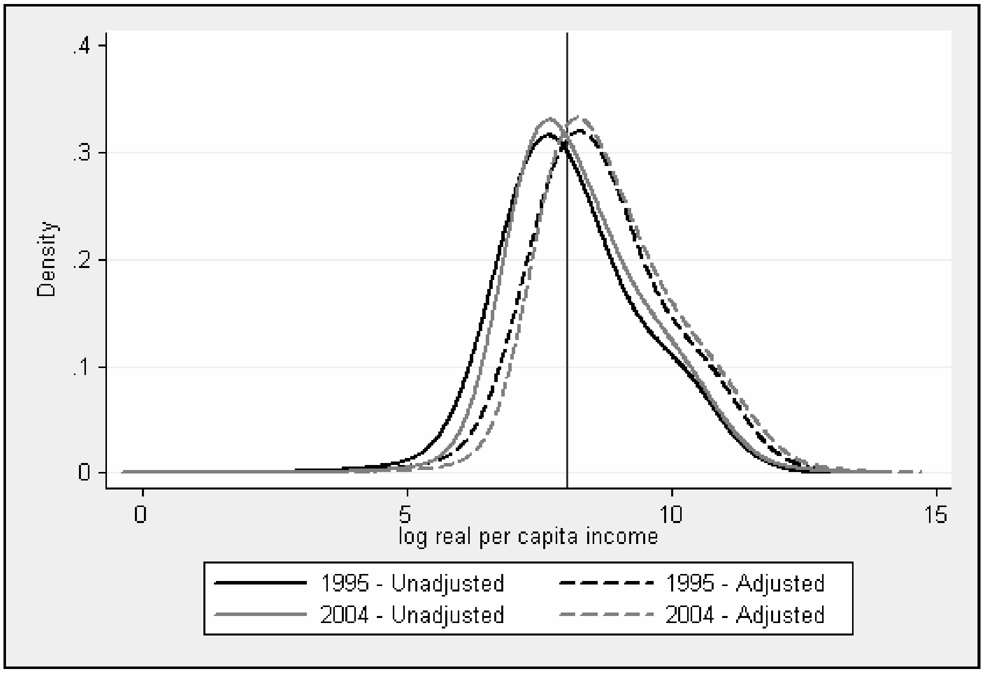
Stochastic dominance testing involves plotting cumulative distribution functions (CDFs) to determine the sensitivity of a number of income distributions (spread across time or space) to the choice of poverty line. Figure 6 below contains CDFs reflecting national accounts-scaled AMPS income distributions for 1995, 2000 and 2004. While there is visibly less poverty in 2004 than in either 1995 or 2000 regardless of the level at which the poverty line is set, there is no strict poverty dominance for the two earlier years. The CDFs intersect near the bottom of the distribution, with the 1995 CDF lying slightly above the 2000 CDF over a range associated with extreme poverty. This suggests that severe deprivation may have been less widespread in 2000 than 1995. However, this result is reversed for higher, more commonly used poverty lines. Consequently, the argument that poverty increased between 1995 and 2000 before falling to below 1995 levels by 2004 is convincingly supported by the data.

Fig 6: Cumulative distribution functions, AMPS 1995-2004



Secondly, the impact of scaling the data to be consistent with national accounts data is considered. For this purpose, kernel densities are estimated on both the adjusted and raw AMPS datasets for 1995 and 2004. Figure 7 below captures the results. Since the selected poverty line lies just to the right of the mode of the income distribution before adjustment, a small rightward shift of the income distribution has obviously important consequences for the size of the population classified as poor. Nonetheless, both the raw and adjusted AMPS distributions show improvements with respect to poverty between 1995 and 2004. Further, the shape of each distribution remains largely unchanged with scaling, apart from a slight flattening of the distribution at the mode and smoothing of the bump located towards the upper end of the income distribution. The practical consequence of the change in the shape of the distribution is slightly increased income inequality (as measured by the Gini coefficient) in the adjusted distribution compared with the raw distribution. Interested readers are referred to Van der Berg et al. (2007) for a full set of comparable poverty and inequality measures estimated using the raw AMPS datasets.

Fig 7: Kernel density functions, AMPS unadjusted and adjusted



7. CONCLUDING REMARKS

The poverty estimates arrived at in this paper have a number of virtues compared with the official data presently available on poverty, based on the Income and Expenditure Surveys of 1995 and 2000. Firstly, the estimates presented here are more recent, allowing policymakers to venture beyond 2000 in evaluating the effect of policy. Secondly, they are consistent with the national accounts, whereas the official data sources (the two IESs) are clearly at odds with the national accounts - another official data source). Thirdly, as the estimates draw on a large range of official data sources, they are also consistent with most other official sources, including the remuneration data from the OHS and LFS. Finally, the estimates offer the added benefit, of great importance for time series econometric work, of being available on an annual basis.

The results obtained in this paper point to a decline in poverty after the turn of the century. It is illuminating that this is broadly in line with the AMPS data itself, although AMPS is only used to obtain the intra-race distribution estimates applied to the national accounts based mean incomes by race. Moreover, these results intuitively make sense, given the expansion of the social grant system in this period. There is growing evidence to support at least these broad conclusions about poverty decline. This comes from *inter alia* the latest wave of the Kwazulu-Natal Income Dynamics Study (KIDS) and the General Household Surveys (GHS) for 2002-2005; the former shows a decline in money-metric poverty while the latter reports a decline in people reporting going hungry. Critics of an earlier version of this paper now acknowledge that the broad conclusions are probably correct (Seekings 2006; Meth 2006).

Two criticisms to our results remain: one is methodological, the second argues that using the national accounts adjustment lowers poverty estimates. Regarding the first, no final word can be spoken. The paper has provided ample evidence that there is no simple and universally accepted answer as to how to deal with conflicts between survey and national accounts data. Also, it has been mentioned that an adjustment of survey data to make it national accounts consistent - as used in this paper - was common in India for a long time, has been the basis for much work by prominent authors on estimates of global poverty, is the norm in Latin America, and is also favoured by many others. Further, it is shown that South African national accounts data are more consistent than the two post-transition IESs with other evidence about the course of the South African economy between 1995 and 2000.

The lower poverty estimates obtained when making adjustment of survey data to national accounts data are not seen as a real problem. Poverty lines are at the best of times subjective; in South Africa there has hitherto been no commonly accepted poverty line. If one believes that these estimates understate poverty, then the appropriate response is to use a higher poverty line for intertemporal and other comparisons.

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APPENDIX

Table A1: Poverty trends, 1993-2004

Group	FGT	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
All	P_0 headcount rate	33.63%	32.06%	33.19%	33.98%	33.84%	33.88%	35.01%	36.43%	36.62%	37.42%	32.02%	28.11%
	P_0 headcount	13 426 144	13 034 375	13 724 926	14 279 932	14 434 285	14 690 561	15 417 686	16 287 231	16 544 280	17 072 199	14 749 008	13 063 241
	P_1	0.1491	0.1358	0.1493	0.1488	0.1489	0.1463	0.1499	0.1631	0.1661	0.1723	0.1359	0.1128
	P_2	0.0879	0.0776	0.0889	0.0864	0.0858	0.0833	0.0847	0.0946	0.0980	0.1023	0.0771	0.0612
Blacks	P_0 headcount rate	41.73%	40.01%	41.42%	42.77%	42.34%	42.63%	43.66%	45.33%	45.05%	45.78%	39.08%	34.13%
	P_0 headcount	12 697 247	12 428 049	13 114 982	13 791 263	13 885 831	14 244 148	14 851 424	15 687 471	15 805 714	16 266 731	14 050 372	12 403 318
	P_1	0.1858	0.1699	0.1885	0.1886	0.1877	0.1856	0.1883	0.2045	0.2054	0.2128	0.1662	0.1375
	P_2	0.1095	0.0970	0.1130	0.1097	0.1084	0.1060	0.1067	0.1189	0.1213	0.1270	0.0942	0.0745
Coloureds	P_0 headcount rate	19.17%	15.73%	16.41%	12.53%	13.53%	10.78%	14.06%	14.57%	17.63%	19.21%	16.15%	15.22%
	P_0 headcount	648 524	540 672	572 815	444 477	487 510	394 007	521 322	547 874	671 057	739 909	628 945	598 543
	P_1	0.0743	0.0589	0.0553	0.0437	0.0446	0.0350	0.0490	0.0522	0.0685	0.0703	0.0631	0.0552
	P_2	0.0404	0.0321	0.0267	0.0223	0.0213	0.0167	0.0249	0.0269	0.0374	0.0358	0.0354	0.0292
Indians	P_0 headcount rate	4.51%	3.41%	2.66%	3.05%	3.18%	3.42%	3.12%	3.29%	3.49%	3.57%	3.12%	2.98%
	P_0 headcount	45 814	35 093	27 778	32 171	33 959	36 920	34 015	36 256	38 767	40 020	35 229	33 939
	P_1	0.0188	0.0122	0.0083	0.0111	0.0125	0.0102	0.0087	0.0117	0.0130	0.0127	0.0110	0.0111
	P_2	0.0123	0.0075	0.0044	0.0070	0.0080	0.0047	0.0040	0.0064	0.0072	0.0069	0.0058	0.0064
Whites	P_0 headcount rate	0.96%	0.83%	0.28%	0.33%	0.71%	0.35%	0.27%	0.37%	0.71%	0.56%	0.80%	0.62%
	P_0 headcount	48 907	42 305	14 479	17 073	36 962	18 381	13 992	19 151	36 746	28 854	40 469	31 302
	P_1	0.0072	0.0060	0.0013	0.0014	0.0050	0.0014	0.0012	0.0015	0.0051	0.0026	0.0047	0.0038
	P_2	0.0064	0.0054	0.0009	0.0010	0.0045	0.0009	0.0008	0.0010	0.0045	0.0017	0.0037	0.0031

Table A2: Income inequality measures, 1993-2004

Gini coefficient												
	1993	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**
Blacks	0.547	0.544	0.568	0.564	0.573	0.577	0.585	0.609	0.611	0.607	0.605	0.598
Coloureds	0.529	0.506	0.507	0.516	0.516	0.509	0.523	0.537	0.551	0.556	0.551	0.550
Indians	0.465	0.444	0.473	0.462	0.479	0.480	0.506	0.500	0.511	0.508	0.542	0.542
Whites	0.443	0.445	0.438	0.442	0.444	0.453	0.452	0.467	0.467	0.480	0.518	0.500
Total	0.678	0.670	0.677	0.691	0.690	0.689	0.701	0.716	0.715	0.724	0.709	0.700
Theil-T index												
	1993	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**
Blacks	0.584	0.571	0.631	0.640	0.648	0.660	0.687	0.764	0.755	0.758	0.775	0.740
Coloureds	0.505	0.464	0.459	0.470	0.485	0.471	0.495	0.525	0.558	0.580	0.564	0.562
Indians	0.374	0.338	0.420	0.382	0.411	0.410	0.485	0.479	0.490	0.498	0.610	0.608
Whites	0.341	0.348	0.334	0.337	0.347	0.361	0.355	0.385	0.380	0.439	0.530	0.479
Total	0.938	0.916	0.929	0.978	0.977	0.976	1.018	1.081	1.071	1.143	1.121	1.066
Within-Race	0.440	0.437	0.457	0.453	0.467	0.479	0.488	0.530	0.531	0.561	0.630	0.594
Between-Race	0.498	0.479	0.472	0.525	0.511	0.497	0.530	0.550	0.540	0.582	0.491	0.471
Contribution of within-race component to the total	47%	48%	49%	46%	48%	49%	48%	49%	50%	49%	56%	56%
Theil-L index / Mean logarithmic deviation												
	1993	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**
Blacks	0.559	0.547	0.616	0.591	0.611	0.619	0.633	0.695	0.709	0.703	0.688	0.666
Coloureds	0.527	0.479	0.475	0.497	0.491	0.476	0.513	0.545	0.594	0.588	0.599	0.584
Indians	0.421	0.375	0.404	0.400	0.435	0.425	0.466	0.462	0.488	0.488	0.546	0.552
Whites	0.386	0.382	0.345	0.356	0.378	0.372	0.370	0.398	0.415	0.426	0.505	0.469
Total	0.935	0.902	0.979	0.982	0.976	0.976	1.013	1.083	1.090	1.118	1.042	1.000
Within-race	0.530	0.516	0.549	0.568	0.573	0.573	0.587	0.642	0.660	0.657	0.657	0.635
Between-race	0.405	0.386	0.430	0.414	0.403	0.403	0.425	0.441	0.430	0.461	0.385	0.366
Contribution of within-race component to the total	57%	57%	56%	58%	59%	59%	58%	59%	61%	59%	63%	63%