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The dynamics of poverty in South Africa

by
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Abstract

We analyse the determinants of South Africans moving into and out of poverty over the first four waves of the National Income Dynamics Study (NIDS) for the years 2008 to 2014/2015. The first descriptive sections of the study focus on the balanced panel of NIDS respondents and find that a relatively high poverty exit rate was accompanied by a substantial proportion of the population being trapped in severe poverty. The roles of demographic versus income changes over time reveal that changing household composition is the largest trigger of poverty entry and exit, and that increasing income from government grants is the main trigger precipitating poverty exit for about one quarter of our sample. We then estimate an endogenous switching model that controls for initial conditions and selective attrition on the full sample of respondents in order to better understand what traps South Africans in poverty. We find that ignoring the correlations between the unobservables affecting initial conditions, sample retention and poverty transitions can lead to substantially biased results, and that there is significant genuine state dependence underlying poverty dynamics. This has important policy implications, as preventing people from falling into poverty in the first place is likely to yield greater returns that targeting the individual correlates of poverty directly.

I Introduction

There is general consensus that the extent of money-metric poverty in South Africa has declined over the last decade and a half. Various cross-sectional studies of poverty using household survey data have chronicled a decline in the poverty headcount that is largely attributable to the role of state support of household incomes (Leibbrandt et al., 2010; Bhorat et al., 2012; Leibbrandt et al., 2012; Leibbrandt and Levinsohn, 2016). However, far less is known about contemporary poverty dynamics in the country.

In the current South African policy milieu there is a rising emphasis on understanding how and why people enter and exit poverty. The aim of this chapter is to investigate the dynamics of poverty in South Africa using the first four waves of the National Income Dynamics Study (NIDS). The focus is on absolute, rather than relative, poverty transitions. In this chapter absolute poverty refers to using absolute poverty lines when analysing poverty dynamics. That is, a line is chosen that is agnostic both to how many people are above or below it, and to its position in the distribution of income. This line is held constant in real terms over the different years for which data are available. A relative poverty line (for example some fraction of mean or median income) is not used. The use of an absolute rather than a relative poverty line is preferred as it is based on a cost-of-basic-needs approach, which attempts to quantify the minimum amount of household per capita income required to cover basic food and non-food costs. This is thought to be more informative than a relative line such as 50% of the median, given how unequal South African society is, and given the large proportion of South Africans who fall below any reasonably defined absolute poverty line. Furthermore, the focus on absolute rather than relative poverty lines is in keeping with much of the preceding poverty literature in South Africa, and allows for a more natural comparison with previous findings. One of the key features of NIDS is the ability to model these dynamics of poverty over time. We are less interested in describing cross-sectional poverty and more interested in understanding the extent of movements into and out of poverty, who is making these transitions and the reasons for these changes.

This chapter has two distinct sections. In the first we present a wide-ranging descriptive analysis of poverty in South Africa using the balanced panel sample of respondents from the first four waves of NIDS. In doing so we uncover how much absolute mobility (both upwards and downwards) was experienced by balanced sample members between 2008 and 2014/2015. We also document the poverty-time interaction by breaking down poverty into chronic and transitory components. In the second section we move beyond the simple enumeration of poverty by shifting our focus to an econometric analysis of welfare dynamics using the full sample available to us over the four waves of NIDS. In doing so, the focus changes from an analysis of four wave poverty transitions using the balanced panel to an analysis of transitions using a pooled dataset of all respondents. Our modelling strategy allows us to model poverty dynamics while controlling for initial conditions and non-random attrition. It also allows us to separate genuine state dependence from aggregate state dependence, and this has potentially important policy implications.

This chapter contributes to the existing South African literature by being the first to use nationally representative data to study changes in money-metric welfare over this extended time period. It also takes seriously the questions of how to model these dynamics. This means being cognizant of two phenomena that need to enter our estimation. First, we ask how important is state dependence - whether or not an individual is initially poor or non-poor - in determining poverty dynamics. Second, we ask how important is selective attrition in our panel sample in determining poverty dynamics. It is also the first South African study that attempts to separate genuine state dependence from aggregate state dependence - that is, it measures the relative importance of initial poverty status versus individual-level unobserved heterogeneity in driving dynamics.

Section II of this chapter follows Finn and Leibbrandt (2016) by briefly outlining the South African literature on poverty dynamics,[1] and section III discusses the data and weights used in the first part of the analysis. Section IV develops a number of univariate and multivariate measures of poverty transitions, with inter-wave poverty entry and exit being treated separately. Section V elicits the relative contributions of trigger events that are associated with poverty transitions. The chapter shifts focus to a Markovian model of poverty transitions in section VI, while section VII provides some concluding remarks.

II The South African literature on poverty dynamics

Although there have been many studies of cross-sectional poverty in South Africa since the end of apartheid (see Finn, Leibbrandt and Ranchhod (2014) for a short review), there is a relative paucity of literature using panel data to analyse transitions. The best known study of poverty dynamics in post-apartheid South Africa is Carter and May (2001). The authors use the first two waves (1993 and 1998) of the KwaZulu-Natal Income Dynamics Study (KIDS) to decompose poverty transitions into what they term ‘structural’ and ‘stochastic’ components, using a sample of approximately 1 200 African households in the KwaZulu-Natal province. The authors find a significant increase in poverty rates in African households in the province, and also find that the economic processes driving poverty dynamics served to increase inequality. That is to say, upward economic mobility was stronger for those at the top of the income distribution than it was for those at the bottom. The authors find that approximately one fifth of the sample was poor in both 1993 and 1998, with a further 35% transitorily poor (that is, poor in at least one wave).

[1]The working paper cited undertakes an earlier analysis of some of the transitions contained in the first section of this chapter, but with only the first three waves of NIDS. This chapter extends that analysis by considering data and transitions over a longer period of time, and by explicitly modelling poverty transitions over the 2008 to 2015 period in a Markovian framework.

Woolard and Klasen (2005) also use the first two waves of KIDS to model the determinants of mobility and poverty transitions for just over 1 000 African households in KwaZulu-Natal. The authors identify the main event associated with a transition into or out of poverty in a univariate sense. These events are themselves split into demographic (household composition) changes and income changes. It is found that about one quarter of transitions into and out of poverty are due to demographic effects. The most important income effect for transitioning into poverty is the household head losing a job, while the most important income event for transitioning out of poverty is another household member finding employment. The importance of demographic effects is confirmed in a multivariate regression analysis, though the sample sizes are quite small with 129 households entering poverty and 223 households exiting poverty over the two waves.

Agüero et al. (2007) add the third (2004) wave of KIDS to the study of dynamics. Parts of the paper are a natural update to Carter and May (2001), as the third wave is added as a new data point. The authors complement the income analysis by calculating poverty rates using expenditure data, though there are some serious misgivings about using the 1993 expenditure data (see Leibbrandt et al. (2010)). The study finds that access to basic household services improved significantly between 1993 and 2004, and this improvement is in contrast to the backward steps taken on the poverty front in the mid-1990s. Finally, the authors highlight the importance of government grants and, particularly, the child support grant, in shifting the bottom of the income distribution to the right, and find that the impact of grants as inequality reducers increased over time.

Finn et al. (2013) use the first two waves of NIDS to explore absolute and relative transitions over the 2008 to 2010/2011 period. They find that almost three quarters of those who were below the poverty line in 2008 were still below it in 2010/2011. This equates to approximately 34% of the total sample being poor in both waves for their poverty line. Poverty exits slightly outweighed poverty entries over the period, and this resulted in a small fall in the national poverty headcount ratio.

Finally, Finn and Leibbrandt (2013) expand on this previous study by adding a third wave to the analysis. They find that although the rate of exiting poverty was higher between waves 2 and 3 than between waves 1 and 2, a large percentage of the South African population was trapped in severe poverty (defined as living in a household with income per capita of less than half the poverty line) in all three waves. They also document that the reduction in non-money-metric (multidimensional) poverty was significantly larger than the concurrent reduction in income poverty over the period.

III Data and summary statistics of the balanced panel

The data used in this part of the chapter come from the first four waves of NIDS, covering 2008-2014/15 (SALDRU, 2016*a*,*b*,*c*,*d*). The four waves of NIDS were collected in 2008, 2010/2011, 2012 and 2014/2015, respectively. NIDS is a nationally representative longitudinal dataset of individuals. Respondents are tracked over time, even if they change residence. In order to be considered a resident member of a household, an individual must usually reside in a dwelling unit for at least four nights a week, and must share food and resources from a common source with other household members. As the focus in this first part of the chapter is on describing poverty dynamics and transitions, the analysis is restricted to the balanced panel – those for whom we have complete interview data in all four waves.[2]

Although the focus of this chapter is on the use of micro data to understand poverty transitions, it should be noted that South Africa's macroeconomic environment between 2008 and 2015 was not conducive to the reduction of poverty. Table 1 presents GDP and GDP per capita numbers as well as their growth rates for the country covering the same period as the first four waves of NIDS. The effect of the recession which lasted from the final quarter of 2008 until the end of the second quarter of 2009 is clear, with GDP per capita shrinking by 2.7% in 2009. Even though the recession technically ended in 2009, growth rates thereafter were generally quite low and were barely above zero during the collection of the fourth wave of data. Trends in unemployment over the same period were equally concerning. Essers (2017) shows how unemployment increased as a result of the recession and remained high at least until the end of wave 3, and this was driven by reduced inflows of workers into jobs, rather than increase outflows of workers from jobs. The post-apartheid trend of the economy shedding low skilled jobs continued over the late 2000s and early 2010s, and the labour market failed to pull poor households into employment (Leibbrandt et al., 2016).

[2]The sample includes adults and children for whom we have interview information in all four waves. For children aged 0 to 14 a child questionnaire is administered to the mother or primary caregiver of the child, or to another household member who is knowledgeable about the child. An adult questionnaire is administered directly to respondents who are aged 15 and above.

Table 1: Macroeconomic trends in South Africa: 2008 to 2015

Year	GDP (ZAR million)	GDP growth (%)	GDP per capita	GDP per capita growth (%)
2008	2 708 600	3.2	54 322	1.9
2009	2 666 939	-1.5	52 838	-2.7
2010	2 748 008	3.0	53 823	1.9
2011	2 838 258	3.3	54 968	2.1
2012	2 901 076	2.2	55 543	1.0
2013	2 973 292	2.5	56 234	1.2
2014	3 023 826	1.7	56 469	0.4
2015	3 063 101	1.3	56 449	0.0

Source: Data from South African Reserve Bank (2017)

The timing of the collection of NIDS data raises two immediate points of concern. First is the relatively long intervals between waves. Given that the time between waves was generally more than a year (and, on average, more than two years), it must be the case that NIDS underestimates the prevalence of short spells of poverty. The average number of months between interviews for balanced panel members between wave 1 and wave2, wave 2 and wave 3, and wave 3 and wave 4 were 30.0, 21.4 and 30.6, respectively. The second concern is the unequal nature of the spacing between interviews over waves. For example, some of the balanced panel members had only 8 months in between being interviewed for wave 2 and wave 3. At the other extreme, other members of the balanced panel had 42 months in between being interviewed for wave 1 and wave 2.[3] It does not appear that differential intervals between waves are systematically related to different population subgroups, though, of course, the longer the time between interviews, the less likely we are to pick up short run dynamics.

Selective attrition over the successive waves of NIDS is something that has been a concern – see, for example, de Villiers et al. (2013) and Baigrie and Eyal (2013) who note the disproportionate loss of white respondents and relatively wealthy respondents (as separate from race) between the first and second waves of NIDS. The attrition rates for NIDS are relatively high compared to those in other countries with national longitudinal surveys (though these are almost all OECD countries). This is particularly true for the wave 1 to wave 2 interval. Chinhema et al. (2016) provides the overall attrition rates for wave 1 to wave 2, wave 2 to wave 3, and wave 3 to wave 4. These stand at 21.95%, 15.82%, and 13.75% respectively. These high attrition rates mean that constructing attrition-corrected weights for the balanced panel sample is an important undertaking. In order to adjust the balanced sample for the presence of selective attrition between waves 1 and 2, 2 and 3, and 3 and 4, we constructed a balanced panel weight. This was done by adjusting the original wave 1 post-stratified weight to account for unfolding

[3]Figure 9 in the appendix presents the distributions of time in between interviews for balanced panel members for wave 1 to wave 2, wave 2 to wave 3, and wave 3 to wave 4.

attrition. For each successive wave a probit model was run with the dependent variable being a dummy indicating whether the individual attritted or not. Wave 1 to wave 2 balanced panel members then received a new weight which was the product of the original wave 1 weight and the inverse of the conditional probability of re-interview. The same process was applied to the wave 2 to wave 3, and the wave 3 to wave 4 periods. Given that the original wave 1 weight was multiplied by the inverse of the probability of re-interview, those belonging to groups that were more likely to attrit in between waves received a relatively higher weight. This means the attrition corrected weights are higher for, for example, white respondents, wealthier respondents, and the elderly, all of whom were relatively more likely than their counterparts to drop out of the sample, albeit for differing reasons. In some cases a high wave 1 calibrated weight was multiplied by a high attrition weight, resulting in an extremely high panel weight. In light of this, and in line with the NIDS methodology outlined in Chinhema et al. (2016), the panel weights were trimmed at the 1st and 99th percentiles.

There are 17 265 members of the balanced panel, and Table 2 presents some summary statistics for this subsample. 83% of our sample is African, with coloured and white proportions standing at about 8% and 7% respectively. The Indian part of the balanced panel is very small, with only 151 respondents being successfully interviewed in all four waves. For this reason, racial breakdowns including this group are generally avoided, because of the lack of power associated with such a small sample size.

As expected in a subsample that is ageing, the average level of educational attainment rose with each successive wave.[4] The large decrease in the proportion of the balanced panel with no education is because of the inclusion in wave 1 of children of all ages, many of whom started primary school over the course of the first four waves of NIDS. The share of the balanced panel with no schooling dropped from 20% in wave 1 to 6% in wave 4, and almost a quarter had obtained at least a matric by wave 4.

The evolution of the household size variable is interesting to observe. The share of the balanced panel living in single-person households rose by almost four percentage points between wave 1 and wave 4. This category and the next smallest (2 to 3) were the only two to grow between 2008 and 2015. The proportion of balanced panel members living in households with 4 to 6 people was 39% in wave 4, down from 44% in wave 1. The trend to smaller household sizes in the balanced panel is reflected in the cross-section as well. In the cross-section, average household size decreased from 3.53 in wave 1 to 3.20 in wave 4.

Turning to the three geo-types we see that the proportion of balanced panel members living in urban areas rose from 57% in wave 1 to 60% in wave 4, while the shares in traditional areas and farming areas decreased between 2008 and 2015. The provincial breakdown of balanced panel members was relatively stable over the period, with small decreases in the share living in the Eastern Cape and Limpopo, and a rise in the proportion living in Gauteng (not shown).

[4] The education columns do not sum to 100% within each wave due to missing values for some respondents.

Table 2: Summary statistics of the balanced panel

	Wave 1	Wave 2	Wave 3	Wave 4
Race				
African		82.75%		
Coloured		8.23%		
Asian/Indian		2.34%		
White		6.67%		
Gender				
Male		47.04%		
Female		52.96%		
Age	26.47	28.89	30.70	33.21
Education				
None	20.33%	16.33%	12.71%	5.76%
Primary	32.73%	31.77%	30.75%	29.56%
Inc. Sec.	28.70%	31.88%	34.55%	38.57%
Matric	16.27%	17.92%	19.68%	22.25%
Tertiary	1.48%	1.71%	1.99%	2.39%
Household Size				
1	5.46%	6.17%	7.19%	9.25%
2-3	21.75%	19.59%	22.18%	23.94%
4-6	43.85%	41.71%	41.27%	39.04%
7-10	20.60%	23.85%	21.94%	20.61%
>10	8.33%	8.68%	7.43%	7.16%
Geo-type				
Traditional	37.55%	37.65%	36.82%	35.53%
Urban	57.23%	56.92%	58.44%	59.85%
Farming	5.22%	5.43%	4.75%	4.63%
N		**17 265**		

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

Before presenting poverty transition matrices, it is worth spending some time looking at the composition of household income of poor and non-poor households in each of the four waves. Our welfare measure in this chapter is real monthly household income per capita.[5] We make use of the household income variable in the public-release dataset which was adjusted to remove imputed rent from owner-occupied housing in each wave. This was done because the imputed rent variable in each wave contained a high percentage of missing values, making it a very noisy component of income (even after single regression imputations were used to predict the missing values). This follows the practice in many papers using the household income variable in NIDS (for example see Leibbrandt et al. (2010)). Disposable household income is defined as the sum

[5]We remain agnostic to the dynamics of non-monetary measures of well-being, which, by all accounts, have improved more rapidly than improvements in household income (Finn and Leibbrandt, 2016).

over individuals in the same household of wages, remittance income, grants and income from investments. Wages include the net income received from primary jobs, secondary jobs, self-employment and casual work. Remittance income includes all monetary transfers received by the household from non-resident household members. Grant income includes the state old age pension, the child support grant, the disability grant, the care dependency grant, the foster child grant and the war veteran's grant. The sum of these components across all individuals in the household is then divided by household size in order to reach a measure of monthly household income per capita.

The choice of any equivalence scale when defining a welfare measure is going to involve some trade-offs. In this thesis, dividing total household income by the number of resident household members in order to reach the chosen welfare measure assumes that there are no economies of size within the household. This approach continues the precedent set in the analysis of poverty in South Africa (see, for example Woolard and Leibbrandt (2006)). Although the assumption of no economies of size is quite an extreme one, it is not clear that any of the alternatives offer a superior approach. For example, an equivalence scale such as the one used in Woolard and Klasen (2005) in which household income is divided by $(adults + 0.5 \times children)^{0.9}$. However, as noted in Budlender et al. (2015), defending the choice of these parameters is far from easy, and their use may raise more questions than answers. Woolard and Leibbrandt (2006) provides some evidence that poverty analysis in South Africa is generally robust to the choice of equivalence scale, although there is still some debate about the issue (see, for example, the analysis in Posel and Rogan (2016). Given the number of issues that would be raised by the choice of any equivalence scale, the chapter proceeds by appealing to precedent and to the simplest option, and simply divides total household income by the number of resident members.

We used Statistics South Africa's (StatsSA) headline CPI index to deflate the nominal income data to their real values. The base period is January 2015, as this was the modal month of interview for wave 4. All analysis that follows reports the income variables at their January 2015 price levels. The use of headline CPI assumes that price changes facing people in different parts of the country, and in different parts of the income distribution are the same. This is almost surely a simplification of reality, as in practice different households consume different bundles of goods, and therefore face different inflation rates. The use of plutocratic weights in the construction of CPI means that the fixed basket of goods underlying CPI is more representative of households with relatively higher expenditure. Leibbrandt et al. (2016) calculate percentile-specific inflation rates for South Africa and show that price changes between 2005 and 2010 were anti-poor. That is, the rate of inflation faced by poor households was higher than that faced by non-poor households, and also higher than the inflation reflected in headline CPI. However, it is far from clear that deflating prices for urban and rural households separately would lead to an improved measure of household income over time. As noted in Finn, Leibbrandt and Oosthuizen (2014), the rural price indices released by StatsSA are calculated on the basis of combining urban prices and rural expenditure weights. This creates a rather murky version of rural inflation, as it would only be accurate if the prices faced by rural households were exactly the same as those faced by urban households. For this reason we choose to use a single headline price index to deflate incomes over time. If one extends the findings in Leibbrandt et al. (2016) to the NIDS dataset, then choosing headline CPI rather than a percentile-specific CPI is likely to slightly underestimate the true prevalence of poverty in the country.

In Figure 10 in the appendix, we present eight bar charts - four for poor households in each wave and four for non-poor households in each wave. The y-axis represents the proportion of total household per capita income made up of each component of household income. These components are wages, government grants, remittances and investment income. Investment income comprises stocks, rentals, private pensions and retirement annuities.

A comparison of the share of wages in total household income for poor versus non-poor households shows that labour market income is substantially more prominent in the latter than in the former. The wage share in poor households for this period ranged from 46% to 52%, while in non-poor households it was stable at around 86%. The importance of income from government grants for poor households is clear in this figure, with the share of income coming from this source in the mid 40%s. As we show later, in Table 7, an increase in income from government grants was a very important trigger leading households to exit poverty between wave 1 and wave 4. Remittances play a more important part in the composition of income for poor households versus non-poor households - reaching a peak of 11% compared to 3% in wave 4. Finally, investment income makes up between 7% and 10% of household income for non-poor households in waves 1 to 4, compared to between 1% and 3% for poor households.

IV Descriptive poverty transitions

The NIDS wave 3 poverty transitions report (Finn and Leibbrandt, 2013) used a cost-of-basic-needs poverty line of R636 per capita per month (in August 2012 price levels) which itself was based on the line in Özler (2007). In this chapter, however, we use a poverty line that was derived by Budlender et al. (2015) of R1 283 in January 2015 rands.[6] This poverty line was calculated by first deriving a nutrition poverty line to reflect the minimum cost of a daily caloric intake of 2 100 kilocalories. This food poverty line was added to the average amount of non-food expenditure of households with food expenditure at the nutrition line in order to reach the amount of R1 283. In adjusting the original Budlender et al. (2015) line to its real January 2015 equivalent, we deflate the food and non-food components separately using CPI reports from StatsSA.

[6]There is some sensitivity analysis to the choice of poverty line through the use of a measure of ‘severe’ poverty later in this chapter. Additional sensitivity tests using the StatsSA upper bound poverty line of R945 are available from the authors.

Transition matrices

In Table 3 we present poverty transition matrices for the balanced panel members. The four panels of the table show transitions from wave 1 to 2, 2 to 3, 3 to 4, and 1 to 4 respectively. Focusing on the wave 1 to wave 4 transition (shaded in grey) we see that of those balanced panel members who were poor in wave 1, almost three quarters were also poor in wave 4. Of those who were non-poor in wave 1, 79% were also non-poor in wave 4, while 21% transitioned into poverty between 2008 and 2014/2015. The probability of transitioning out of poverty over the four waves was therefore approximately five percentage points higher than the probability of transitioning into poverty over the same period for the balanced panel members.

Table 3: Transitions into and out of poverty across waves

		Wave 2				**Wave 3**	
		Poor	**Non-poor**			**Poor**	**Non-poor**
Wave 1	**Poor**	88.40	11.60	**Wave 2**	**Poor**	84.09	15.91
	Non-poor	26.48	73.52		**Non-poor**	20.26	79.74
		Wave 4				**Wave 4**	
		Poor	**Non-poor**			**Poor**	**Non-poor**
Wave 3	**Poor**	79.30	20.70	**Wave 1**	**Poor**	73.40	26.60
	Non-poor	20.74	79.26		**Non-poor**	21.36	78.64

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

In Table 4 each cell within each panel gives the total proportion of balanced sample members in each transition state. The four cells in each panel sum to 100%, rather than each row summing to 100% as was the case in Table 3. Focusing on the shaded panel once again, we see that almost 54% of the sample of balanced panel respondents were poor in both wave 1 and wave 4. Just over 21% of respondents had real per-capita household incomes above R1 283 in both wave 1 and wave 4. Almost one fifth of respondents were poor at the start of the period, and non-poor at the end, while the opposite is true of 5.7% of the balanced panel.

Our final set of transition matrices, shown in Table 5, draws on the definition of 'severe' poverty used in Carter and May (2001), and classifies individuals as being in severe poverty if their real per-capita household income is less than half of the poverty line. Therefore the threshold for severe poverty in this context is R641.50, and the threshold for poverty is between R641.40 and R1 283 in January 2015 rands.

Of those who were in severe poverty in wave 1, 78.4% were either in severe poverty or in the 'poor' category in wave 4, implying that just over one fifth of the severely poor in wave 1 were non-poor in wave 4. The transition rates for those who were poor in wave 1 are higher when compared to the severely poor category, and this is to be expected as respondents could move in two directions if they were in the middle category at the beginning of the time period. Of

Table 4: Poverty transitions: Proportion of sample by transition status

		Wave 2				Wave 3	
		Poor	**Non-poor**			**Poor**	**Non-poor**
Wave 1	**Poor**	64.69	8.49	**Wave 2**	**Poor**	60.37	11.42
	Non-poor	7.10	19.71		**Non-poor**	5.71	22.49
		Wave 4				**Wave 4**	
		Poor	**Non-poor**			**Poor**	**Non-poor**
Wave 3	**Poor**	52.41	13.68	**Wave 1**	**Poor**	53.72	19.47
	Non-poor	7.03	26.88		**Non-poor**	5.73	21.09

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

those who were poor in wave 1, 27.5% transitioned down into the poorest category in wave 4, while just over 40% escaped poverty in the 2008 to 2014/2015 period. The non-poor/non-poor cell shows the highest level of stability, with 79% of respondents remaining non-poor in wave 4, conditional on being non-poor in wave 1. The proportions of non-poor wave 1 respondents transitioning into poverty or severe poverty by wave 4 are 13% and 8.5% respectively.

The final panel in the bottom left section of the table contains cells that sum to 100%. This allows us to see the overall proportion of respondents in each of the nine cells corresponding to different poverty transitions. 53.72% of the members of the balanced panel were in poverty or severe poverty in both wave 1 and wave 4.[7] This table highlights that most of those who were trapped in poverty were in fact trapped in severe poverty - 29% of all the balanced panel members were in this category. The proportion of the sample that was severely poor in wave 1 and non-poor in wave 4 stands at 11.5%, while 8% were poor in wave 1 and non-poor in wave 4. Just over one fifth of balanced panel members were non-poor in both waves, while about 6% transitioned from being non-poor into being either poor or severely poor.

[7]This corresponds to the proportion in the upper left cell of the shaded area in Table 4.

Table 5: Transitions with finer poverty levels

			Wave 2					Wave 3	
		Severe	**Poor**	**Non-poor**			**Severe**	**Poor**	**Non-poor**
	Severe	73.16	19.48	7.36		**Severe**	63.14	25.64	11.21
Wave 1	**Poor**	42.31	34.77	22.92	**Wave 2**	**Poor**	35.49	37.33	27.18
	Non-poor	12.25	14.23	73.52		**Non-poor**	8.30	11.95	79.74
			Wave 4					**Wave 4**	
		Severe	**Poor**	**Non-poor**			**Severe**	**Poor**	**Non-poor**
	Severe	60.21	24.36	15.43		**Severe**	53.88	24.55	21.57
Wave 3	**Poor**	33.35	36.87	29.78	**Wave 1**	**Poor**	27.47	32.48	40.04
	Non-poor	9.36	11.38	79.26		**Non-poor**	8.52	12.83	78.64

Note: In this panel the cells sum to 100%

			Wave 4	
		Severe	**Poor**	**Non-poor**
	Severe	28.69	13.07	11.49
Wave 1	**Poor**	5.48	6.48	7.98
	Non-poor	2.29	3.44	21.09

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

Roughly 83% of balanced panel members are African, and although this group drives the overall results discussed in the previous three tables, it is interesting to highlight the results for African respondents in isolation. This analysis can be found in Tables 12, 13 and 14 in the appendix. A comparison of Table 3 to Table 12 shows that approximately three quarters of the full sample of balanced panel members (including Africans) were poor in wave 4 if they were poor in wave 1. The proportions transitioning out of poverty were therefore also approximately the same. There is a fairly large difference when comparing those who started off non-poor. 78.64% of the full sample who started off non-poor remained non-poor, but for Africans this proportion was lower at 71.52%. Although the transitions out of poverty were similar for African and non-African panel members, Africans were far more likely to transition into poverty than the rest of the sample. Of course, with Africans making up more than 83% of the balanced panel sample, the overall numbers are largely driven by this group. Comparing Africans with non-Africans (rather than with the full sample) reveals some starkly different numbers. Table 13 in the appendix shows that 60.36% of Africans were poor in wave 1 and wave 4. This compares to only 21.82% of non-Africans.[8] On the other hand, 56.58% of non-Africans were non-poor in both wave 1 and wave 4, while the corresponding number for African panel members was only 13.68%. Finally, as can be expected given the previous results, the proportion of Africans who were in severe poverty in both wave 1 and wave 4 was higher than for the rest of the balanced panel (see a comparison between Table 5 and Table 14). African respondents were more likely to transition from severe poverty into non-poverty (12.69% of

[8]This table is not shown in the appendix. Full tables of comparisons are available from the author.

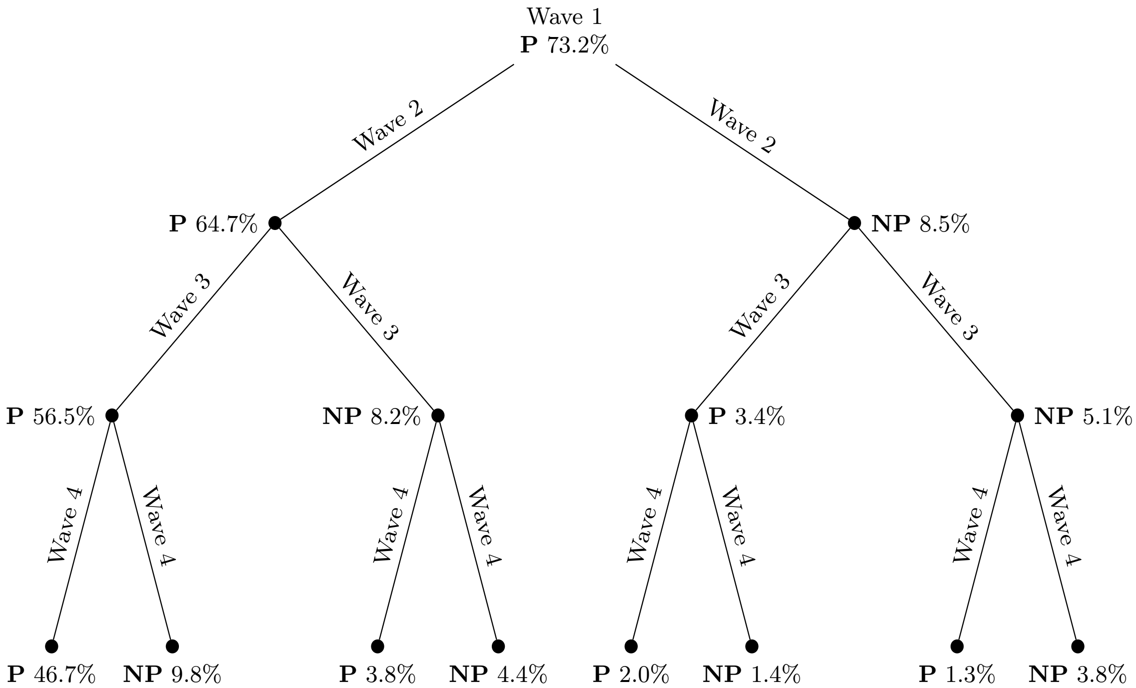
the African sample experienced this transition), but were also more likely to transition from non-poverty into either poverty or severe poverty.

Poverty over four waves

Presenting all possible combinations of poverty status for balanced panel members across four waves is a significant challenge. There are 16 different possible states (PPPP, PPPN, PPNN,...,NNNN), compared to 8 different states if three waves are used, and 4 different states if two waves are used. The approach of presenting the different combinations of states of poverty and non-poverty over four waves as 16 possible paths can be found in Table 1 of Jarvis and Jenkins (1997), who provide all 16 possible combinations for the first four waves of the British Household Panel Survey. In this chaper a different approach is taken, and in Figure 1 and Figure 2 we use poverty transition trees to show the proportion of the balanced sample that was in each possible state over each of the four waves. The choice to show poverty transitions in this way is made because the trees contain more information than a table of 16 states, as the proportion of sample at each node is reported, rather than only the proportions who end up in each of the mutually exclusive final 16 categories. Showing the paths as a single table can be thought of as a special case of the transition tree approach, with the 16 terminal nodes in Figure 1 and Figure 2 representing the 16 possible final states. Each node of the tree represents an unfolding combination of possible states that a respondent could be in. For example, the top node in Figure 1 shows that 73.2% of balanced panel respondents fell below the poverty line of R1 283 per capita per month (P) in wave 1. Moving down a node, 64.7% of balanced panel members were poor in wave 1 and in wave 2 (PP). Moving down another node and going to the right this time, we see that 8.2% of balanced panel members were poor in wave 1, poor in wave 2, and non-poor in wave 3 (PPN). The terminal nodes show the final four wave combinations, along with the proportion of sample members in each. The PPPP node (the first terminal node in Figure 1) shows that 46.7% of balanced panel members were poor in each wave in which they were interviewed. Almost 10% of the sample was poor in the first three waves but exited poverty in the fourth wave. Going right from the initial node, we see that 8.5% of the balanced panel transitioned out of poverty between wave 1 and wave 2 (PN). Of that 8.5%, just over 5% remained non-poor in wave 3 (PNN), while 3.4% transitioned back into poverty between wave 2 and wave 3 (PNP). Finally, 3.8% of the balanced panel was in poverty in wave 1, but transitioned out of poverty in wave 2 and remained non-poor in all subsequent waves (PNNN).

Figure 2 adopts the same approach, except this time for the 26.8% of balanced panel members who were non-poor in wave 1. The eight terminal nodes of this tree combined with the eight terminal nodes of the previous tree provide all 16 possible poverty transition states. The same goes for the eight possible states in wave three, and the four possible states in wave 2. In this figure we see that only 16.3% of all our balanced panel members were non-poor in each of the four waves. In fact, 7.1% of the total sample was non-poor in wave 1 and fell into poverty

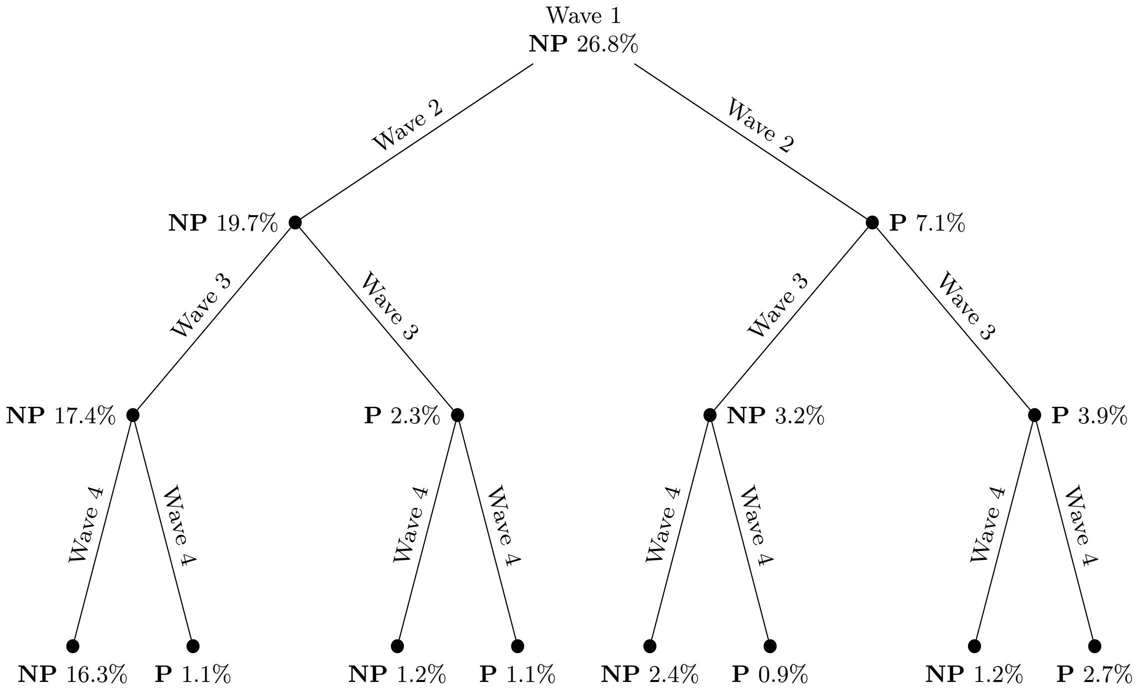
Figure 1: Poverty transition tree: Poor in wave 1



Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel. **P** = Poor, **NP** = Non-poor.

in wave 2 (NP). A slightly higher proportion of those on the NP path remained in poverty by wave 3 (3.9% at the NPP node) than exited poverty by wave 3 (3.2% at the NPN node). The terminal node of the far right of the tree shows that 2.7% of the balanced panel were non-poor in the first wave, but then feel into poverty and did not transition out in any subsequent wave (NPPP). Just under 1% of the sample transitioned at each wave, conditional on starting off non-poor (NPNP), and this is roughly the same proportion as those who started off poor and also transitioned in every wave (PNPN). 7.7% of the balanced panel sample started off non-poor in wave 1, but experienced one wave of poverty during either wave 2, 3 or 4 (calculated as the sum of NPNN, NNPN and NNNP). This is in contrast to 3.8% of balanced panel members who were in poverty only in wave 1 (PNNN).

Figure 2: Poverty transition tree: Non-poor in wave 1



Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel. **P** = Poor, **NP** = Non-poor.

Although the unconditional poverty rates of the balanced panel in each wave are of less interest to us than poverty transitions between waves, they are nevertheless embedded in the transition trees, and can be calculated by summing the percentages at each 'P' node. Doing so reveals the unconditional poverty rates as 73.2%, 71.8%, 66.1% and 59.5% in each of the first four waves respectively.[9]

Another way of displaying poverty states across four waves is presented in Table 6 which shows the number of times respondents were recorded as being in poverty and severe poverty over the total time period. Although this is a simpler display of poverty states, we sacrifice the ability to show every possible state over every wave, as was done in the previous two figures. As we have already seen, only 16.28% of the sample of balanced panel respondents were classified as non-poor in every wave in which they were observed. This is in stark contrast to the 46.7% of respondents who were living below the poverty line of R1 283 per month in each of the four waves in which they were interviewed. The proportion of respondents who were in severe poverty (living on less than half the poverty line) ranges from 29% who were never recorded as being in severe poverty to 16% who were recorded as being in severe poverty in a single wave. Just over 18% of respondents were recorded as being in severe poverty in all four waves, though 55.3% experienced severe poverty in at least half the waves in which they

[9]The unconditional poverty rates of balanced panel members should not be treated as being representative of national poverty rates, which can be calculated by using each separate wave as a cross-section.

were interviewed. The middle column of the table presents the proportion of African balanced panel members who were poor between zero and four times over the first four waves of NIDS. As expected, given the analysis of the transition matrices earlier in the chapter, dynamics in the African subsample drive the overall findings. Although just over 16% of the full sample did not experience poverty in any wave, the corresponding proportion for African respondents was just under 9.5%. The proportion of African respondents experiencing poverty in either 2 or 3 waves lines up relatively closely with the overall numbers, but significantly more Africans were poor in every wave compared to the full sample (53% versus 46.7%). Perhaps a more telling comparison is between African and non-African respondents. As already noted, only 9.5% of African sample members were non-poor in all four waves of NIDS. The proportion in this category amongst non-African sample members was close to 50%. At the other extreme, over one fifth of African respondents were in severe poverty every time they were observed, while the corresponding proportion for non-Africans was a little under 4%.

Table 6: Number of times observed in poverty between 2008 and 2014/2015

	Overall		**African**		**Non-African**	
	Poverty	**Severe poverty**	**Poverty**	**Severe poverty**	**Poverty**	**Severe poverty**
0	16.28	28.81	9.48	20.77	48.89	67.38
1	8.51	15.89	7.79	16.2	11.98	14.37
2	10.30	17.74	9.86	19.23	12.42	10.61
3	18.24	19.41	19.8	22.67	10.73	3.76
4	46.67	18.15	53.07	21.13	15.98	3.88

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

Chronic versus transitory poverty

We have seen that a large proportion of the sample remained in poverty in all four waves. It would be useful to complement this finding by considering the extent to which the overall poverty rate is made up of chronic versus transient poverty in each of the four waves.

This is, in some ways, an extension of the two-period conception of chronic poverty in South Africa that is presented in Carter and May (2001). The authors find that 18% of African households were in chronic poverty in KwaZulu-Natal between 1993 and 1998, and reinforce the fact that a large proportion of South Africans were unable to take advantage of the early post-apartheid economy.

Carter and May (2001), focus in particular on the role of assets in driving poverty over time using the KIDS dataset. The authors use a combination of money metric and asset measures in order to classify households as being either stochastically poor or structurally poor. von

Fintel et al. (2016) use the framework developed by Carter and May (2001) in order to investigate child poverty in general, and chronic child poverty in particular in South Africa. Other studies that deal *inter alia* with chronic poverty in South Africa (also using the KIDS dataset) are Roberts (2001) who delineates chronic and transitory poverty by demographic characteristics, and Aliber (2003) who discusses chronic poverty in light of some of the macroeconomic strategies adopted by the South African government in the late 1990s.

Given that we have four waves of data to work with, we can characterize the poverty-time interaction in a number of ways. We follow Hulme and Shepherd (2003) who conceptualise different five types of poverty in an adaptation of the methodology found in Jalan and Ravallion (2000). The original Jalan and Ravallion (2000) study of chronic versus transient poverty in China uses longitudinal data over a six year period. The transient component of poverty in that study is thought of as the contribution of inter-temporal variability in living standards to poverty, while the chronic (or non-transient) component is thought of simply as time mean consumption/income for all dates. The authors use the squared poverty gap as their poverty measure and find that just under half of poverty in China can be explained by the transient component. However, only 6% of individuals lived in households which were persistently poor, and 54% were classified as never-poor. The five different characterisations of poverty over time are applied to NIDS in the following way.

- Always poor: household income per capita measures are below the poverty line in all four waves of NIDS.
- Usually poor: mean household income per capita over the four waves of NIDS is less than the poverty line, but the panel member is not poor in every period.[10]
- Churning poor: mean household income per capita over the four waves of NIDS is in the neighbourhood of the poverty line[11] but the panel member is sometimes poor and sometimes non-poor in different periods.[12]
- Occasionally poor: mean household income per capita over the four waves of NIDS is above the poverty line, but the respondent is poor in at least one wave.
- Never poor: household income per capita is above the poverty line in all waves of NIDS.

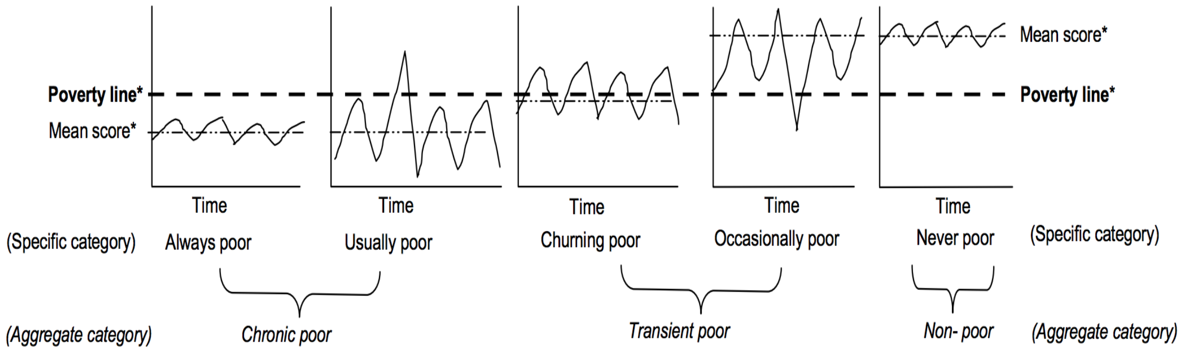
These five characterisations of poverty are represented graphically in Figure 3:

[10]This is effectively the same definition used by Jenkins (2011) in defining chronic poverty.

[11]In this study we choose a window of 10% below the poverty line.

[12]This can be thought of as a special case of 'usually poor' with the additional restriction being that the respondent's average household income per capita is close to the poverty line.

Figure 3: Five different characterisations of poverty over time

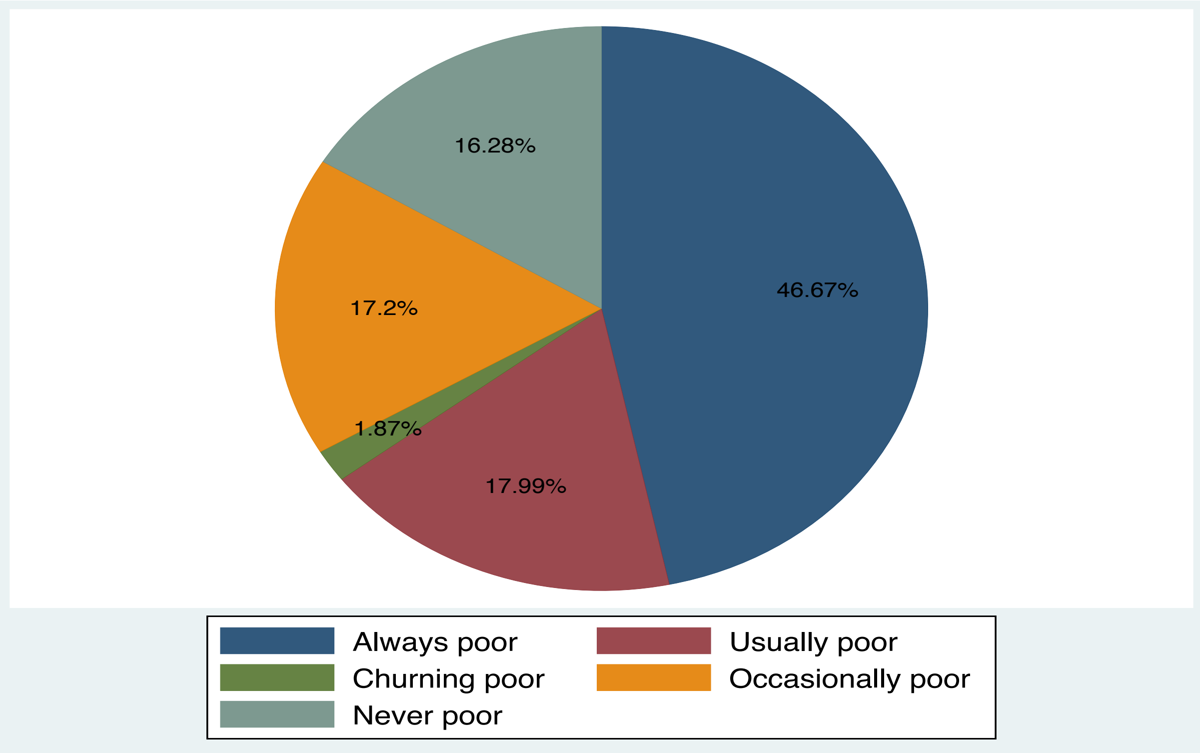


Source: Reproduced from Hulme and Shepherd (2003).

In Figure 4 we present the five different poverty states for members of the NIDS balanced panel. The single largest group is the 46.67% of panel members who were poor in all four waves. This proportion, added to the 18% of respondents who were usually poor, gives a 'chronic poverty' percentage of almost two-thirds over the period of 2008 to 2014/2015. By far the smallest group is those who we have defined as 'churning' poor - their average household income per capita was within 10% below the poverty line, but who were non-poor in at least two waves. The second category comprising 'transient poverty' is made up of those panel members whose average household income per capita was above the poverty line, but who were poor in at least one wave. These made up 17.2% of respondents, meaning that almost one fifth of the balanced panel members were in the 'transient poor' category. Finally, only 16.28% of respondents were non-poor in every single wave.[13]

[13]This corresponds to the number presented in the leftmost terminal node of Figure 2.

Figure 4: Types of poverty experienced by the balanced panel



Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

V Trigger events associated with movements into and out of poverty

Demographic versus income events

Given that our poverty line is a threshold of real monthly household income per capita, we can expect changes either through the numerator (income events) or through the denominator (demographic events). The trigger events that we use in this chapter are a combination of those found in Jenkins (2011) and Woolard and Klasen (2005), both of which are based on the original exposition in Bane and Ellwood (1986). The first kind of demographic event is a change in the household head and/or a change in the composition of the household. This is typically one or more people entering/leaving the household due to birth, migration or death. Thus the dynamics of household composition affects our sample, even though the people entering/leaving the household may not be balanced panel members.[14] The first category of 'head or composition changed' therefore includes headship changes as well as other household formation changes.

[14]Each wave of NIDS collects data on all members of the household in which panel members reside, whether or not these members were part of the base wave in 2008.

The second category is assigned to cases where the head of the household did not change in between waves, but the composition of the household did. Given that the head did not change, it was necessary to determine whether changes in needs outweighed changes in income. This was accomplished by comparing the proportional change in the household size for each individual compared to a proportional change in total household income, following Jenkins (2011). If the proportional change in needs was larger (in absolute terms) than the proportional change in income, then the trigger event 'needs > money' was assigned to all individuals in the relevant household.

There is, of course, a link between demographic events and income events affecting the welfare of household members. This takes place primarily through the migration of household members. Changes in the composition of the household may themselves be driven by changes in income sources, as some research on the role of the South African old age pension on labour supply suggests (Posel and Casale (2003), Posel et al. (2006) and Ardington et al. (2009) find positive labour supply effects, while Bertrand et al. (2003), Ranchhod (2009) and Sienaert (2008) find negative effects). Although this form of physical mobility is not the focus of the chapter, it is worth highlighting some key findings about migration that have been uncovered using NIDS data. The literature on physical migration and mobility in South Africa is very thin, as noted in Posel (2010), which uses NIDS data to investigate some of the correlates of physical mobility in the country. The paper compares findings from 1993 PSLSD data to 2008 NIDS data and concludes that a larger proportion of those who migrated around 2008 did so for employment reasons, compared to those who migrated around 1993. Another, perhaps surprising, finding is that although migration was driven by perceptions about labour market access, the connection to origin households via remittances was weaker in the NIDS data than in the PSLSD data. Clarke and Eyal (2014) use the first two waves of NIDS to study migration and find that receipt of the state old age pension and, to a lesser extent, receipt of the child support grant is negatively associated with the probability of migration of co-resident, non-eligible adults in the household. They also find an inverse-U relationship between the probability of migrating and household income. Respondents aged between 18 and 30 are the most likely to migrate, while those with school-aged children and those living in rural areas are less likely to move.

There are five types of income trigger events. The first three are: changes in formal earnings of the household head, formal earnings of the spouse of the household head, and formal earnings of any other household members. The final two income triggers are changes in remittance income received by the household, and changes in income from government grants received by the household.[15] Income events are ranked according to the size of the change between waves.

[15]The state old age pension and the child support grant make up by far the largest share of household income from state grants. The pension is means tested and is paid to eligible recipients who are aged 60 and above. It is a relatively high amount at about 1.75 times the median of income for African respondents (Clarke and Eyal, 2014). The child support grant is also means tested and is paid to the primary caregiver of the child until the child reaches 18 years old. The amount of the child support grant is approximately one quarter of the amount of the old

So, for example, if the household head's real formal earnings fell by R200, the spouse's real formal earnings fell by R800 and there was no change in the other income triggers, then the appropriate trigger event is 'fall in spouse's formal labour market earnings'. Finally, there is an 'inconclusive' category which indicates households in which no clear ranking can be established.

More formally (and assuming that all trigger events are assigned), we borrow notation from Jenkins (2011) to show that the probability of exiting poverty[16] is made up of mutually exclusive events 1 to J.[17]

$$Pr(\text{exit poverty}) = \sum_{j=1}^{J} Pr(\text{exit poverty via trigger j}) \tag{1}$$

Given that each event 1 to J can be formulated as the product of the probability of poverty exit, conditional on event j, and the probability of event j itself occurring, we have:

$$Pr(\text{exit poverty}) = \sum_{j=1}^{J} Pr(\text{exit poverty}|\text{trigger j}) \times Pr(\text{trigger j}) \tag{2}$$

It is important to note that although this analysis of demographic versus income events is interesting and useful, we should be very cautious about assigning causality from the trigger to the transition. As Jenkins (2011) notes, it is tempting to say that losing an employed member caused a particular household to enter poverty, but it could also be the case that a household entered poverty first, and this stress caused the household to break up.

The role of trigger events

The first feature to note about Table 7 is the fact that demographic events were more heavily weighted than income events in terms of their importance in explaining transitions both into and out of poverty during the period under study. A demographic change in the household was the main trigger for 56% of individuals who entered poverty between wave 1 and wave 4. A fall in the real formal labour market earnings of the household head was the primary income correlate of entering poverty. This was the primary trigger for poverty entry for about one fifth of those who entered poverty between wave 1 and wave 4. Falling earnings for household members who were not the household head or spouse of the household head triggered poverty entry for between 10% and 14.5% of balanced panel members, depending on which transition is the focus. The shares of falling remittances and falling income from government grants were relatively similar for poverty entry during each of the three time periods under study, and were generally the relevant triggers for between 3% and 5% of balanced panel members.

age pension.

[16] The notation for the probability of entering poverty via trigger k is easily seen from this example.

[17] Jenkins (2011) and Jenkins and Rigg (2001) also provide estimates that do not assume mutually exclusive trigger events, though these do not form part of this chapter.

For those respondents who exit poverty, the head change/compositional change share from wave 1 to wave 4 is almost 14 percentage points higher than its counterpart in the poverty entry category. It is interesting that the needs $>$ money category (no change in the household head but a compositional change in the household) contributes relatively little to the total explanation of poverty exit – dropping to as low as 0.4% for the wave 1 to wave 3 transition.

The income triggers tell quite a different story for poverty exit than they do for poverty entry. An increase in the earnings of the household head is the main poverty exit trigger for almost one quarter of those who left poverty between wave 1 and wave 2, but its importance falls to only 4% for the full wave 1 to wave 4 period. The importance of the earnings of the spouse of the household head is relatively muted over the whole period, reaching a high of 3.9% for the wave 2 to wave 3 transition. An increase in labour market earnings from household members who are not the head or married to the head is the main poverty exit trigger for about 10% of balanced panel members for the wave 1 to wave 4 transition. This share is similar to its counterpart in the poverty entry panel. The importance of increased remittance income is fairly muted for poverty exit triggers, as it was for poverty entry triggers. One significant difference between wave 1 to wave 4 poverty entry and poverty exit triggers is the role of income from government grants. A drop in grant income was the main poverty entry trigger for only 3.5% of those who entered poverty. In stark contrast, an increase in income from government grants was the main trigger precipitating poverty exit for 23% of balanced panel members. This is a reflection of both the success of the targeting and expansion of the state's grant system, and the failure of the labour market to act as the main driver of poverty reduction in the country.[18]

Woolard and Klasen (2005) also analyse demographic versus income events in triggering poverty exit. Their focus is on African households, and they use two waves of data from 1993 and 1998. The sample sizes are relatively small, with 129 households entering poverty and 223 exiting poverty over the two waves. In contrast to the findings in this chapter, Woolard and Klasen (2005) attribute most of the transitions into and out of poverty to income, rather than demographic events. They find that demographic events are responsible for 27.4% of households falling into poverty, and 23.6% of households exiting poverty. This is far less than this chapter's corresponding figures of 55.8% and 58.6% for poverty entry and exit respectively. Of income events between 1993 and 1998, Woolard and Klasen (2005) find that the single most important factors for households entering poverty are the head of the household losing a job, followed by another household member losing a job, followed by a drop in remittances. Income events most strongly associated with poverty exit are another household member gaining employment, followed by the household head gaining employment, followed by a rise in remittances.

[18]Eyal and Burns (2016) show the rapid growth in the reach and effect of the child support grant over the first three waves of NIDS. By the third wave of NIDS 89% of those who were age and income eligible to receive the child support grant actually received it. This equates to about 59% of all household in the third wave of NIDS. A report by the department of social development shows that the number of children covered by the child support grant increased from 2 million in 2002, to 8 million in 2008, to 11 million in 2011 (DSD et al., 2012). Evidence of the effective targeting of the countrys state old age pension can be found *inter alia* in Abel (2013) and Standish-White and Finn (2015).

Table 7: Trigger events associated with poverty entry and exit

	Poverty entry				Poverty exit			
	W1 to W2	**W2 to W3**	**W3 to W4**	**W1 to W4**	**W1 to W2**	**W2 to W3**	**W3 to W4**	**W1 to W4**
Demographic								
Head changed	34.83	49.49	52.02	42.10	34.34	47.50	50.55	55.91
Needs > money	11.70	6.75	12.96	13.73	3.75	0.62	0.37	2.64
Demographic share	**46.53**	**56.24**	**64.98**	**55.83**	**38.09**	**48.12**	**50.92**	**58.55**
Income								
Head labour earnings	18.86	15.72	10.02	19.11	23.57	16.99	4.60	4.00
Spouse labour earnings	4.64	1.75	2.82	3.15	2.70	3.86	3.59	1.38
Other labour earnings	14.47	12.45	9.56	10.60	17.58	13.65	10.39	10.19
Remittances	4.67	3.65	3.91	3.98	2.18	5.08	4.50	2.10
Grant income	4.52	3.31	2.26	3.53	9.89	7.39	23.97	23.16
Income share	**47.16**	**36.88**	**28.57**	**40.37**	**55.92**	**46.97**	**47.05**	**40.83**
Inconclusive	6.32	6.88	6.44	3.80	5.99	4.91	2.02	0.62
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**
Observations	963	925	1 266	804	1 317	1 937	2 324	3 228

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

The prominence of demographic trigger events over income trigger events in explaining paths into and out of poverty may be driven in part by the choice of the per capita equivalence scale. In order to investigate how sensitive the results are to the choice of the equivalence scale, Table 15 in the appendix presents the demographic and income trigger events for the same equivalence scale used in Woolard and Klasen (2005). That is, total household income is divided by $(adults + 0.5 \times children)^{0.9}$, rather than simply by household size. Note that in comparing Table 7 and Table 15 we are not comparing exactly the same subsamples, as the choice of equivalence scale has an effect on which households transition into and out of poverty. The first thing to note about the use of the new equivalence scale is that the number of observations falling into poverty between wave 1 and wave 4 is lower than if household income is divided by the number of household members (479 compared to 804). The effect works in the same way when considering those who exited poverty (5 945 using the new equivalence scale compared to 3 228 using the old equivalence scale).

The overall effect of using the modified equivalence scale changes the relative weightings of the demographic and income effects differently whether one considers poverty entry or poverty exit. For the former, the share of demographic trigger events in explaining poverty entry rises from 55.83% to 58.92% when analysing transitions between wave 1 and wave 4. However, this is the only transition in which the demographic share rises – it falls for the wave 1 to wave 2, wave 2 to wave 3 and wave 3 to wave 4 transitions. This increase is entirely due to the rise in the importance of a change in the head of the household, rather than a change in the needs to money ratio. Continuing with the wave 1 to wave 4 poverty entry transitions, the importance of a negative change in the labour market earnings of a household member who was not the head, or married to the head, decreases substantially if the modified equivalence scale is used. This change has the opposite effect on the importance of a change in grant income in the household, with the share of trigger events attributable to this factor rising from 3.53% to 7.38%.

The dynamics underlying poverty exit are also affected by a change in the underlying equivalence ratio, but the qualitative result of demographic events outweighing income events remains the same. If a per capita equivalence scale is used, then 58.55% of poverty exits can be explained by demographic events. The corresponding share if the modified equivalence scale is used is slightly lower at 54.26%. The fall in the demographic share is due to lower weighting of both components of that measure. The change in equivalence scale raises the shares of all the items in the income change category except for changes in grant income, which falls very slightly from 23.16% to 22.71%. In summary, the choice of whether to use a per capita equivalence scale or the equivalence scale used in Woolard and Klasen (2005) makes very little difference to the qualitative findings of the trigger events approach to explaining transitions into and out of poverty.

VI A Markovian model of poverty transitions

We now change the focus of the chapter from descriptive statistics to a careful modelling of the dynamics. Although it may be tempting to adopt a univariate probit approach to modelling poverty transitions, this approach may produce biased results by not controlling for initial conditions and selective attrition. In this section we model transitions while specifically controlling for both of these factors. The model exposition and implementation closely follows Cappellari and Jenkins (2004) and Jenkins (2011).

As noted by Jenkins (2011), much of the international literature on poverty dynamics adopts either a hazard model approach or a variance-component approach to understanding transitions. A third approach, and one that has not been applied very often in the international literature nor, indeed, at all to South African data, is a so-called first order Markov model of poverty dynamics.

The Markovian approach to poverty dynamics has, as a first advantage over alternative methods, the ability to take initial conditions (the presence of a lagged dependent variable in the model that is correlated with unobserved heterogeneity) and non-random attrition into account. The approach, in theory, allows the researcher to overcome the biases presented by both the initial conditions and non-random attrition by modelling both jointly with the probability of transitioning into or out of poverty. This is not something that can easily be incorporated into a more traditional hazard model of poverty dynamics.

The initial conditions problem in the analysis of transitions was first suggested by Heckman (1981*a*). Essentially, the problem is that if we find a certain level of state dependence when analysing poverty, it may be that those who are more likely to be permanently poor are over-represented in the sample. Another way of thinking about the problem is that the start of the period of analysis (in our case wave 1) does not coincide with the start of the process that generates poverty or non-poverty outcomes. As noted in Arulampalam et al. (2000),[19] a model may control for unobserved heterogeneity, but it is also important to separate out the effect of state dependence from unobserved heterogeneity. That is, the initial condition must be modelled explicitly as it may be correlated with the unobservables.

A second advantage of the approach is that it allows for left-censored poverty spells to be incorporated into the model. A conventional hazard model would drop all data for respondents who are poor in every period (almost half our sample), and data for those who are non-poor in every period (a further 16% of our sample). This means that a lot of individuals would fall out of the dataset, which increases the probability of the estimation sample being unrepresentative (Jenkins, 2011). The cost of this second advantage relative to other methods is that it is gained by the assumption that there is no duration dependence.

A third advantage that this model offers over its alternatives is the ability to circumvent the strict exogeneity assumption made about the explanatory variables. In other words, as noted in Biewen (2009), a Markovian approach to poverty transitions avoids having to make the assumption that there is no feedback from dependent variables on future values of the explanatory variables. The cost of doing so is that this approach will yield inefficient estimates due to the fact that the longitudinal nature of the data is not fully exploited.

In summation, the use of a Markovian model to analyse poverty dynamics in South Africa allows us to buy identification while accounting for unobserved heterogeneity, non-random attrition and initial conditions in a single framework, by making some strong distributional and exogeneity assumptions. The estimates obtained can be used to predict poverty spell lengths for individuals with different characteristics.[20]

The data suggest that controlling for initial conditions and selective attrition when modelling poverty dynamics in South Africa is warranted.[21] This is motivated by the output in Table 8 which shows poverty transitions for the pooled sample of respondents over the four waves of NIDS. It is important to note that this table is different to Tables 3, 4 and 5, as our modelling strategy requires us to used pooled data to model transitions, and so we do not restrict ourselves to the balanced panel in any future analysis in the chapter.

The first panel of the table presents poverty transitions for all respondents for whom household income was recorded in two consecutive waves. Just over 29% of those who were non-poor in year $t-1$ were poor in year t. Of those who were poor in year $t-1$, 14% were non-poor in year t. This panel confirms the findings in the descriptive section of this chapter by showing how the probability of being poor in a given year is highly dependent on the probability of being poor in the previous time period. Clearly, initial conditions are important here, and state dependence should not be ignored. Indeed, the poverty rate for those who were poor in year

[19] In the context of unemployment dynamics.

[20] One of the downsides of modelling poverty under the assumption of a first-order Markov process is that the model is not fully efficient as it only uses data from $t-1$ and t.

[21] A full summary of the descriptive statistics for the observations used in the Markovian model can be found in Table 16 in the appendix.

$t-1$ is almost 57 percentage points higher than it is for those who were non-poor in the same year.

This 'naïve' transition matrix presents poverty transitions without controlling for individual and household heterogeneity, and may be thought of as reflecting 'aggregate' state dependence, something to which we will return. The estimation strategy that follows allows us to control for the determinants of initial poverty status, and allows for these determinants to be correlated to current poverty status. This allows us to uncover a measure of 'genuine' state dependence - the measurement of which we will return to after the results of the model have been presented.

While panel a) highlights the importance of initial conditions in determining poverty transitions, panel b) shows that ignoring selective attrition could be problematic at the estimation stage. The final column in Table 8 shows the extent of attrition between $t-1$ and t for non-poor and poor sample members respectively. The rate of attrition from $t-1$ to t differs substantially between the initially non-poor and the initially poor, and is 23.4% and 16.5% respectively. The relatively higher rate of attrition amongst non-poor sample members compared to poor sample members may result in a selected sample that biases our estimation of poverty dynamics.[22]

An overview of the nature of attrition across the first four waves of NIDS can be found in Chinhema et al. (2016), while Baigrie and Eyal (2013) contains a more detailed analysis of the determinants of attrition between the first two waves of NIDS. Chinhema et al. (2016) notes that non-contact[23] was the primary reason for respondents dropping out between waves 1 and 2, and waves 3 and 4. The biggest reason for attrition between wave 2 and 3 was the refusal of respondents to participate. The share of attrition attributable to respondents dying between waves was stable at around 15% for all three wave-to-wave transitions. Attrition amongst African respondents was mainly driven by non-contact, while the dominant reason for coloured and white respondents dropping out of the sample was refusal to participate. The overall attrition rate dropped from 22% to 16% to 14% for each successive wave-to-wave transition. This, however, hides stark differences in the attrition rates of each racial group. More than 50% of white respondents attritted in each new wave, while the rate of attrition of coloured respondents dropped from 27% to 18% to 16%. The African attrition rate decreased significantly with each additional wave of data - from 19% to 13% to 11%.

[22]Modelling non-random attrition in this way is different to correcting for attrition using panel weights, (as was done in the descriptive sections of this chapter) because the model explicitly takes account of the unobservables.

[23]By this we mean the inability of enumerators to locate the panel member.

Table 8: Poverty transitions with and without missing data

Poverty status at t-1	**Poverty status at t**		
	Non-poor	**Poor**	**Missing**
a) Sample with non-missing income at t			
Non-poor	70.86	29.14	
Poor	14.08	85.92	
Total	26.48	73.52	
b) All respondents			
Non-poor	54.28	22.32	23.40
Poor	11.75	71.74	16.51
Total	21.68	60.20	18.12

Source: Own calculations from the first four waves of NIDS. Pooled transitions with sample size of 40 850 individuals (panel b), and 88 090 person-waves. Rows sum to 100%.

Our estimation strategy in the chapter allows us to model poverty transitions while at the same time accounting for initial conditions and non-random attrition. The following section provides an outline of the theory underlying the empirics for our estimation of poverty dynamics.

Theoretical background to the estimation

The Markovian approach to poverty transitions models dynamics from base period $t-1$ to the next period t. There are four components to the model which are:

- The determination of poverty status in $t-1$ to account for initial conditions.
- The determination of whether monthly household per capita income is observed in periods $t-1$ and t, in order to account for selective attrition.
- The determination of poverty status in period t.
- The correlation between unobservables that influence each of the three processes above.

Initial poverty

In the base year there is a latent propensity for poverty over individuals $i = 1, ..., N$, individual and household explanatory variables in the vector x_{it-1}, parameters β and error term $u_{it-1} = \mu_i + \delta_{it-1}$ which is distributed N(0,1) and contains an individual-specific component plus an orthogonal white noise component:

$$p^*_{it-1} = \beta' x_{it-1} + \mu_i + \delta_{it-1} \tag{3}$$

As we only observe discrete outcomes of this latent model, we define a poverty indicator variable $P_{it-1} = 1$ if $p^*_{it-1} > 0$ (where 0 is the unobserved threshold) and zero otherwise.

Retention

We now move to model the probability that a respondent is observed in both the base and the subsequent wave of data. The latent propensity for retention, r^*_{it}, is given by the relationship:

$$r^*_{it} = \psi' w_{it-1} + \eta_i + \xi_{it} \tag{4}$$

where the error term v_{it} is once again distributed N(0,1) and is composed of an individual fixed effect η_i and a normal white noise error term ξ_{it}. R_{it} is a binary indicator for whether the respondent is observed in both periods, and is assigned a value of 1 if $r^*_{it} > 0$ where, once again, the threshold has been normalized to 0.

Current poverty

The third part of the model is the determination of poverty in period t. Once again, we adopt a latent variable approach with poverty status in period t being characterized by the following relationship:

$$p^*_{it} = \left[(P_{it-1})\, \gamma'_1 + (1 - P_{it-1})\, \gamma'_2 \right] z_{it-1} + \tau_i + \zeta_{it} \tag{5}$$

where γ_1, γ_2 and z_{it-1} are vectors and the composite error term ϵ_{it} is distributed N(0,1) and once again comprises individual (τ_i) and white noise (ζ_{it}) components. The vector of covariates z_{it-1} contains individual and household characteristics, as well as a constant term. Finally, let the observed poverty status $P_{it} = 1$ if $p^* > 0$ and zero otherwise. This is, of course, only observed if $R_{it} = 1$.

The specification above allows not only for base characteristics to impact poverty in the final period, but also for a characteristic to have a differing impact on the probability of entering or exiting poverty.

The three error terms, u_{it-1}, v_{it} and ϵ_{it}, are assumed to be distributed trivariate standard normal. There are three important correlations that we will estimate in order to parameterize the unobserved heterogeneity in the model. These are:

$$\rho_1 \equiv corr(u_{it-1}, v_{it}) = cov(\mu_i, \eta_i) \tag{6}$$

which gives the relationship between unobserved heterogeneity determining poverty in the base year and the probability of remaining in the sample. In this case, a positive correlation implies that poor respondents at $t-1$ are less likely to have attritted by period t.

$$\rho_2 \equiv corr(u_{it-1}, \epsilon_{it}) = cov(\mu_i, \tau_i) \tag{7}$$

which gives the relationship between unobserved heterogeneity that impacts on base year and final year poverty status. If this correlation is positive then it implies that respondents who started off poor are more likely to be poor in the next period than those who started off non-poor.

$$\rho_3 \equiv corr(v_{it-1}, \epsilon_{it}) = cov(\eta_i, \tau_i) \tag{8}$$

which is the relationship between the unobservables determining the probability of being retained in the sample and poverty status in the final period. In this case a positive correlation implies that those who are retained in the sample are more likely to remain poor or transition into poverty than those who attrit between the two time periods.

In any event, there are some interesting testable relationships to consider. If $\rho_1 = \rho_2 = \rho_3 = 0$, then poverty dynamics can be estimated separately using any univariate binary dependent variable model, such as a probit. However, if $\rho_1 = \rho_3 = 0$ then the process of attrition is ignorable and the model to be estimated becomes a bivariate probit. Finally, if $\rho_1 = \rho_2 = 0$ then we do not have to take initial conditions into account, and the poverty status in the base period may be treated as exogenous.

Given the descriptive statistics that have been presented, it is likely that the probability of the unobserved factors being uncorrelated with one another is very small. Incorporating initial conditions, non-random attrition and unobserved individual heterogeneity into the model requires the estimation of a partial likelihood estimator of the type used in Jenkins (2011) and Cappellari and Jenkins (2004).

From panel b) in Table 8 we see that there are six possible outcome combinations for a given sample member between $t-1$ and t. These are, non-poor to non-poor, non-poor to poor, poor to non-poor, poor to poor, non-poor to missing, and poor to missing. The setup of the model implies the following equations for poverty persistence (poor in both time periods) and poverty entry (non-poor in the first period, poor in the second) respectively:

$$s_{it} \equiv Pr(P_{it} = 1 | P_{it-1} = 1) = \frac{\Phi_2(\gamma_1' z_{it-1}, \beta' x_{it-1}; \rho_2)}{\Phi(\beta' x_{it-1})} \tag{9}$$

and

$$e_{it} \equiv Pr(P_{it} = 1 | P_{it-1} = 0) = \frac{\Phi_2(\gamma_2' z_{it-1}, -\beta' x_{it-1}; -\rho_2)}{\Phi(-\beta' x_{it-1})} \tag{10}$$

In the two equations above Φ_2 and Φ refer to the CDFs of the bivariate and univariate standard normal distributions respectively. Note that the regressors in these transition probabilities are measured using data from period $t-1$. This allows us to calculate transitions (or persistence) for those respondents with $R_{it} = 0$.

The sample log likelihood function contains six possible outcomes based on poverty status in the initial wave and on sample retention. Sample members who were retained in the panel fall into four possible outcome categories, depending on initial poverty status, while those who attritted are only observed as either non-poor or poor in the initial period. Therefore the log likelihood contribution of individual i whose poverty status is observed in the initial period is given by the following sample log likelihood function:

$$\begin{aligned} logL_i = {} & P_{it-1}R_{it}log\left[\Phi_3(k_i\gamma_1' z_{it-1}, m_i\psi' w_{it-1}, q_i\beta' x_{it-1}; k_i m_i\rho_3, k_i q_i\rho_2; m_i q_i\rho_1)\right] \\ & + (1-P_{it-1})R_{it}log\left[\Phi_3(k_i\gamma_2' z_{it-1}, m_i\psi' w_{it-1}, q_i\beta' x_{it-1}; k_i m_i\rho_3, k_i q_i\rho_2; m_i q_i\rho_1)\right] \\ & + (1-R_{it})log\left[\Phi_2(m_i\psi' w_{it-1}, q_i\beta' x_{it-1}; m_i q_i\rho_1)\right] \end{aligned}$$

where $k_i \equiv 2P_{it} - 1$, $m_i \equiv 2R_{it-1} - 1$, $q_i \equiv 2P_{it-1} - 1$. The first term in the sample likelihood function corresponds to the contribution of an individual who was poor in the initial wave and was retained in the sample. The second term is the contribution of an individual who was non-poor in the initial wave and was retained in the sample. The third term is the contribution of an individual whose poverty status was observed in the initial wave, but who was not retained in the sample.

The presence of the trivariate standard normal distribution function in the sample log likelihood function means that estimation of the model is rather complicated, and because of this we rely on the simulation methods outlined in Gouriéroux and Monfort (1996), and presented in the context of an endogenous switching model in Cappellari and Jenkins (2006). Our estimation in this study uses the GHK simulator with 250 random draws.

One important part of the estimation process to consider is the fact that by pooling observations we are violating the maximum likelihood estimation assumption of independently and identically distributed observations. In order to correct for this we cluster our standard errors at the household level in the wave in which each respondent first appears in the data. For example, if a respondent appears in all four waves, the cluster is defined as the household identifier in wave 1. Respondents who are added to the sample from wave 2 onwards (such as TSMs) are allocated a cluster according to the household in which they are first observed. This allows us to account for arbitrary levels of intra-household correlation while maintaining the assumption of independence across households.

Identification in this model can come in two ways. One can either force the cross-equation correlations to equal zero, or invoke a set of exclusion restrictions that impact on initial poverty or the probability of attrition, but do not have an effect on the transitions themselves. The first method is not attractive, as one of the strengths of this particular way of thinking about poverty transitions is that we can, in fact, estimate these cross-equation correlations. This means we have to argue for identification of the model through a set of exclusion restrictions that allow us to test whether initial conditions and attrition are exogenous. If we find that $\rho_1 = \rho_2 = \rho_3 = 0$ then we can simply use univariate probit models to estimate poverty dynamics. Similarly, if we find that $\rho_1 = \rho_3 = 0$ then we can treat attrition as random and ignorable, and our estimation reduces to a bivariate probit model. Finally, if we find that $\rho_1 = \rho_2 = 0$, then we are able to treat poverty in $t-1$ as exogenous. These are interesting questions even if asked independently of the trivariate model itself.

The first set of exclusion restrictions requires us to find a variable (or a set of variables) that determine initial poverty status but are unrelated to the transition into or out of poverty. To this end we follow Cappellari and Jenkins (2004) and Jenkins (2011) who use the argument in Heckman (1981b) that initial conditions for labour market outcomes may be instrumented by information on the individual prior to labour market entry. In our model we use variables of the head of the household's parental occupation and education as instruments for initial conditions.[24] That is, these variables appear in x_{it-1} but not in z_{it-1}.

The second exclusion restriction requires us to include a variable (or set of variables) in w_{it-1} that is not included in z_{it-1}. That is to say we need a variable that affects the probability of attrition, but not poverty retention or transition. We take advantage of the panel structure of NIDS and include a dummy variable for whether a respondent is a continuing sample member (CSM) or a temporary sample member (TSM). CSMs are sample members who appear in the first wave of NIDS, while TSMs are those respondents who joined the household of a CSM in waves 2, 3 or 4. CSMs are tracked from wave to wave, while TSMs are not. In using this exclusion restriction we are asserting first that CSMs and TSMs have different probabilities of being retained in the sample, and second that the propensity to transition into or out of poverty is unrelated to whether a respondent is a CSM or a TSM.

The coefficient vectors in our model share a core of common variables, all of which are contained in z_{it-1}. The vector in the initial conditions equation, x_{it-1}, is comprised of z_{it-1} with additional variables controlling for parental education and occupation categories. Likewise, the vector in the sample retention equation, w_{it-1} contains z_{it-1} plus a dummy variable which identifies whether a respondent is a CSM or a TSM.

We are able to test the validity of our exclusion restrictions by treating the non-linear functional form of the model as being sufficient for identification, and using the parental background variables and CSM dummy as over-identifying restrictions for the initial conditions and sample retention equations, respectively. The results of these tests are presented in Table 9, along with our estimates of the ρ correlation coefficients.

The first panel of Table 9 shows the three ρ correlations that were defined earlier, all of which are statistically significant at the 1% level. The fact that ρ_1 is positive indicates that poor respondents in the initial period are less likely to have attritted compared to those who started

[24] NIDS includes a module in the adult questionnaire that records the education and occupational category of each respondent. The dummy variables include the following sectors: agriculture/elementary, professional, semi-skilled/operator, crafts, clerks, and a dummy variable for missing occupational sector.

off non-poor. This is unsurprising, as the disproportionate loss of wealthier households from wave to wave has been a feature of the panel dynamics of NIDS (de Villiers et al., 2013; Baigrie and Eyal, 2013). The correlation between unobservables affecting initial poverty and poverty transitions, ρ_2, is also positive, reflecting the fact that respondents who were poor in the initial period were more likely to be poor in the next period, compared to those who were non-poor to start off with. Finally the correlation between the unobservables determining the relationship between retention in the sample and conditional current poverty status, ρ_3 is negative. This implies that, for example, for the subsample of individuals who were poor in $t-1$, those who were retained in the sample are less likely to be poor in t than those who attritted would have been had they been retained.

Tests of the exogeneity of the different processes are contained in the second panel of Table 9. A Wald test of ρ_1 and ρ_2 is rejected at the 1% level, implying that initial conditions are not exogenous and should be accounted for in the modelling of poverty transitions. The null hypothesis of the exogeneity of sample retention is rejected at the 1% level (test statistic 59.73), indicating that sample retention is endogenous when modelling poverty transitions, and that accounting for it in the model is important. Finally, a joint test of ρ_1, ρ_2 and ρ_3 being zero is also rejected at the 1% level, confirming that initial conditions and sample retention are endogenous, and lending weight to our strategy of modelling poverty dynamics using a trivariate probit.

The next part of the table presents tests of the suitability of the instruments that are added to the vector of coefficients in the transition and retention equations. Wald tests show that parental background variables of the household head and sample membership status can be excluded from the transition equation both separately and jointly. In contrast, these were found to be statistically significant in the initial conditions equation and the retention equation, respectively. Thus it appears that the NIDS data support the use of these instruments in the estimation of poverty transitions and that we do not have to rely solely on non-linearity as our identifying factor. Finally, we tested for state dependence by calculating a Wald statistic for the equality of γ_1 and γ_2 from the equation estimating current poverty, and the null hypothesis of no state dependence was rejected at the 1% level.

Table 9: Model correlations and test statistics

Correlations between unobservables	**Estimate**	**p-value**
Initial conditions and retention (ρ_1)	0.039	0.000
Initial conditions and conditional current poverty (ρ_2)	0.196	0.000
Retention and conditional current poverty (ρ_3)	-0.228	0.000
Null hypotheses	**Test statistic**	**p-value**
Unobservables:		
Exogeneity of initial conditions (ρ_1=ρ_2=0)	56.06	0.000
Exogeneity of sample retention (ρ_1=ρ_3=0)	73.89	0.000
Joint exogeneity (ρ_1=ρ_2=ρ_3=0)	117.47	0.000
Transition equation:		
Exclusion of parental background (d.f.=10)	11.40	0.250
Exclusion of sample membership status (d.f.=2)	1.11	0.574
Exclusion of both (d.f.=12)	12.31	0.341
Initial conditions equation:		
Inclusion of parental background (d.f.=5)	42.10	0.000
Retention equation:		
Inclusion of sample membership status (d.f.=1)	3 439	0.000
State dependence:		
No state dependence, $\gamma_1 = \gamma_2$ (d.f.=50)	5 933	0.000

Source: Own calculations from the first four waves of NIDS.

The evidence presented suggests that our estimation strategy is sound. We turn now to the impacts of the independent variables on the probabilities of poverty transition and poverty persistence.

We calculate two sets of marginal effects - one set for poverty persistence and one for poverty entry, corresponding to poverty status in $t-1$. These are derived from the equations defining s_{it} and e_{it} respectively. We follow Stewart and Swaffield (1999) and Cappellari and Jenkins (2004) in defining the marginal effects of this model. The following explanation is related to the poverty persistence equation defining s_{it}. The corresponding explanation for poverty entry, e_{it} is constructed analogously. Because of the three related processes being modelled in this estimation strategy, a marginal change in one of the components of z_{it-1} will also result in a change in x_{it-1} because of the common elements in both vectors. This implies a change in the denominator of s_{it}, that is, the probability of being poor in $t-1$. In order to hold this constant in the calculation of the marginal effects we applied the following steps. We calculate the predicted probability of being poor in $t-1$ for all those respondents who were poor at this time. Next we take the average of these predicted probabilities which we call c. Then, into the denominator of the equation for s_{it} we substitute in $d \equiv \Phi^{-1}(c)$ which gives us the expression $\Phi_2(\gamma_1' z_{it-1}, d; \rho_2)/d$. Marginal effects for continuous variables are calculated by inducing an infinitesimal change in the covariate with all other covariates held constant at their means. For binary variables the marginal effect is calculated as the change in s_{it} implied by a unit change in the variable of interest, relative to a reference person. This reference person is defined by setting all continuous variables to their median values, and setting all binary covariates equal to zero.

The first two columns of results in Table 10 present the marginal effects and associated t-ratios for poverty in t conditional on being poor at $t-1$.[25] Females were four percentage points more likely to remain in poverty than males. African and coloured sample members had a conditional poverty probability that was around 31 percentage points higher than white sample members. Of the household head's characteristics, having a completed secondary or tertiary education was associated with a lower conditional poverty probability of 13.5 percentage points, relative to the base category of no education. The marginal effect of living in a household in which the head is employed is not statistically significant at the 5% level. Urban households were 6.4 percentage points less likely to remain in poverty than the base category of rural households. The presence of at least one employed household member is associated with a 5.8 percentage point reduction in the probability of remaining poor, while the presence of at least one child aged 15 or under results in a 4 percentage point increase in the probability of being poor in both time periods.

The third and fourth columns in the table present the marginal effects of conditional poverty entry between periods $t-1$ and t. The economic significance of each individual covariate is similar to the estimates of conditional poverty persistence, though the t-ratios of age, age squared and the female dummy variable are three to four times smaller. Africans are almost 30% more likely to enter poverty than the base group of whites, on average, even after controlling for individual, household head and overall household characteristics. The corresponding effect for coloured respondents is 23%. Living in a household with a female household head is associated with a higher conditional probability of poverty entry of 8.5 percentage points - more than four times larger than the effect for conditional poverty persistence. The protective effect of having at least a matric is more than twice as strong against the conditional probability of entering poverty than it is against the conditional probability of remaining in poverty. The largest difference in these columns compared to the previous two is that having at least one household member aged 65 and above increases the probability of poverty entry by almost 16 percentage points, whereas the effect was not statistically significant at the 5% level in the poverty persistence estimates.

[25] The table shows that there are 40 850 individuals who form part of the estimation sample, and three pairs of wave-to-wave transitions (wave 1 to wave 2, wave 2 to wave 3, and wave 3 to wave 4). The mapping to the number of person-waves is as follows. Balanced panel members appear three times in the wave-to-wave pairs, and each of these will show up in the number of person-waves considered. However, because we are using the pooled sample of NIDS respondents over all four waves, we also include those who experience one or two transitions (appearing in only two or three consecutive waves) in the estimation of the model.

Table 10: Model estimates of poverty in t, conditional on poverty status in $t-1$

Covariate at $t-1$	Poor at $t-1$		Non-poor at $t-1$	
	Marginal effect	|t-ratio|	Marginal effect	|t-ratio|
Individual				
Age	-0.002	(11.37)	-0.003	(3.62)
Age squared	0.00004	(8.62)	0.00004	(2.12)
Female	0.040	(8.82)	0.042	(2.46)
African	0.314	(11.71)	0.294	(13.71)
Coloured	0.312	(11.54)	0.231	(10.77)
Household head				
Age	-0.001	(2.05)	-0.005	(7.11)
Age squared	0.00002	(3.03)	0.00002	(4.92)
Female	0.021	(4.35)	0.085	(4.54)
Matric and above	-0.135	(17.18)	-0.279	(17.85)
Employed	0.009	(1.53)	-0.039	(1.84)
Household				
Urban	-0.064	(10.69)	-0.084	(3.77)
Farm	-0.005	(0.46)	-0.029	(0.78)
Adult 65 and above	0.009	(1.24)	0.157	(4.74)
Children 15 and below	0.040	(25.67)	0.028	(3.12)
Any workers	-0.058	(9.88)	-0.006	(0.20)
Own dwelling	0.041	(6.56)	0.006	(0.29)
Log likelihood	-94 355			
Model chi-squared (d.f. = 54)	4 306 (p<0.000)			
No. of clusters	13 238			
No. of observations	40 850			
No. of observations (person-waves)	88 090			

Source: Own calculations from the first four waves of NIDS. Reference categories for binary covariates: male, white, male household head, household head does not have matric, household head is not employed, Western Cape province, rural area, no adults over 65 in the household, no children under 15 in the household, no workers in the household, household members do not own the dwelling. The base wave is wave 1.

Another way of interrogating the findings is to run the full Markovian model on the subsample of African respondents only. As was shown in the poverty transition matrices earlier in the chapter, although the African subsample drives most of the results, there are often important differences in the dynamics between African and non-African panel members. Table 17 in the appendix estimates the marginal effects from the same type of Markovian model that was reported in Table 10, but restricts the analysis to African respondents only.[26] The change in sample also implies a change in the underlying correlations between unobservables, and the underlying distributions of the explanatory variables. The base category for the calculation of the marginal effects remains the same except for the fact that there is no longer a base category

[26]Full results along with the estimated correlations between the unobservables are available from the author.

for race, as the variable does not vary in this subsample.

The marginal effects for poverty persistence are relatively similar when comparing the full sample to the African subsample. However, the protective effect of a household head having at least a matric education decreases from 13.5% to 11.5%. The marginal effect on poverty persistence of living in an urban area, relative to the rural base category, decreases in absolute terms from -6.4% to -5.5%, on average.

There are more differences between the samples in the poverty entry marginal effects, compared to the poverty persistence marginal effects. The individual marginal effects of age and gender for the poverty entry model are very similar for the overall sample and for the African subsample. In the full sample having a female household head is associated with an 8.5% increased probability of transitioning into poverty, on average. This decreases to 6% when the model is estimated on the African subsample only. The protective effect of living in a household in which the head has at least a matric is lower in the African subsample – 23.1% compared to 27.9% in the full sample. Living in a household in which the head is employed has a larger effect amongst Africans than non-Africans in protecting against poverty entry, and this is in contrast to the smaller protective effect of living in urban rather than rural areas for this group. Interestingly, for the African subsample there is no statistically significant effect of the presence of an elderly person in the household on the probability of transitioning into poverty, in contrast to the overall effect (and therefore the effect amongst non-Africans). As was the case previously, the presence of children in the household has no statistically significant effect on the probability of transitioning into poverty, on average.

Although contexts and methodologies vary greatly between countries, it is worth pointing out some of the other existing research on poverty transitions that uses a similar estimation strategy to the one found in this chapter. The seminal Cappellari and Jenkins (2004) study uses BHPS data for Britain. The authors find statistically significant correlations between initial conditions and retention (ρ_1), and between initial conditions and current poverty (ρ_2). Although there is no statistically significant relationship between the unobservables affecting retention and the unobservables affecting conditional current poverty (ρ_3), the full set of unobservable correlations are jointly significant. The results in this study suggest that living in a household in which the head has at least completed A-levels is associated with a lower probability of poverty persistence. The presence of children in the household significantly increases the probability of conditional poverty persistence. In general, there are more statistically significant relationships in the poverty entry equation, compared to the poverty persistence equation. Older respondents and households with male heads are both associated with higher probabilities of transitioning into poverty, as are single parent families and multi family households. Another example of a Markovian approach to studying poverty transitions in an OECD country is Buddelmeyer and Verick (2008) which uses the first five waves of the HILDA longitudinal dataset in Australia. This paper finds that poverty is largely a transient phenomenon in Australia, and that having a tertiary education is a large buffer against both poverty persistence and poverty entry. The study also uncovers an important geographic aspect to who becomes who and who remains in poverty, with poverty concentrated in remote and rural areas of the country.

Although there are few examples of this data-intensive approach to studying poverty dynamics in developing countries, Faye et al. (2011) use the 3rd and 13th waves of a large dataset which tracks welfare in Nairobi slums. Their results suggest that in this context, only the correlation between the unobservables affecting initial conditions and the unobservables affecting retention are statistically significant. The presence of children in the household is associated with a higher probability of remaining in poverty, but not of entering poverty. Neither the gender of the respondent nor that of the household head has a significant effect on either poverty persistence or poverty entry. Finally, Azomahou and Yitbarek (2015) follow a sample of 837 households in Ethiopia in order to study poverty transitions. The results of this study show that the education level of the household head is an important buffer against poverty persistence, but that it has no significant effect on the probability of poverty entry. Perhaps surprisingly, there are once again no gender differentials in the probability of remaining in or transitioning into poverty.

How does estimating conditional poverty dynamics in this way change our understanding compared to a simple univariate probit model? Table 18 in the appendix presents results from a univariate probit model using the same vector of covariates that as in Table 10, except without controlling for initial conditions and non-random attrition. The marginal effects in the Markovian model are generally more economically significant than they are in the probit. For example, being female increases the conditional poverty entry probability by 4.2 percentage points in the Markovian model, but only by 1.4 percentage points in the univariate probit. The presence of at least one adult aged 65 and above increases conditional poverty entry in the Markovian model by almost 16 percentage points, while the corresponding increase in the univariate probit stands at 5 percentage points. The protective value of having at least a matric is heightened in the Markovian estimation with a marginal effect of -28 percentage points, compared to almost -16 percentage points in the univariate probit. One interesting point to observe is that the sign of the dummy variable denoting the presence of children aged 15 and below in the household switches from negative to positive as we move from the probit model to the Markovian estimation in the poverty entry equations.

What do the results suggest about the length of poverty spells?

In an early paper using a first-order Markovian model to estimate transitions into and out of welfare, Boskin and Nold (1975) show that the conditional probabilities of being in each state follow a geometric distribution and can be used to generate statistics on the length of time that each sample member can expect to be in a given state. In the South African context, Carter and May (2001) also assume a stationary Markov process in order to try to uncover the long run distribution of poverty status using six different categories of welfare.[27] For the trivariate case, Jenkins (2011) shows that, assuming stationarity, equations 9 and 10 can be used to calculate the average length of time that an individual is expected to be in poverty. This is given by $1/(1-s_i)$, while the median duration is given by $log(0.5)/log(s_i)$.[28] The average length of time that an individual will spend out of poverty is $1/(e_i)$, with median time out of poverty given by $log(0.5)/log(1-e_i)$. Finally, the unconditional probability that an individual is poor is expressed as $e_i/(e_i+1-s_i)$. Given the way in which the model was estimated, these spell length estimates control for the biases introduced by initial conditions and non-random attrition by construction.

As noted in the introduction to the Markovian model, projections like these rely on the assumption of no state dependence (thus allowing for left-censored poverty spells to be incorporated). In practice this means that predictions of mean and median poverty spell lengths rely on a fundamental stationarity assumption. The choice of base category and subsequent variations in Table 11 therefore relies on variables that are more likely to be stable over time (for example education of the household head, race and gender). In addition, rather than displaying the predicted lengths of poverty and non-poverty spells, the table and discussion present the lengths of these spells relative to the base category.

Table 11 presents the predicted poverty transition probabilities, steady state probabilities and relative spell lengths of poverty and non-poverty for a range of different characteristics. In the first case, the reference person is a 40 year old African male living in urban KwaZulu-Natal in a household in which the household head has at least a matric level of education, in which there are no children under the age of 15 and in which there are no adults aged 65 and over. The poverty persistence rate associated with this individual is 0.435, while the predicted poverty entry rate is 0.229. The predicted probability of this man being poor is just under 0.3. Given the stationarity assumption, the average lengths of time spent poor and non-poor have both been set to 1, so that all other results can be interpreted relative to this base category. In practice the mean length of time spent poor or non-poor is higher than the median for the base category and all subsequent comparisons. This reflects the relatively wide distribution and relatively long right hand tail of poverty spell lengths for individuals with the same characteristics.

In the next row of Table 11 we change the sex of the reference person to female, while keeping all other characteristics the same. This increases the predicted probability of remaining in poverty by about four percentage points, and the predicted probability of entering poverty by almost three percentage points. The overall probability of being poor is 33%, which is four percentage points higher than a male with the same characteristics. This number is broadly in line with the marginal effects presented in Table 10, though the reference characteristics are different. The implication of these relatively higher persistence and entry rates is that the mean

[27]This is a slightly different application to what we are interested in, as the authors uncover the long-run distributions of poverty classes, while we are more interested in relative poverty and non-poverty spell lengths.

[28]The time subscript has been omitted because of the assumption of stationarity.

and median poverty spell lengths are longer, while the mean and median non-poverty spell lengths are shorter, relative to the base category.

In the third row we keep the characteristics of the person in row 1, except for changing the racial group from African to white. In line with the results of the model and the descriptive statistics, this has a very large impact on the predicted poverty states. The predicted probability of remaining poor is just under 13%, compared to 43.5% for African respondents with the same characteristics, while the predicted probability of entering poverty is just 3%, compared to 23% for African respondents with the same characteristics. The average length of time that a person with these characteristics can expect to remain poor 35% lower for whites than for Africans, and the mean length of time spent non-poor is 7.67 times longer for whites than for Africans.

The fourth row keeps the same characteristics as the first row apart from changing the education of the household head from matric and above to less than matric. In line with the large economic significance reported in Table 10, this single change increases the probability of an individual being in poverty from 29% to 60%. The predicted poverty persistence and poverty entry rates are higher, as are the mean and median lengths of time for the predicted spell length of poverty, relative to the base category.

The remaining rows show that the highest probability of being poor is for individuals living in a household with children aged 15 and under, with at least one adult aged 65 and above, and with a household head who does not have a matric level of education. This predicted probability is 70%, over 40 percentage points higher than the base category in row 1. The longest relative average poverty spell is for those individuals who live in a rural household with a household head who does not have a matric level of education (see row (8)). As can be seen in row (10), an individual who lives in a household with children under 15 years old and elderly adults, in which the household head does not have a matric can expect to be in poverty for 46% longer than the base category, on average, and can expect to experience spells of non-poverty that are only about a quarter as long as those experienced by the base category, on average. The median poverty spell length for someone with these characteristics is 71% longer than that experienced by the base category, while the median length of time spent non-poor is only 12% of the time that someone with the base category characteristics can expect to experience.

How sensitive are our results to the choice of poverty line?

The choice of which poverty line to use always involves some level of arbitrariness, and one obvious robustness check is to investigate how results change for different poverty lines. Using poverty status as a binary dependent variable is very different to using other binary dependent variables in estimation. For example, it is generally objective whether an individual is employed or not, whether an individual receives a pension or not, or whether a child is enrolled in school or not. Converting money metric welfare into a binary variable reflecting poverty, however, necessarily involves some subjective judgements. This means that checking the sensitivity of

Table 11: Predicted transition probabilities, steady-state probabilities and relative spell lengths

Characteristics	Poverty persistence rate (s_{it})	Poverty entry rate (e_{it})	Pr(poor)	Poverty spell length relative to (1)		Non-poverty spell length relative to (1)	
				Mean	Median	Mean	Median
(1) Male, aged 40, African, male HHH with matric, KZN province, urban, no adults 65 and over, no children 15 and under	0.435	0.229	0.289	1.00	1.00	1.00	1.00
(2) As (1) except female	0.474	0.257	0.328	1.07	1.12	0.89	0.88
(3) As (1) except white	0.128	0.030	0.033	0.65	0.41	7.67	8.58
(4) As (1) except HHH no matric	0.573	0.641	0.601	1.33	1.50	0.36	0.25
(5) As (4) except female	0.606	0.698	0.639	1.44	1.66	0.33	0.22
(6) As (4) except female HHH	0.622	0.819	0.684	1.50	1.76	0.28	0.15
(7) As (4) except with adults over 65	0.581	0.851	0.670	1.35	1.53	0.27	0.14
(8) As (4) except rural	0.627	0.775	0.675	1.51	1.78	0.30	0.17
(9) As (7) except workers in HH	0.528	0.841	0.641	1.20	1.31	0.27	0.14
(10) As (7) except with children in the HH	0.614	0.896	0.699	1.46	1.71	0.26	0.12

Source: Own calculations from the first four waves of NIDS. HH = household. HHH = household head.

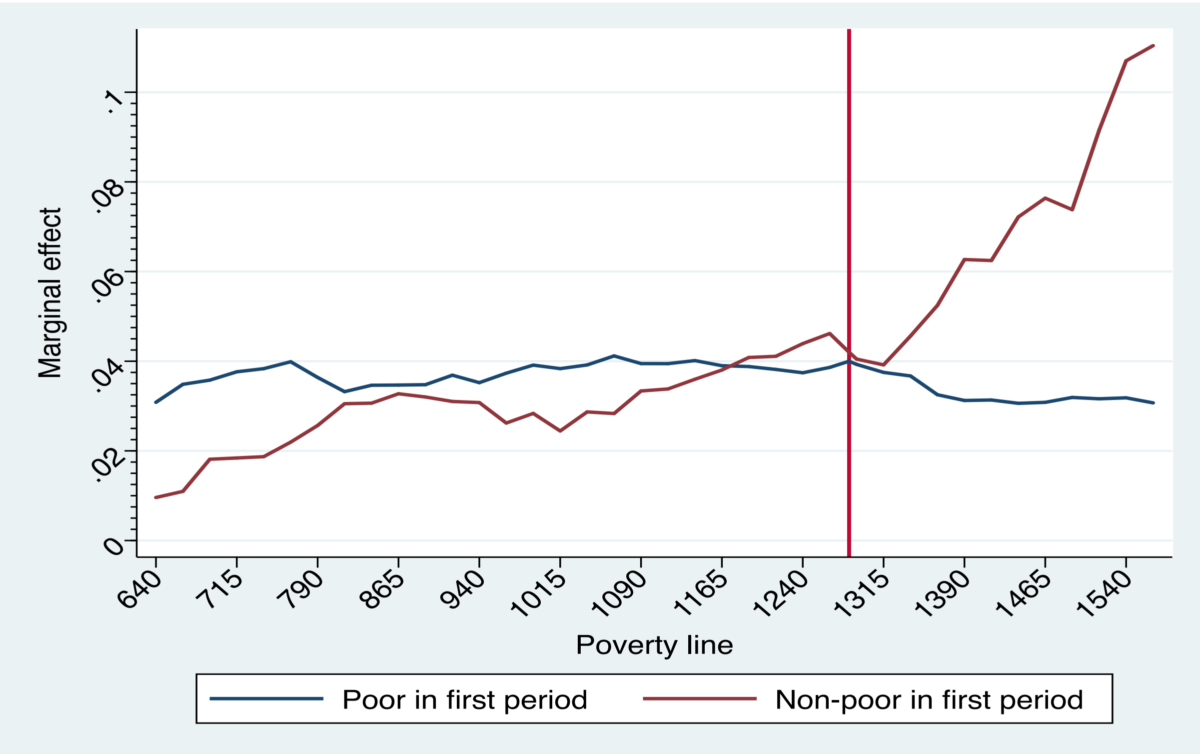
the model's results for different poverty lines is important. The primary reason for this is so that we are not 'hostage to an…arbitrarily selected poverty line' Deaton (1997). A second reason for doing so is that it may be interesting in itself to see how the effect of a particular variable on poverty transitions changes as the definition of poverty changes. For example, we may be interested in whether the effect of having a household head with a matric education has an increasingly protective effect against falling into poverty as the poverty line rises.

We use a wide range of possible poverty lines in order to see both how marginal effects change from a low to a high poverty line, and also to see how stable the marginal effects are in the neighbourhood of our poverty line of R1 283. The lower bound for our poverty line range is R640, which is just under half the poverty line used in the estimation. It is also close to the StatsSA lower bound poverty line of R608 (Statistics South Africa, 2015), and it is unlikely that any reasonable poverty line for South Africa would be below this amount. The upper bound for our robustness check is a very high poverty line of R1 565, giving us a total window of just over R900 in which to assess the sensitivity of our results. The poverty line of R1 283 is the highest line in general use in the South African academic discourse, and the results for poverty lines above this level should be interpreted with this in mind

In Figure 5 we show the marginal effects for the female dummy variable for poverty lines from R640 to R1 540. Recall from the table of results that females who were poor in period $t-1$ were, on average, 4 percentage points more likely to remain in poverty than males. The corresponding marginal effect for females who were not in poverty in $t-1$ was almost the same, at 4.2 percentage points. This small difference is reflected at the vertical line in the figure, corresponding to the model's poverty line of R1 283.

The female marginal effect for those who were poor in $t-1$ is far more stable than the corresponding marginal effect for females who were non-poor in $t-1$. In fact, any poverty line from R950 to R1 350 would give a marginal effect of around 4 percentage points for females who remain in poverty. The marginal effect for females entering poverty is relatively stable in the vicinity of the R1 283 poverty line, but it explodes thereafter - jumping by over 150% from a poverty line of R1 283 to a poverty line of R1 540. Had we chosen the StatsSA lower bound poverty line, we would have seen female marginal effects of 3 percentage points and 1 percentage point for poverty retention and poverty entry, respectively.

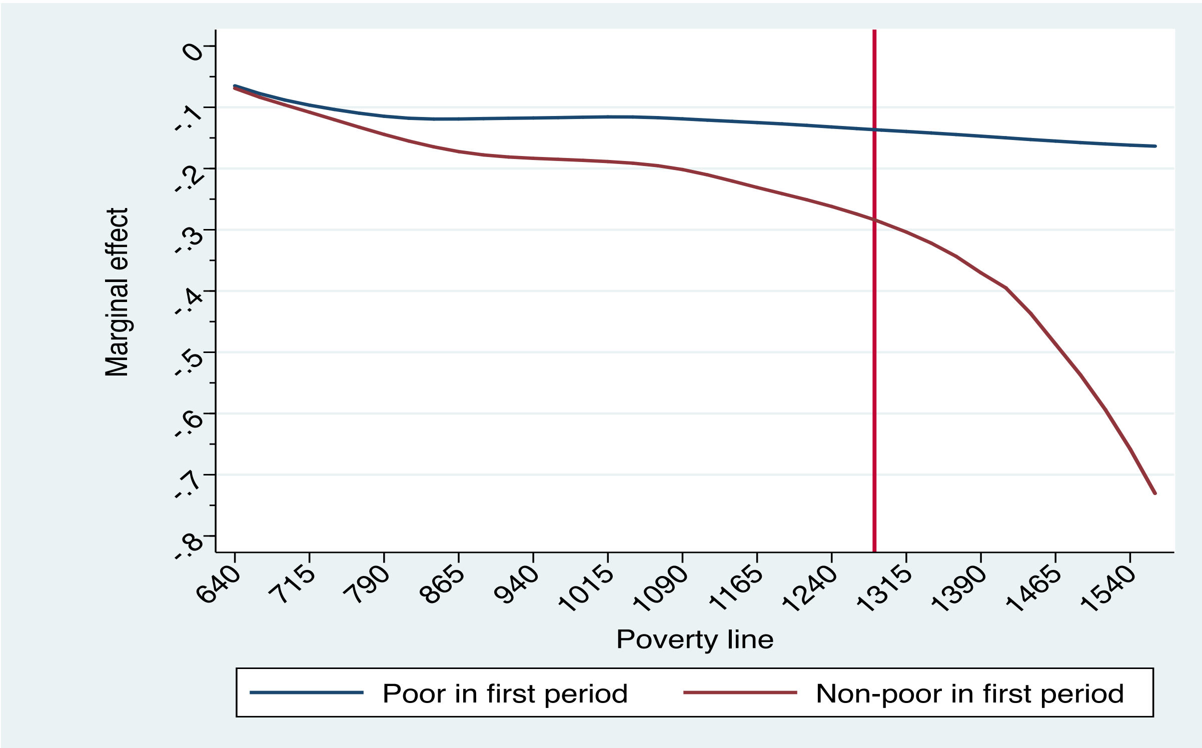
Figure 5: Female marginal effect on the probability of being poor in the second period for different poverty lines



Source: Own calculations from the first four waves of NIDS.

The sensitivity of the marginal effect of having a household head with at least a matric is interesting because it is the single largest marginal effect apart from the race categories (in absolute terms) in both results columns of Table 10. While the female marginal effects diverge for poverty lines higher than R1 283, the marginal effects of having a household head with at least a matric begin to diverge much earlier. This can be seen in Figure 6, where the marginal effects at a poverty line of R640 are identical at -6 percentage points. Had we chosen this lower bound poverty line, we would not have been able to identify any discernible difference between the two different states in $t-1$. The 'protective' effect against remaining in poverty of having a household head with at least a matric increases steadily up to our poverty line of R1 283, where it stands at -13.5 percentage points. From there the effect increases gradually in absolute terms to -16.5 percentage points for a poverty line of R1 540. The lower line in Figure 6 shows very different marginal effects across the distribution of poverty lines. These significant differences over the range of poverty lines are likely driven by the fact that relatively few people living in a household in which the head of the household has at least a matric actually fell into poverty between $t-1$ and t. At our poverty line of R1 283 we find that the economic significance of having a household head with at least a matric is double for those who were non-poor in the first period, compared to those who were poor, on average. This difference would be zero if we used the lowest poverty line in the figure, but would be almost of the order of 4.5 if we used a poverty line as high as R1 540.

Figure 6: Household head with matric or above marginal effect on the probability of being poor in the second period for different poverty lines



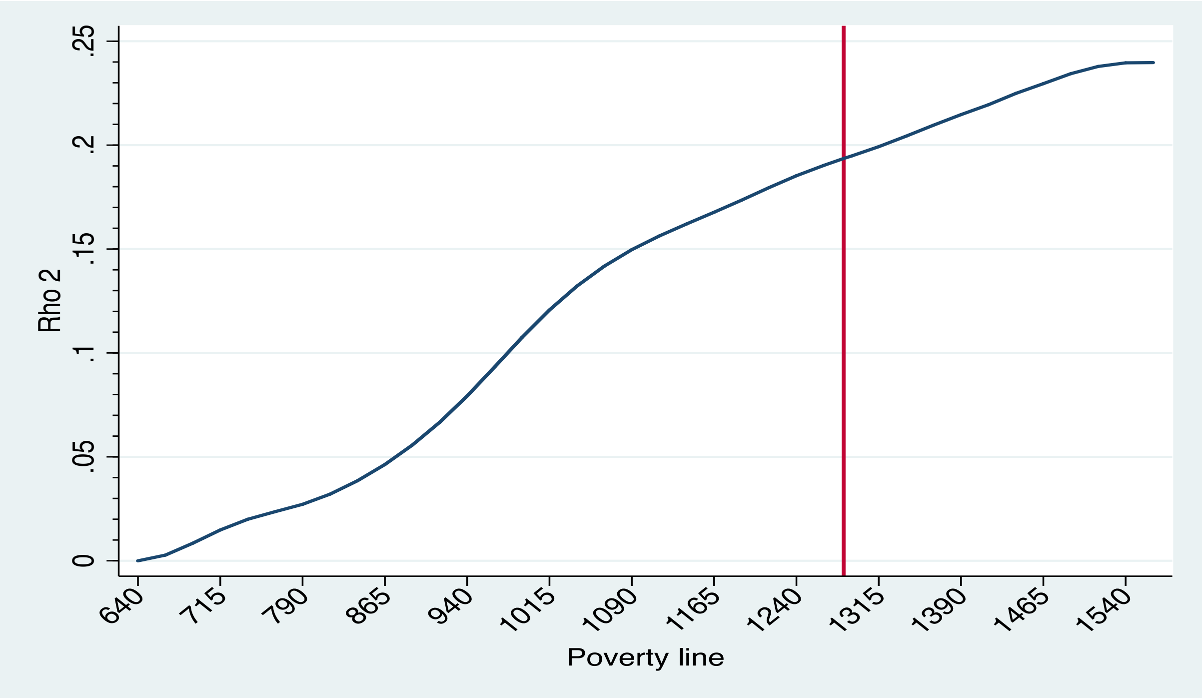
Source: Own calculations from the first four waves of NIDS.

We also check the sensitivity of the results if we had ignored initial conditions and non-random attrition, and instead estimated a probit model of poverty transitions. The marginal effects for the female and household head with at least a matric covariates for this can be seen in figures 11 and 12 in the appendix. In general the marginal effects from the probit models do not change as much for higher poverty lines as they do in our Markovian model. The marginal effect for females who were both poor and non-poor in $t-1$ generally decreases as the poverty line increases. Interestingly, while the Markovian model produced diverging effects, conditional on initial poverty status, for those living in a household in which the head had at least a matric, the univariate probit model shows convergence over the same range of poverty lines, to the point where the difference is negligible for the highest poverty line of R1 540.

Figures 13 and 14 compare the marginal effects of the African and coloured variables for the poverty persistence versions of the Markovian and probit models respectively. In both cases the marginal effects from the Markovian model are higher than the marginal effects of the probit model, at any reasonable poverty line. The difference between the marginal effects is highest at the lowest poverty line of R640 - in both cases the Markovian marginal effect is about double the probit marginal effect. The marginal effects from both models converge as the poverty line increases, and are quite close to one another at the highest poverty line of R1 565. As shown in Table 10 and Table 18, the African and coloured marginal effects are extremely high, relative to the base category of white. On average, Africans are 31% and 24% more likely to remain in poverty than whites according to the Markovian model and the probit model respectively. The Markovian model shows that the marginal effect for coloured respondents remaining in poverty is also 31%, relative to the base category, while the corresponding marginal effect from the probit model is that this group is 23% more likely to remain in poverty than whites, on average. Interestingly, although the African marginal effect is generally slightly below the coloured marginal effect, the shape of the line of marginal effects over the range of poverty lines is similar for both groups, whether a Markovian model or a probit model is used in the estimation.

One of the reasons for the large differences in the marginal effects at different poverty lines between the Markovian and univariate probit estimations is the change in ρ_2 over the range of poverty lines. Recall that ρ_2 enters the calculation of the marginal effects via its presence in the numerator of equation 9 and equation 10. That is to say, the correlation between the unobservables affecting initial conditions and conditional current poverty changes over the range of poverty lines. In fact, as shown in Figure 7, the estimated correlation is very close to zero for the lowest poverty line, and then rises steadily until it reaches 0.196 at the poverty line of R1 283. The growth in the correlation over the range of poverty lines shows that state dependence becomes increasingly important as the poverty line increases, and reinforces the fact that our findings cannot remain agnostic to the choice of poverty line. The intuition behind the positive slope shown in this figure is that a) a lower poverty line means fewer people will be found to be in poverty and b) there will be more transitions out of poverty compared to a higher poverty line, by construction. More transitions out of poverty means a lower level of state dependence, which implies a lower correlation between the initial conditions and the conditional current poverty status. Therefore the positive slope of the line is a result of a higher poverty line being associated with a higher correlation between initial conditions and conditional current poverty.

Figure 7: Correlation between unobservables affecting initial conditions and conditional current poverty status for a range of poverty lines



Source: Own calculations from the first four waves of NIDS.

What do the results tell us about aggregate state dependence versus genuine state dependence?

An attractive feature of modelling poverty transitions in the way that we have is that it allows us to distinguish between aggregate state dependence (ASD) and genuine state dependence (GSD). ASD is simply the unconditional difference between the probability of being poor in t for those who were poor in $t-1$, and the probability of being poor in t for those who were non-poor in $t-1$. Measuring state dependence in this way does not take account of individual heterogeneity. It is easily calculated using the top panel of Table 8 as follows:[29]

$$ASD = \left(\frac{\sum\limits_{i\epsilon\{P_{it-1}=1\}} Pr(P_{it}=1|P_{it-1}=1)}{\sum\limits_{i} P_{it-1}} \right) - \left(\frac{\sum\limits_{i\epsilon\{P_{it-1}=0\}} Pr(P_{it}=1|P_{it-1}=0)}{\sum\limits_{i}(1-P_{it-1})} \right)$$

The calculation of GSD controls for observed and unobserved individual-level heterogeneity, and is particularly important if initial conditions matter for poverty in the current period. As explained in Cappellari and Jenkins (2004), "the experience of poverty itself might induce a

[29]In the ASD equation $\sum\limits_{i} P_{it-1}$ is the number of individuals who were poor in $t-1$, as for these individuals $P_{it-1}=1$. Likewise, $\sum\limits_{i}(1-P_{it-1})$

loss of motivation, lowering the chances that individuals with given attributes escape poverty in the future." One possible formal test for GSD is to test the null hypothesis that γ_1 and γ_2 from equation 5 are equal. The result of this test is shown in the final row of Table 9, in which the null hypothesis of no GSD is decisively rejected. Our equation for calculating GSD involves calculating the difference between the predicted probability of being poor in t, if poor in $t-1$, and the predicted probability of being non-poor in t, if non-poor in $t-1$ using the equations defining s_{it} and e_{it}. This is then summed over all individuals and divided by the number of individuals in the sample as follows:

$$GSD = \left(\frac{1}{N}\right) \sum_{i=1}^{N} [Pr(P_{it} = 1|P_{it-1} = 1) - Pr(P_{it} = 1|P_{it-1} = 0)]$$

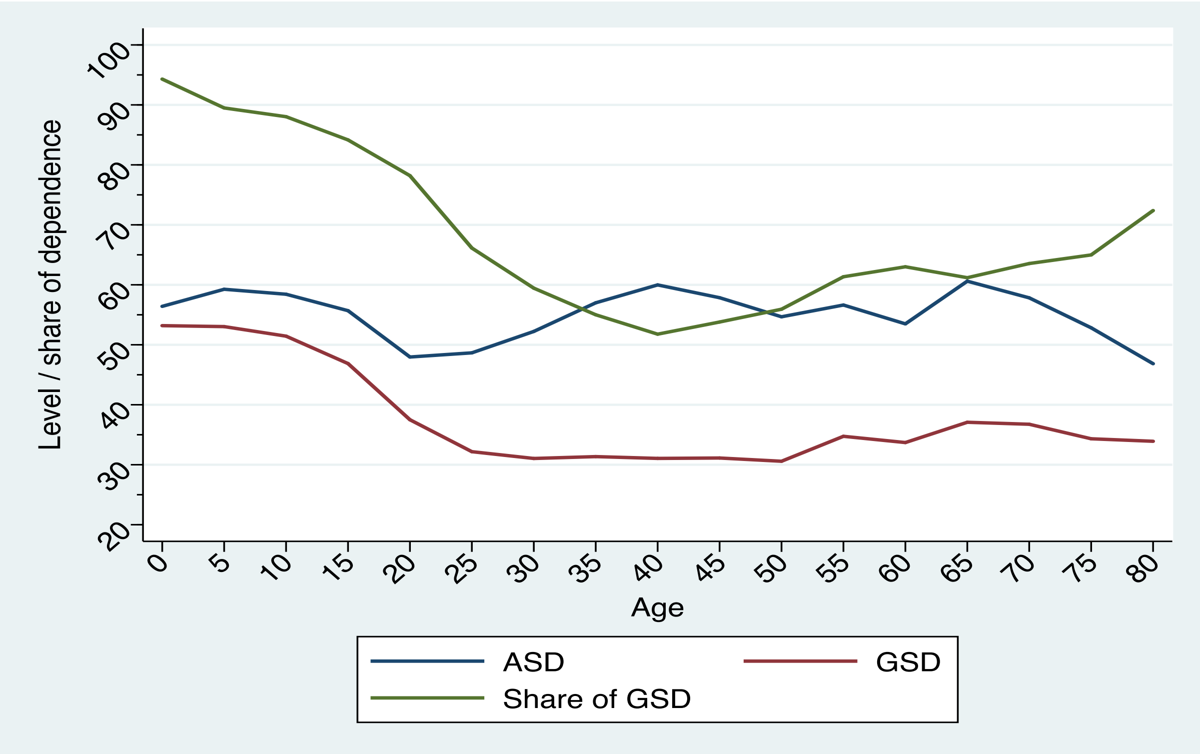
The distinction between ASD and GSD is useful because the policy implications depend on the relative importance of each kind of dependence. As argued in Arulampalam et al. (2000), "Identification of the extent of true state dependence...is more than just an academic exercise."[30] If there is very little GSD of poverty at the individual level, then short-run interventions to reduce poverty will have little impact, as poverty will mainly be generated by adverse individual heterogeneity. However, if there is a high level of GSD, then reducing the probability of the initial experience of poverty becomes crucial in the process of reducing long-run poverty in the country. This echoes Devicienti and Poggi (2011) who argue that the greater the share of GSD in overall state dependence, the higher the payoffs are to short-term income support programmes that prevent people from falling into poverty today. If, however, poverty persists mainly because of individual heterogeneity, then short-term income support schemes will have little effect on the long-run distribution of poverty in the country.

Our model estimates a level of ASD of 0.568 and a corresponding level of GSD of 0.416. This implies that the share of genuine state dependence in overall state dependence is very high at 73.30%. Figure 8 presents three statistics of interest, ASD, GSD and the share of GSD in total dependence across the age range of sample members.[31] ASD is relatively stable and is generally between 50 and 60, while GSD stands at about 53 for the youngest age cohort and then drops to around 30 for those between the ages of 25 and 50. The shape of the green line representing the share of GSD in overall dependence falls at first, in line with the decline in GSD, and then rises for those aged 40 and above. Even at its lowest point, genuine state dependence accounts for more than half of total poverty dependence in South Africa.

[30] Arulampalam et al. (2000) study unemployment persistence rather than poverty persistence, but their insights generalise to our context.

[31] Dependence levels were calculated for five-year age bands from 0 to 80. Those older than 80 were excluded because of low observation numbers.

Figure 8: ASD, GSD and the share of GSD by age group



Source: Own calculations from the first four waves of NIDS. Note: observation numbers for age cohorts are as follows. 0-4 (8 193), 5-9 (8 609), 10-14 (8 706), 15-19 (8 268), 20-24 (5 136), 25-29 (4 037), 30-34 (3 861), 35-39 (3 512), 40-44 (3 372), 45-49 (3 019), 50-54 (2 612), 55-59 (1 979), 60-64 (1 486), 65-69 (1 133), 70-74 (752), 75-80 (450).

VII Conclusion

In this chapter we began our investigation into the dynamics of poverty in South Africa by using the balanced four wave sample of NIDS comprising 17 265 respondents to analyse poverty dynamics in South Africa from 2008 to 2014/2015. Using a poverty line of R1 283 in January 2015 rands we found that the rate of exiting poverty was higher between waves 2 and 3, and between waves 3 and 4 than it was between waves 1 and 2. About 47% of the sample was below the poverty line in each of the four waves in which they were interviewed. Transition matrices showed that 54% of the balanced panel were poor in both wave 1 and wave 4, with more than half in 'severe' poverty - defined as having real household income per capita of less than half the poverty line.

The importance of demographic events in shaping dynamics was highlighted by the role of household composition changes as drivers of poverty entry and exit. Inter-wave demographic changes were the main triggers for 56% of those who entered poverty and 59% of those who exited poverty between wave 1 and wave 4. One needs panel data such as NIDS to disentangle these demographic events from income events. The value of such work is shown here in highlighting the central importance of migration and household instability in driving who gets ahead and who falls behind in contemporary South Africa.

The increasing longer-run importance of access to government grants was highlighted, with grant income being the main trigger precipitating poverty exit for 23% of previously poor balanced panel members between wave 1 and wave 4. By implication this flags as a major concern the muted role of the labour market in driving the dynamics of poverty exit between 2008 and 2014/2015.

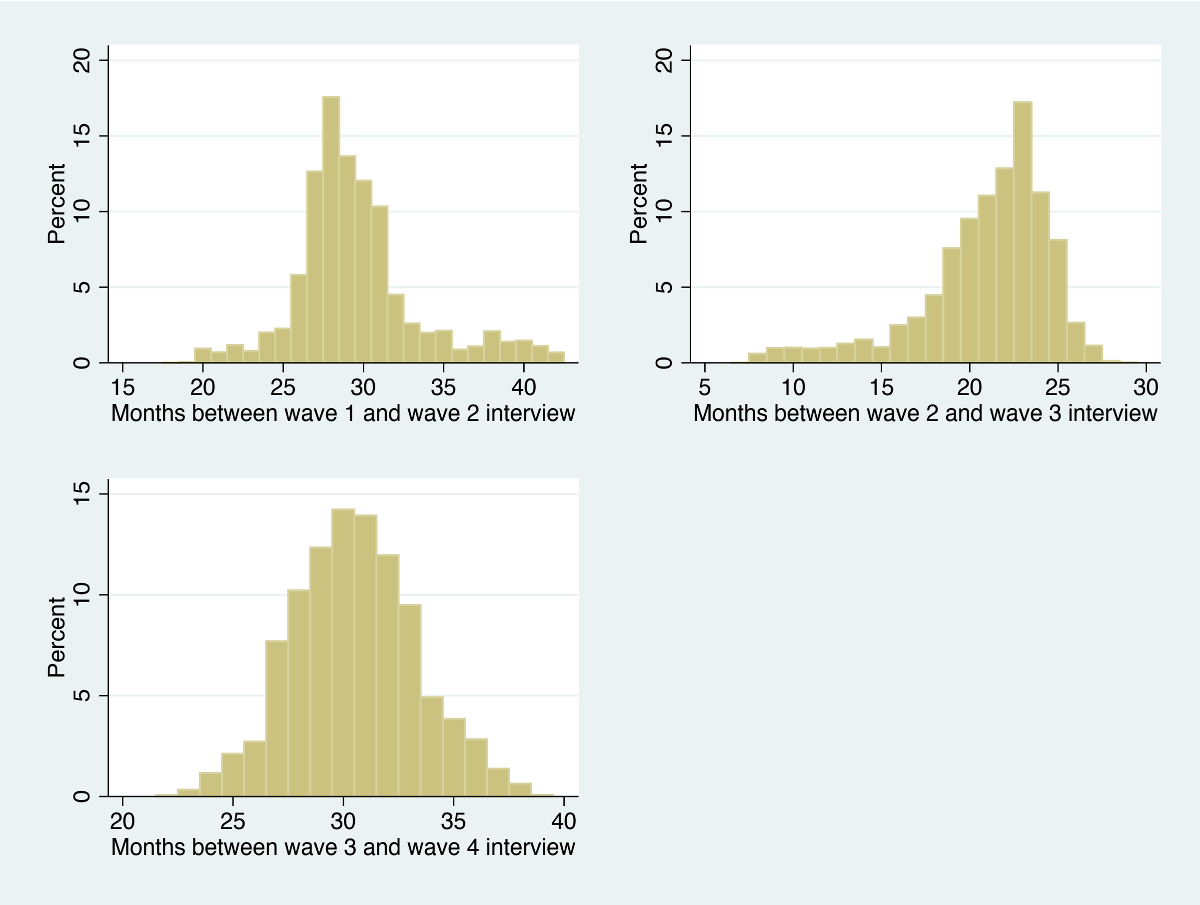
We then turned our attention to modelling poverty dynamics using a Markovian approach that simultaneously estimated poverty transitions along with initial conditions and selective attrition. We found that if researchers ignore the correlations between unobservables affecting initial conditions, sample retention and poverty transitions, then this could lead to substantially biased results. We also separated state dependence into the part attributable to aggregate state dependence and the part attributable to genuine state dependence, and found that the latter is dominant. From a policy perspective, this implies that preventing people from falling into poverty in the first place will likely yield greater returns in the long-run, rather than targeting the individual correlates of poverty directly.

Taken together, our results add to the body of literature showing that even after 22 years of democracy in South Africa, a very large proportion of its people have been unable to realise the economic freedom that should have come with political freedom. The task of us as researchers and policymakers is to ensure that this void is bridged as swiftly and justly as possible.

Appendices

A Number of months between being interviewed

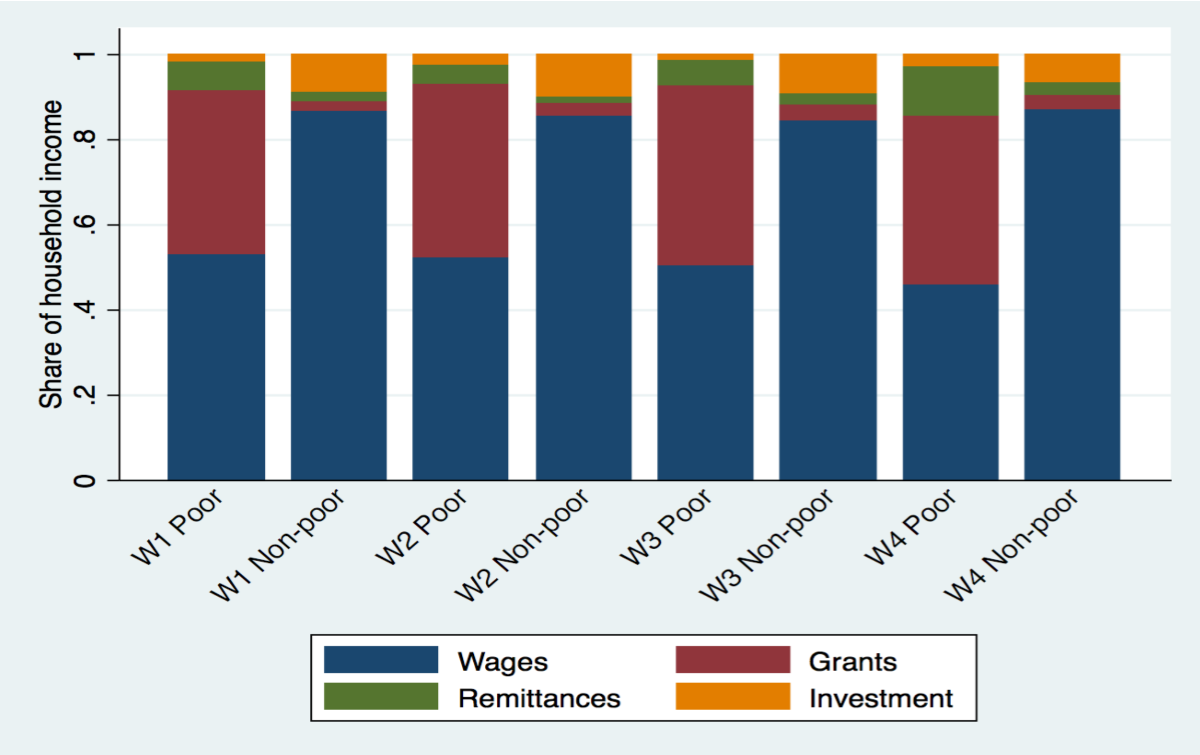
Figure 9: Number of months between interviews by wave interval for balanced panel members



Source: Own calculations from the first four waves of NIDS.

B Composition of household income

Figure 10: Household income composition for poor and non-poor respondents by wave



Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

C Transition matrices for African respondents

Table 12: Transitions into and out of poverty across waves: African balanced panel members only

		Wave 2				Wave 3	
		Poor	**Non-poor**			**Poor**	**Non-poor**
Wave 1	**Poor**	89.55	10.45	**Wave 2**	**Poor**	85.56	14.44
	Non-poor	35.59	64.41		**Non-poor**	26.47	73.53
		Wave 4				**Wave 4**	
		Poor	**Non-poor**			**Poor**	**Non-poor**
Wave 3	**Poor**	80.41	19.59	**Wave 1**	**Poor**	74.65	25.53
	Non-poor	25.77	74.23		**Non-poor**	28.48	71.52

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

Table 13: Poverty transitions: Proportion of sample by transition status: African balanced panel members only

		Wave 2				Wave 3	
		Poor	**Non-poor**			**Poor**	**Non-poor**
Wave 1	**Poor**	72.41	8.45	**Wave 2**	**Poor**	67.79	11.44
	Non-poor	6.81	12.33		**Non-poor**	5.50	15.28
		Wave 4				**Wave 4**	
		Poor	**Non-poor**			**Poor**	**Non-poor**
Wave 3	**Poor**	58.93	14.36	**Wave 1**	**Poor**	60.36	20.50
	Non-poor	6.88	19.83		**Non-poor**	5.45	13.69

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

Table 14: Transitions with finer poverty levels: African balanced panel members only

		Wave 2					Wave 3		
		Severe	**Poor**	**Non-poor**			**Severe**	**Poor**	**Non-poor**
	Severe	74.44	18.75	6.81		**Severe**	64.69	24.82	10.49
Wave 1	**Poor**	45.23	33.62	21.15	**Wave 2**	**Poor**	38.42	36.61	24.98
	Non-poor	17.95	17.64	64.41		**Non-poor**	10.64	15.84	73.53
		Wave 4					**Wave 4**		
		Severe	**Poor**	**Non-poor**			**Severe**	**Poor**	**Non-poor**
	Severe	60.92	24.31	14.77		**Severe**	54.67	24.29	21.05
Wave 3	**Poor**	35.71	35.67	28.62	**Wave 1**	**Poor**	30.23	31.79	37.98
	Non-poor	12.13	13.64	74.23		**Non-poor**	11.88	16.60	71.52

Note: In this panel the cells sum to 100%

		Wave 4		
		Severe	**Poor**	**Non-poor**
	Severe	32.97	14.65	12.69
Wave 1	**Poor**	6.21	6.53	7.80
	Non-poor	2.27	3.18	13.69

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

D Trigger events with a modified equivalence scale

Table 15: Trigger events associated with poverty entry and exit: Modified equivalence scale

	Poverty entry				Poverty exit			
	W1 to W2	**W2 to W3**	**W3 to W4**	**W1 to W4**	**W1 to W2**	**W2 to W3**	**W3 to W4**	**W1 to W4**
Demographic								
Head changed	36.05	50.79	51.87	47.88	35.96	49.70	48.77	53.74
Needs > money	9.70	3.74	10.99	11.04	0.81	1.26	0.79	0.52
Demographic share	**45.75**	**54.53**	**62.86**	**58.92**	**36.77**	**50.96**	**49.56**	**54.26**
Income								
Head labour earnings	24.64	12.14	9.38	16.79	13.49	16.99	5.28	4.52
Spouse labour earnings	2.05	5.55	2.07	1.65	2.03	2.48	3.00	1.68
Other labour earnings	11.83	12.18	11.95	6.85	24.10	14.40	12.48	12.44
Remittances	3.95	3.10	3.28	3.88	2.43	3.87	7.56	3.56
Grant income	5.65	3.31	3.09	7.38	8.85	8.74	20.06	22.71
Income share	**48.12**	**35.85**	**29.77**	**36.56**	**56.21**	**42.98**	**48.39**	**44.92**
Inconclusive	6.13	9.62	7.37	4.52	5.99	6.06	2.05	0.62
Total	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**
Observations	926	1 233	1 342	479	2 122	2 855	3 990	5 945

Source: Own calculations from the first four waves of NIDS. Attrition-corrected panel weights applied to members of the balanced panel.

E Descriptive statistics for sample included in Markovian model

Table 16: Descriptive statistics for sample included in Markovian model

	Poor in t-1	Non-poor in t-1
Individual		
Age	23.42	30.59
Race		
African	87.22%	59.71%
Coloured	11.94%	19.94%
Asian/Indian	0.44%	3.96%
White	0.39%	16.38%
Gender		
Male	44.79%	50.31%
Female	55.21%	49.69%
Retention		
Retained to period t	83.49%	76.60%
Household head		
Age	51.34	46.19
Female	60.67%	35.84%
Matric and above	8.49%	47.94%
Employed	34.75%	71.37%
Household		
Province		
W. Cape	9.04%	22.09%
E. Cape	14.06%	7.63%
N. Cape	6.82%	9.06%
Free State	5.43%	5.38%
KZN	33.27%	15.49%
North West	6.47%	6.31%
Gauteng	7.12%	20.30%
Mpumalanga	7.36%	7.95%
Limpopo	10.42%	5.80%
Geo-type		
Traditional	53.26%	17.01%
Urban	38.78%	75.43%
Farming	7.64%	7.42%
Composition		
Adults 65 and above	27.18%	15.82%
Children 15 and below	88.77%	61.76%
Any workers	57.90%	91.53%
Ownership		
Own dwelling	83.35%	71.21%
Observation numbers		
Individuals	40 850	
Person-waves	88 090	

Source: Own calculations from the first four waves of NIDS.
Variables reported at the individual level in period $t - 1$.

Table 17: Model estimates of poverty in t, conditional on poverty status in $t-1$: African respondents only

Covariate at $t-1$	Poor at $t-1$		Non-poor at $t-1$	
	Marginal effect	|t-ratio|	Marginal effect	|t-ratio|
Individual				
Age	-0.002	(11.91)	-0.003	(4.30)
Age squared	0.00005	(9.55)	0.00006	(3.22)
Female	0.037	(8.08)	0.045	(2.82)
Household head				
Age	-0.001	(0.40)	-0.004	(1.30)
Age squared	-0.00001	(1.45)	0.000004	(0.11)
Female	0.023	(4.61)	0.060	(3.52)
Matric and above	-0.115	(14.92)	-0.231	(11.12)
Employed	0.022	(3.58)	-0.047	(2.29)
Household				
Urban	-0.055	(9.70)	-0.032	(1.59)
Farm	-0.018	(1.72)	0.006	(0.17)
Adult 65 and above	0.007	(0.91)	0.006	(0.17)
Children 15 and below	0.034	(22.24)	-0.007	(0.88)
Any workers	-0.053	(9.34)	0.087	(2.56)
Own dwelling	0.049	(7.31)	0.020	(0.96)
Log likelihood	-72 960			
Model chi-squared (d.f. = 52)	8 644 ($p<0.000$)			
No. of clusters	10 753			
No. of observations	33 199			
No. of observations (person-waves)	71 643			

Source: Own calculations from the first four waves of NIDS. Reference categories for binary covariates: male, male household head, household head does not have matric, household head is not employed, Western Cape province, rural area, no adults over 65 in the household, no children under 15 in the household, no workers in the household, household members do not own the dwelling. The base wave is wave 1.

F Probit model of poverty dynamics

Table 18: Probit model of poverty in t, conditional on poverty status in $t-1$

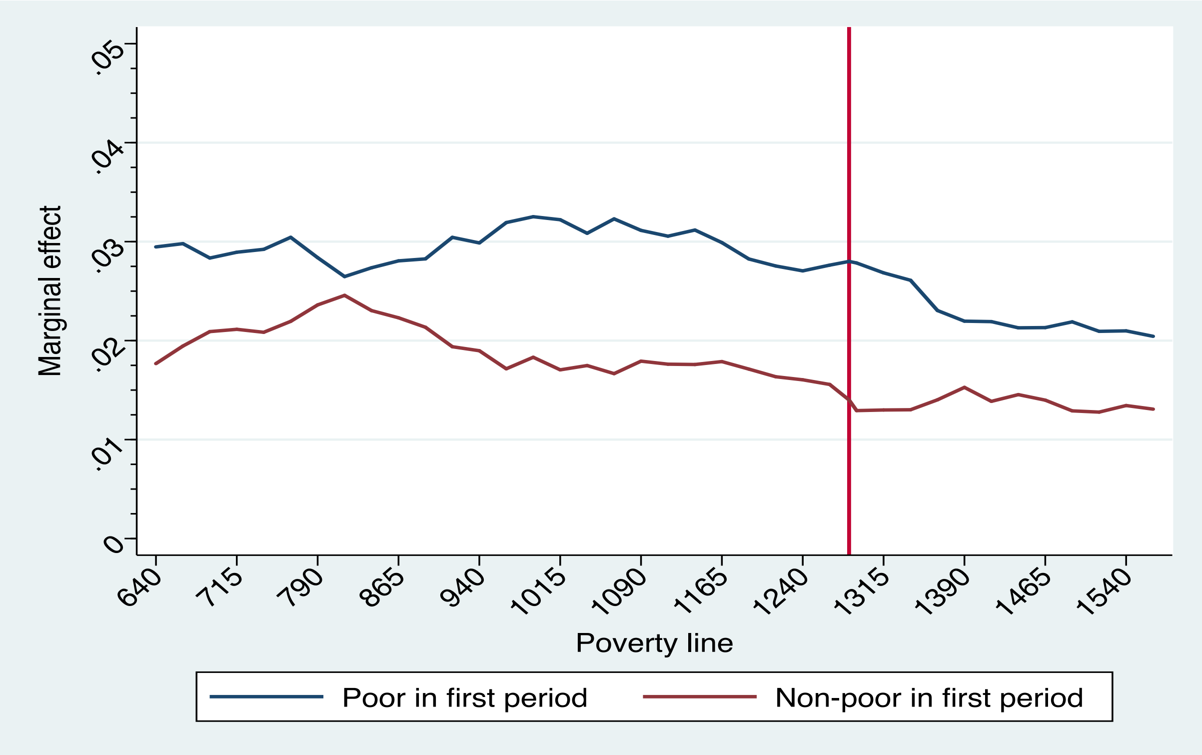
Covariate at $t-1$	Poor at $t-1$		Non-poor at $t-1$	
	Marginal effect	|t-ratio|	Marginal effect	|t-ratio|
Individual				
Age	-0.003	(12.540)	-0.001	(3.280)
Age squared	0.00003	(9.130)	0.00001	(1.520)
Female	0.028	(9.370)	0.014	(2.790)
African	0.235	(6.080)	0.220	(10.830)
Coloured	0.227	(5.830)	0.167	(7.770)
Household head				
Age	0.000	(0.060)	-0.006	(3.090)
Age squared	-0.00001	(0.830)	0.00004	(1.810)
Female	0.018	(2.880)	0.032	(3.390)
Matric and above	-0.125	(13.420)	-0.157	(14.910)
Employed	0.001	(0.100)	-0.021	(1.700)
Household				
Urban	-0.052	(6.590)	-0.038	(2.840)
Farm	-0.001	(0.070)	-0.003	(0.140)
Adult 65 and above	0.006	(0.570)	0.051	(2.670)
Children 15 and below	0.032	(15.380)	-0.031	(2.010)
Any workers	-0.053	(7.000)	0.002	(0.300)
Own dwelling	0.027	(3.530)	0.000	(0.010)
Log likelihood	-28 877			
Model chi-squared (d.f. = 54)	6 142 ($p<0.00$)			

Source: Own calculations from the first four waves of NIDS. Reference categories for binary covariates: male, white, male household head, household head does not have matric, household head is not employed, Western Cape province, rural area, no adults over 65 in the household, no children under 15 in the household, no workers in the household, household members do not own the dwelling. The base wave is wave 1.

G Difference in marginal effects for probit model

I Female marginal effects

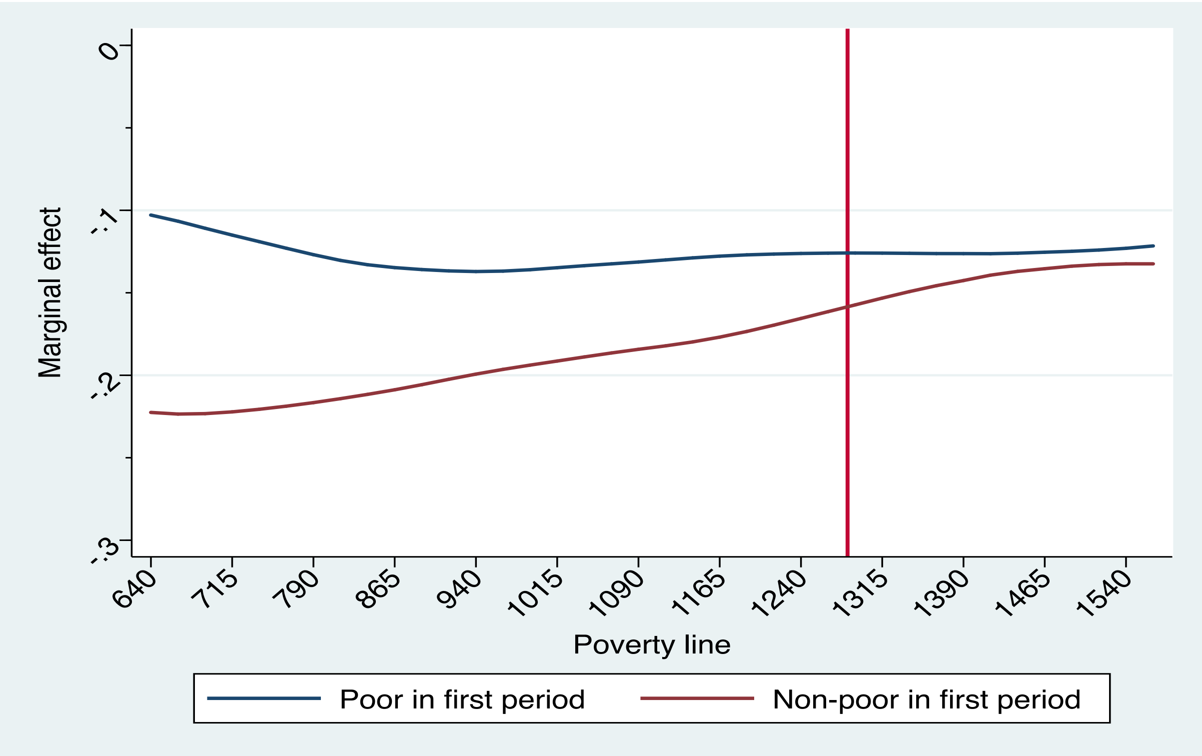
Figure 11: Difference in female marginal effect for different poverty lines: Probit model only



Source: Own calculations from the first four waves of NIDS.

II Household head with at least a matric marginal effects

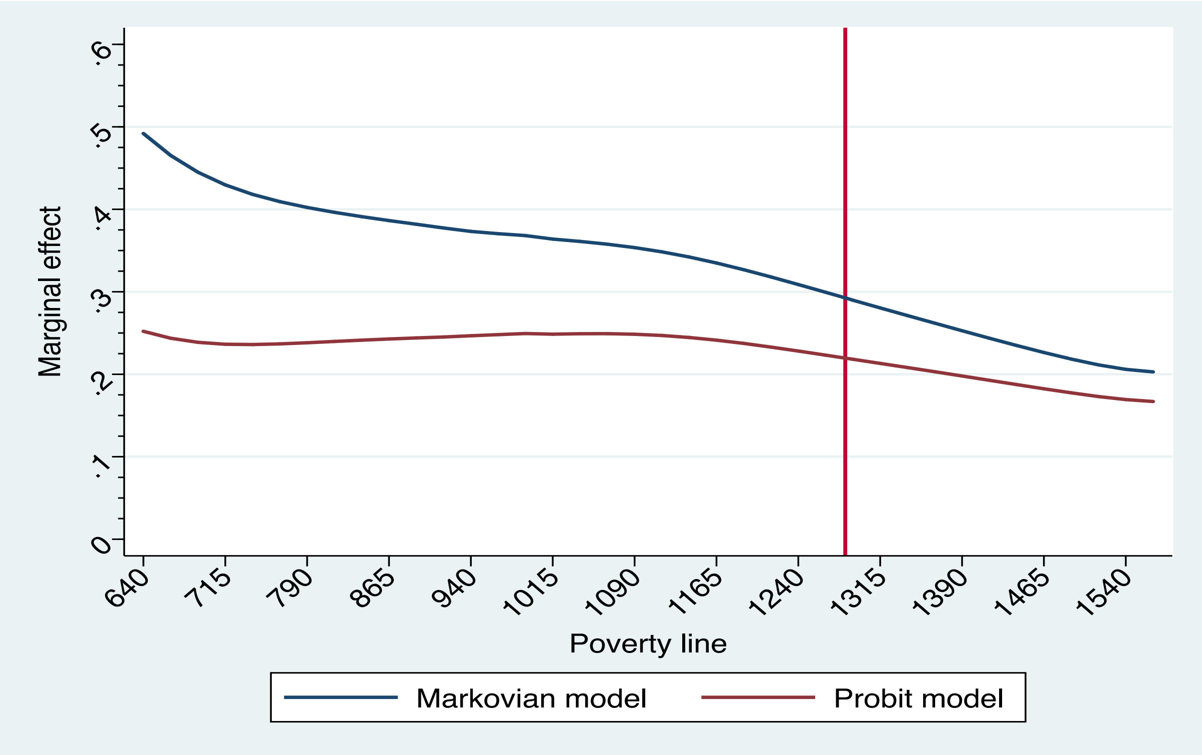
Figure 12: Difference in household head with matric or above marginal effect for different poverty lines: Probit model only



Source: Own calculations from the first four waves of NIDS.

III African marginal effect: Markovian model compared to probit model

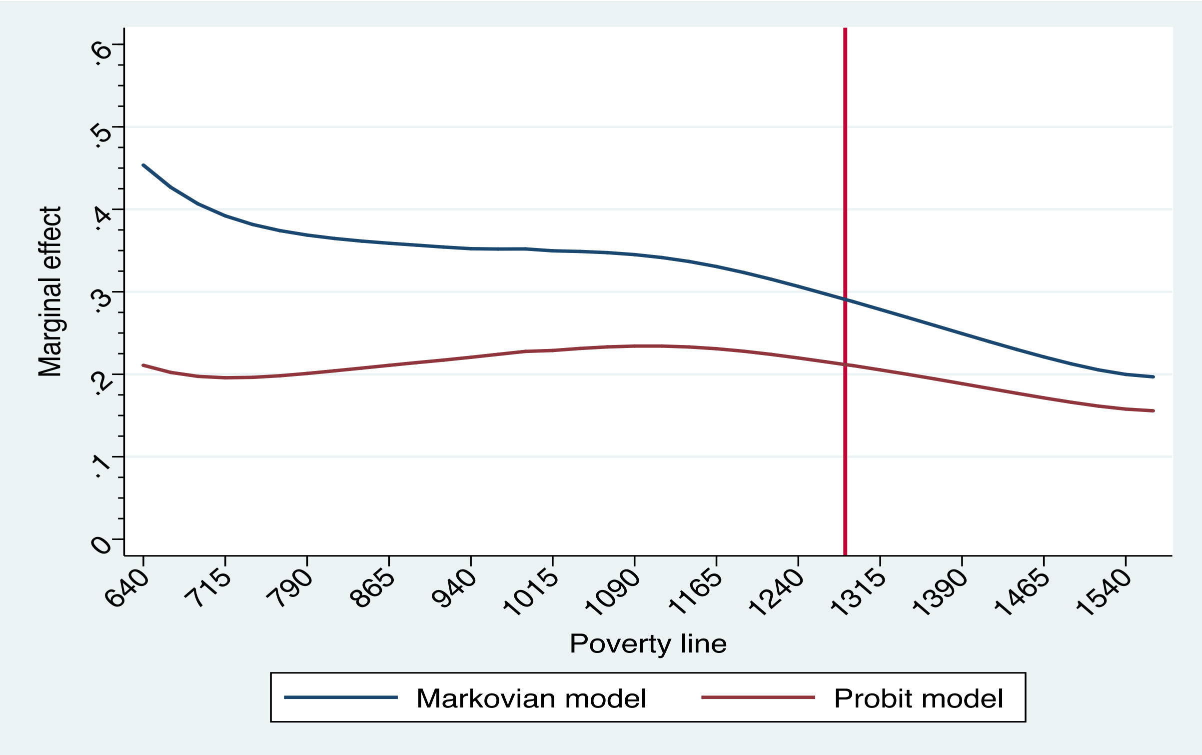
Figure 13: Difference in African marginal effect for different poverty lines: Markovian model compared to probit model



Source: Own calculations from the first four waves of NIDS.

IV Coloured marginal effect: Markovian model compared to probit model

Figure 14: Difference in Coloured marginal effect for different poverty lines: Markovian model compared to probit model



Source: Own calculations from the first four waves of NIDS.

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southern africa labour and development research unit

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

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

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