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MARISA VON FINTEL AND ASMUS ZOCH

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MARISA VON FINTEL
DEPARTMENT OF ECONOMICS
UNIVERSITY OF STELLENBOSCH
PRIVATE BAG X1, 7602
MATIELAND, SOUTH AFRICA
E-MAIL: MARISA.VONFINTEL@GMAIL.COM

ASMUS ZOCH
DEPARTMENT OF ECONOMICS
UNIVERSITY OF STELLENBOSCH
PRIVATE BAG X1, 7602
MATIELAND, SOUTH AFRICA
E-MAIL: ASMUSZOCH@GMAIL.COM

UNIVERSITEIT STELLENBOSCH UNIVERSITY

BER BUREAU FOR ECONOMIC RESEARCH

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ABSTRACT

The aim of this study is to use data from three waves of the National Income Dynamics Study (2008, 2010 and 2012) in order to examine and decompose the dynamics of child poverty over the period. The study is specifically aimed at examining the poverty dynamics of children, as they have been shown to one of the more vulnerable groups in South Africa. We use the framework of an asset poverty line first developed by Carter and May (2001) in order to identify those children in households that are in structural poverty with an asset base which is too low to escape poverty in the long run. We find that almost 40% of the children in our sample found themselves in this structural poverty trap between 2008 and 2012. As expected, these children have suffered as a result of this deprivation, even in comparison to their peers who have also been chronically poor over the period, but were living in households with access to more assets. We conduct some preliminary investigations into the potential causes of welfare changes over time. In line with previous work on the topic, we identify low initial levels of education, low asset-holdings, low initial employment and adverse household formation as possible causes of these poverty traps. Finally, we also conduct some robustness checks of the income changes by correcting for measurement error using an instrumental variables approach.

Keywords: Poverty measurement, poverty dynamics, children, South Africa, National Income Dynamics Study
JEL codes: I32, D63, J13

1. **Introduction**

The measurement of poverty in South Africa has a long history, dating back to the Poverty Datum Line of the 1940's (May, 2012).[1] Although the direction of poverty trends in South Africa has been contested in the past, there seems to be some conclusion that the rate of poverty has decreased since the mid-2000s. However, despite this decline in poverty, there are many households for whom it has been impossible to break the cycle of poverty in which they find themselves.[2] The existence of a poverty trap as well as the causes and consequences arising from this have stimulated much research.

Among the more important findings emerging from this literature is the evidence that the best chance of success in stemming poverty traps relies on early-life intervention. In particular, investment in children at the earliest stages of development is now seen as a critical policy intervention for positively influencing later welfare (Currie and Vogl (2012) and Heckman and Masterov (2007))[3]. This linkage between tomorrow's economic development and a healthy and nurturing environment for today's children is what underpins UNICEF's (2013, p. 2) "call to action to put children at the centre of sustainable development".

As a result, much focus has been placed on the measurement of poverty among children. Starting in 2005 the University of Cape Town's Children's Institute has been publishing an annual report, 'The Child Gauge', which aims to track legislative and other developments as they relate to children. The publication also reports on 'child-centred' data, which is compiled from the various national surveys as well as administrative data (Hall & Lake, 2012). Using data from the General Household Survey (GHS)[4], the most recent Child Gauge (2012) indicates that in the year 2010 60.5% of all children (defined as persons younger than 18 years) in South Africa resided in households that were deemed poor (the poverty line used was R575 per person per month[5]). In absolute terms, this translates to just over eleven million children (out of 18.5 million) that are living in poverty. These numbers reflect a strong improvement over the 2003 figure which stood at 13.2 million (or 73%) poor children.

Another study, by Streak, Yu and Van der Berg (2009), using the 2005 Income and Expenditure Survey (IES) data, finds similar poverty ratios among children. The authors demonstrate that applying various scaling strategies when calculating poverty ratios for children do not significantly affect the measured result. They apply a poverty line arrived at by taking the 40th percentile of average household income and find that 65.5% of children are poor. They also decompose children into three age cohorts (0-4, 5-14, and 15-17 years) to ascertain whether there are any differences in poverty ratios between younger and older children. It is found that the youngest cohort reflects the highest poverty head count ratio (Streak, et al., 2009, p. 196). Leibbrandt et al. (2010, p. 37) document similar measured outcomes. They consider three separate surveys in

[1] Most recently see Leibbrandt et al (2010) and Finn et al (2012). For a summary of the work on poverty measurement in South Africa, see the Appendix in Posel and Rogan (2013).

[2] A poverty trap can be defined as "any self-reinforcing mechanism which causes poverty to persist" (Azariadis & Stachurski, 2005, p. 326)

[3] This idea is sometimes conveyed in the nomenclature 'predistribution'.

[4] It should be noted that the GHS does not contain full income or expenditure data, so that these estimates are, even at the quite high poverty lines drawn, somewhat over-stated. However, it is likely that the change over time referred to below broadly reflects the underlying trend that would have been obtained if more complete data and other poverty lines were used.

[5] This is an inflation adjustment of the unofficial but commonly used lower bound poverty line proposed by Özler (2007).

order to estimate the changes in child poverty over time[6]. They report child poverty to be highest in younger cohorts (with the 0-10 aged cohort having the highest poverty head count). Little change in child poverty is reflected over the fifteen year period they consider. The head count was measured at 67% for children under 16 years in 2008, which almost exactly what it had been in 1993.

Although research on child poverty in South Africa, as set out above, exists, there is a scarcity of studies examining the depth of deprivation among children as well as tracking the changes in child poverty over time. The aim of this paper is to examine and decompose the determinants of child poverty, understand who is falling behind, and to look more specifically at how children were affected by these trends. For this purpose, we make use of the theoretical framework first developed by Carter and May (2001) and later applied by May and Woolard (2007).

To conduct our study we use data from the National Income Dynamics Study (NIDS). The NIDS dataset, which comprises longitudinal data on approximately 18 000 individuals interviewed in all three waves over the period 2008 and 2012, is the first nationally representative panel dataset in South Africa. Of the approximately 18 000 individuals interviewed, 43% were 18 years old or younger in 2012. Using data on households who remained in the sample over this period, we are able to not only track the changes in income and expenditure, but also decompose and examine these changes further using the wealth of household - and individual-level information included in the survey.

The paper is set out as follows. First we provide some background on the NIDS data and define some of the concepts we use in the paper, including how we define and measure poverty for the purposes of this study. Thereafter, we explore the movements in income, expenditure and poverty over time, focussing specifically on children. We then set out the theoretical framework to identify children trapped in poverty and explore the nature and correlates of these of poverty traps. Finally, we conduct a robustness check of the findings to control for measurement error by making use of an instrumental variables approach.

2. The data

2.1. The National Income Dynamics Study

The data we use come from the latest release of the National Income Dynamics Study (NIDS) which includes three waves of data collected in 2008, 2010 and 2012. NIDS is conducted by the Southern Africa Labour and Development Research Unit at the University of Cape Town. It includes information on individuals and households over this four year period and is therefore very appropriate for examining trends in poverty over time. As with any panel dataset, attrition is a problem, and was highest among individuals with certain characteristics. Within the white population group, attrition was 50.31%, mostly as a result of refusal to complete a questionnaire (De Villiers, et al., 2013, pp. 21-22), whereas attrition in the black population group was much lower at 13.39%, mostly attributable to loss of contact.

Table 1 below sets out the nature of the attrition out of and into the data, and provides an indication of the number of individuals who completed interviews. For the current study, we are

[6] These are the PSLSD, the Income and Expenditure Survey (IES) for 2000 and the National Income Dynamics Study (NIDS) for 2008.

limiting our focus to individuals who were successfully interviewed in all three waves, which amounts to 18 818 individuals in total (56 454 observations over the three waves).

Table 1: Attrition in NIDS wave1-wave3 (all interviews completed in parenthesis)

	2008	2010	2012	Total
Only 2008	3 214 (2 970)	0	0	3 214 (2 970)
Only 2010	0	2 582 (2 490)	0	2 582 (2 490)
Only 2012	0	0	6 330 (6 161)	6 330 (6 161)
2008 & 2010	2 394 (2 089)	2 394 (2 089)	0	4 788 (4 178)
2010 & 2012	0	4 152 (3 953)	4 152 (3 953)	8 304 (7 906)
2008 & 2012	2 365 (2 138)	0	2 365 (2 138)	4 730 (4 276)
2008, 2010 & 2012	20 253 (18 818)	20 253 (18 818)	20 253 (18 818)	60 759 (56 454)
Total	28 226 (26 015)	29 381(27 350)	33 100 (31 070)	84 435(84 435)

Notes: Unweighted data.

In order to explore the differences between attriters and those individuals who remain in our sample, we compare the means of certain key variables within each of these groups. Table 2 reports the means and standard deviations as well as the t-statistics. It is clear that there is a significant difference between attriters and non-attriters in that the group of attriters is wealthier and more educated. They also come from households with more employed individuals and have higher levels of subjective well-being.

Table 2: Differences between attriters and non-attriters

	Mean (standard error)		
	Attriters	**Non-attriters (2008-2012)**	**t-statistic**
Per capita monthly hh income (2010 Rands)	1 506.96 (20.58)	1 274.89 (16.78)	8.32
Pc monthly hh expenditure (2010 Rands)	1155.85 (15.89)	956.04 (9.35)	11.50
Mean household education in years	8.22 (0.02)	7.93 (0.01)	13.03
Number of children in household	2.82 (0.01)	2.76 (0.01)	3.23
Household with any children (=1 if yes)	0.85 (0.00)	0.86 (0.00)	-4.93
Mean age of household	26.22 (0.07)	26.97 (0.05)	-9.47
Household size	6.00 (0.02)	5.91 (0.01)	3.59
Number of employed members in hh	1.03 (0.01)	1.00 (0.00)	5.23
Mean level of subjective well-being (scale 1-10)	5.00 (0.01)	4.97 (0.01)	2.12
Proportion black	0.81 (0.00)	0.83 (0.00)	-9.45

This pattern holds true for the black African population, as is illustrated in Table 3. However, for the white population, individuals who did not remain in the sample are significantly less wealthy and educated, as well as younger than those individuals who remained in the sample throughout. This is most likely explained by the fact that those who remained in the sample are older individuals with more time at hand, while younger households who have not yet reached the peak of their earnings potential dropped out.

Table 3: Attrition by race

	Mean (standard deviation)			
	Black African		White	
	Attriters	Non-attriters (2008-2012)	Attriters	Non-attriters (2008-2012)
Per capita monthly hh income	1 033.85 (14.51)	984.47* (9.26)	8 060.57 (193.57)	9 459.02* (571.42)
Pc monthly hh expenditure	733.83 (9.32)	733.22 (7.16)	7 152.07 (194.08)	7 240.84 (199.75)
Mean household education in years	7.98 (0.02)	7.76* (0.01)	11.89 (0.05)	12.15* (0.05)
Number of children in household	3.02 (0.02)	2.91* (0.01)	0.94 (0.03)	0.90 (0.03)
Household with any children (=1 if yes)	0.87 (0.00)	0.88 (0.00)	0.52 (0.01)	0.46* (0.01)
Mean age of household	25.08 (0.06)	26.20* (0.05)	38.88 (0.47)	42.38* (0.51)
Household size	6.26 (0.03)	6.08* (0.02)	3.32 (0.04)	3.17* (0.04)
Number of employed members in hh	0.92 (0.00)	0.91 (0.00)	1.44 (0.03)	1.32* (0.03)
Mean level of subjective well-being (scale1-10)	4.63 (0.01)	4.68* (0.01)	6.97 (0.05)	7.08 (0.05)

Notes: * if there is a significant difference between the attriters and non-attriters group within each of the race categories at the 5% level of significance.

Since we are specifically interested in the impact of movements in poverty on children, we also specifically consider this sub-sample. We define "children" as any individual who remains in the dataset in all three waves and who was 18 years old or younger in 2012. Accordingly, we follow all children aged roughly 4 to 14 years in 2008.

Table 4: Children as proportion of total sample

	Unweighted number and Percentage (Balanced panel)			Unweighted number and Percentage (Unbalanced panel)		
	2008	**2010**	**2012**	**2008**	**2010**	**2012**
Children (balanced definition, i.e. <18 in 2012)	6 739 (35.81%)	6 739 (35.81%)	6 739 (35.81%)	6 739 (23.88%)	6 739 (22.94%)	6 739 (20.36%)
Children (attriters and new births)	-	-	-	4 770 (16.90%)	5 334 (18.15%)	6 798 (20.54%)
Adults (older than 18 in 2008)	12 079 (64.19%)	12 079 (64.19%)	12 079 (64.19%)	16 717 (59.23%)	17 308 (58.91%)	19 563 (59.10%)
Total (100%)	18 818	18 818	18 818	28 226	29 381	33 100

Table 4 provides some indication of the relative size of the sample of children in the data. It contains the unweighted number of observations as well as percentage within the total sample, for the balanced as well as the unbalanced sample. In total, there are 6 739 individuals who have been defined as children according to our definition and who remain in the sample.

2.2. **Measuring Poverty**

Before delving into the data, it is important to further clarify some definitions used in our analysis. In the first place, we follow the suggestion by Woolard and Klasen (2005) by looking both at the changes in per capita monthly household income as well as expenditure in our initial analysis.[7] Although income was captured better than expenditure in the NIDS data, we include both as a robustness check in order to minimise the impact of measurement error. Once we have conducted our initial analysis of the poverty trends over time, we focus only on income in our final analysis.

In addition, we use monthly per capita household income and expenditure as our main variable of interest. However, when measuring the poverty, we calculate the percentage of children, not households, that are living in poverty.[8] Also, it should be clarified that we do not make use of adult equivalence scales in our analysis. We include a per capita household measure of well-being, where the monthly expenditure and income is divided by the number of members of the household, irrespective of what share of household consumption each member is actually responsible for.

There has been motivation against and for the use of equivalence scales in poverty measurement in South Africa. While many studies have made use of adult equivalence scales, Streak et al. (2009) find that the main trends and conclusions from the measurement of child poverty are not significantly influenced by the use of adult equivalent income or expenditure compared to household per capita income or expenditure.[9]

Last, we select a poverty line of R575 in 2010 Rands.[10] This poverty line has been used in many studies but has its origin in the work of Özler (2007), where it was used as a poverty line of R322 in 2000 prices.

In order to provide a clearer picture of what is happening at different levels of income, we also construct a poverty index, by dividing the monthly household per capita income or expenditure by the poverty line, which provides an index which takes a minimum value of zero and is equal to one if the household lies exactly on the poverty line. Using this index, it is clear to identify the number of individuals in households below or on the poverty line, as well as those living below 0.5 of the poverty line and those living at a level which is double the poverty line.

[7] It should be noted that the estimations in this paper use the imputed income and expenditure values included in the NIDS data.
[8] Of course the child's poverty status is inextricably linked to that of the household she lives in.
[9] Although there has been some preliminary findings more recently by Posel and Rogan (2013), who have shown how the use of adult equivalence scales may improve the measurement of poverty and indeed narrow the gap between objective and subjective (perceived poverty), we have decided against the use of adult equivalence scales here.
[10] We have deflated all prices in the NIDS panel to reflect August 2010 prices.

3. **Trends in income, expenditure and poverty for children 2008-2012**

The NIDS panel was constructed to observe income and expenditure dynamics of a representative sample of households in South Africa. Table 5 shows the development of household mean income and the different income sources for the period 2008 to 2012. For the full sample as well as the sub-sample of children, there was a positive trend in per capita household income from 2008 to 2012. Children are, however, clearly residing in more deprived households, as the mean monthly household income is significantly lower for children compared with the rest of the population. While income from government grants seems to be equally distributed in households with and without children, labour income is not. Therefore, the access to labour market income appears to be the main driver explaining difference in per capita income. This is in line with the study by Leibbrandt et al. (2012) who find that the labour market has been and remains the main driver of aggregate inequality for the period 1993 to 2008.

Table 5: Trends in mean income and expenditure for balanced sample 2008-2012 (2010 Rands)

In Rand 2010 prices	All ages			Children (0-17 years in 2012)		
	2008	**2010**	**2012**	**2008**	**2010**	**2012**
Per capita monthly hh income	1650.9	1665.8	1942.1	962.4	1034.2	1195.2
Per capita monthly hh labour income	1081.5	1024.1	1221.3	601.4	623.8	719.7
Per capita monthly hh grant income	123.9	139.9	160.2	124.1	136.2	154.8
Per capita monthly hh expenditure	1383.5	1348.7	1312.6	854.7	815.0	769.4

While the mean household income increased from 2008 to 2010 and to 2012, the exact opposite trend can be found using household expenditure. Furthermore, the mean expenditure level is much lower than mean household income.

We find confirmation of the downward trend in child poverty since 2000 using the NIDS data. Using the poverty line of R575 monthly per capita household income, we find that in 2008 more than 61% of the children lived in poor households. The percentage decreased to about 51% in 2012. Figure 1 also shows that households with children are still more vulnerable than those without. Comparing the poverty levels for a poverty line of R575 using income and expenditure, the poverty levels are much higher using household expenditure and there even appears to be an increase from 2008 to 2010 in poverty levels. This finding would stand in sharp contrast to other studies observing child and overall poverty discussed earlier. For this reason, we believe expenditure might be underreported in the NIDS dataset and concentrate on using per capita household income measure in this paper.

The longitudinal aspect of NIDS enables us to follow the same children over time and to study the poverty dynamics of those children. However, exactly because of the longitudinal nature of the data, we would expect there to be some measurement error in the measurement of income. This would typically increase the likelihood of a household misclassified as moving into or out of poverty from one period to the next, confounding the poverty estimates.

In order to minimise the impact of measurement error, we only classify households as moving out of poverty if the per capita household income crossed the poverty line and the difference in the real income between the two periods exceeds 10%. This approach is in line with May and Woolard (2007) and Woolard and Klasen (2005).

Figure 1: Poverty headcount for balanced sample 2008-2012

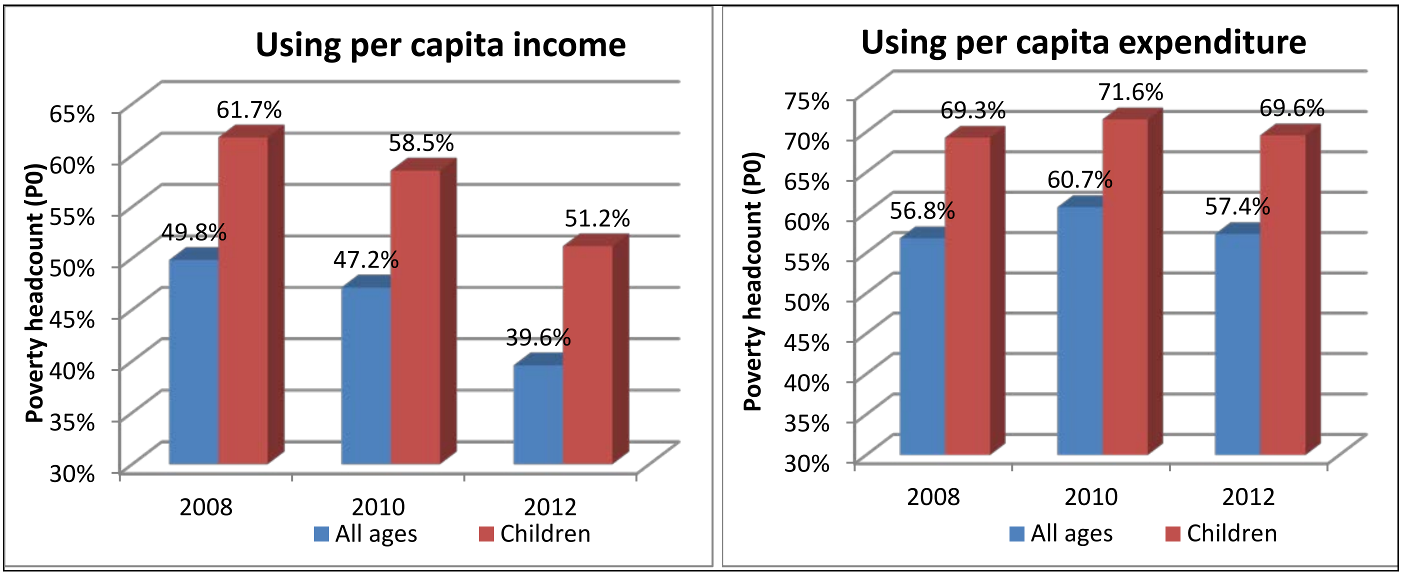
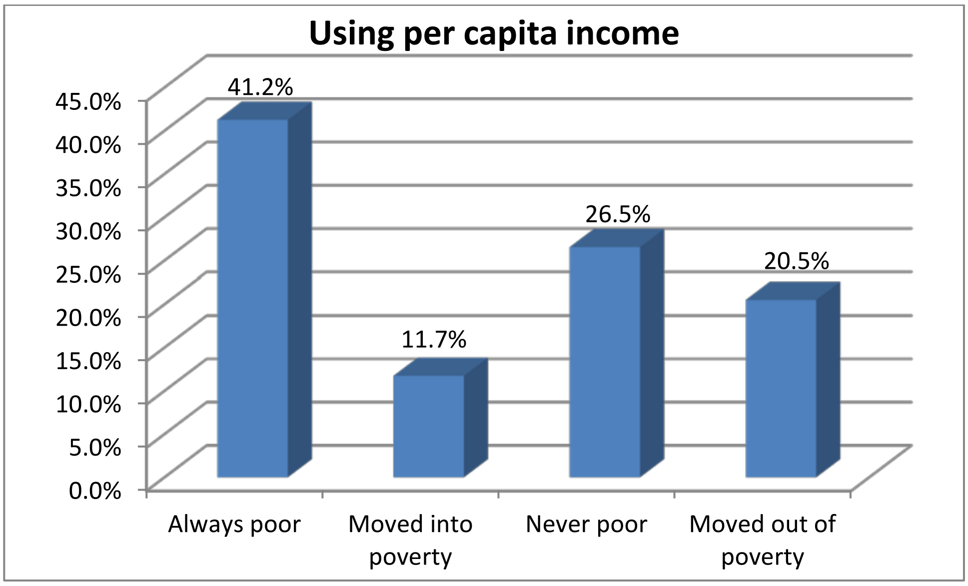


Figure 2 shows the poverty dynamics of children over the period 2008 to 2012, taking this robustness check into account. Children who were in poor households when they were first observed in 2008, and then again in poor households in 2012 when they were observed in the last wave of the data, constituted 41.2% of our sample of children. We label these children those who were chronically poor. Conversely, children who were observed in a non-poor household in both 2008 and 2012 constitute 26.5% of our sample. The remaining sample of children either moved into or out of poverty (or are misclassified as a result of measurement error that has not been dealt with). Those children who were able to "get ahead", i.e. who were observed in a poor household in 2008 but not in 2012, make up 20.5% and those who fell behind (non-poor in 2008; poor in 2012) 11.7%.

Although these poverty transitions are very informative to provide some indication of how children fared during the period 2008 to 2012, they do not provide a more detailed insight into what exactly happened within the households where children reside. Why were certain households "lucky" enough to escape poverty and others not? Does luck have anything to do with it? Why do some children remain in poverty over the 4- year period? The rest of the paper is aimed at answering these questions by first looking at a theoretical model to further break down poverty dynamics and then examining the main causes of these movements.

Figure 2: Poverty dynamics for children (NIDS 2008-2012)



4. **Theoretical Framework**

As indicated above, this section is aimed at breaking down the poverty dynamics which we observed in the previous section so as to enable us to make some preliminary conclusions about the reasons for chronic poverty.

For this purpose, we use the theoretical framework developed by (Carter & May, 2001) to classify poverty dynamics. Carter and May (2001) list two main reasons why households might be in poverty at any point in time. First, households may be poor because they are not in possession of a sufficient number of assets. Second, they may be poor because they do not have the financial means to use the assets that they do possess. Over time, households are able to make strategic decisions or receive unexpected endowments so as to move out of poverty. However, over time, these households could also make financially unsound decisions or experience negative shocks which might propel them into poverty. Time can therefore be seen as either a source of opportunity or vulnerability.[11]

Using this background, Carter and May set out a dynamic theoretical framework to capture these possibilities. They denote the money-metric poverty line as $\underline{c}$. A household i is therefore in poverty in period t if the following holds true:

$$c_{it} \leq \underline{c} \tag{1}$$

In addition to this traditional poverty line, Carter and May (2001) estimate an asset poverty line $\underline{A}$ which is defined as:

$$\underline{A} = \{A | \hat{c}(\underline{A}) = \underline{c}\} \tag{2}$$

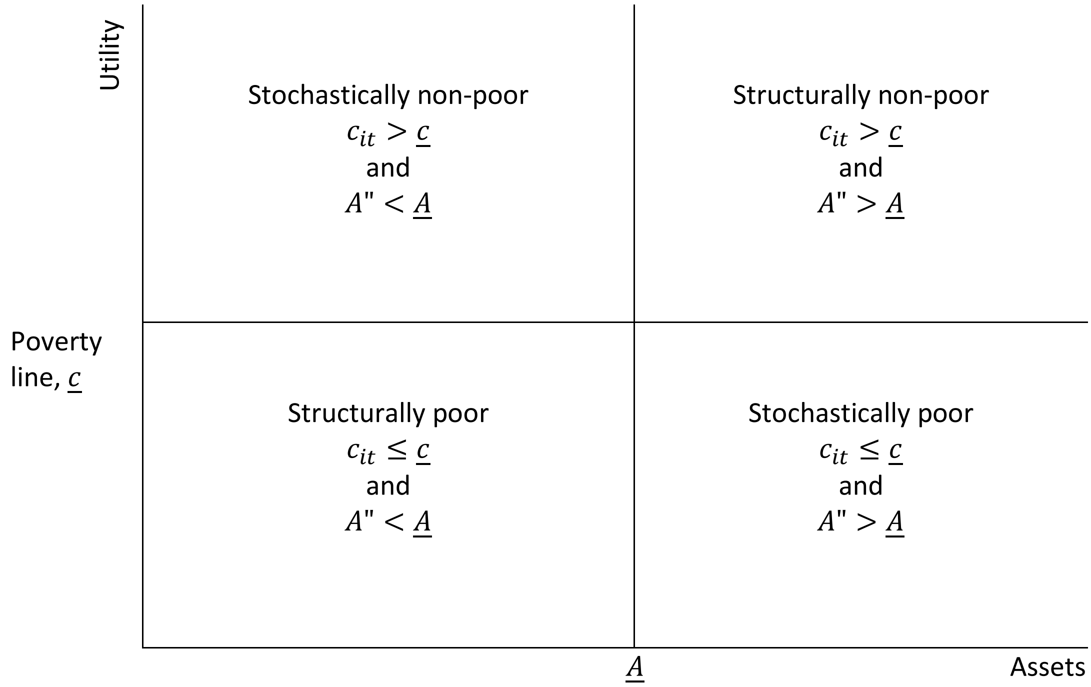
In other words, $\underline{A}$ is the combination of assets that yield a household income that is exactly equal to the poverty line in that time period. The term "assets" should be understood to refer

[11]In essence, Carter and May (2001) argue that the household faces a dynamic optimization problem. It wishes to maximize its discounted future income given its present endowment of assets as well as stochastic income shocks. Its asset endowment can include any actual asset as well as other non-typical endowments such as social capital.

to the broadest definition of the term, including "…*conventional, privately held productive and financial wealth, as well as social, geographic and market access positions that confer economic advantage*" (Carter & Barrett, 2006, p. 179).

For the single period case with a single asset, we reproduce a simplified version of the original figure by Carter and May (2001, p. 1990) as Figure 3 below.

Figure 3: Dynamic income and asset poverty lines



Source: (Carter & May, 2001, p. 1990)

All households with income above the money-metric poverty line, $\underline{c}$, are classified as being non-poor. Similarly, all households with income equal to or below $\underline{c}$ are classified as being poor. However, within each of these categories, using the asset poverty line $\underline{A}$, it is possible to distinguish potential reasons why these households are observed to be in poverty in this period. Households that are observed to own assets from which they are expected to earn an income in excess of $\underline{c}$ are observed to the right of the asset poverty line $\underline{A}$. Households whose asset ownership is low, so that they are not expected to be in poverty are observed to the left of the asset poverty line $\underline{A}$.

Using the intersection of these two lines, four sub-categories of households may be defined. Those in the top left quadrant are labelled the stochastically non-poor households. These households are observed as being non-poor in terms of their earned income for the period, but given their asset ownership, we expect them to be in poverty (hence the term "stochastic", which provides some indication that the poverty status of the household is not what we would expect, given their assets, and there is accordingly some room for mobility over time). These households have assets below the asset poverty line, $A" < \underline{A}$, however because of positive shocks (entitlement windfalls[12]), their income is above the poverty line.

[12] Using the language of Sen (1981).

Households in the bottom right quadrant are also stochastic in their poverty, however they are observed to earn an income below the money-metric poverty line $\underline{c}$ (because of negative shocks to their income, or entitlement failures) and are accordingly classified as being in poverty. However, since they are observed to the right of the asset poverty line, we would expect them to not be in poverty given their asset ownership.

The last two groups are classified as follows. Households in the top right quadrant are labelled structurally non-poor. They are households whose income is expected to exceed the income poverty line, given their combination of assets and indeed are observed to also be non-poor in the current period. Last, households that are in the bottom left quadrant have been classified structurally poor because their observed income is below the poverty line and they are expected to be in poverty given their asset ownership.

The dynamic analogue of the above one-period is denoted by the dynamic poverty line, which Carter and May (2001) as $\underline{J}$, which captures the discounted present value of multiple sequential poverty lines. Households are then classified as being dynamically poor if their long-term expected income (conditional on their current asset-holding and optimal accumulation behaviour) is less than the discounted present value of future money-metric poverty lines:

$$J^*(\boldsymbol{A}_{0i}) < \underline{J} \tag{3}$$

Carter and May (2001) refer to this threshold as the "Micawber line".[13] Households who find themselves below this threshold, in dynamic poverty, are in a poverty trap from which they are unable to escape. In other words if the household's asset levels are too low, they are unable to accumulate sufficient assets to be upwardly mobile. The dynamic poverty line is therefore a way in which to identify those households who are unable, given their initial endowment of assets, to be upwardly mobile and move out of their current levels of deprivation.

The introducing the concept of an asset poverty line enables a more nuanced way to identify households that are poor. Carter and May (2001) point out that households which are observed to move out of poverty and are usually classified as being transitorily poor (in the sense that they are in poverty in one period and out of poverty the next of *vice* versa) may either be structurally mobile (in the sense that they were able to accumulate the right assets in order to move out of poverty or they suffered the loss of assets from one period to the next) or stochastically mobile (in the sense that they were lucky in receiving positive windfalls which lifted their income above the poverty).

Similarly, households who are traditionally classified as being chronically poor (in the sense that they are in poverty in consecutive periods) may be structurally poor in all time periods (because their asset ownership was below the asset poverty line) or may have experienced multiple income shocks (leading to an income which is below the poverty line in all time periods, even though their asset holding may have been above the asset poverty line in one or all periods).

5. **Breaking down the poverty dynamics of children from 2008 to 2012**

Using this more nuanced definition of poverty, we are able to break down each of the four poverty categories we identified above. In classifying households as being either structurally or

[13] Named after the character in Charles Dickens' book *David Copperfield* who was in poverty but lived in hopeful optimism that things would change in the future.

stochastically poor, we follow the approach of May and Woolard (2007, p. 13). In the first place, the expected level of income, conditional on the household's asset endowment, is estimated using OLS. Using the output from these regressions, the expected levels of income, $\hat{c}(\underline{A})$, are predicted for each household for each year. The results from these regressions are set out in Table 6 below.

Table 6: Regression output for estimating asset poverty

	2008	2010	2012
Number of employed in hh	0.321***	0.423***	0.406***
	(0.006)	(0.006)	(0.005)
Log(subsistence)	-0.679***	-0.752***	-0.712***
	(0.011)	(0.011)	(0.010)
Proportion of hh pension-age	1.288***	1.201***	1.098***
	(0.040)	(0.040)	(0.034)
Poverty in district council	-0.178***	-0.522***	-0.052
	(0.066)	(0.069)	(0.061)
Living Index	0.185***	0.126***	0.166***
	(0.009)	(0.009)	(0.007)
HH lives in rural area	-0.182***	-0.356***	-0.184***
	(0.045)	(0.047)	(0.042)
Mean years of educ in hh	0.061***	0.059***	0.067***
	(0.002)	(0.002)	(0.002)
Proportion of hh children (<18 years in 2012)	-0.143***	-0.041	-0.055**
	(0.030)	(0.030)	(0.026)
HH owns dwelling	0.139***	0.137***	0.124***
	(0.014)	(0.014)	(0.012)
HH owns radio	0.102***	0.132***	0.116***
	(0.012)	(0.012)	(0.012)
HH owns television	0.090***	0.086***	-0.003
	(0.014)	(0.016)	(0.015)
Constant	4.565***	5.125***	4.820***
	(0.089)	(0.089)	(0.077)
N	17600	17600	17600
R-squared	0.504	0.505	0.559

Notes: OLS regressions. Specification also includes provincial fixed effects as well as interaction effects between province and rural. *** p<0.01, ** p<0.05, * p<0.1

The outcome variable is the log of the poverty index. The higher the household income, the larger the log poverty index. We then include controls which we believe meet the definition of "assets" discussed earlier, i.e.in the sense that they are a precondition for households to be able to be able to earn an income above the poverty line.

The variables include the log of the subsistence amount (calculated as R575 times the number of household members – an indication of what level the household's income should be at in order for it to reach subsistence levels)[14]; the number of household members who are employed, the proportion of the household that is of an pension-eligible age (60 for females and 65 for males) in the household; a living index (which is an index measuring the household's access to basic

[14] A control suggested by May and Woolard (2007).

amenities such as flush toilets, running water and electricity); the mean years of education in the household (calculated only for household members older than 16 years); the proportion of children in the household (as a proxy measure for whether the household receives a child support grant); whether anyone in the household owns the dwelling that the household lives in[15] and an indication of whether the households has access to a television or radio (these are proxies for whether the household has access to information which will assist household members with finding employment).

In addition to these variables, the regression also includes a number of controls to capture the spatial variation in poverty in South Africa. We include provincial fixed effects (not reported above) as well as a dummy variable for whether the household resides in a rural area. We also include interactions between these two variables (not reported above). In addition, we include a variable capturing the poverty headcount index of the district council in which the household lives. This is to ensure that we capture all unobserved geographic characteristics which may have a significant impact on the household members' ability to find employment and earn a living which is larger than the poverty line.

The coefficients have the expected signs. Having more members in the household who are employed and have more years of education are positively correlated with a higher income. Asset ownership and access to basic services and amenities are also positively correlated with the household's income. In addition, poverty in the district council and living in a rural area are negatively correlated with income. Having a larger proportion of household members who are of pension-eligible age is positively correlated with higher income, however having more children relative to the household size is negatively correlated with income.

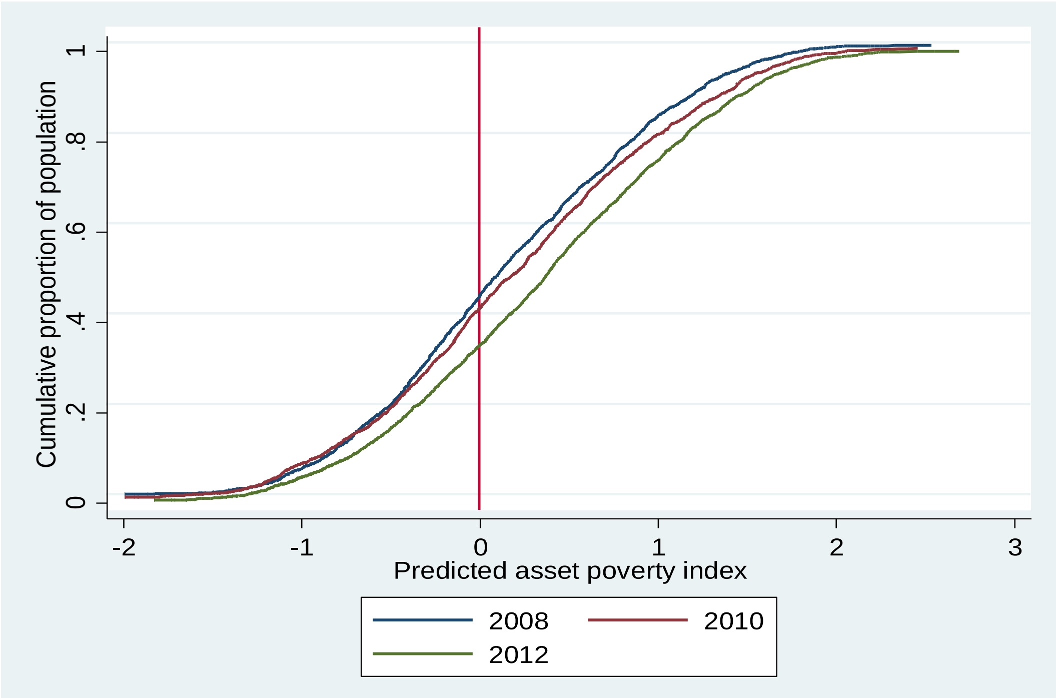
Some sense of the magnitude of asset poverty is provided in Figure 4, which plots the cumulative density of children in households which have been classified as poor using asset poverty as a concept. It is clear to see the decrease in poverty over time, in line with the poverty trend when using income.

From these regressions, we predict each household's asset poverty index, conditional on its actual asset ownership. Since we expect this prediction to be influenced by measurement error, we again follow the approach taken by May and Woolard (2007) and make use of a 80% confidence level around each predicted poverty index, as a robustness check to minimise the impact of measurement error. Accordingly, we only identify a household as being stochastically non-poor if the lower bound of the confidence interval of the predicted poverty index lies above 0 (i.e. the log of 1, which is all instances where the household is earning exactly on the poverty line). Also, a household is only identified as being stochastically poor if the upper bound of its confidence interval lies below 0. For all other cases, where the confidence intervals are both sides of zero, we are unable to classify the household as being either stochastically poor or non-poor based on their asset ownership and we therefore leave these households out of our final sample.[16]

[15] Since there were many households who responded in the affirmative to this question, we only code it as being equal to one if the dwelling is a formal house with brick walls.
[16] In 2008, we lose 3.80% of the 2008 sample of children and in 2012, we lose 3.23% of the 2012 sample of children.

In other words, a household is expected to be poor (lie below the asset poverty line) if we are able to reject $H_0\colon \hat{c}_{it} > \underline{c}$. Conversely, households are classified as non-poor if we are able to reject $H_0\colon \hat{c}_{it} < \underline{c}$.

Figure 4: Predicted poverty using asset index



Using this framework of Carter and May (2001), May and Woolard (2007) assess the prevalence of structural poverty in the province of KwaZulu-Natal between the time period 1993 and 2004, using the KwaZulu-Natal Income Dynamics Study (KIDS).[17] They find that approximately 30% of the sample was structurally poor over the period. We set out the transition matrix for the period 2008 to 2012 using the NIDS data below.

Table 7: Structural and Stochastic poverty 2008-2012

		2012	
		Poor	**Non-Poor**
2008	**Poor**	**41.24% are chronically poor, of which** -5.54% experienced dual entitlement failures*** -Structurally poor ≤ 94.46%	**20.50% got ahead, of which** -26.06% stochastically poor in 2008* -Structurally mobile ≤73.92%
	Non-Poor	**11.73% fell behind, of which:** -52.09% stochastically poor in 2012** -Structurally downward ≤ 47.91%	**26.53% were never poor, of which** -6.39% had benefitted from dual windfalls**** -Structurally never poor ≤ 93.61%

Notes:
* Households for which reject $H_0\colon \hat{c}_{i08} < \underline{c}$.
**Households for which reject $H_0\colon \hat{c}_{i12} < \underline{c}$.
***Households for which reject $H_0\colon \hat{c}_{i08} < \underline{c}$ and reject $H_0\colon \hat{c}_{i12} < \underline{c}$.
****Households for which reject $H_0\colon \hat{c}_{i08} > \underline{c}$ and reject $H_0\colon \hat{c}_{i12} > \underline{c}$.

[17] In many ways the predecessor of the NIDS data.

Now using the asset-poverty framework, we are able to further break these sub-samples down into those children who were stochastically poor and those who were structurally poor. Of the children who were observed to be chronically poor (poor in both periods), there is a small proportion (5.54%) who were not expected to be in poverty, given the asset ownership of their households. These children live in households where the income was below the poverty line in both periods, not because of their inability to generate more income, but because they suffered dual entitlement failures. We estimate an upper bound of 94.46% who are in structural poverty (i.e. expected to be poor in at least one or both period). It is these 94.46% children who have the greatest risk of being in dynamic poverty or in a poverty trap, which they will not be able to escape over time.

Calculating the number of children affected by structural poverty, we find that 38.96% of children in our sample were structurally poor during the period 2008 to 2012, whereas 24.83% of the sample was structurally non-poor. Of the remaining sample, 15.15% of the children were structurally upward mobile and 5.62% of them were structurally downward mobile. These statistics are summarised in Table 8.

Table 8: Structural versus stochastic poverty summarized

		2012	
		Poor	**Non-Poor**
2008	**Poor**	38.96% structurally poor * 2.28% stochastically poor	15.15% structurally mobile (upward)* 5.34% stochastically mobile
	Non-Poor	5.62% structurally mobile (downward)* 6.11% stochastically mobile	24.83% structurally non-poor* 1.70% stochastically non-poor

Notes: *Upper bound.

In comparison to the results by May and Woolard (2007), we find a larger proportion of the sample to be in structural poverty. However, given that we are only focussing on the sub-sample of children, and the fact that children are generally from more deprived households, this result is not surprising.

The next question of interest is to find out more about these children who were dynamically poor, i.e. the children who were observed to be in structural poverty in both 2008 and 2012 and were therefore in a poverty trap. In order to explore the differences between children who were in a poverty trap and those who were chronically poor (i.e. observed to be below the poverty line in 2008 and 2012) but not structurally poor (i.e. were observed above the asset poverty line), we calculate the mean and standard error per group. These statistics are set out in Table 9. We also report the t-statistic in order to highlight statistically significant differences.

Table 9: Children in structural chronic poverty versus children in stochastic chronic poverty 2008-2012

	Children in structural chronic poverty (trapped in poverty) Mean (standard error)	Children in stochastic chronic poverty Mean (standard error)	T-stat
Initial conditions 2008			
HH per capita monthly income	285.66 (2.30)	391.27 (10.00)	9.78
HH per capita monthly expenditure	268.44 (3.52)	491.57 (24.84)	13.09
Asset index of hh	-0.85 (0.01)	0.02 (0.04)	14.90
Crowding in hh (>2 persons per room)	0.46 (0.01)	0.33 (0.04)	-3.08
Mean subjective well-being in hh (scale from 1 to 10)	4.71 (0.04)	5.07 (0.18)	2.01
HH size	7.37 (0.06)	5.51 (0.25)	-6.67
HH has insurance =1 if yes	0.39 (0.01)	0.46 (0.04)	1.68
Proportion of hh children	0.48 (0.00)	0.43 (0.01)	-4.00
Proportion of hh pensioners	0.05 (0.00)	0.03 (0.01)	-1.96
Mean age of hh	20.20 (0.10)	21.22 (0.53)	2.11
Number of employed in hh	0.78 (0.02)	1.54 (0.11)	8.97
Mean years of education in hh	6.28 (0.05)	9.17 (0.17)	12.20
Female-headed hh	0.56 (0.01)	0.62 (0.04)	1.25
Rural hh	0.79 (0.01)	0.48 (0.04)	-9.08
Poverty head-count in district	0.51 (0.00)	0.43 (0.01)	-7.56
HH owns dwelling	0.36 (0.01)	0.54 (0.04)	4.45
HH owns TV	0.48 (0.01)	0.84 (0.03)	8.56
HH owns radio	0.62 (0.01)	0.72 (0.04)	2.31
HH experienced at least one shock in last 24 months (self-reported)	0.24 (0.01)	0.30 (0.04)	1.26
HH received grants==1 if yes	0.88 (0.01)	0.77 (0.04)	-3.88
Mother's education	7.27 (0.07)	9.61 (0.22)	2.97
Child stunted ==1 if yes	0.16 (0.01)	0.13 (0.03)	-0.99
Child hunger = 1 if often or always	0.34 (0.01)	0.21 (0.03)	-3.22
Child ill (3 days in last month, self-reported)	0.08 (0.00)	0.11 (0.03)	1.18
Child repeated a grade=1 if yes	0.27 (0.01)	0.18 (0.04)	-1.76
Child double orphaned	0.03 (0.00)	0.04 (0.02)	0.96
Black African child	0.94 (0.00)	0.87 (0.03)	-3.36
Changes from 2008-2012			
Change in number of pensioners in hh	0.01 (0.01)	-0.06 (0.04)	-1.42
Change in hh size 2008-2012	0.58 (0.18)	0.27 (0.06)	1.17
Child moved households between 2008 and 2012 ==1 if yes	0.13 (0.01)	0.17 (0.03)	1.27
Change in number of employed in hh	-0.22 (0.02)	-0.45 (0.09)	-2.47
HH experienced at least one shock in period 2008-2012 (self-reported)	0.37 (0.01)	0.41 (0.09)	0.55
Observations	**3 155**	**150**	

As expected, the initial conditions in the households of children in 2008 already diverged depending on whether the household was in structural or stochastic poverty. The households of children who were in structural poverty were significantly poorer in terms of asset-ownership, income and expenditure measures. In addition, these children were living in more crowded conditions, with more individuals per household and in younger households where there were significantly more children and pension-age individuals. Household members of these children who were in a structurally poor household were less educated and less likely to be employed. They were also less likely to have access to insurance. In addition, these children were more likely to live in rural areas. All of these factors took their toll on the household's average levels of satisfaction with life, which were significantly lower than that of households that were stochastically poor.

The children in these structurally poor households also had mothers who are less educated on average. Deprivation had already taken its toll on these children when they were observed in 2008. They were more likely to report being hungry, and more likely to be stunted and to have repeated a grade (although these last two differences are not significant). However, there was no indication that these children were more likely to be ill, given the measure of self-reported health (which has its own problems, as it is often closely linked to expectations which are highly correlated with wealth).

In terms of the movements between 2008 and 2012, children in households who were structurally poor were significantly less likely to move over the period than children in households who were stochastically poor. This fact, in addition to the fact that these structurally poor households had an increase in pension-age members (whereas in households who were stochastically poor there was a decrease in pension-age members), provides some indication that there might be some form of household formation which is correlated with the poverty status of the household.

Using these descriptive statistics, some additional insights into the characteristics of these households who are trapped in poverty can be gleaned. It is clear that these households are the most vulnerable and that children make up a large proportion of these households. However, in order to obtain more robust estimates of the potential causes, a more robust analysis is required.

6. The determinants of welfare change over time

Although the analysis above provides additional information about the household conditions of these dynamically poor children who were trapped in poverty between 2008 and 2012, we cannot make any causal inference from these comparisons without using a more robust technique. In order to be able to make conclusions about the possible causes of the existence of a poverty trap, it is necessary to look at the determinants of welfare changes over time. In other words, we need to identify the causal mechanisms through which some households change their income so as to escape the poverty trap over time in order to highlight the binding constraints precluding other households from escaping poverty.

Woolard and Klasen (2005) explore the determinants of welfare changes in more detail and classify these as being either economic events or demographic events, broadly speaking. In their analysis, they find several potential characteristics which are more prevalent under households that display no mobility over time. These characteristics are accordingly highlighted as being correlated with households that find themselves in a poverty trap. These include large initial household sizes, especially households with many children (a so-called “demographic poverty trap”). Also, Woolard and Klasen (2005) find that low initial levels of education in the household are typically associated with low levels of mobility over time. Third, low initial levels of assets are also associated with a higher likelihood of remaining poor. Fourth, households with low initial levels of employment within the household were also associated with remaining in poverty rather than escaping poverty. All of these factors have an especially negative impact on the well-being of children and influence children directly.

Before we use regression analysis to decompose the causes of poverty traps further, we start out by comparing the four groups of households, as identified above. Table 10 compares some initial household characteristics in 2008 and then again some changes which took place between 2008 and 2012.

By merely comparing the means of each of these groups, it is clear to see how much more deprived and vulnerable children are within the three groups of households who have been exposed to a period of poverty compared with the group who has never been in poverty. Income, expenditure and asset ownership are less. Households are larger and with more children. Households are more likely to be female-headed and reside in rural areas. In addition, the education levels of these household members are much lower and consequently labour market prospects much less, as evidenced by the small number of employed individuals in these households.

In addition, some of the changes in poverty status seem to correlate with changes in household circumstances. For example, children in households who got ahead and moved out of poverty over the period had a greater loss of household members. In addition, these households managed to increase the number of employed individuals in the household.

In order to explore the spatial elements of poverty, we also include the mean headcount ratio of the districts for each of the four groups. Clearly, those children in chronically poor households were living in districts which were more deprived than the other three groups. In the Appendix, we take a closer look at the distribution of child poverty across the various provinces. Child poverty seems to be highest in KwaZulu-Natal, the Eastern Cape province and Limpopo.

Table 10: Descriptive statistics per poverty category

	Chronically poor (poor in 2008 and 2012) Mean (standard deviation)	Non-poor (non-poor in 2008 and 2012 Mean (standard deviation)	Fell behind (poor 2008 and non-poor 2012 Mean (standard deviation)	Got ahead (non-poor in 2008 and poor in 2012 Mean (standard deviation)
Initial conditions 2008				
HH per capita monthly income	290.44 (128.89)	1814.73 (2146.05)	1062.86 (937.19)	339.74 (135.33)
HH per capita monthly expenditure	278.53 (205.89)	1535.87 (2100.59)	752.81 (1179.84)	396.10 (345.79)
Asset index of hh	-0.81 (0.71)	0.50 (0.87)	-0.21 (0.83)	-0.33 (0.76)
Crowding in hh (>2 persons per room)	0.46 (0.50)	0.17 (0.37)	0.25 (0.43)	0.35 (0.48)
Mean subjective well-being in hh (scale from 1 to 10)	4.73 (2.08)	6.17 (1.93)	5.35 (1.91)	5.24 (2.12)
HH size	7.29 (3.31)	5.30 (2.28)	6.03 (2.64)	6.67 (3.32)
HH has insurance =1 if yes	0.40 (0.49)	0.72 (0.45)	0.55 (0.50)	0.47 (0.50)
Proportion of hh children	0.48 (0.15)	0.38 (0.14)	0.41 (0.15)	0.43 (0.15)
Proportion of hh pensioners	0.05 (0.08)	0.05 (0.11)	0.08 (0.12)	0.05 (0.10)
Mean age of hh	20.25 (5.71)	24.90 (6.80)	24.20 (6.87)	22.12 (6.40)
Number of employed in hh	0.81 (1.02)	1.55 (1.05)	1.31 (1.14)	0.78 (0.88)
Mean years of education in hh	6.41 (2.85)	9.46 (3.03)	7.69 (2.74)	7.35 (2.73)
Female-headed hh	0.57 (0.50)	0.36 (0.48)	0.53 (0.50)	0.52 (0.50)
Rural hh	0.78 (0.42)	0.32 (0.47)	0.57 (0.50)	0.61 (0.49)
Poverty head-count in district	0.51 (0.13)	0.37 (0.15)	0.44 (0.15)	0.46 (0.14)
HH owns dwelling	0.36 (0.48)	0.67 (0.47)	0.56 (0.50)	0.51 (0.50)
HH owns TV	0.50 (0.50)	0.86 (0.35)	0.72 (0.45)	0.70 (0.46)
HH owns radio	0.63 (0.48)	0.71 (0.46)	0.70 (0.46)	0.67 (0.47)
HH experienced at least one shock in last 24 months (self-reported)	0.24 (0.60)	0.27 (0.64)	0.27 (0.56)	0.27 (0.60)
HH received grants==1 if yes	0.87 (0.34)	0.52 (0.50)	0.84 (0.37)	0.81 (0.39)
Mother's education	7.37 (3.75)	10.27 (3.04)	9.13 (3.17)	8.60 (3.41)
Child stunted ==1 if yes	0.16 (0.37)	0.10 (0.30)	0.12 (0.33)	0.14 (0.34)
Child hunger = 1 if often or always	0.34 (0.47)	0.09 (0.28)	0.19 (0.39)	0.24 (0.43)
Child ill (3 days in last month, self-reported)	0.08 (0.28)	0.10 (0.30)	0.08 (0.26)	0.08 (0.27)
Child repeated a grade=1 if yes	0.27 (0.44)	0.19 (0.39)	0.20 (0.40)	0.22 (0.41)
Child double orphaned	0.03 (0.17)	0.03 (0.16)	0.04 (0.19)	0.03 (0.18)
Black African child	0.94 (0.25)	0.67 (0.47)	0.85 (0.36)	
Changes from 2008-2012				
Change in number of pensioners in hh	0.01 (0.55)	0.01 (0.47)	-0.04 (0.57)	-0.02 (0.53)
Change in hh size 2008-2012	0.29 (3.08)	-0.01 (1.86)	0.02 (2.43)	-0.51 (2.90)
Child moved households between 2008 and 2012 ==1 if yes	0.13 (0.34)	0.17 (0.37)	0.19 (0.40)	0.22 (0.42)
Change in number of employed in hh	-0.23 (1.08)	-0.16 (1.11)	-0.38 (1.30)	0.64 (1.15)
HH experienced at least one shock in period 2008-2012 (self-reported)	0.37 (0.74)	0.38 (0.69)	0.28 (0.62)	0.36 (0.72)
Observations	3 305	1 451	790	1 412

In order to explore the potential causes of poverty dynamics in a more robust way, we run two regressions using the change in the log of per capita income as the outcome variable. In this way, we are able to capture both the economic (income) and demographic (household size) impacts identified by Woolard and Klasen (2005). The results from these regressions are reported in Table 11.

Table 11: OLS regression on income changes 2008-2012

	(1) OLS Change in log (Income per Capita) between 2008 and 2012	(2) Pooled OLS Change in log (Income per Capita) between 2008-10 and 2010-12
Ln (Income per Capita in last wave)		-0.628***
Ln (Income per Capita in 2008)	-0.668***	
Female household head	-0.035	-0.075***
Years of education household head	-0.047***	-0.037***
Years of education squared household head	0.007***	0.006***
Age household head	0.008***	0.007***
Urban	0.022	0.021
Coloured	0.059	0.025
Indian	0.380***	0.312***
White	0.440***	0.362***
Household head employed	0.277***	0.313***
Number of household residents	-0.034***	-0.038***
Share of elders	0.159**	0.173***
Share of children	-0.814***	-0.685***
Household moved	0.096**	0.056
Living index in last wave		0.133***
Living index in 2008	0.066***	
HH received grants in last wave		-0.234***
HH received grants in 2008	-0.323***	
HH got new grants	-0.207***	-0.118***
Change in number of workers in HH	0.174***	0.186***
Change in household size	-0.048***	-0.061***
Year 2010		-0.102***
Constant	4.723***	4.250***
Observations	5 799	11 291
R-squared	0.540	0.457

*** p<0.01, ** p<0.05, * p<0.1

We also include a list of control variables which may be roughly divided into four categories, in order to test four hypotheses of the causes of changes in income which we have. We discuss each of these hypotheses below, as well as the conclusions regarding the hypotheses to be drawn from the regression analysis.

6.1. **Convex returns to education**

In the first place, poverty theory postulates that individuals are poor because they (or their parents) couldn't invest enough in education. In the presence of convex returns to education, educational attainment needs to exceed a certain threshold in order to alleviate poverty. South African labour market is highly segmented with excess demand for high-skill and a large excess supply of low-skill workers (Özler, 2007, p. 489). Therefore, such convex "returns" are very likely to occur. The results of our regression analysis indeed show significant convex returns to education, captured by the inclusion of the education and education squared variables for the household head, as a proxy of the education levels for the rest of the household members. A threshold of 7 years of education needs to be exceeded to gain significant, positive returns to education.

6.2. **A lack of productive assets**

Following the established literature, inadequate access to financial services (formal loans, savings and insurance), as well as low savings and assets, are a classic example for possible poverty traps. Using the Cape Area Panel Study data, Adato et al (2006), identify a dynamic asset poverty threshold, below which households are expected to collapse toward a low-level poverty trap. The results of the regression in Table 11 indeed show that the asset index of the last period is highly significantly correlated with positive income change.

6.3. **Access to the labour market**

The labour market is identified by many authors (Leibbrandt, et al., 2010) as a key driver of inequality in South Africa because of a different development in wages for skilled as compared to less-skilled workers (Agüero, et al., 2007, p. 808). Moreover, in their study Woolard and Klasen (2005) identify poor initial participation on the labour market as one of four poverty traps in South Africa. Table 11 confirms the importance of the labour market. Having an employed household head as well as the change in number of workers in the household are significant positive factors explaining income change.

6.4. **Household formation**

Woolard and Klasen (2005) highlight the importance of household formation explaining poverty traps in South Africa. Therefore, we have included several variables testing the impact of household composition. As expected the household size as well as the change in household size have a significant negative impact on income growth. Interesting is the finding that receiving grants in 2008 or getting a new grant in-between 2008 and 2012 also has a negative impact on income change. Woolard and Klasen (2005) explain this finding by the observation that unemployed attach themselves to household's with old age pensions even though this disadvantage them in terms of finding a new job in the long run. On the other hand, the share of pension-age individuals has a positive coefficient and the share of children in a household a negative one. Hence, having too many children in the household can lead to some kind of poverty traps whereas older people and their income can have a positive growth effect.

7. **Robustness check: Measurement error in NIDS**

While progress in poverty alleviation is important, it remains unclear just how much these dynamics are affected by measurement error. It is well known that the collection of income and consumption data in household surveys is often very imprecise. In case of individual heterogeneity and measurement error a dynamic panel model will always be biased and giving wrong estimates of income mobility. In other words "[…] measurement error in initial income contributes to an apparent negative correlation between base-year income and subsequent income change" (Fields, et al., 2003, p. 87).

The risk of a strong tendency of a regression towards the mean in panel data-sets is highlighted by Woolard and Klasen (2005). That means that a significant number of poor households appear to have a noteworthy share of mobility. This is in line with most existing studies, suggesting that income mobility in developing countries is higher than in industrialized countries, especially at the bottom end of the distribution (Woolard & Klasen, 2005, p. 869). Yet, to make a valid statement on income mobility one has to take the measurement error into account, a problem all of the previous studies have highlighted. Fields et al. (2003), for example, argue that measurement errors are a serious concern in developing countries. A finding that is supported by most studies using panel data estimates of income (Antman & McKenzie, 2007). Following Agüero et al. (2007), the problem is that when income or expenditure are measured with errors, the observed data are "noisy". This means that stable households that did not really change their economic position may appear to change their position because of measurement error.

Following a methodology introduced by Glewwe (2011) to uncover the degree of measurement errors, Agüero et al. (2007, p. 796) note that measurement error could account for up to 60% of mobility between 1993 and 1998 in KIDS. Furthermore, Woolard and Klasen (2005) observed very huge differences in welfare trends when comparing income and expenditure measures. These discrepancies are an indication that measurement error indeed plays an important role when looking at income changes over time. To our knowledge, there have been no studies observing income convergence and the effect of measurement error for NIDS. In this part of our study, we use some instrumental approach to determine how much of the observed mobility is caused by measurement error. Using this method we can then predict a lower bound for the poverty dynamics in NIDS.

7.1. **Methodology**

This section briefly describes the econometric approach to estimate income measurement error using the NIDS panel data-set. This largely follows existing studies that have highlighted the problem of measurement error when dealing with income estimations (Fields et al., 2003; Woolard and Klasen, 2005). A natural starting point for the analysis is the true income Y^*_{it} which is not observable. Instead, only self-reported income Y_{it} is available which is potentially biased by ε_{it} which can be expressed as:

$$Y_{it} = Y^*_{it} + \varepsilon_{it} \qquad (4)$$

The measurement error is particularly problematic for estimating income dynamics when it occurs in the initial year because it can produce a spurious negative association between reported base year income and the measured income change (Fields, et al., 2003). When the true relationship between the initial income and income change is negative, it implies that true income might be converting towards the overall mean (Fields, et al., 2003). However, when measurement error contributes to the negative relationship it causes an overestimation of the true effect or, in other words, a downwards bias of the initial income coefficient, falsely leading to the conclusion that there is less persistence in the income process that there actually is (Antman & McKenzie, 2007). To deal with this problem Antman and McKenzie (2007) propose using the lagged income variable $Y_{i,t-2}$ instead of the basic year income $Y_{i,t-1}$. In the absence of autocorrelation in the measurement error this approach will give consistency. Yet, since we are interested in the full time period 2008 to 2012 we cannot use the second lag of income as an instrument. Instead we will use the asset index of 2008 as an instrument for basic year income $Y_{i,t-1}$. The resulting IV regression has the following form:

$$\Delta Ln\ (Income\ per\ Capita)_{i,t} = \alpha + \beta_1 X_{it} + \beta_2 \Psi_{it} + \beta_3 * ln(Asset\ index)_{i,t-1} + \varepsilon_{it} \tag{5}$$

The IV first stage regression shows that the instrument has a significant effect at a 1% level on initial income (as shown later in column 2 of Table 12). Second the weak identification test rejects the H_0 hypothesis that initial income is not adequately instrumented on a 1% level. Therefore, it can be assumed that ln(Asset Index)$_{i,t-1}$ is a valid instrument.

7.2. **Results**

Table 12 shows the results for the classic linear panel model in column (1). Columns (2) and (3) give the first and second stage of the IV regression for the period 2008-2012. All control variables show the expected sign and are mostly highly significant, as discussed in section 6. For the classic linear panel model the initial income variable is highly significant and has a strong negative impact on income change. The outcome of this naïve estimator implies that those with one unit higher log initial income in 2008 experience 66.8% lower log of income change. However, using the IV approach results in a significantly lower coefficient, which highlights the problem of measurement error and suggests that such error leads to an overestimation of mobility and convergence.

Using the predicted income changes from the IV regression we can then estimate the poverty dynamics controlling for measurement error. Comparing the predicted versus the observed numbers in Figure 5 confirms that fewer households actually change their poverty status. While the naïve estimate was that 20.5% of children moved out of poverty in the period, the estimate is only 10.8% allowing for measurement error. Furthermore, using the predicted income changes we find that 37% of all children are never poor, which is significantly higher than the initial estimate of 26.5%. The percentage of children that are chronically poor does not, however, change significantly and remains at 43.7% (41.2% previously).

Finally, the trend in poverty decline might also be overestimated using the initial estimates. Using our new estimation we predict a poverty rate of 54.5% poor in 2008 and 52.2% in 2012 (for those we can predict their income).

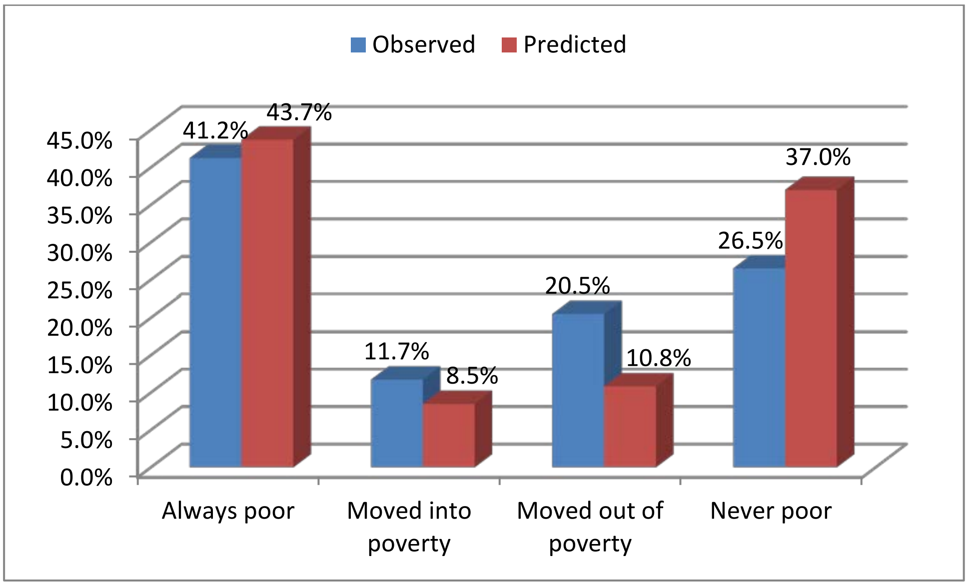
In conclusion, using an IV approach and estimating income changes allowing for measurement error we find significant less income mobility. While about the same number of children is classified as chronically poor, we estimate 63% of children being poor at some point in time versus 73.5% using the old calculations.

Table 12: Income Convergence and measurement error in NIDS

	(1) OLS	(2) IV 1st stage	(3) IV 2nd stage
	Change in log (Income per Capita) between 2008 and 2012	**Change in log (Income per Capita) between 2008-10 and 2010-12**	**Change in log (Income per Capita) between 2008 and 2012**
Ln (Income per Capita in 2008)	-0.668***		-0.362***
Female household head	-0.035	-0.129***	0.004
Years of education HH head	-0.047***	-0.029**	-0.033***
Years of education squared HH head	0.007***	0.005***	0.005***
Age household head	0.008***	0.009***	0.005***
Urban	0.022	-0.027	0.032
Coloured	0.059	0.170***	-0.042
Indian	0.380***	0.496**	0.142
White	0.440***	0.516***	0.151
Household head employed	0.277***	0.365***	0.163***
Number of household residents	-0.034***	-0.093***	-0.011
Share of elders	0.159**	0.217**	0.115
Share of children	-0.814***	-0.273***	-0.733***
Household moved	0.096**	-0.065	0.111**
Living index in 2008	0.066***	-0.192***	-0.028
HH received grants in 2008	-0.323***	-0.246***	-0.220***
HH got new grants	-0.207***	-0.159***	-0.148***
Change in number of workers in HH	0.174***	-0.247***	0.254***
Change in household size	-0.048***	0.127***	-0.084***
Asset index in 2008		0.659***	
Constant	4.477***	6.633***	2.546***
Observations	5,799	5,799	5,799
R-squared	0.539	0.628	0.482

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Figure 5: Predicted and observed poverty change (NIDS 2008-2012)



8. Conclusion

In this paper we set out to examine the poverty dynamics of children in South Africa over the period 2008 to 2012. For this purpose, we have made use of three waves of the NIDS data. We find that child poverty has decreased over the period and that in 2012, only 51% of children in our sample were observed to be in poverty.

We further break down the poverty dynamics by using the theoretical framework first developed by Carter and May (2001). Using the concept of an asset poverty line, we are able to identify households who were in chronic poverty not because of changes in their income, but because their asset endowment was so low that they were not able to escape the poverty trap. Using this approach, we estimate that almost 40% of the children in our sample found themselves in this structural poverty trap between 2008 and 2012. As expected, these children have suffered as a result of this deprivation, even in comparison to their peers who have also been chronically poor over the period, but were living in households with access to more assets

We further explore the characteristics of these households and then proceed to make use of regression analysis to identify the main causes of a poverty trap. In line with Woolard and Klasen (2005), we identify low initial levels of education, low asset-holdings, low initial employment and adverse household formation as possible causes of these poverty traps.

Last, we control for measurement error which may affect the poverty estimates by using an instrumental variables approach. Correcting for measurement error reduces our initial estimates of the number of children who were living in households where they moved into or out of poverty over the period. However, it does not significantly affect our initial estimates of the percentage of children who were living in chronically poor households for whom there was no escape from the poverty trap.

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Appendix

Table 13: Distribution of structurally poor children by province in 2012

Province	Percentage structurally poor per province
Western Cape	4.43%
Eastern Cape	22.04%
Northern Cape	1.31%
Free State	4.18%
KwaZulu-Natal	31.38%
North West	6.03%
Gauteng	6.90%
Mpumalanga	6.13%
Limpopo	17.60%
Total	**100**

Table 14: Distribution of poverty status of children by province in 2012

	Chronically poor (poor in 2008 and 2012)	Non-poor (non-poor in 2008 and 2012)	Fell behind (poor 2008 and non-poor 2012	Got ahead (non-poor in 2008 and poor in 2012	Total
Western Cape	21.56%	50.95%	11.71%	15.77%	100
Eastern Cape	55.99%	16.54%	12.34%	15.14%	100
Northern Cape	28.17%	38.94%	15.44%	17.45%	100
Free State	34.79%	32.49%	10.69%	22.02%	100
KwaZulu-Natal	55.41%	15.00%	8.65%	20.94%	100
North West	33.21%	36.75%	10.54%	19.50%	100
Gauteng	20.01%	41.06%	17.29%	21.64%	100
Mpumalanga	36.59%	22.99%	12.43%	28.00%	100
Limpopo	51.49%	15.61%	9.22%	23.68%	100
Total	**41.24%**	**26.53%**	**11.73%**	**20.50%**	**100**