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Factors influencing the comparability of poverty estimates across household surveys

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ABSTRACT
The South African existing literature on poverty mainly adopted the money-metric approach to examine poverty levels and trends since the advent of democracy. In general, poverty increased until the end of the 1990s, before a downward trend took place. Despite the robust findings on the trends, poverty levels differed because of various reasons, ranging from the use of different poverty lines across the studies, to the adoption of different approaches to collect the income and expenditure information, and the presence of a high proportion of households reporting zero or unspecified income. This article aims to fill the existing research gap by explaining the possible factors accounting for the contrasting poverty levels across the eight commonly used South African censuses and household surveys between 1993 and 2012.

KEYWORDS
poverty; income; expenditure; recall method; diary method; sequential regression multiple imputation

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1. Introduction

To evaluate the extent to which a country achieved the objective of poverty reduction, reliable income and expenditure data are required. Since the advent of democracy, a major advance by Statistics South Africa (Stats SA) was the improvement of the Income and Expenditure Survey (IES) and the October Household Survey (OHS), as the sample was extended to all areas (the IES sample covered households in both metropolitan and non-metropolitan areas, while the OHS sample no longer excluded people residing in the Transkei–Bophuthatswana–Venda–Ciskei states). New surveys were conducted, such as the General Household Survey (GHS) introduced in 2002, the Labour Force Survey (LFS) which has been replacing the OHS since 2000, and the Quarterly Labour Force Survey which has been replacing the LFS since 2008. Institutions other than Stats SA have been conducting surveys, such as the Project for Statistics on Living Standards and Development (PSLSD) and the National Income Dynamic Study (NIDS) conducted by the Southern Africa Labour and Development Research Unit (SALDRU). Although the All Media Products Survey (AMPS) has been conducted by the South African Advertising Research Foundation since 1975, it has only been used for poverty analysis in recent years.

The South African money-metric poverty studies employed the above-mentioned datasets. Although different poverty lines were used, their findings generally reflected poverty

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increased until 2000, after which there was a continuous downward trend. Despite the robust findings on trends, poverty levels differed amongst the studies. It is always a problem to compare poverty levels because of various reasons. Firstly, the studies might have simply examined surveys from different years (e.g. study X examined IES 1995 and 2005, while study Y compared AMPS 1998 with 2008). Even if some studies used surveys taking place in the same year, different poverty lines were used (e.g. US$1 in one study but US$2 in another study). Furthermore, the income and expenditure data were captured differently across the surveys, thereby affecting the reliability and comparability of the ensuing poverty estimates. Finally, few studies adjusted the income and expenditure to derive a revised per-capita variable before estimating poverty levels.

This study aims to fill the existing research gap by examining how different the poverty levels are across the surveys and the factors accounting for these differences. Section 2 provides a literature review on the main factors affecting the comparability of income and expenditure information across the surveys as well as the recent studies examining money-metric poverty levels and trends. Section 3 discusses how the income and expenditure information was captured, and poverty levels and trends across all the surveys and censuses during 1993–2012 if the same poverty line is used. Section 4 concludes.

2. Literature review

2.1 Factors affecting the comparability of poverty estimates across surveys and censuses

A general argument for different poverty levels is that respondents report different income and expenditure amounts. Most rich countries use the income variable, as income mainly comes from salaries and wages and hence is easier to measure, while it is difficult to quantify the volumes and amounts of purchases when capturing expenditure. In poor countries, income is relatively harder to measure as much of it comes from self-employment, or own-account agricultural and informal activities associated with volatile earnings (Deaton & Grosh, 2000:93–4; Haughton & Khandker, 2009:30). Although random irregularities and seasonal patterns could be present in expenditure, they are normally smaller than those of income, because expenditure is less tied to seasonal and weather-related patterns in agriculture (Deaton & Grosh, 2000:93–4).

The ways in which the income and expenditure information is captured could affect the comparability of such information and the ensuing poverty estimates. In the South African surveys, the recall method was adopted – except in IES 2005/06 and 2010/11, which adopted the diary method to complement the recall method. Recall bias often happens under the recall approach, as the respondents could not remember income earned a long time ago and purchases long after they have been made (Deaton, 1997:24–5; Deaton & Grosh, 2000:109–10), leading to inaccurate guesses. This recall bias becomes more serious as the recall period increases.

The recall approach also leads to the telescoping phenomenon, as the respondents may include consumption events that took place before the beginning of the recall period, thereby resulting in overestimation of expenditure (Deaton & Grosh, 2000:110), and subsequently an underestimation of the poverty level. Deaton (2005:16) suggests a shorter recall period, but many visits are required to ensure that data on high-frequency non-durable purchases are collected accurately, assuming the respondents' memories of their consumption activities fade quickly. However, the increase of the interview frequency is time-consuming and costly. As the consumption of durable items only take place occasionally during the year, a longer recall period is required, yet this is associated with a greater likelihood of recall bias and telescoping.

Because of the drawbacks of the recall method, the diary method becomes an alternative approach. This is designed to reduce the likelihood of recall bias and telescoping, as consumption events are recorded on the diary as they take place or close to that time (Deaton & Grosh, 2000:109; Battinstin, 2003:2; Wiseman et al., 2005:395). However, diaries are less suitable where literacy levels are low because the diary keepers might not write down the purchase items correctly if given an unstructured diary.[1] In other words, the data collected from the diaries might be biased towards the competent, literate diary keepers (Corti, 1993). A pictorial diary might be required to improve the accuracy of the responses of those with lower literacy levels. Since the participants were asked to keep the diaries for a very short period of time (e.g. four weeks in the IES), the diary method might work better for non-durable items with higher purchase frequency, but is not suitable to record the consumption of more durable items with low purchase frequency (Deaton & Grosh, 2000:119–22; Battinstin, 2003:2).

Recall bias and telescoping could still take place under the diary approach, as respondents may not report the consumption events immediately after the purchases took place (Deaton, 1997:24–5; Wiseman et al., 2005:398). A one-day effect could happen in the diary approach (Deaton & Grosh, 2000:119–22; Wiseman et al., 2005:395; Ahmed et al., 2006:9–10), as the first week of diary keeping shows higher reporting of consumption than the following weeks because the novelty of diary keeping wears off as time goes by, and the respondents feel exhausted of keeping records and become less detailed in their reporting.

Posel & Casale (2005:10), Von Fintel (2006:1) and Malherbe (2007:25) argue that some respondents were reluctant to disclose the exact amount due to privacy concerns, while others really do not know this exact amount and hence could not specify how much they earned or spent. The interval approach permits the respondents to report income and expenditure with a margin of error, especially if they do not know the exact amounts earned or spent. However, the income or expenditure brackets need to be adjusted as survey years progress, or an increasing proportion of households fall in the higher-income or higher-expenditure categories due to the impact of inflation if the brackets are left unadjusted.

If the respondents are asked to declare the exact amounts earned or spent, the next issue to decide is whether to ask the respondents to declare the 'one-shot', single estimate (by asking questions such as 'What is the total income you earned from all sources in the past 12 months?') or to aggregate the amounts from sub-categories (i.e. by asking questions such as 'How much do you earn from income source X?'). The single estimate approach, despite being relatively less time-consuming and costly, may confuse the respondents, as they are unsure about what items should be included as part of the total income or expenditure. This may result in a low response rate, and/or under-reporting of total income or expenditure (Deaton, 1997:27; Browning et al., 2002:7–10). Note

[1]This is the case in IES 2005/06 and 2010/11, as the participants were given a diary with blank pages to fill in the consumption activities.

that the interval approach already discussed also relates to the single estimate method, as the respondents were asked to declare the 'one-shot' amount by choosing the relevant category.

If the aggregation method is used, the appropriate level of disaggregation should be considered. Deaton (2005:16) claims that the greater the degree of disaggregation of the number of items that are separately distinguished, the more accurate the measured income or expenditure in total. However, Browning et al. (2002:12–18) and Deaton (2005:16) suggest that, if the level of disaggregation is too high, it could be time-consuming and exhausting to both the interviewers and interviewees, and the latter might end up deliberately providing misleading amounts and even not answering some questions (i.e. item non-response). This leads to an inaccurate aggregate amount, compared with the single estimate method.

If the information was collected in bands, the data need to be made continuous. That is, the amount of each band needs to be determined. Commonly used approaches are the midpoint Pareto method, interval regression, the random midpoint method and the equal distribution method (Cloutier, 1988; Fields, 1989; Whiteford & McGarth, 1994; Gustavsson, 2004; Malherbe, 2007).

The accuracy of the income and expenditure information could be influenced by the number of intervals and the width of each band. For instance, if a household's exact monthly income is R8200 in nominal terms, this household would fall in the 'R6401–R12 800' category in CS 2007, 'R5000–R9999' interval in the GHS and 'R8000–R9999' interval in the AMPS. The derived income or expenditure amount would be estimated as R9600, R7500 and R9000 respectively in each survey. These different amounts could result in different poverty estimates across the surveys. There is a lack of both South African and international studies to investigate the impact of the number of intervals and width of each interval on poverty estimates, except that Seiver (1979) found that fewer, wider brackets result in overestimation of inequality measures.

The presence of households reporting zero or unspecified income or expenditure could also affect reliability of poverty estimates. Ardington et al. (2006) argue that if those with missing data fall excessively in the bottom of the income distribution, then poverty levels will be under-estimated if they are ignored. If non-response is higher among the affluent, poverty estimates are likely to be biased upwards. If the zero-income households are included unadjusted for the analyses, this leads to a serious over-estimation of measured poverty. Looking at the missing data in greater detail, unless the data are missing completely at random, ignoring these households would lead to biased poverty estimates. Commonly used methods to deal with missing data are case-wise deletion, available-case deletion, single imputation (e.g. cell mean substitution, hot deck imputation, cold deck imputation) and multiple imputation (Lacerda et al., 2008). For the latter approach, a commonly used approach when data are missing at random is the sequential regression multiple imputation (SRMI).[2] This approach will be adopted in the forthcoming sections when investigating the comparability of poverty levels across surveys that include a high proportion of respondents with zero or unspecified income or expenditure.

[2]For more detailed explanation of the SRMI methodology, refer to Raghunathan et al. (2001), Ardington et al. (2006), Lacerda et al. (2008) and Vermaak (2008).

Because of the various reasons discussed (e.g. fatigue, illiteracy, and recall bias), surveys are more likely to under-estimate income (expenditure), and subsequently over-estimate poverty levels. Some surveys might have under-estimated income more seriously, and this makes it difficult to compare poverty levels across the surveys. Hence, the distributional estimates of the survey data could be adjusted rightwards in line with the national accounts series for aggregate income, before poverty levels are re-estimated. That is, household survey means are replaced by the national accounts mean, but the distribution of the household survey is retained. This takes place under the following two assumptions (Deaton, 2001:135): the national accounts estimates are correct; and survey estimates of the mean are correct.

Person weights in the household surveys are post-stratified to the external population totals (for instance, the mid-year population estimates at the time of the survey, derived using the Census information), with the pre-census and post-census years' populations being calculated using exponential interpolation and extrapolation. However, there are concerns regarding the reliability of the post-stratification design weights, as the mid-year population estimates could be inconsistent over time; that is, temporal consistency is not considered (Branson & Wittenberg, 2014:20). This leads to problems when the cross-sectional data are used for time-series poverty analysis. Therefore, there is a need to re-weight the weight variables so that the population data and poverty estimates derived would become more time-consistent and comparable. One possible solution is the cross-entropy estimation approach,[3] which adjusts the weights to conform to the race, gender and age distribution of the population estimates derived by the Actuarial Society of South Africa 2003 model, as the population data derived from this model are more time consistent.

Finally, other factors affecting the reliability of poverty estimates include the length of the questionnaire, quality of training received by the interviewers prior the start of the interviews, their experience and efforts devoted to capture information during the interviews.

2.2 Review of recent studies examining poverty levels and trends

There is an abundance of recent studies examining money-metric poverty levels and trends. The commonly used poverty lines are R250 and R322 per capita per month in 2000 prices and the international US$1 and US$2 a day. These studies could be categorised into two groups. First, various studies used the data unadjusted. For example, Hoogeveen & Özler (2006), Özler (2007), Yu (2008) as well as Bhorat & Van der Westhuizen (2012) examined the IES data; Meth & Dias (2004) and Vermaak (2005) used the OHS and LFS data; Van der Berg et al. (2007a, 2008) looked at the AMPS data; and Agüero et al. (2005) used a provincial dataset known as the KwaZulu-Natal Income Dynamics Study. Although different poverty lines were used, these studies found that poverty levels increased in the 1990s, before a downward trend took place.

The second group of studies considered the factors as discussed in Section 2.1 and hence adjusted the survey data, before poverty levels were estimated. For instance, Van

[3]Detailed explanation of the methodology of this approach falls beyond the scope of this study, but the reader can be referred to Wittenberg (2010:315–19) as well as Branson & Wittenberg (2014:26–8).

der Berg & Louw (2004) as well as Pauw & Mncube (2007) were concerned that the rapid decline in household income between IES 1995 and IES 2000 was inconsistent with the increase of current household income as captured in the national accounts. Therefore, Van der Berg and Louw calculated mean incomes by race using national accounts and other sources of data, before applying these income values to the intra-group distributions of income in these IEs. Using the poverty line of R250 per month in 2000 prices, they found that the poverty headcount ratio was stable across the two surveys (from 0.39 to 0.38), but the absolute number of people living in poverty increased. Pauw & Mncube (2007) imputed the food and tax expenditures in IES 2000 to replace unexpected missing or zero values or cases of obvious under-reporting. They assumed that for each household in both surveys, the larger of total income and expenditure was the correct measure to be used to derive the per-capita variable. In the end, they found that poverty levels increased moderately between 1995 and 2000.

Van der Berg et al. (2005, 2007b) adjusted the AMPS distributional estimates of income rightwards to be consistent with the national accounts series for aggregate household income, and found that the poverty headcount ratio has been increasing slightly since 1993, before a moderate downward trend was observed in the 2000s. Leibbrandt et al. (2006) estimated poverty with Census 1996 and Census 2001. If the data were used unadjusted, at a poverty line of R250 per month in 2000 prices, the poverty headcount ratio increased from 0.59 to 0.65. However, once the zero-income households were excluded, although the poverty trend remained the same, the poverty level was lower in both censuses (0.50 in 1996 and 0.55 in 2001). Yu (2009) used the above two censuses and CS 2007, but he imputed the income of households with zero or unspecified income by SRMI. He found that the poverty trend was unchanged (poverty increased between 1996 and 2001, before a decline took place in 2007), but the poverty levels were lower in all three years after SRMI.

Leibbrandt et al. (2010) was one of the rare studies using different data sources (PSLSD 1993, IES 2000 and NIDS 2008) to investigate poverty trends. Certain income items were excluded (e.g. imputed rent, agricultural income, sale of vehicles and property) so that the per-capita income derived across the data sources would be more comparable across the surveys. Using the revised per-capita income variable, they found that the poverty headcount ratio showed a negligent decline (0.56, 0.54 and 0.54 in 1993, 2000 and 2008 respectively using the R211 poverty line, and 0.72. 0.71 and 0.70 using the R322 poverty line). Simkins (2004) also used different data sources to examine poverty (IES 1995 and 2000; Census 1996 and 2001). However, he did not explain clearly the decision rules he applied to impute the income of households with unspecified incomes, and did not specify the poverty lines used. Nonetheless, he found that the poverty headcount ratio increased between the two IESs and censuses.

To conclude, with the exception of a few studies, recent studies suggest that poverty increased following the advent of democracy, before a continuous decline took place from 2000. Since these studies examined surveys taking place in different years and/or used different poverty lines, it is difficult to compare the poverty levels amongst these studies.

Table 1. Availability of income and expenditure information in the 1993–2012 South African household surveys: a summary

Survey	Year	Question asked?	Recall or diary method?	Data captured in bands or actual amounts?	Overall amount or aggregation of amounts from different sources?	Number of bands, if the data are captured in bands
Income						
Census	1996 2001 2011	Yes	Recall	Bands	Overall	Between 12 and 14
CS	2007	Yes	Recall	Bands	Overall	12
IES	1995 2000 2005/06	Yes	Recall	Actual amounts	Aggregation	N/A
OHS	1995–99	Yes (1999 only)	Recall	Bands	Overall	8
LFS	2000–07	No	N/A			
QLFS	2008–	No				
GHS	2002–09	No				
PSLSD	1993	Yes	Recall	Actual amounts	Aggregation	N/A
NIDS	2008, 2010, 2012	Yes	Recall	Actual amounts	Aggregation Overall	15
AMPS	1993–2012	Yes	Recall	Bands	Overall	Between 29 and 32
Expenditure						
Census	1996 2001 2007 2011	No	N/A			
IES	1995 2000 2005/06 2010/11	Yes	Recall in 1995 and 2000; recall and diary methods in 2005/06 and 2010/11	Actual amounts	Aggregation	N/A
OHS	1995–99	Yes (in 4 surveys)	Recall	1996–98: actual amounts 1999: bands	Overall	8 (1999)
LFS	2000–07	Yes (in 4 surveys)	Recall	Bands	Overall	8
QLFS	2008–	No	N/A			
GHS	2002–12	Yes	Recall	Bands	Overall	Between 8 and 10
NIDS	2008, 2010, 2012	Yes	Recall	Actual amounts	Aggregation	N/A
AMPS	1993–2012	No	N/A			

QLFS = Quarterly Labour Force Survey; N/A = Not applicable; CS = Community Survey

3. South African poverty estimates: 1993–2012

3.1 How the income and expenditure information was captured in each survey

Table 1 summarises the collection of income and expenditure information in each household survey and census.[4] Income was collected in some surveys but expenditure was collected in others. Only the IESs, NIDS and OHS 1999 collected both income and expenditure. Respondents were asked to declare the actual amounts in some surveys (e.g. IESs, NIDS, OHS 1996–98), but the relevant interval in others (e.g. censuses and CS 2007, LFSs, GHSs, AMPSs). Looking at the former approach in detail, respondents were asked to declare a single-estimate amount in some surveys either in actual continuous

[4]At the time of writing, the author had requested the 2010–2012 AMPS data from the South African Advertising Research Foundation but did not receive a response.

amount (e.g. OHS 1999) or in interval terms (e.g. AMPSs), but in other surveys (IESs and NIDS) they were asked to report the amounts on each income or expenditure source, before these amounts were added to derive total household income or expenditure. Table A1 in Appendix A shows the number of intervals and width of each interval in selected surveys. The nominal brackets have been left unadjusted, except between Census 2001 and CS 2007 and across the AMPSs.

IES 2005/06 and 2010/11 adopted the diary approach to complement the recall method to capture semi-durable and durable expenditure. Non-durable expenditure was captured exclusively by the diary method, while only the recall method was used to collect income information (Yu, 2008). To deal with the one-day effect, only households that completed the main questionnaire and at least two weekly diaries were accepted.[5]

Two further issues need to be taken into consideration. First, the Standard Trade Classification (STC) approach was adopted to categorise the income and expenditure items in IES 1995 and IES 2000, but the Classification of Individual Consumption According to Purpose (COICOP) approach was used in IES 2005/06 and 2010/11.[6] Since COCIOP is different from STC, in order to have consistent income and expenditure variables across the four IESs there are two options: re-categorise the income and expenditure items in the 1995 and 2000 surveys, using the 2005 COICOP structure; or re-categorise the income and expenditure items in the 2005/06 survey using STC. Both approaches will be adopted when comparing the income and expenditure data and poverty estimates in the IESs.

NIDS was the only survey asking the respondents to declare income and expenditure by both the single estimate and aggregation approaches. Looking at the latter in greater detail, household expenditure was derived by adding the respondents' answers on 32 categories of food spending, 54 categories of non-food spending and rent expenditure, while household income was derived by summing the respondents' answers on seven broad components, namely wage income, government grant income, other government income, agricultural income, remittances income, investment income and implied rent income.

SALDRU was concerned about the low response rate to the single-estimate amount questions and that poverty would be over-estimated because the amount derived from the single estimate approach was lower, and decided to use the income and expenditure variables derived by the aggregation approach to conduct poverty analyses in the official NIDS reports (e.g. Argent et al., 2009; Finn et al., 2009; Finn & Leibbrandt, 2013). All households had specified aggregate income and expenditure as imputations were applied to deal with item non-response.

For the interval data, the midpoint Pareto method was used to approximate the total income or expenditure amount in each category. The proportion of households with zero income was 13.0%, 21.0%, 8.2% and 15.1% in Census 1996, Census 2001, CS 2007 and Census 2011 respectively, while the proportion of households with unspecified income was 11.5%, 16.4%, 11.1% and 0.1% respectively. The latter proportion was only ranged between 1.5 and 3.5% in the GHS expenditure data. Therefore, the SRMI approach

[5]If a household had two (three) completed diaries, expenditure from the two (three) diaries was added together and the sum was divided by two (three). This average figure was then used to impute for the remaining two (one) non-completed/missing diaries (diary) (Stats SA, 2006).

[6]For a detailed discussion on the difference between the STC and COICOP approaches, refer to Yu (2008).

at household level[7] would be applied to impute the income of households with zero or unspecified income in the three censuses and CS 2007 to obtain more reliable poverty estimates.

3.2 Comparison of survey income and expenditure estimates with national accounts income

The nominal income and expenditure amounts were converted into real amounts in constant 2013 prices using the South African Reserve Bank's monthly consumer price index series. Table A2 in Appendix A presents the real total annual income and expenditure captured in each census and survey, as well as the census/survey amount as proportion of the national accounts income of the same year. Looking at the three censuses and CS 2007, this proportion was the highest in Census 2011 (71.3%) before SRMI but was the highest in CS 2007 (85.6%) after SRMI. As expected, after dealing with households with zero or unspecified income by SRMI, total income became higher.

With regard to the IESs, the 1995 survey best captured total income and expenditure. Under the STC approach, these amounts were equal to 95% of the national accounts income amount. One notable finding from Table A2 is that total income, expenditure and consumption experienced a sharp decline between 1995 and 2000, contradicting the upward trend in the national accounts total income between the two years.

Total expenditure was seriously under-captured in the OHSs, LFSs and GHSs, as it only amounted to 30 to 50% of the national accounts income (except in GHS 2009–12). The OHS 1999 income variable was an exception because total income amounted to 94.9% of the 1999 national accounts income. In almost all AMPSs, total income was approximately 55 to 65% of the national accounts income.

Comparing the results across the surveys in greater detail, for surveys capturing both income and expenditure the income was greater than expenditure in all surveys except IES 2005/06, as shown in Figure 1. This contradicts the earlier argument in the literature review that expenditure is captured better in poorer countries.

Figure 2 suggests that the interval approach leads to under-estimation of income and expenditure. For instance, the 1995 AMPS total income (captured in bands) was smaller than the 1995 IES total income (captured in exact amount), while in 2005 the GHS expenditure and the AMPS income (captured in bands) were lower compared with the IES income (captured in exact amount). Nonetheless, in 2010 the GHS total expenditure that was captured in bands was greater than income captured in continuous amounts in NIDS and IES.

Table A2 also shows that total expenditure in OHSs, LFSs and GHSs (with very few intervals) was lower. Total income in Census 1996 and 2001 (with fewer intervals and very wide intervals in the higher-income categories) was lower than the total income captured in the same years by AMPSs, which has more income intervals and narrower width in each interval. However, the opposite finding was observed when comparing CS 2007 with AMPS 2007. Finally, the AMPS income was always bigger than the GHS expenditure of the same year, except in 2009.

[7]Refer to Yu (2009) for detailed explanation on how SRMI was conducted.

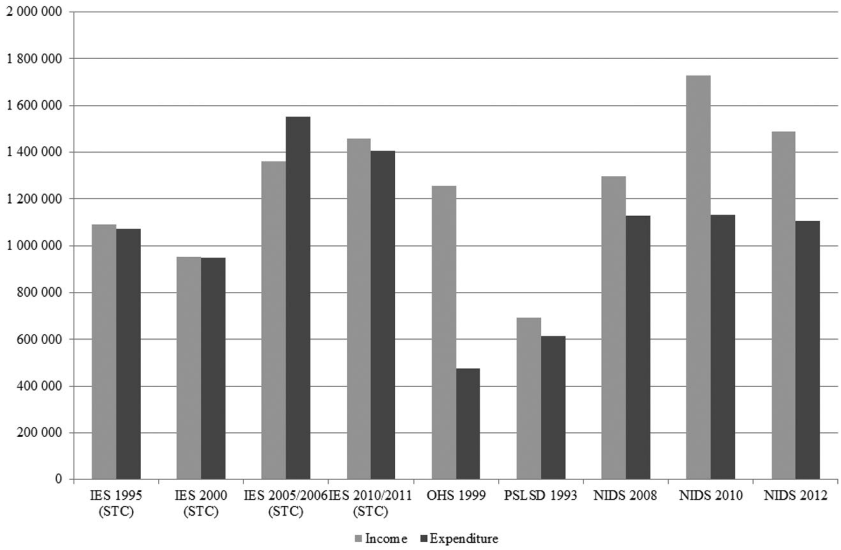

Figure 1. Total income and expenditure (Rand million, 2013 prices) of surveys that collected both income and expenditure.

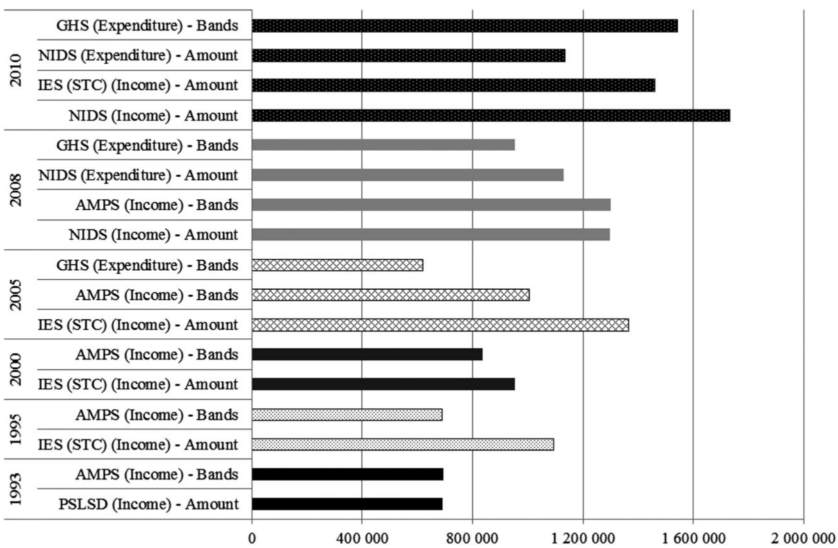

Figure 2. Total income or expenditure (Rand million, 2013 prices) of selected surveys taking place in the same year.

Figure 3 shows that real food expenditure, which was captured entirely by the diary method in IES 2005/06 and 2010/11, was surprisingly lower when compared with the 1995 and 2000 IESs (which captured food expenditure with the recall approach). Food expenditure as a proportion of total expenditure abruptly declined between 2000 and 2005/06, contradicting the results of GHSs, which found that the proportion of households

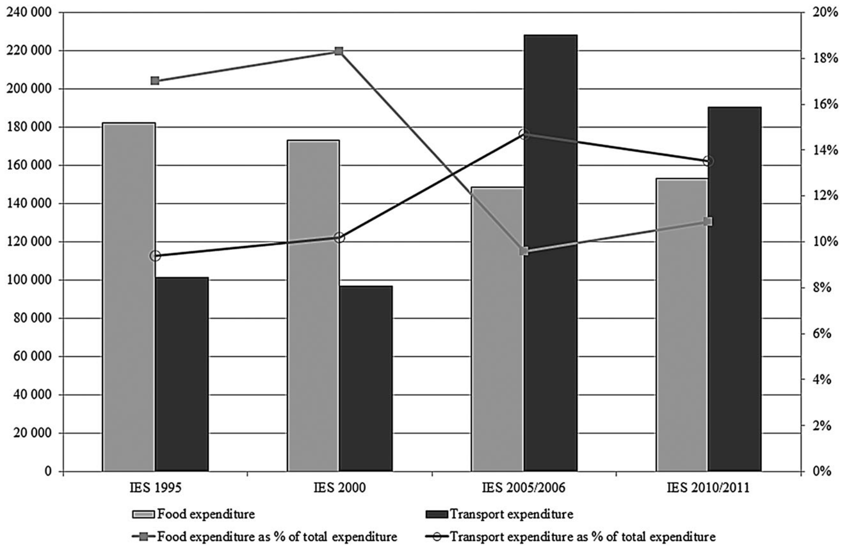

Figure 3. Annual food and transport expenditure (Rand million, 2013 prices) in the IESs (STC approach).

reporting they never experienced adult hunger and child hunger in the past 12 months was higher in recent years.[8]

The diary method may have resulted in the under-estimation of food expenditure due to reasons such as the first-day effect and illiteracy of respondents. It is also likely that the recall method adopted in IES 1995 and IES 2000 resulted in an over-estimation of food expenditure due to factors such as recall bias and telescoping, while the IES 2005/06 and 2010/11 food expenditure estimate might actually be more reliable. In contrast, regardless of whether the STC or COICOP approach was adopted, transport expenditure was much higher in IES 2005/06 and 2010/11 (see Figure 3). This could be attributable to the use of the diary method to complement the recall method, thereby resulting in a better capture of transport expenditure in these two surveys.

For the three NIDS, Table A2 shows that total income and expenditure derived from the single estimate method was much lower than the amount derived from the aggregation approach. The lower amount captured in the single estimate approach might be attributed to the fact that the respondents did not know which items to include in this 'one-shot' amount.

3.3 Poverty levels derived from each survey: 1993–2012

The lower bound poverty line (R322 per capita per month in 2000 prices, or R665 in 2013 prices) proposed by Woolard & Leibbrandt (2006) is used to examine poverty between 1993 and 2012. The focus is the Foster–Greer–Thorbecke poverty headcount ratios.

The results are presented in Figure 4 and the last column of Table A2 in Appendix A. Looking at the three censuses, the poverty headcount ratio increased between 1996 and

[8]The proportion of households never experiencing adult hunger increased from 69% in GHS 2002 to above 80% in GHS 2006–12, while the proportion of households never experiencing child hunger increased from 69% to the 80 to 85% range in GHS 2006–12.

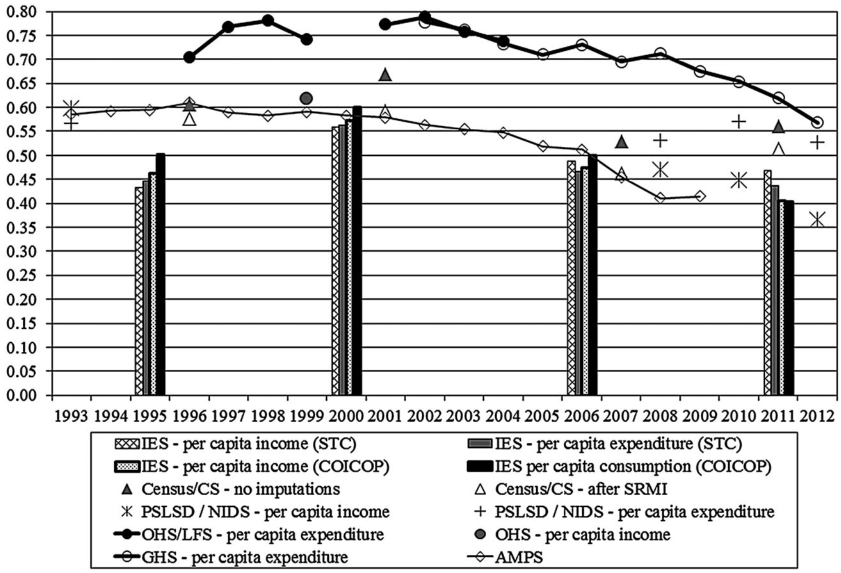

Figure 4. Poverty headcount ratios in each survey, 1993–2012 (Poverty line: R665 per capita per month, 2013 prices).

2001, before a rapid decline took place between 2001 and 2011. After taking CS 2007 into consideration, poverty actually increased between 2007 and 2011. The finding could be due to the fact that a higher proportion of households reporting zero income in 2007. However, even after SRMI was conducted, the 2011 poverty headcount ratio remained higher than the 2007 estimate.

The poverty headcount ratio increased rapidly between IES 1995 and IES 2000, before a downward trend was observed between IES 2000 and IES 2010/11, regardless of whether the STC or COICOP approach was adopted. Van der Berg et al. (2008) argued that the extent of increase of poverty between IES 1995 and IES 2000 could be over-estimated because of the huge drop of recorded income and expenditure between the two surveys, as mentioned earlier.

Looking at the OHS and LFS data, the poverty headcount ratio increased since 1996, before a downward trend was observed from 2002. In the GHSs, a downward trend was observed in 2002–05 and 2009–12, but an unstable trend was observed between 2005 and 2008. In AMPSs, the poverty headcount ratio stabilised at approximately 0.59 between 1993 and 1999, before a continuous downward trend took place between 2000 and 2008. Poverty increased slightly between 2008 and 2009, just like what happened between CS 2007 and Census 2011.

In the NIDS, the poverty headcount ratio was higher if expenditure was used. Poverty declined continuously between 2008 and 2012 using the income variable, but it first increased between 2008 and 2010, before a decline took place in 2012 when the expenditure variable was used. As expected, the single estimate approach resulted in serious under-estimation of total income and expenditure, and hence the poverty headcount ratios using the per-capita variables derived from this approach are much higher when compared with the ratios using per-capita variables derived from the aggregation approach.

Table 2. Poverty headcount ratios in NIDS (Poverty line: R665 per capita per month, 2013 prices), only including respondents reporting income (expenditure) in both the single estimate approach and the aggregation approach before imputations.

	Sample size	Number of households reporting income under both approaches	Poverty headcount ratio: One-shot approach	Poverty headcount ratio: Aggregation approach
Income				
NIDS 2008	7 301	5 441	0.631	0.590
NIDS 2010	6 809	5 557	0.619	0.523
NIDS 2012	8 040	7 381	0.532	0.414
Expenditure				
NIDS 2008	7 301	5 776	0.745	0.629
NIDS 2010	6 809	5 667	0.803	0.684
NIDS 2012	8 040	7 670	0.685	0.683

However, these NIDS poverty estimates might not be fully comparable, because as mentioned in Section 3.1 all households had specified aggregate income and expenditure as imputations were applied to deal with item non-response, while not all households reported single estimate income and expenditure amounts, due to low response rates for these two questions. Hence, the more precise method is to compare the poverty estimates of those reporting both single estimate and aggregate amounts before imputations. The results are presented in Table 2, and confirm that the single estimate approach results in higher poverty estimates. The main reason accounting for the latter finding is that respondents tend to report lower amounts under the single estimate approach as compared with the aggregation approach (see Table 3 as an example on NIDS 2012 – in 63.3% of the households reporting income amounts under both approaches in the sample, total income derived by the aggregation approach was greater than total income derived by the single estimate approach, as the ratio of the two income

Table 3. Total income derived income by the aggregation approach/ total income derived by the single estimate approach ratio, NIDS 2012.

Ratio category	Proportion of households in each ratio category (%)
[0; 0.2)	3.0
[0.2; 0.4)	3.6
[0.4; 0.6)	4.6
[0.6; 0.8)	6.8
[0.8; 1.0)	10.5
1	8.3
(1; 1.2)	18.1
[1.2; 1.4)	12.3
[1.4; 1.6)	8.0
[1.6; 1.8)	4.5
[1.8; 2)	3.7
[2+)	16.7
	100.0
< 1	28.5
= 1	8.3
> 1	63.3

amounts exceeds one), and the under-capture of income from the single estimate approach could be attributed to the reasons discussed in Section 2.

Looking at poverty levels of surveys and censuses taking place in the same year, the 1993 PSLSD poverty headcount ratios, regardless of whether income or expenditure was used, were close to the 1993 AMPS ratio. In 1996, the OHS estimate using expenditure was significantly higher (0.704), while the Census and AMPS estimates were lower (between 0.576 and 0.610). In 1999, the OHS estimate using expenditure was higher (0.742) than the OHS and AMPS estimates using income (0.617 and 0.591 respectively). In 2001, the LFS estimate was the highest (0.773), followed by the Census estimate before SRMI (0.670), while the Census estimate after SRMI (0.592) was very close to the AMPS estimate (0.579).

In 2006, the GHS poverty estimate (0.731) was much higher than the AMPS (0.512) and IES (ranging between 0.466 and 0.500) estimates. The GHS estimate was the highest in 2008 (0.712) compared with the estimates of NIDS (0.471 and 0.532 using income and expenditure respectively) and AMPS (0.410). In 2011, the Census poverty headcount ratio estimates (0.560 before SRMI and 0.513 after SRMI) were sandwiched between the GHS (0.619) and IES (between 0.404 and 0.468) estimates. Finally, the LFS 2002–04 poverty headcount ratios were similar to the GHS 2002–04 estimates.

To conclude, using a consistent poverty line across all surveys/censuses, despite the fact that the levels of poverty differed a lot across the surveys, poverty increased until about 2000 before a downward trend took place in the 2000s. The only four exceptions were: a stable poverty level observed in AMPS in the 1990s; poverty increased negligently between AMPS 2008 and 2009; poverty increased between CS 2007 and Census 2011; and poverty increased between NIDS 2008 and NIDS 2010 using the expenditure variable. Poverty levels were much higher in OHSs, LFSs and GHSs, which collected the income and expenditure information in fewer bands. Finally, the single estimate approach in NIDS resulted in higher poverty estimates, when compared with the aggregation approach.

The poverty estimates could be re-visited by adopting a consistent approach (e.g. cross-entropy method) to re-weight all datasets or by adjusting the survey income or expenditure distribution in line with the national accounts mean income (as in Van der Berg et al., 2005, 2007b). However, this requires a detailed study and would not be conducted here.

3.4 Would the IES poverty levels change significantly if the interval approach is applied?

This section re-visits the IES poverty levels by applying the intervals of the surveys taking place in similar years. The OHS 1996, Census 1996 and AMPS 1995 intervals would be applied to the IES 1995 data, while the GHS 2010, Census 2011 and AMPS 2010 intervals would be applied to the IES 2010/11 data. However, an assumption is made that the respondents would give consistent responses between the two approaches.[9]

The results are presented in Table 4. Poverty estimates using the continuous per-capita income variables, as they are, are similar to the estimates using the per-capita income

[9]For example, if the total monthly household income of a household was derived as R5500 in IES 1995, it is assumed that the household head would report that his/her household falls in the OHS 1996 'R5000–R9999' category, the Census 1996 'R3201–R6400' category and the AMPS 1995 'R5000–R5999' category.

Table 4. Poverty headcount ratios in IESs (Poverty line: R665 per capita per month, 2013 prices), if the interval method is applied.

	Poverty headcount ratio
IES 1995	
Actual continuous income variable	0.434
Applying the OHS 1996 intervals	0.418
Applying the Census 1996 intervals	0.423
Applying the AMPS 1995 intervals	0.435
IES 2000	
Actual continuous income variable	0.559
Applying the LFS 2001 intervals	0.552
Applying the Census 2001 intervals	0.558
Applying the AMPS 2000 intervals	0.547
IES 2005/06	
Actual continuous income variable	0.488
Applying the GHS 2005 intervals	0.476
Applying the CS 2007 intervals	0.481
Applying the AMPS 2005 intervals	0.481
IES 2010/11	
Actual continuous income variable	0.468
Applying the GHS 2010 intervals	0.449
Applying the Census 2011 intervals	0.420
Applying the AMPS 2010 intervals	0.469

variables derived using the single estimate interval methods. For example, in IES 1995 the poverty headcount ratio using the actual continuous income variable was 0.434, but the estimate ranged between 0.418 and 0.435 after the OHS/Census/AMPS intervals were applied. Similar findings could be observed in the other three IESs. However, the results need to be interpreted with great caution, as Section 3.3 already highlighted that the income (expenditure) amount derived by the aggregation approach could be very different from the income (expenditure) amount derived by the single estimate approach.

4. Conclusion

This article first examined the main factors affecting the comparability and reliability of income and expenditure data across household surveys/censuses, before comparing these data across the surveys/censuses. Real per-capita income and expenditure were used to derive the Foster–Greer–Thorbecke poverty headcount ratios between 1993 and 2012. Since the income and expenditure information was captured differently, this led to the variation in the income and expenditure amounts in each survey, and the levels of poverty were different across the surveys/censuses. Poverty trends were similar in all surveys/censuses, except in AMPS, between CS 2007 and Census 2011, and between the 2008 and 2010 NIDS (expenditure variable). In AMPSs, which captured income in a greater number of bands and a narrower width in each band, the poverty levels and trends were much more stable. The poverty estimates were much higher in the OHSs, LFSs and GHSs, which are associated with fewer bands. Finally, the single estimate variables resulted in higher poverty levels in the NIDS data.

As income and expenditure was captured differently, it is hard to expect the poverty estimates to be similar. It is also difficult to expect the income and expenditure information to be captured in exactly the same way (e.g. expecting Stats SA to have the same interval bands in GHSs and censuses). In order to improve the reliability and comparability of these estimates, the institutes conducting the surveys and censuses should at least consider adjusting the number of intervals and the width of each interval frequently to account for the impact of inflation. Unfortunately, this only happens in the AMPSs and between Census 2001 and CS 2007. Had these adjustments taken place more regularly, it could have improved the reliability of the poverty estimates. Also, because the present analysis strongly indicates that surveys with fewer bands (i.e. LFSs and GHSs) are associated with much higher poverty estimates, Stats SA should consider revising the expenditure intervals in GHSs drastically, in order to improve the capture of expenditure and reliability of poverty estimates. Finally, one must interpret the census and CS 2007 poverty estimates using the income variables as they are with great caution, because these censuses and survey are characterised by the presence of a relatively high proportion of households with zero or unspecified income. The income of these households should be imputed, before more precise poverty estimates could be derived.

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Appendix A

Table A1. Number and width of monthly income and expenditure bands in selected surveys

Census 1996 income	Width	AMPS 2009 income	Width
None	N/A	R1–R499	500
R1–R200	200	R500–R599	100
R201–R500	300	R600–R699	100
R501–R1 000	500	R700–R799	100
R1 001–R1 500	500	R800–R899	100
R1 501–R2 500	1 000	R900–R999	100
R2 501–R3 500	1 000	R1 000–R1 099	100
R3 501–R4 500	1 000	R1 100–R1 199	100
R4 501–R6 000	1 500	R1 200–R1 399	200
R6 001–R8 000	2 000	R1 400–R1 599	200
R8 001–R11 000	3 000	R1 600–R1 999	400
R11 001–R16 000	5 000	R2 000–R2 499	500
R16 001–R30 000	14 000	R2 500–R2 999	500
R30 001 above	N/A	R3 000–R3 999	1 000
Census 2001, CS 2007 and Census 2011 – income		R4 000–R4 999	1 000
None	N/A	R5 000–R5 999	1 000
R1–R400	400	R6 000–R6 999	1 000
R401–R800	400	R7 000–R7 999	1 000
R801–R1 600	800	R8 000–R8 999	1 000
R1 601–R3 200	1 600	R9 000–R9 999	1 000
R3 201–R6 400	3 200	R10 000–R10 999	1 000
R6 401–R12 800	6 400	R11 000–R11 999	1 000
R12 801–R25 600	12 800	R12 000–R13 999	2 000
R25 601–R51 200	25 600	R14 000–R15 999	2 000
R51 201–R102 400	51 200	R16 000–R19 999	4 000
R102 401–R204 800	102 400	R20 000–R24 999	5 000
R204 801 or above	N/A	R25 000–R29 999	5 000
OHSs/LFSs/GHSs – expenditure		R30 000–R39 999	10 000
R0–R399[a]	400	R40 000–R49 999	10 000
R400–R799	400	R50 000 or above	N/A
R800–R1 199	400		
R1 200–R1 799	600		
R1 800–R2 499	700		
R2 500–R4 999	2 500		
R5 000–R9 999	5 000		
R10 000 or above	N/A		

[a]The R0–R399 category has been broken down into three categories since GHS 2009, namely R0, R1–R199 and R200–399.

Table A2. Comparison of annual total income, expenditure and consumption in various surveys with annual total income in the national accounts in the same year and poverty headcount ratios in each survey (Poverty line: R665 per capita per month, 2013 prices), 1993–2012

Census / survey	Variable	Year	Amount (Rand million) (2013 prices)	As % of total income in the national accounts	Poverty headcount ratio
Census	Income – before SRMI	1996	608 419	50.5	0.606
		2001	756 903	52.5	0.670
		2011	1 582 899	71.3	0.560
	Income – after SRMI	1996	723 853	60.1	0.576
		2001	1 047 306	72.7	0.592
		2011	1 649 590	74.3	0.513
CS	Income – before SRMI	2007	1 300 457	68.9	0.529
	Income – after SRMI	2007	1 616 287	85.6	0.463
IES	Income – STC	1995	1 090 599	95.0	0.434
		2000	951 595	71.9	0.559
		2005/ 2006	1 362 043	72.2	0.488
		2010/ 2011	1 458 757	65.7	0.468
	Expenditure – STC	1995	1 073 448	93.5	0.447
		2000	948 072	71.7	0.564
		2005/ 2006	1 551 969	82.2	0.466
		2010/ 2011	1 406 229	63.4	0.437
	Income – COICOP	1995	1 023 576	89.2	0.462
		2000	912 800	69.0	0.572
		2005/ 2006	1 458 085	77.3	0.473
		2010/ 2011	1 743 965	78.6	0.406
	Consumption – COICOP	1995	756 064	65.9	0.502
		2000	669 475	47.8	0.601
		2005/ 2006	1 097 905	58.2	0.500
		2010/ 2011	1 388 603	62.6	0.404
OHS	Expenditure	1996	392 791	32.6	0.704
		1997	356 629	28.6	0.768
		1998	312 808	24.6	0.781
		1999	474 573	35.9	0.742
	Income	1999	1 254 855	94.9	0.617
LFS	Expenditure	2001	476 269	33.1	0.773
		2002	545 588	36.9	0.788
		2003	766 094	50.4	0.758
		2004	861 699	52.4	0.738
GHS	Expenditure	2002	438 868	29.7	0.778
		2003	594 820	39.1	0.762
		2004	552 625	33.6	0.733
		2005	618 595	34.9	0.710
		2006	646 148	34.2	0.731
		2007	674 350	33.9	0.695
		2008	953 570	46.7	0.712
		2009	1 252 163	61.1	0.675
		2010	1 538 740	72.7	0.654
		2011	1 672 952	75.4	0.619
		2012	1 893 180	81.7	0.568
PSLSD	Income	1993	691 179	65.3	0.596
	Expenditure	1993	615 039	58.1	0.566

(Continued)

Table A2. Continued.

Census / survey	Variable	Year	Amount (Rand million) (2013 prices)	As % of total income in the national accounts	Poverty headcount ratio
NIDS	Income – aggregation approach	2008	1 297 138	63.1	0.471
		2010	1 729 288	81.7	0.448
		2012	1 486 459	64.2	0.365
	Income – single estimate approach	2008	791 843	38.5	0.631
		2010	1 260 274	59.5	0.618
		2012	1 530 747	66.1	0.532
	Expenditure – aggregation approach	2008	1 129 508	54.9	0.532
		2010	1 133 468	53.5	0.571
		2012	1 105 270	47.7	0.527
	Expenditure – single estimate approach	2008	442 427	21.5	0.744
		2010	349 857	16.5	0.791
		2012	700 969	30.3	0.686
AMPS	Income	1993	695 029	65.6	0.586
		1994	682 605	62.5	0.593
		1995	688 135	59.9	0.594
		1996	721 419	59.9	0.610
		1997	718 971	57.7	0.589
		1998	745 959	58.7	0.583
		1999	744 986	56.3	0.591
		2000	836 762	59.8	0.582
		2001	839 002	58.2	0.579
		2002	834 218	56.4	0.563
		2003	917 755	60.4	0.554
		2004	931 190	56.6	0.548
		2005	1 002 069	56.6	0.519
		2006	1 038 372	55.0	0.512
		2007	1 141 045	57.3	0.455
		2008	1 299 880	63.2	0.410
		2009	1 218 097	59.4	0.414